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The Many Roles of Data Analysis in Planning for Hurricane Impacts

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Conference on Data Analysis

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What is the planning horizon?

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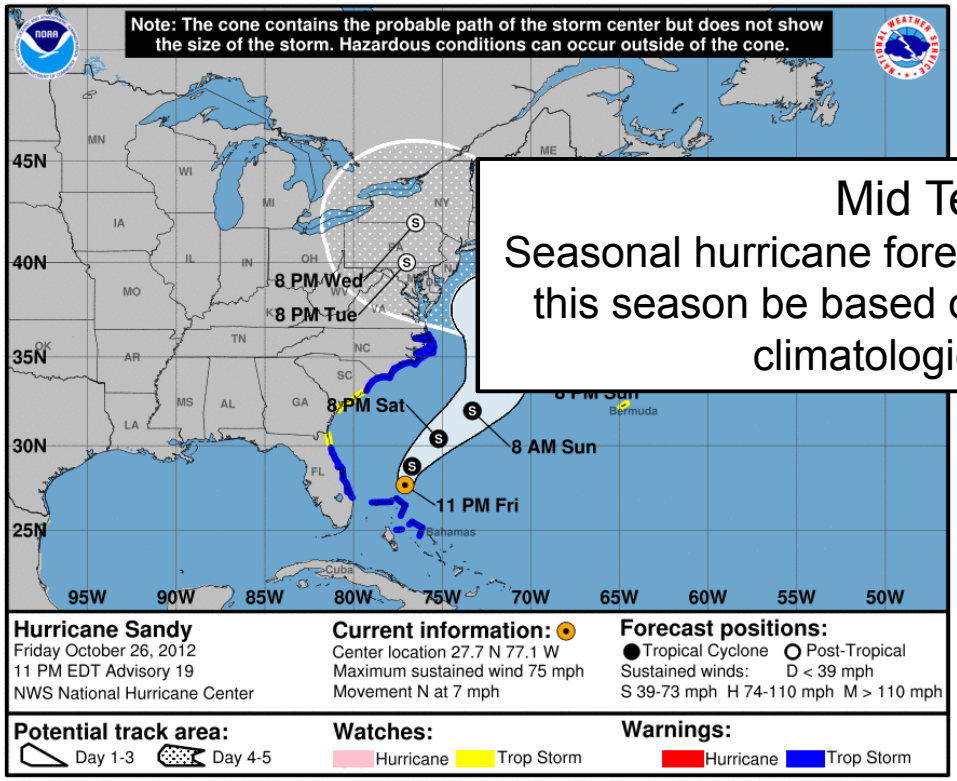
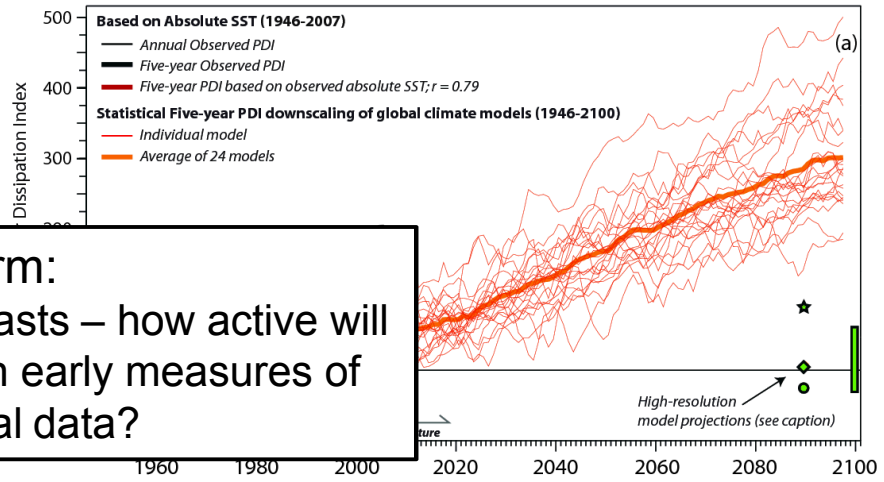
Short Term:
There's a storm coming, with uncertain track and intensity estimates.

Long Term:
Climate is changing, and there is uncertainty as to how future hurricanes will behave.

Mid Term:
Seasonal hurricane forecasts – how active will this season be based on early measures of climatological data?





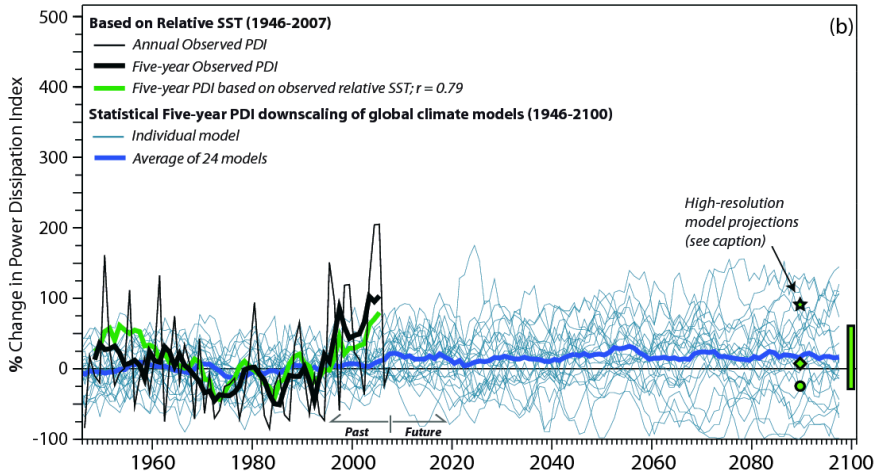
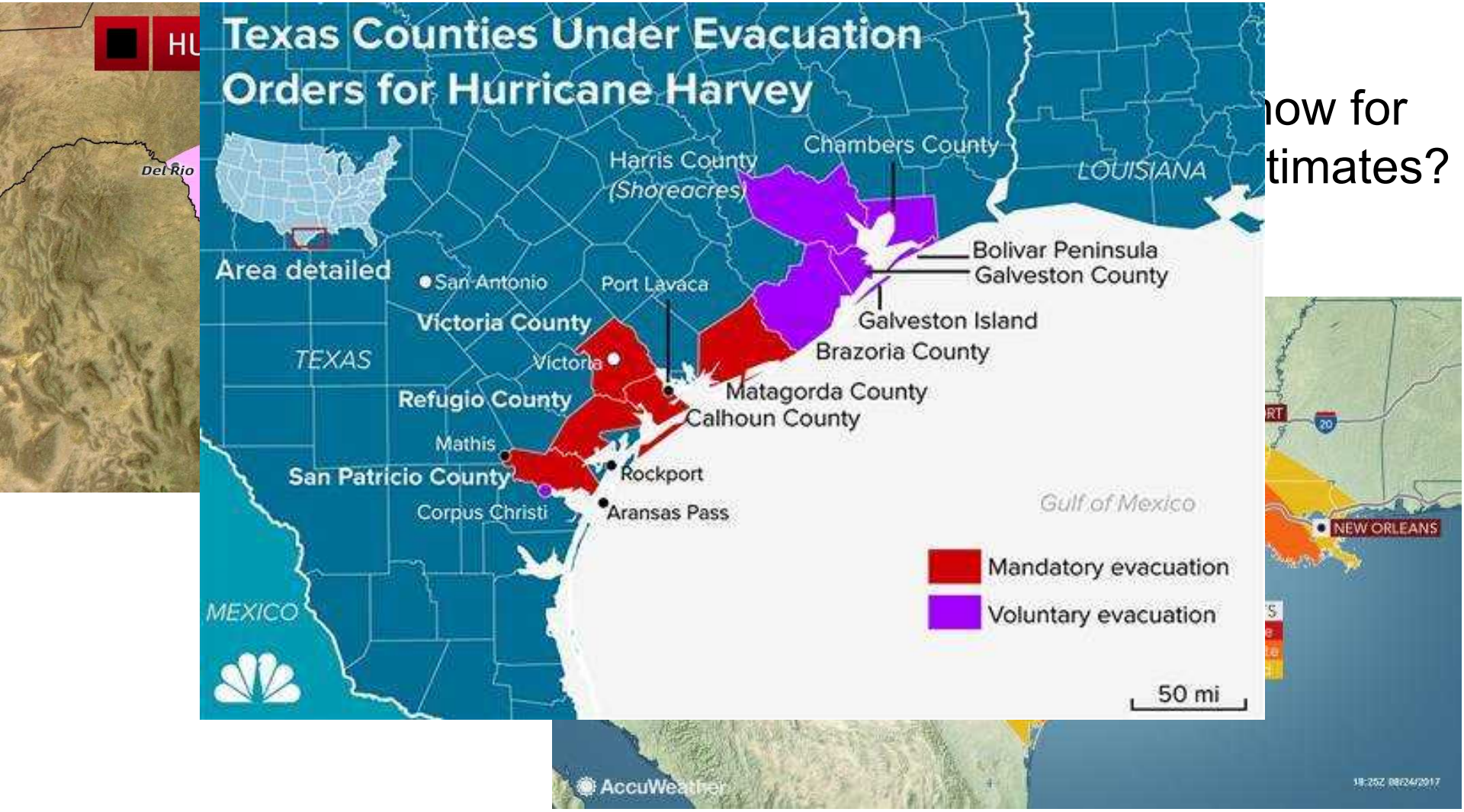


Image courtesy of the National Hurricane Center

Vecchi, Gabriel A., Kyle L. Swanson, and Brian J. Soden. "Whither hurricane activity?." *Science* (2008): 687-689.

Short Term Planning

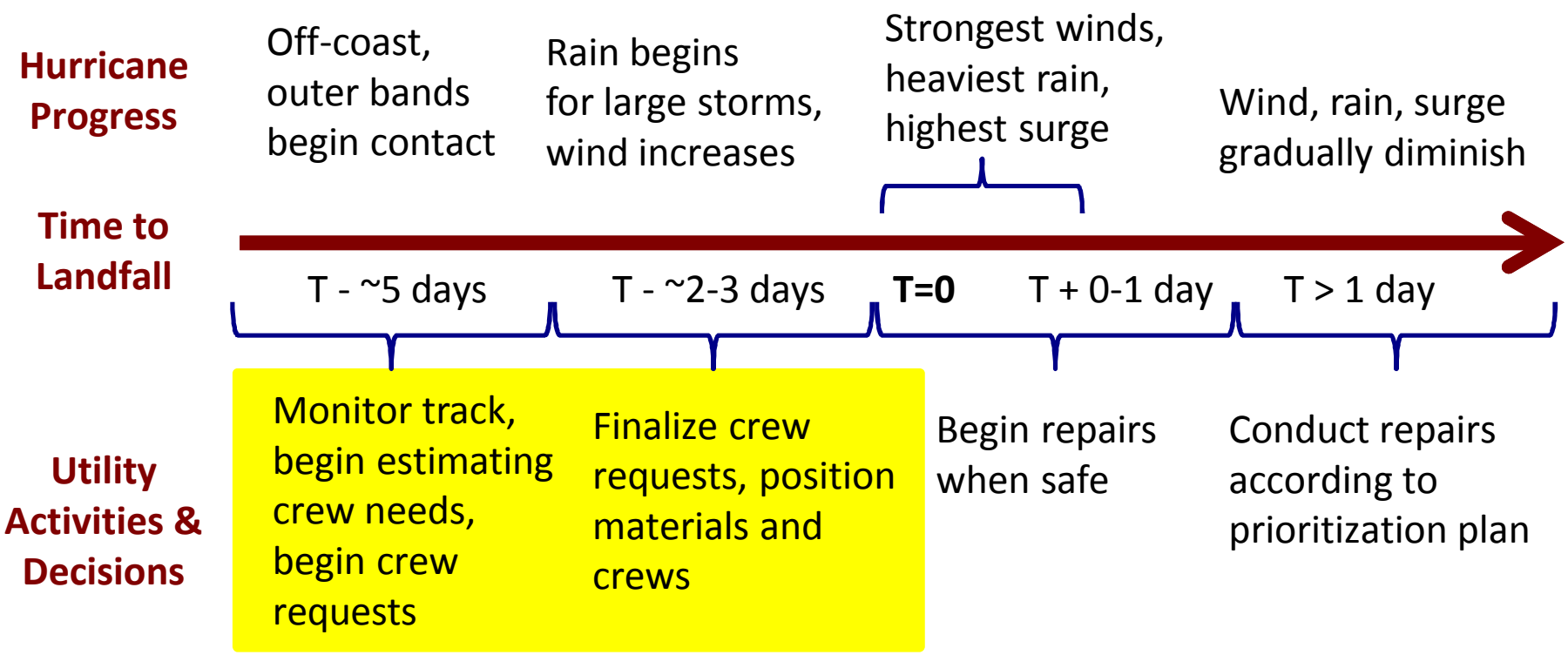
Surely we can do better!



...now for ...timates?

Power Outage Prediction

- Anticipating number and location of outages allows utilities and emergency responders to plan ahead
- Use best storm track projections and intensity forecasts to develop real-time outage predictions



Outage Prediction Model

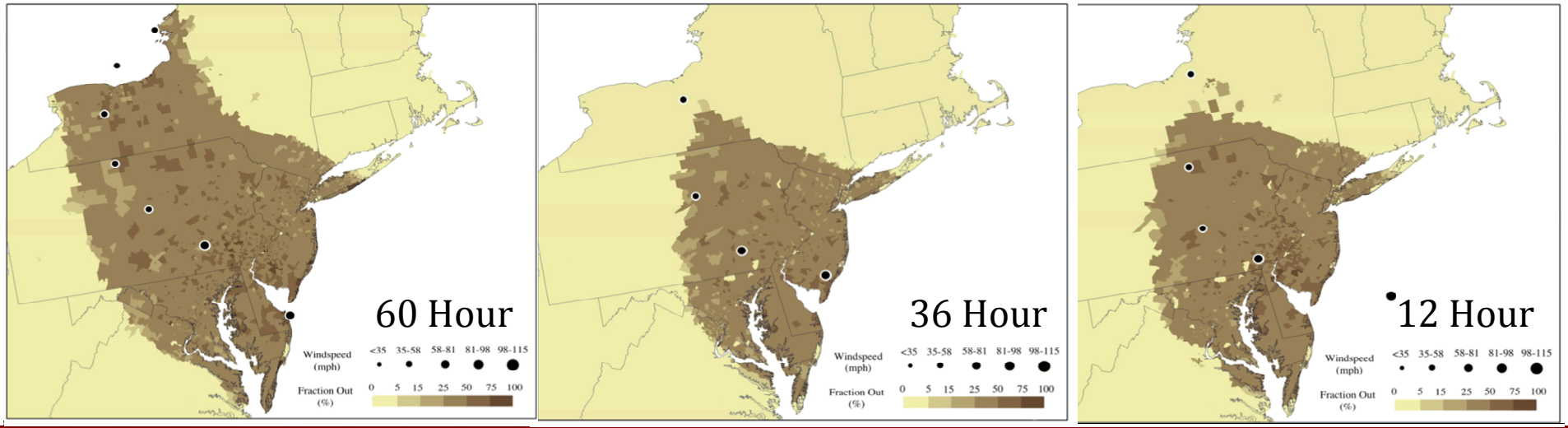
- Started with detailed, utility-specific distribution-level outage data from recent hurricanes hitting the utility service area
- Train and test statistical models for predictive accuracy
  - Random Forest model performed best
- Response variable: Number of customers without power
- Covariates:
  - Wind speeds across region of interest
    - Calculate wind characteristics using a wind field model (Willoughby et al. 2006; Holland 2008)
  - Land Cover, soil moisture, mean precipitation, and drought measures

Utility-specific variables!

Generalizing the Model

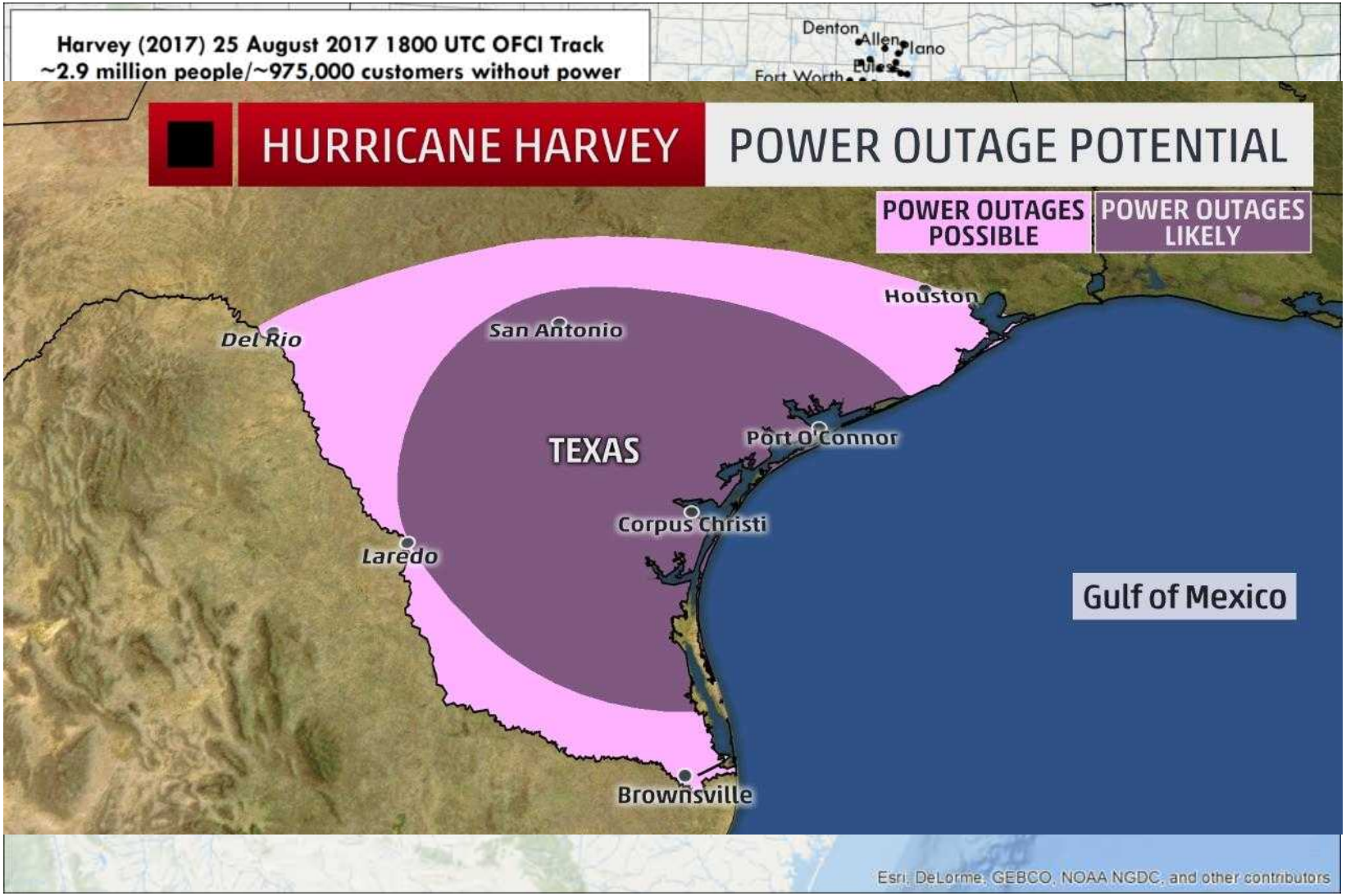
- Evaluate model predictive accuracy *without* utility-specific variables
  - Cross-validation to choose the simplest model while maintaining acceptable prediction errors
  - Validate model across hurricanes; Validate model across states
  - Test and iterate for actual, oncoming storms: Irene and Sandy

Predictions for Superstorm Sandy, for 60, 36, and 12 hours before landfall

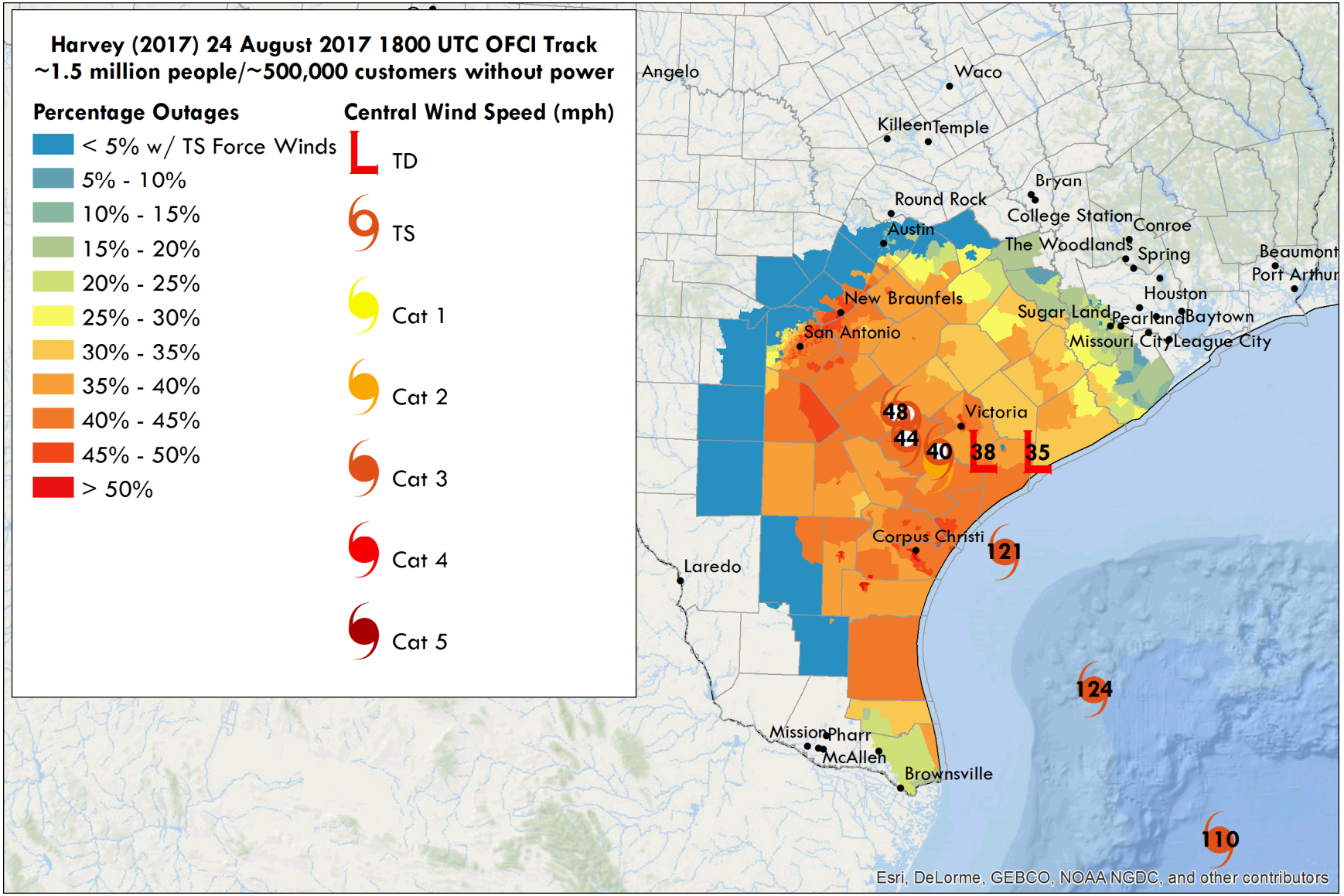


Guikema, S.D., Nateghi, R., Quiring, S.M., Staid, A., Reilly, A.C. and Gao, M., 2014. Predicting hurricane power outages to support storm response planning. *IEEE Access*, 2, pp.1364-1373.

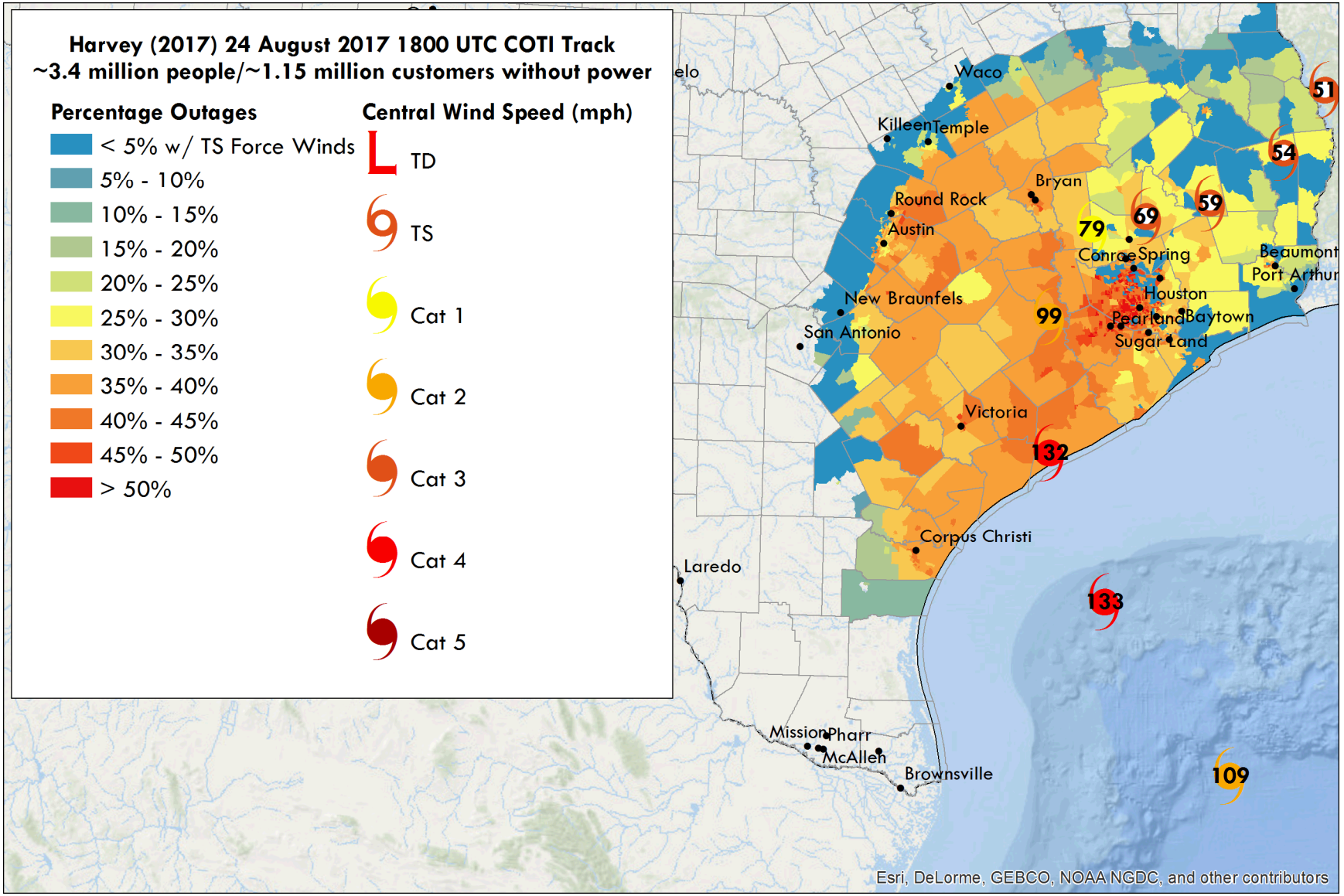
Hurricane Harvey



Official Track Forecast



COTI Track Forecast



Ongoing Development

- Seth Guikema and research group

- Steven Quiring and research group

- Brent McRoberts

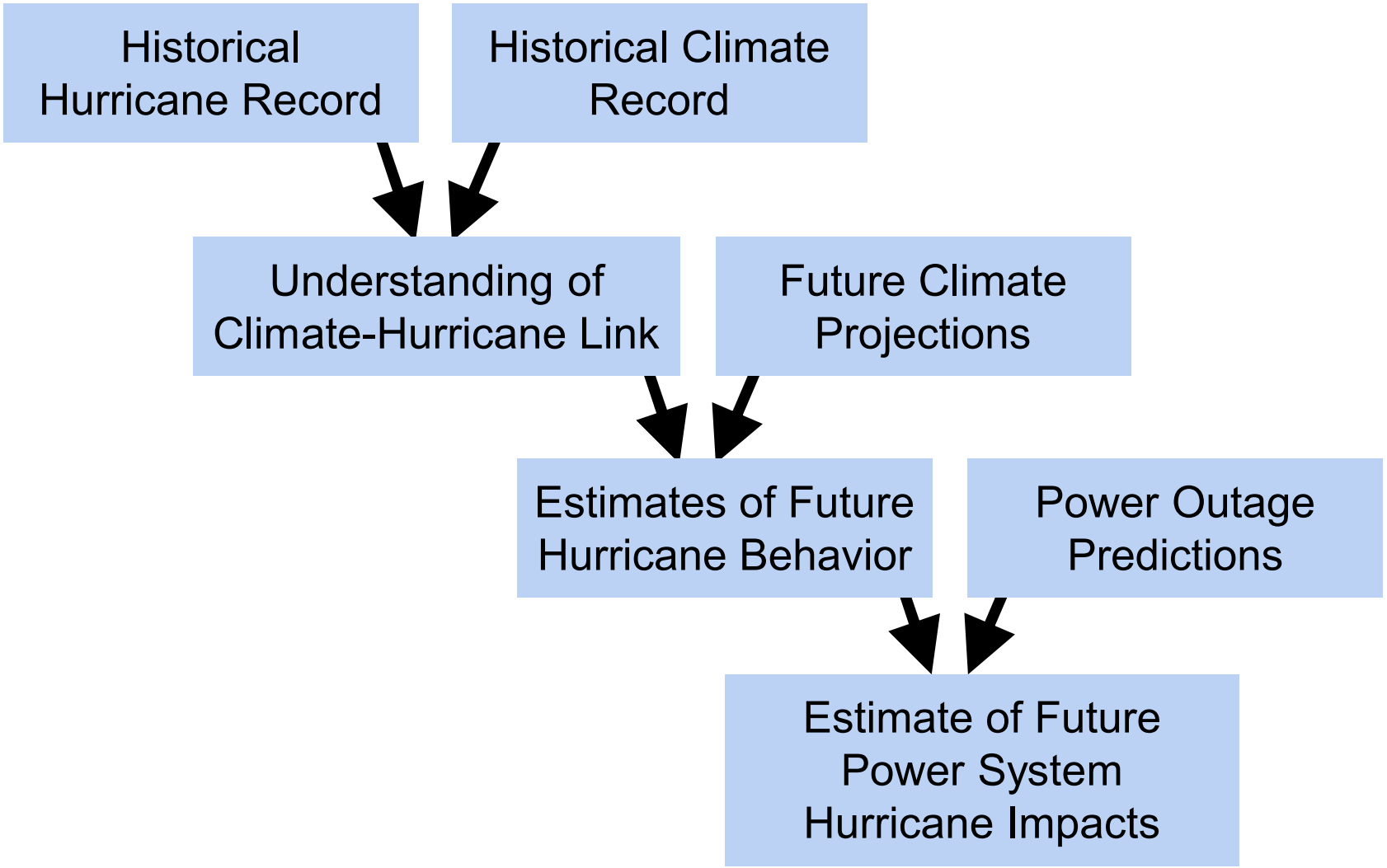
Real-Time Outage Prediction

- Limitations with only publicly-available data
- Currently models only wind-induced outages, does not consider storm surge or flooding
- Heavily dependent on an accurate track/intensity model
- However, provides accurate estimates of the spatial distribution of expected outages for an approaching storm
- Incredibly useful for crew positioning and emergency response preparation efforts

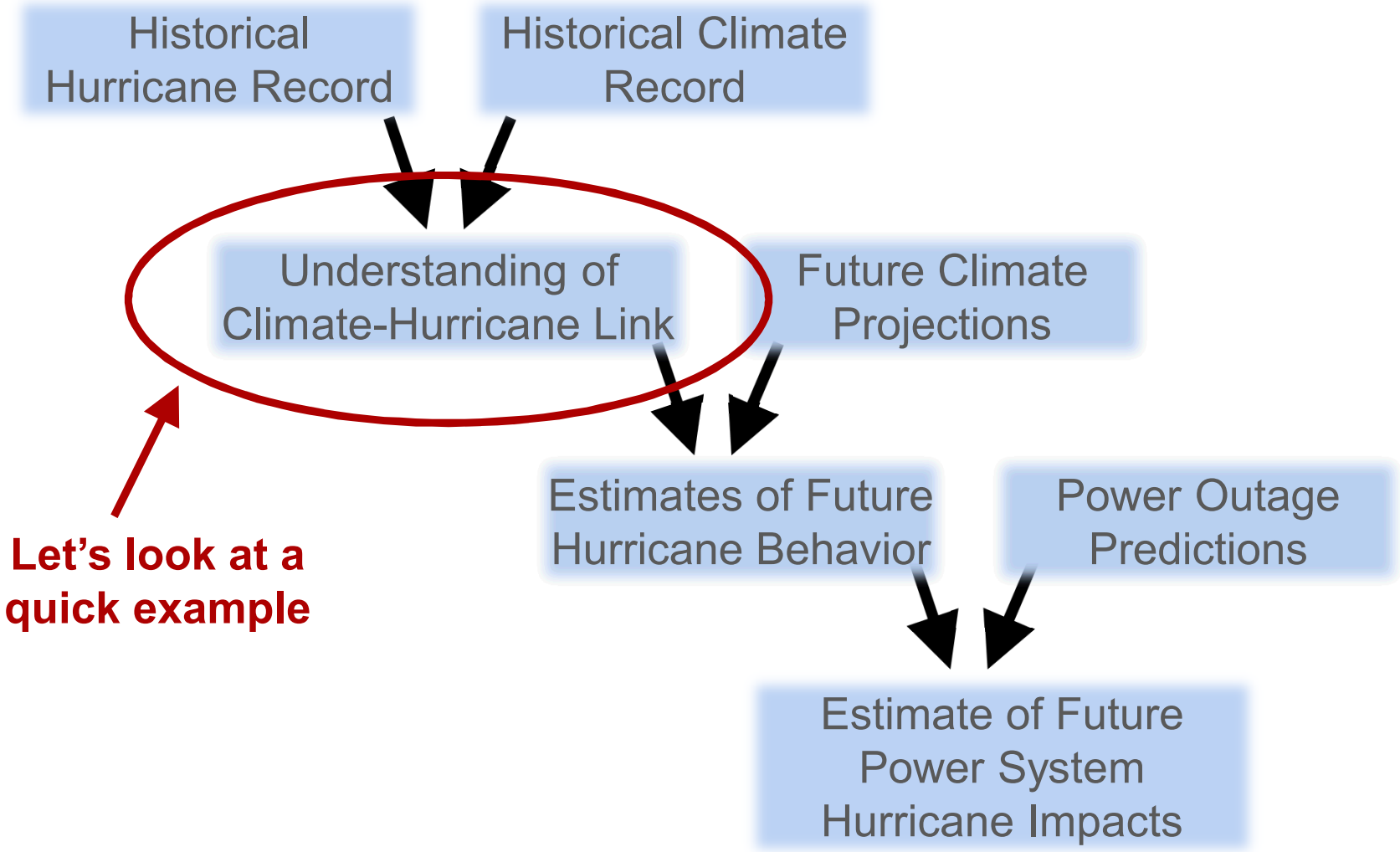
How about long term impacts?

- If we can predict outages for an oncoming storm, we can estimate the impacts of future storms, *on average*
- But, we need to know what future storms will look like!
- To do so, we must consider climate change…

How does this all come together?

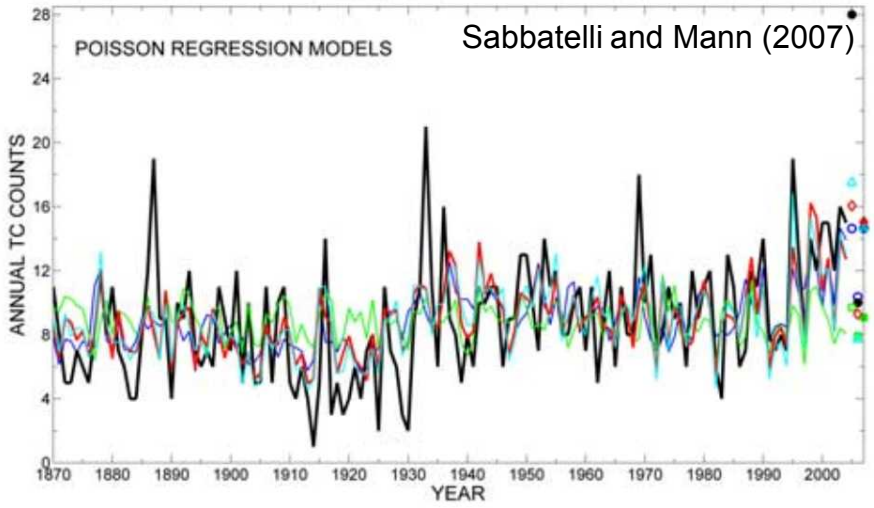


What about Uncertainty?



Seasonal Prediction

- Various agencies issue forecasts for how active the upcoming hurricane season will be, based on current climatology
- 2017 hurricane season was extremely active:
  - 17 named tropical storms (average 12)
  - 10 hurricanes (average 6)
  - 6 major hurricanes (average 2)
- Pre-season (Dec-Apr), all agencies predicted a near-average season:
  - 11-15 named tropical storms
  - 4-6 hurricanes
  - 1-3 major hurricanes
- Mid-season (Jun-Aug) forecasts increased *very* slightly

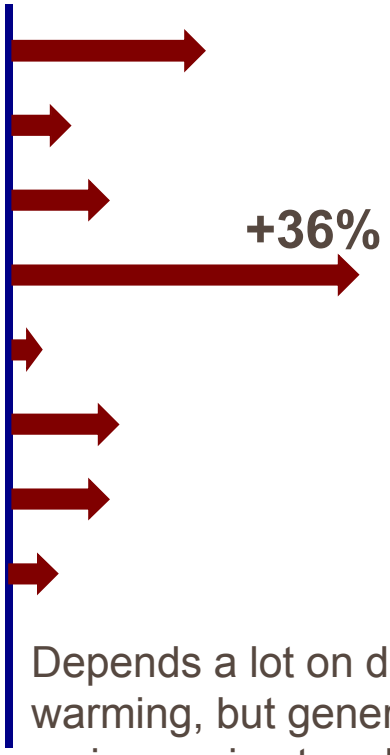


Climate link: How sure are we?

Short answer: Not very.

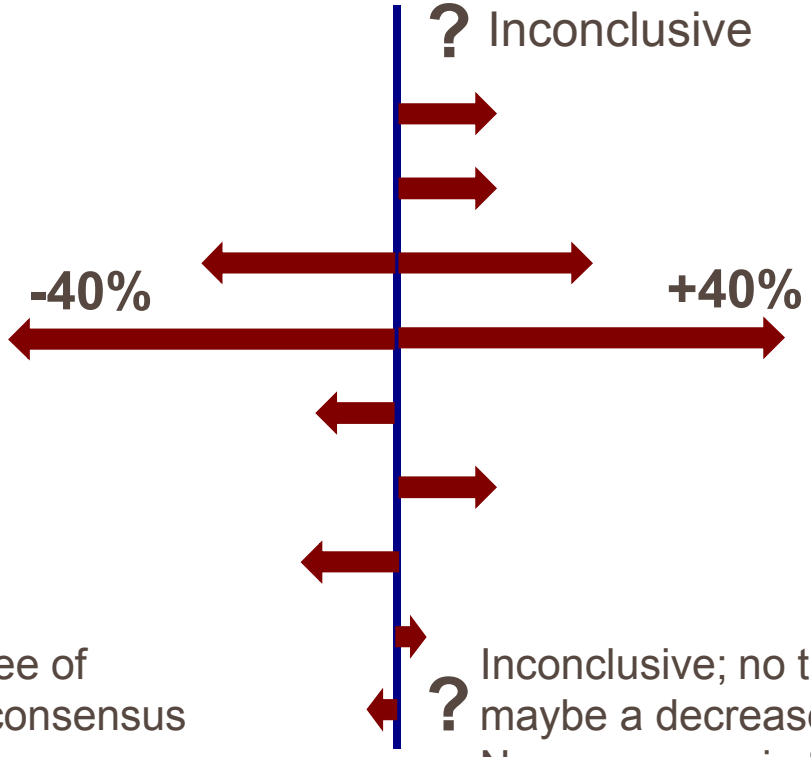
How will climate change affect North Atlantic tropical cyclone:

Intensity?



Depends a lot on degree of warming, but general consensus on increasing trend

Frequency?



Inconclusive; no trend; maybe a decrease? No consensus in the literature

Location?

?

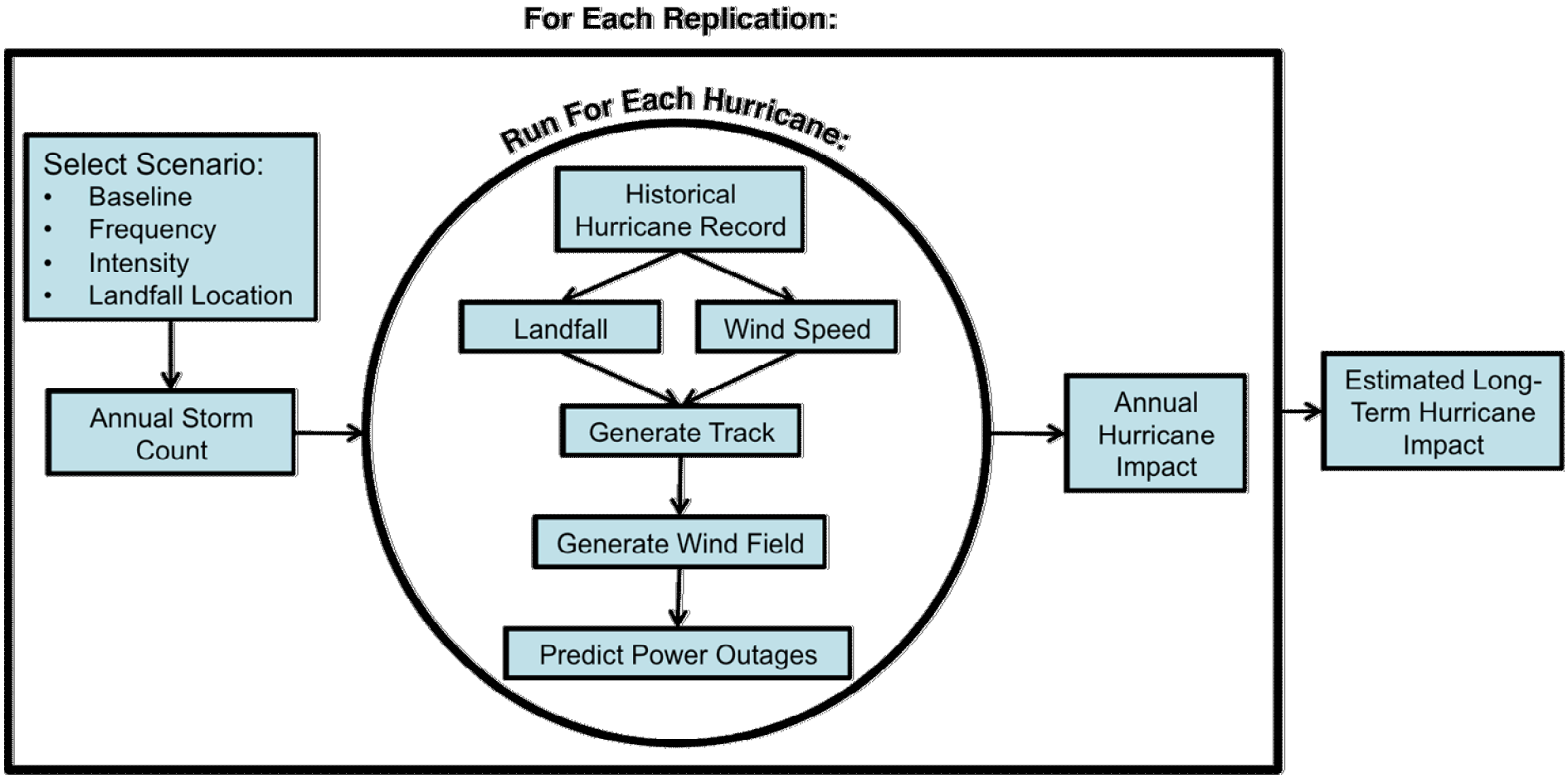
- Poleward migration in certain ocean basins
- Little to no change
- Dependent on atmospheric circulation, unsure

Scenario-Based Analysis

- Scenarios can be used to represent the range of expected change, allowing us to assess sensitivity to potential climate change
- Process:

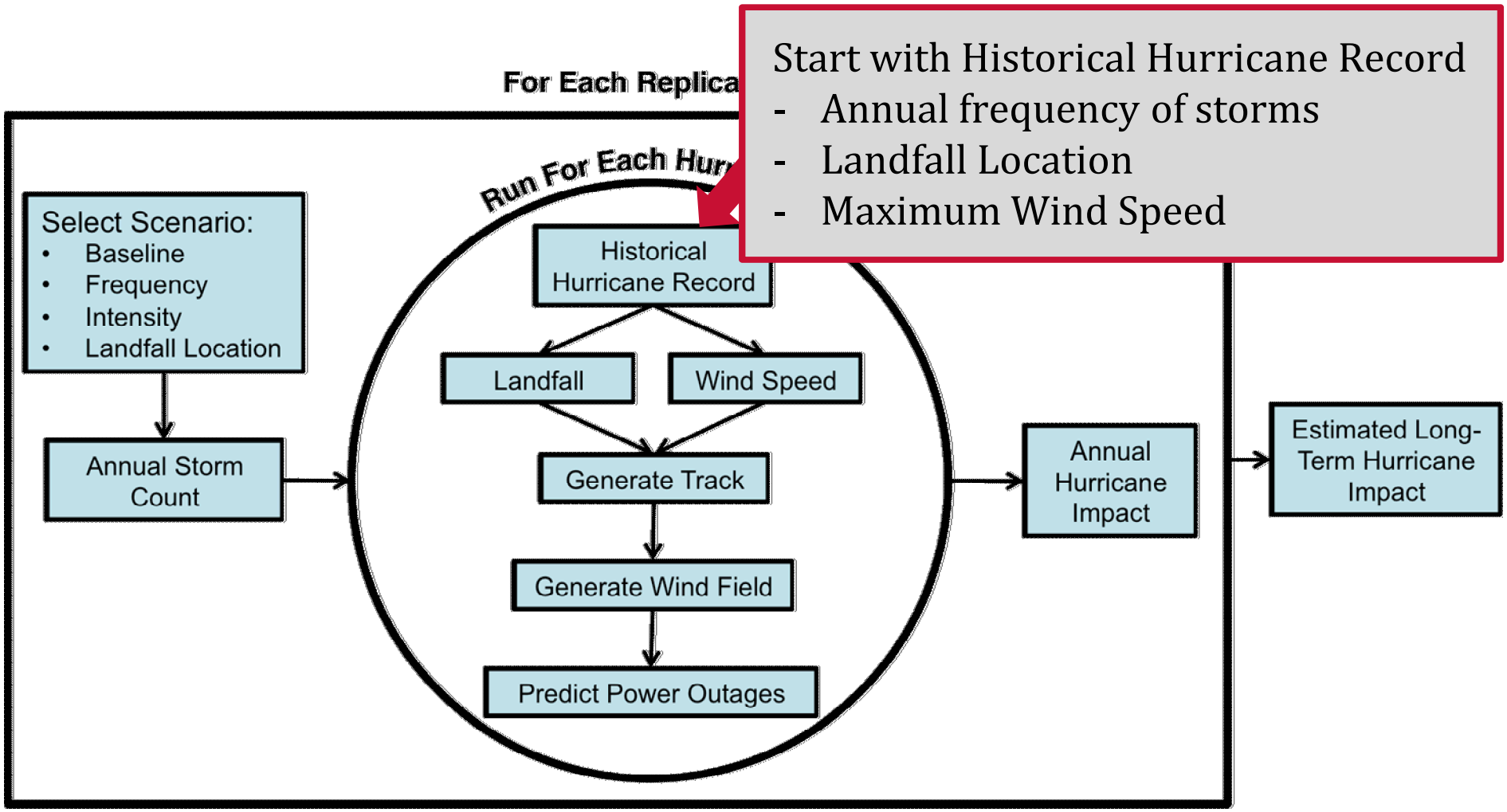
1. Choose a range of hurricane scenarios
   - Vary storm intensity, frequency, and landfall location
2. Generate virtual storms and simulate expected impacts under each scenario along U.S. Atlantic and Gulf Coasts
3. Use wind data and power outages as measures of theoretical future risk to power system infrastructure
4. Assess range of projected impacts; identify greatest risks and most vulnerable locations

Simulation Structure



Repeat to reach convergence of the 99th percentile within 1%

Simulation Structure



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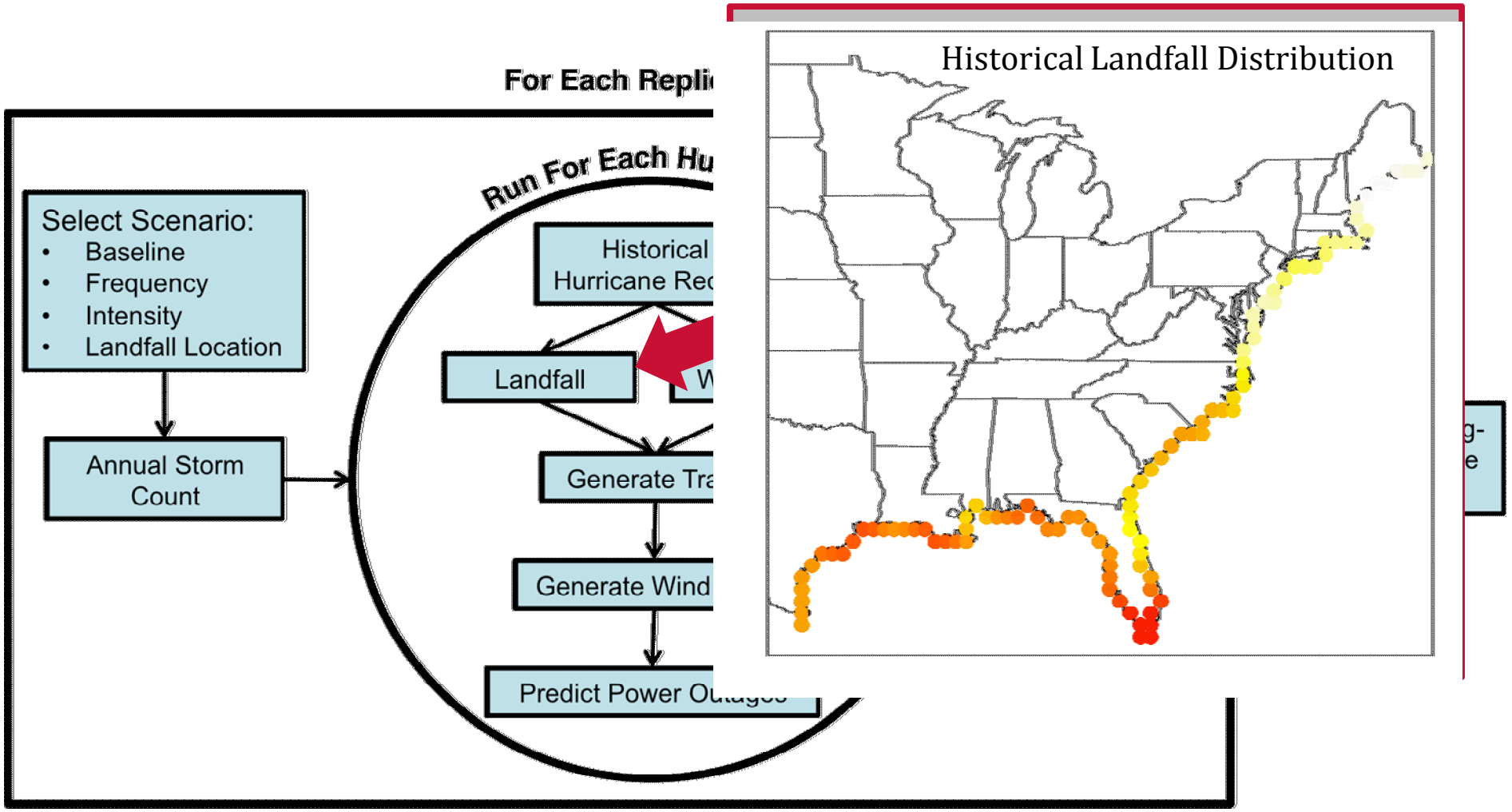

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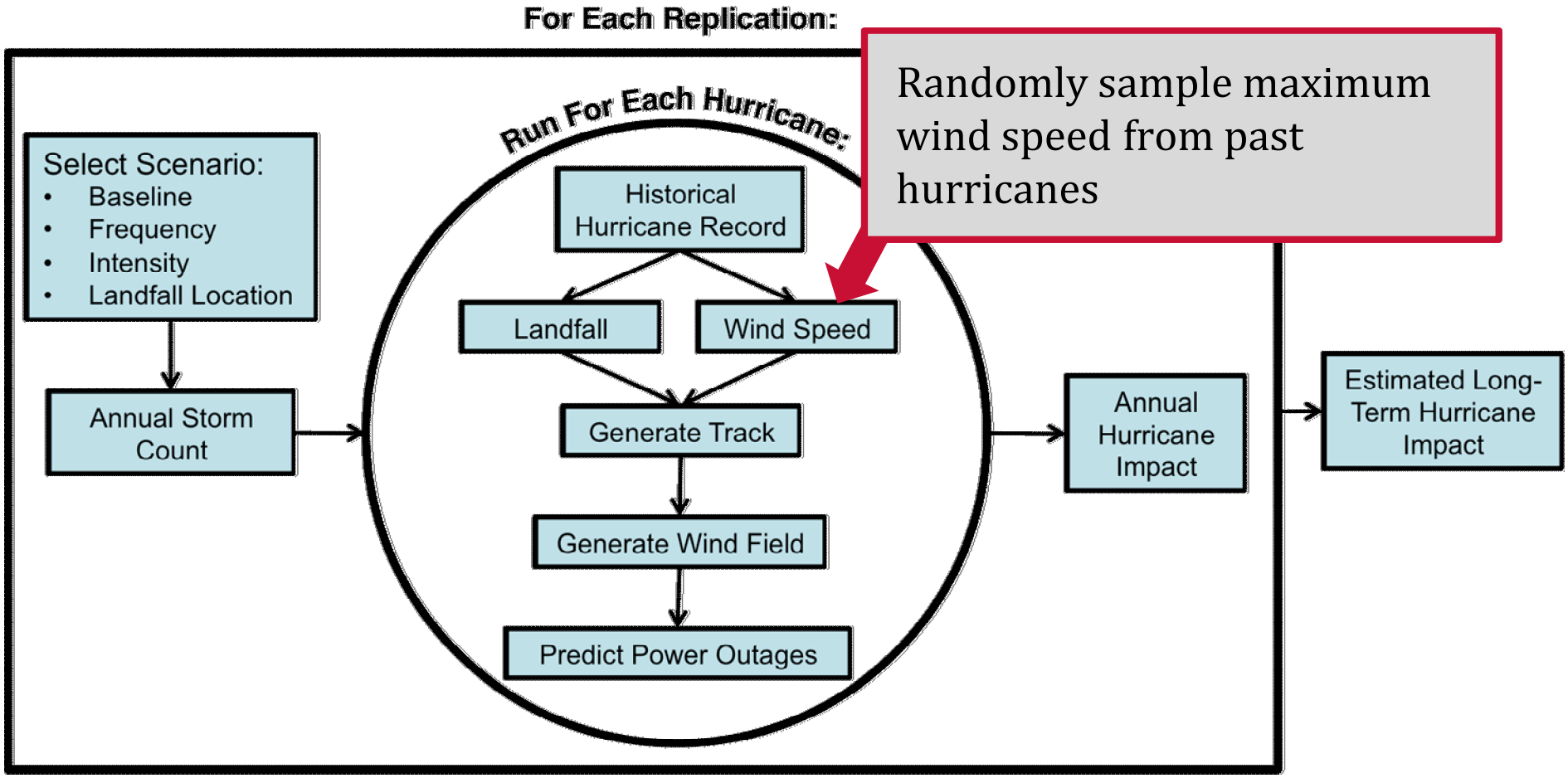

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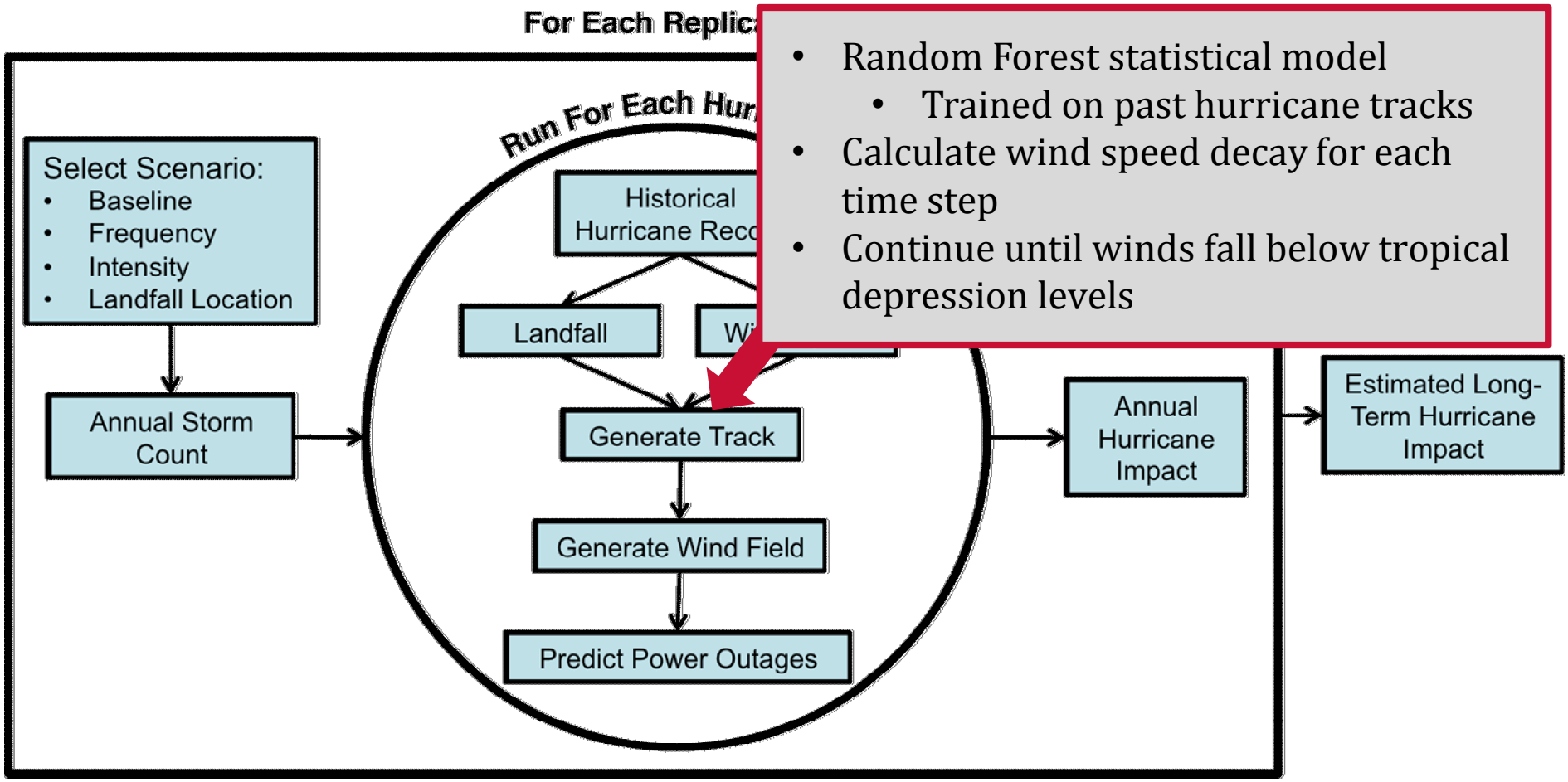
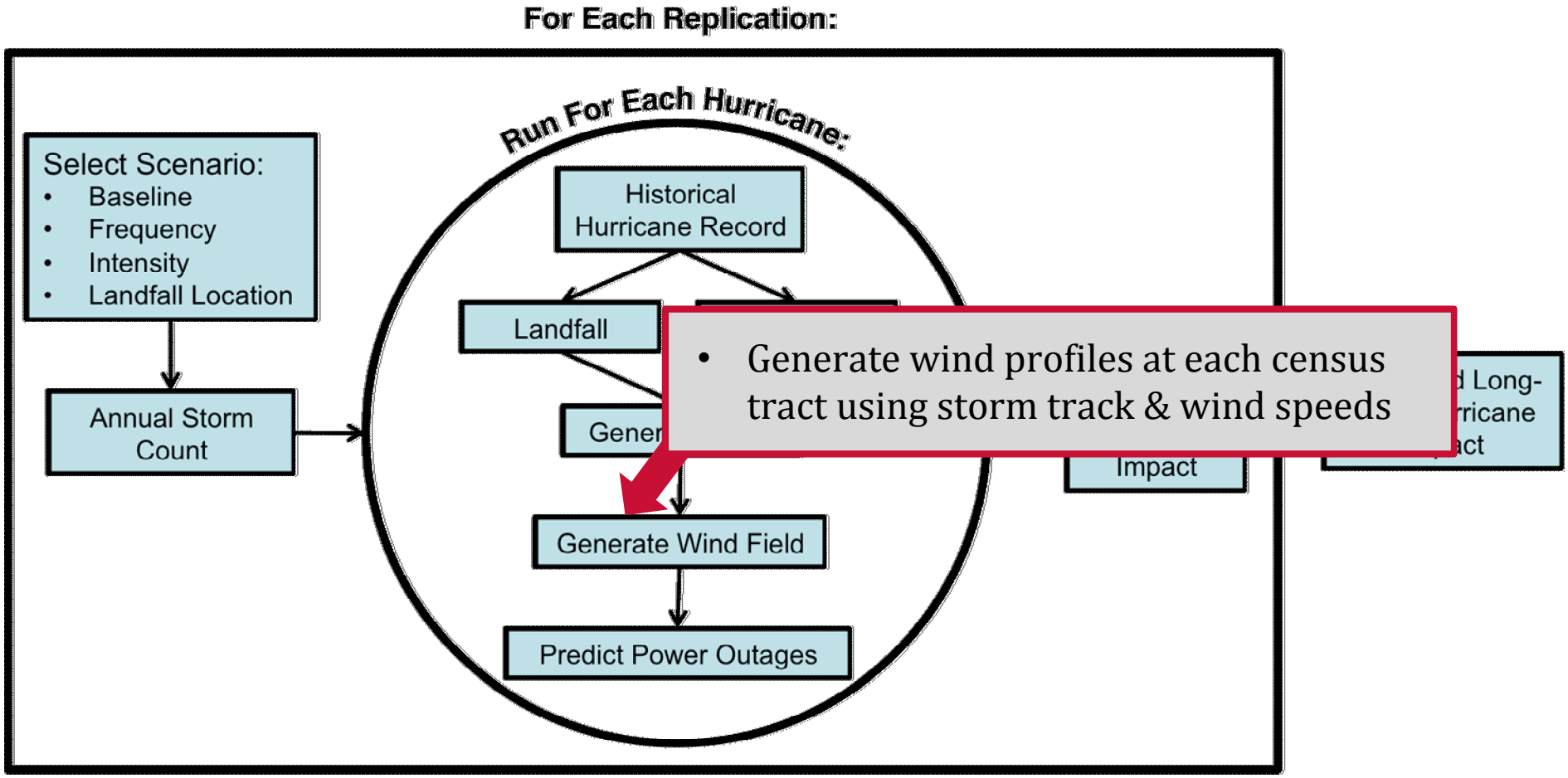


- Random Forest statistical model
  - Trained on past hurricane tracks
- Calculate wind speed decay for each time step
- Continue until winds fall below tropical depression levels

Simulation Structure



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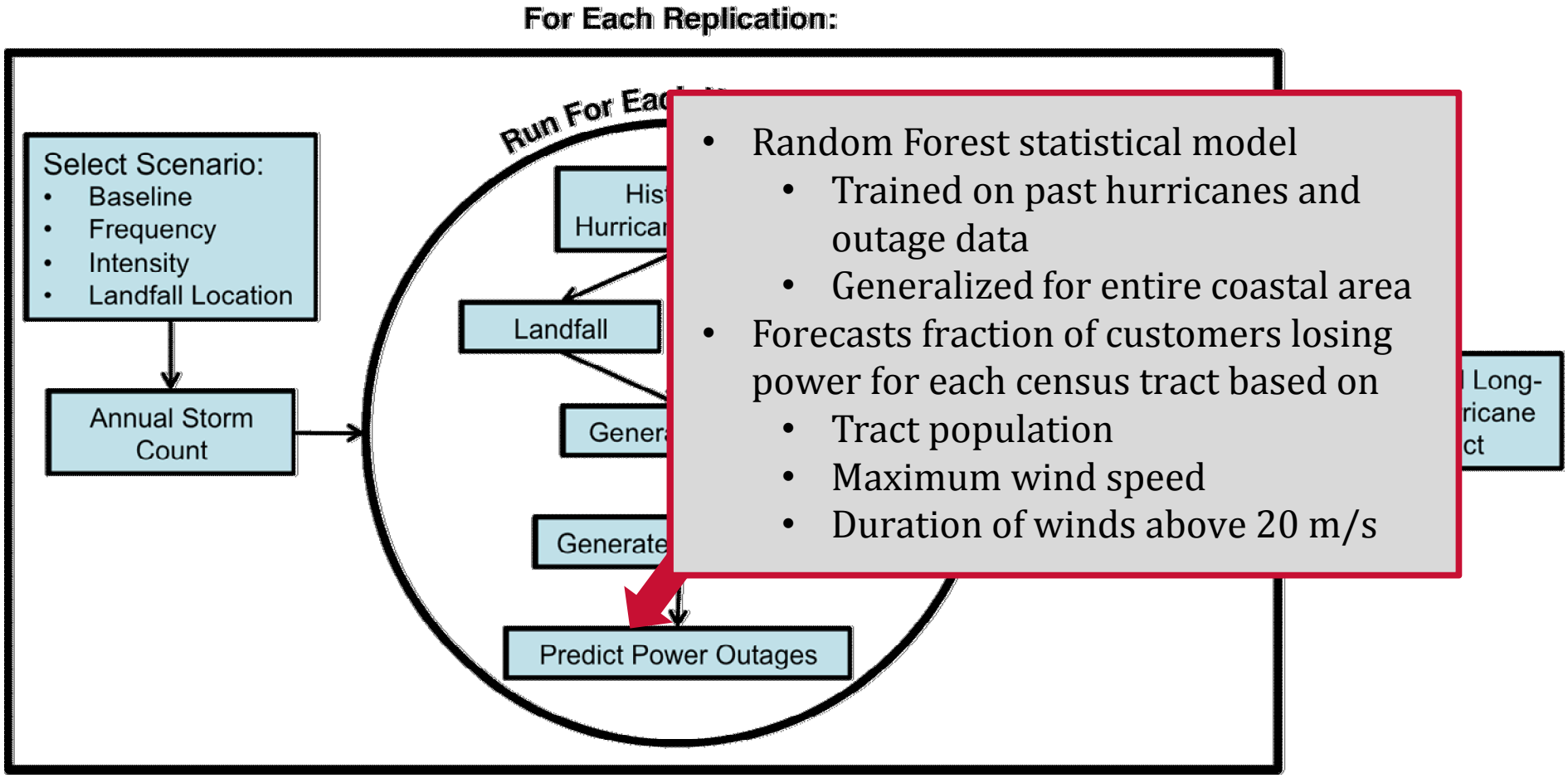
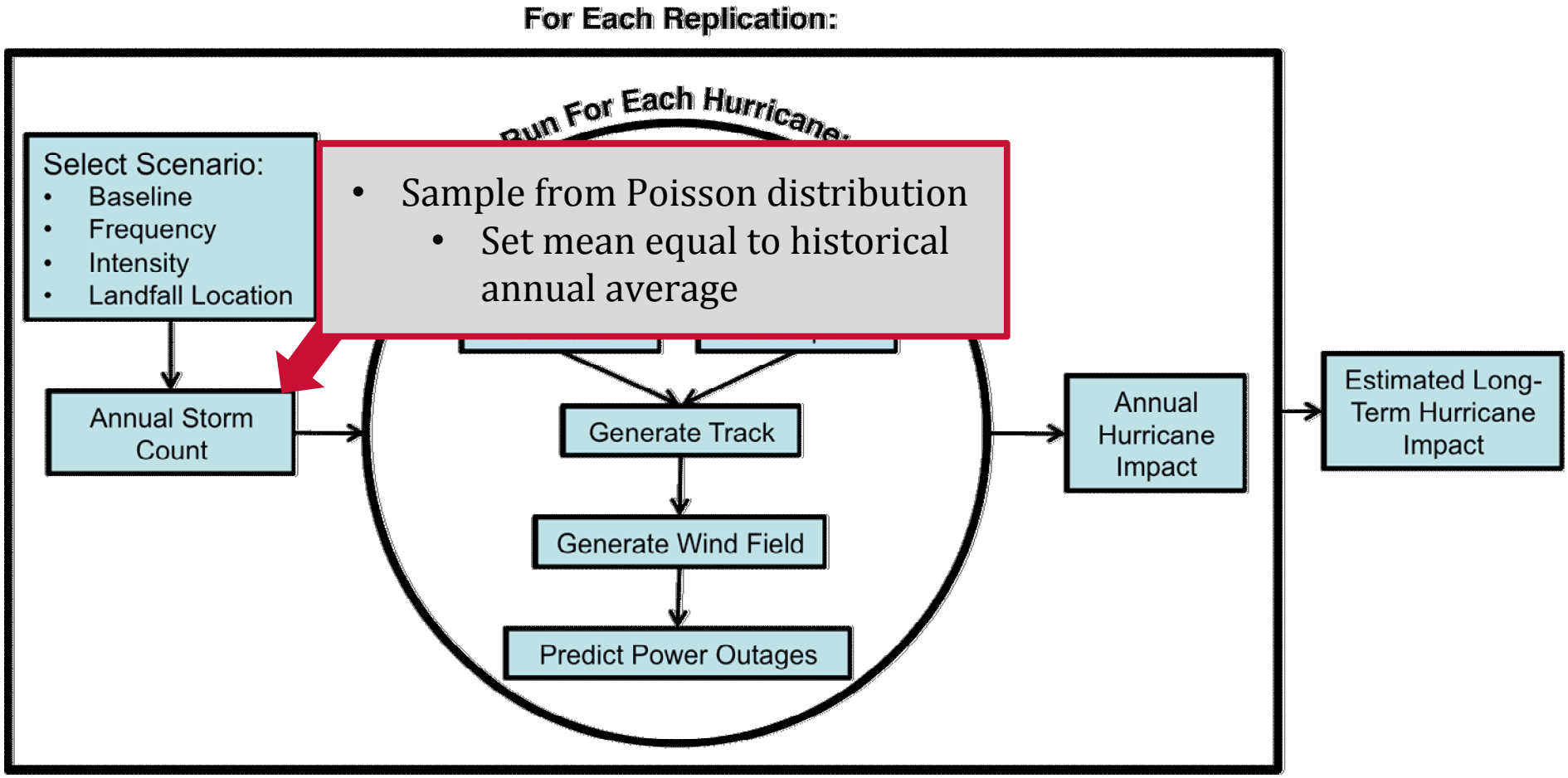


- Random Forest statistical model
  - Trained on past hurricanes and outage data
  - Generalized for entire coastal area
- Forecasts fraction of customers losing power for each census tract based on
  - Tract population
  - Maximum wind speed
  - Duration of winds above 20 m/s

Simulation Structure



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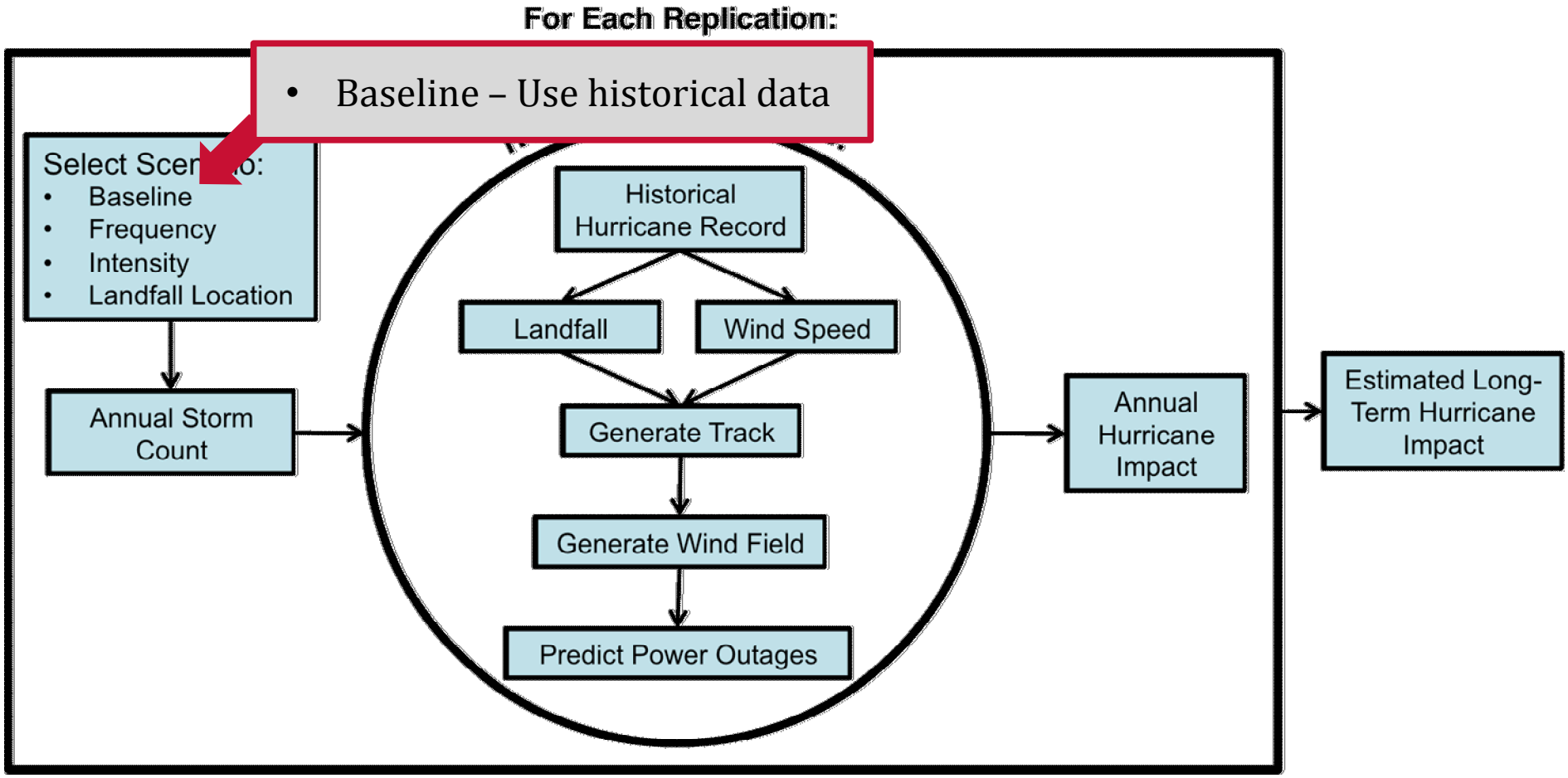

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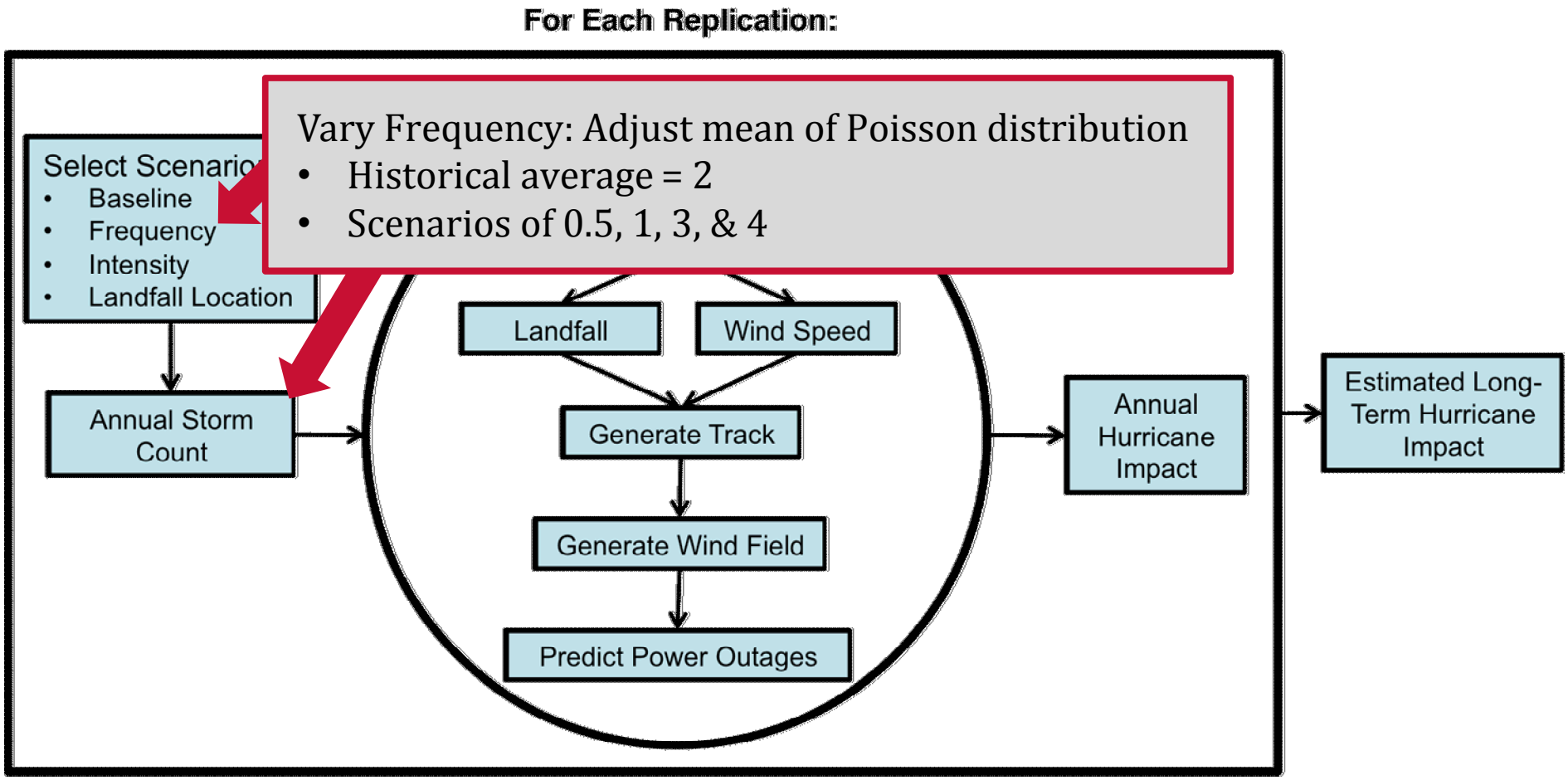

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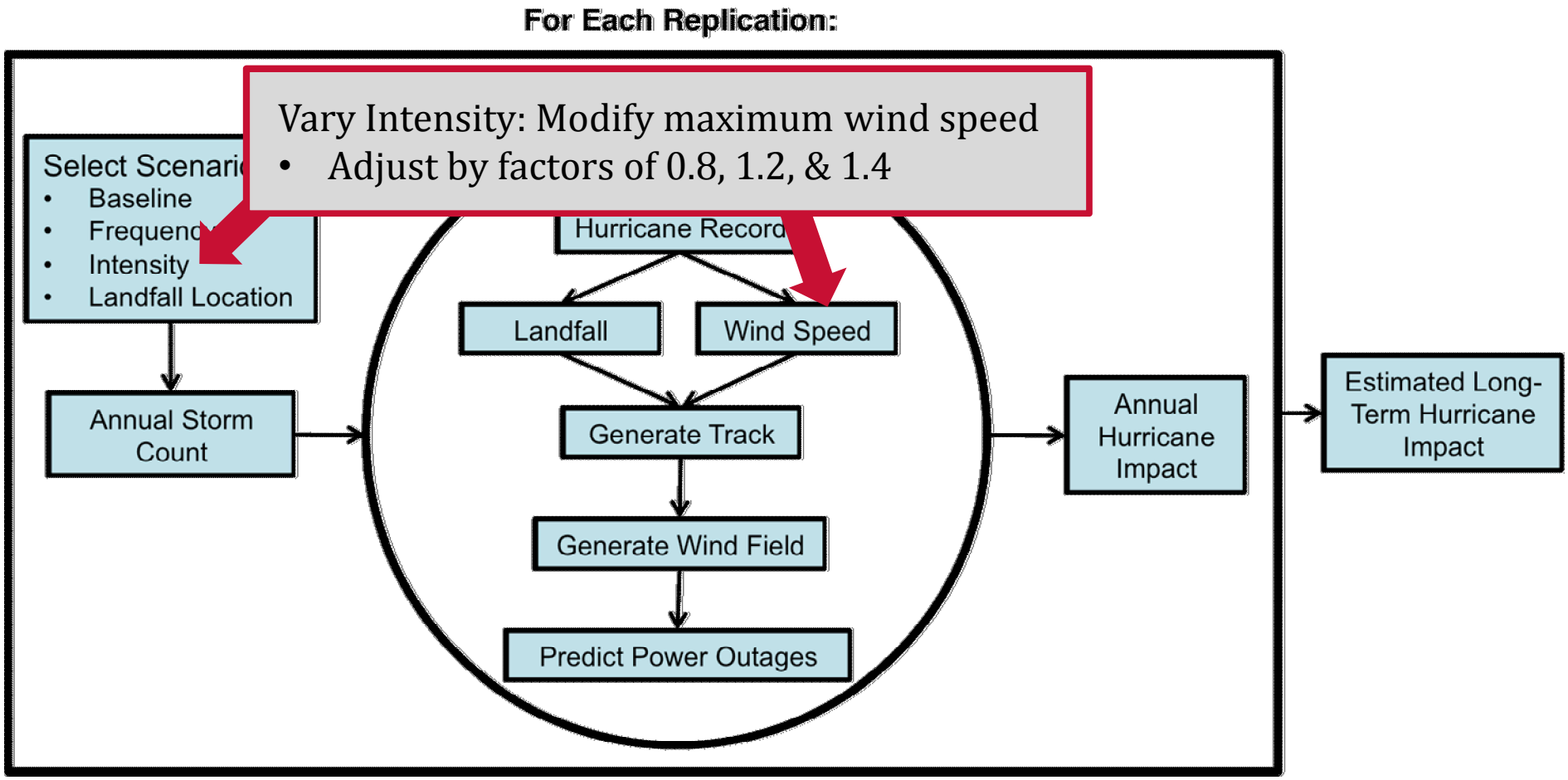

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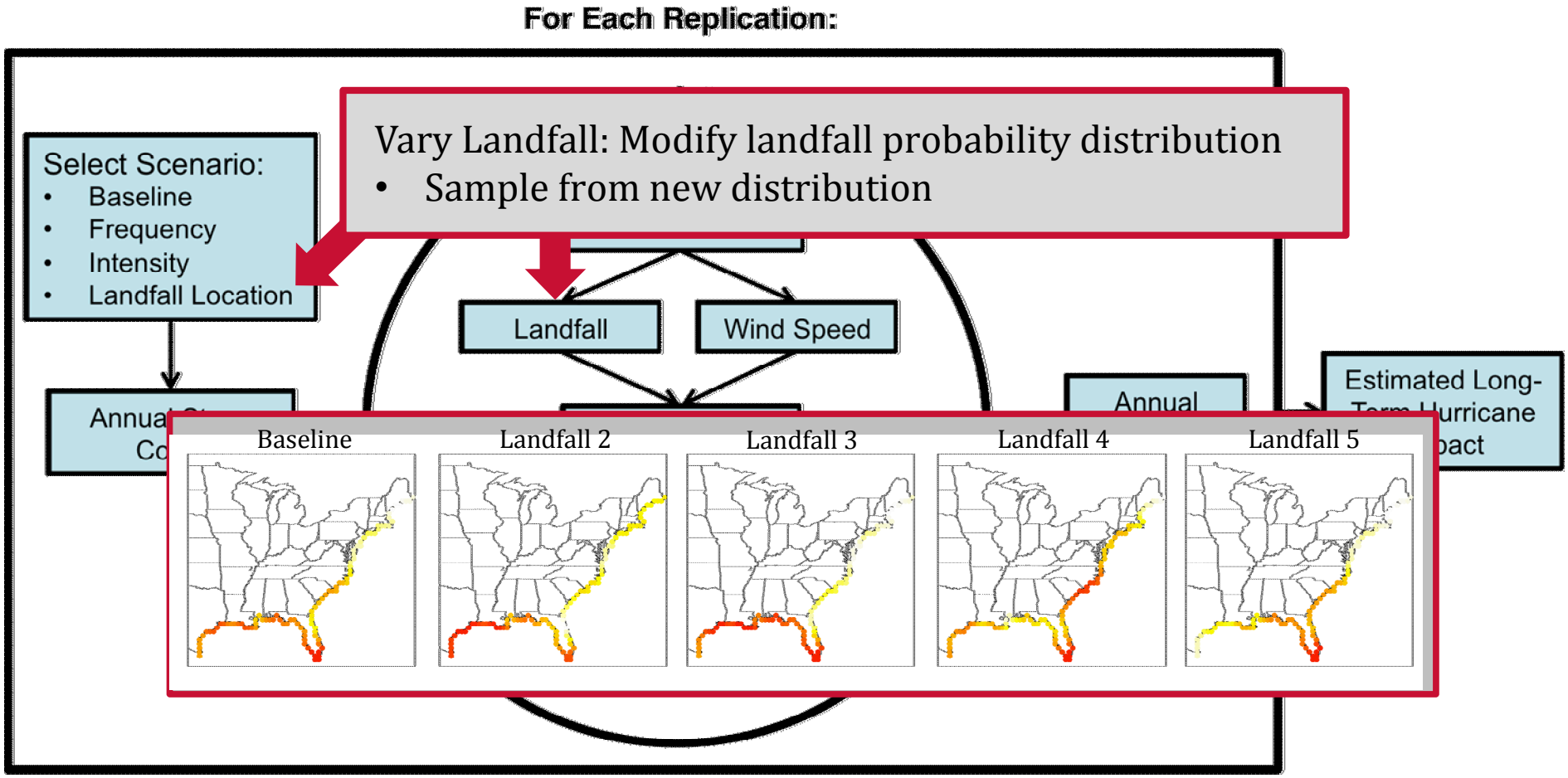

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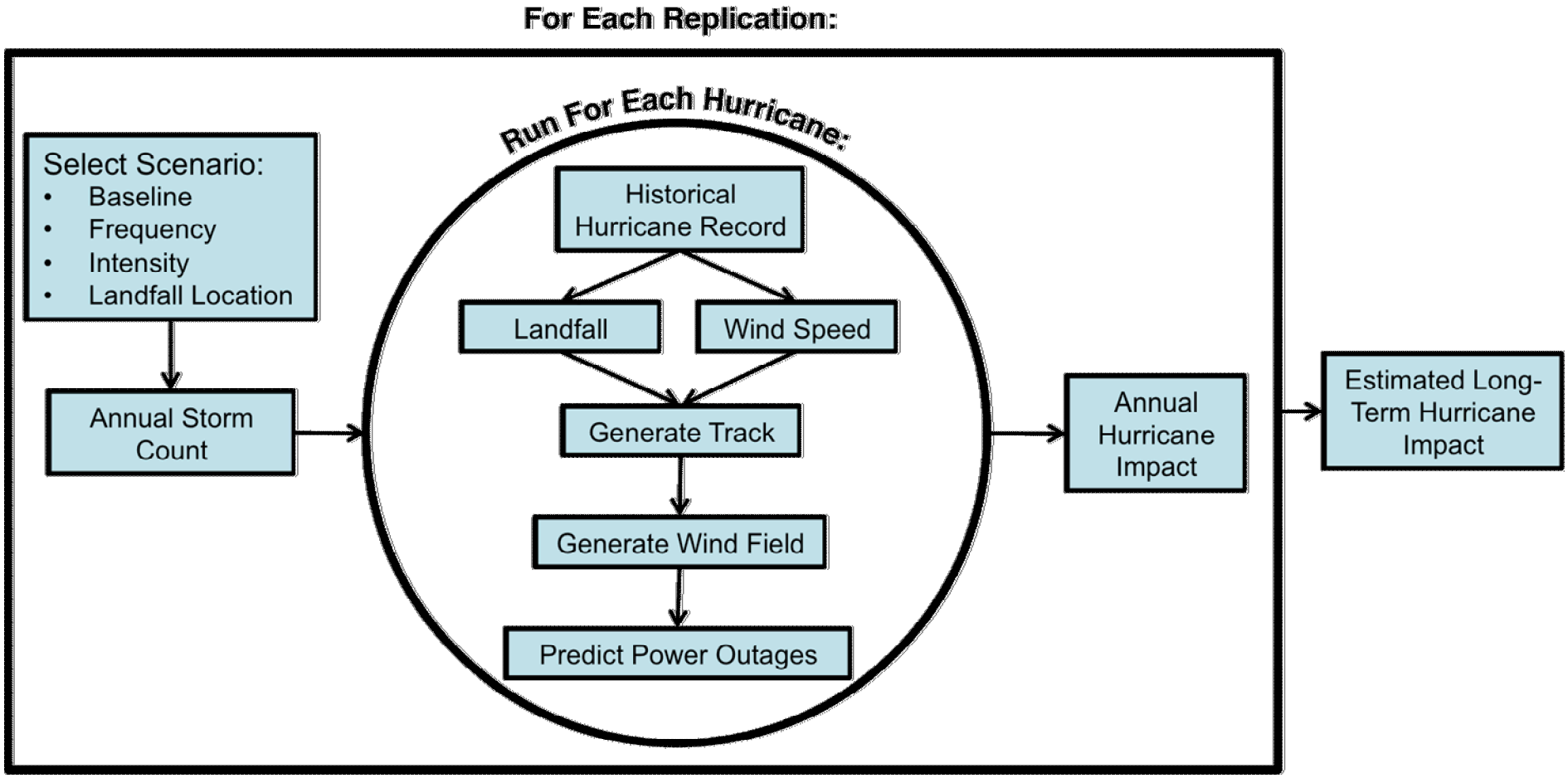


Repeat to reach convergence of the 99th percentile within 1%

Baseline Results

100-Year Wind Speed [m/s]

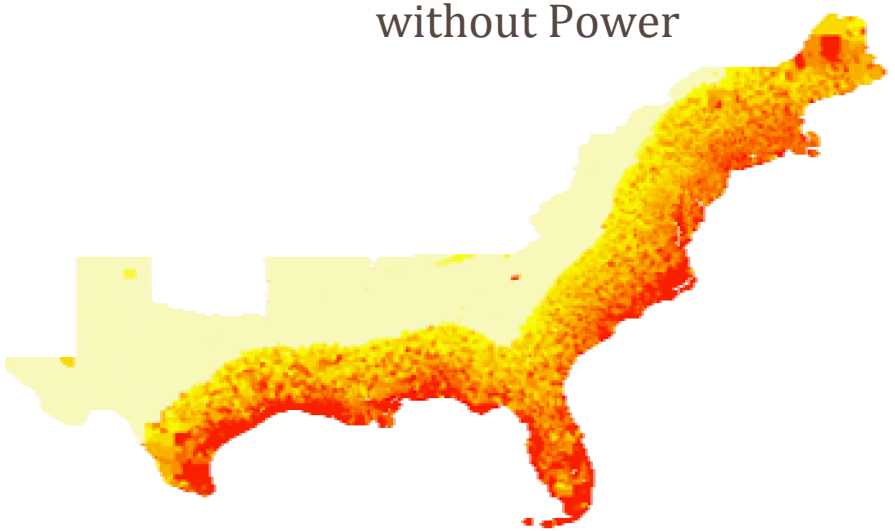
3-sec Gust Wind Speed [m/s]

0 11 22 33 55 66 77 88 110

100 mph

224 mph

100-Year Fraction of Customers without Power



0.0 0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.8 0.9 1.0

100-Year Wind Speed [m/s]

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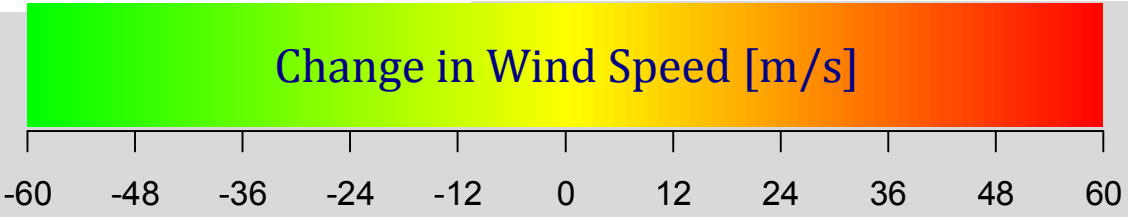
Plotting **Difference** From Baseline:

Intensity = 0.8

Intensity = 1.2

Intensity = 1.4



100-Year Fraction without Power

Plotting **Difference** From Baseline:

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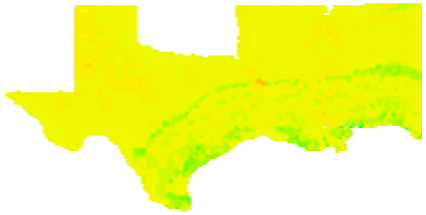
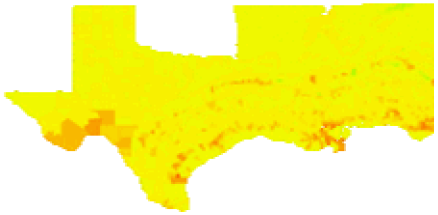
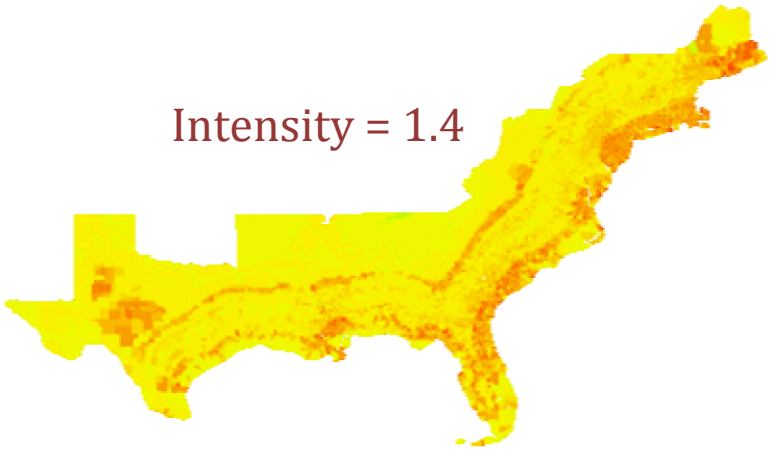
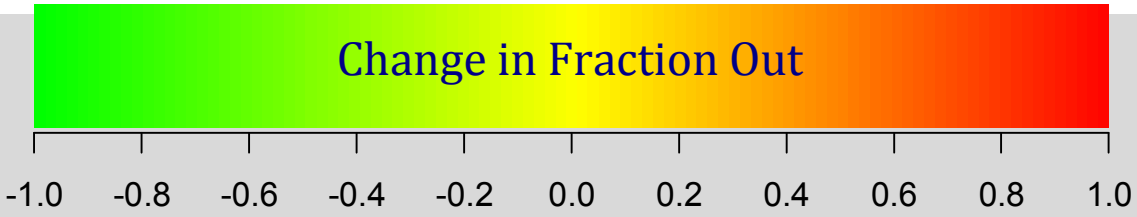


Intensity = 1.2



Intensity = 1.4





*Independent samples result in sample error in very low population density areas

Annual Probability of Outage

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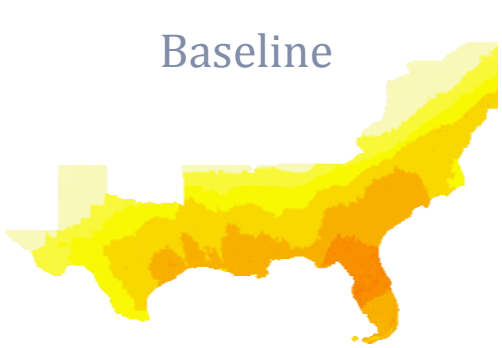
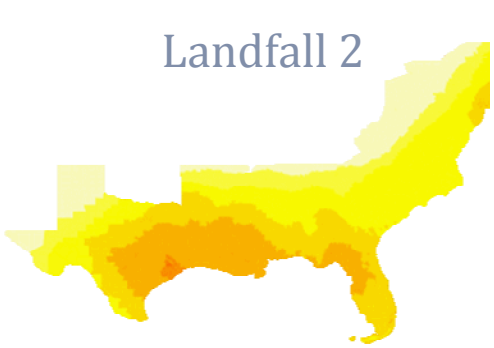
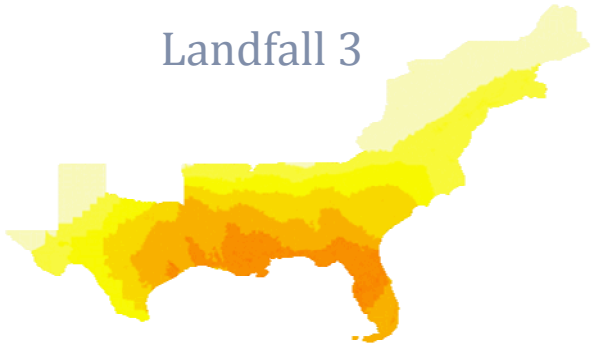
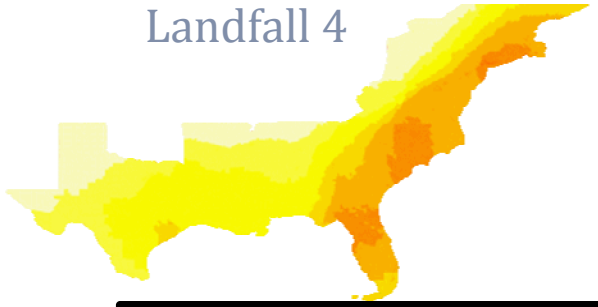
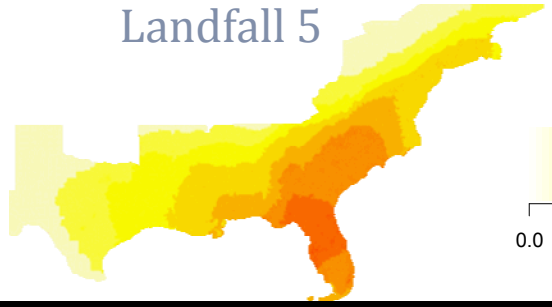
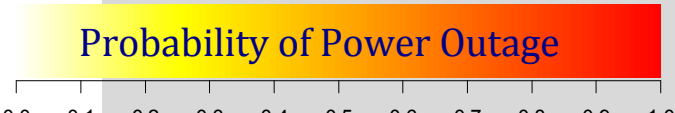


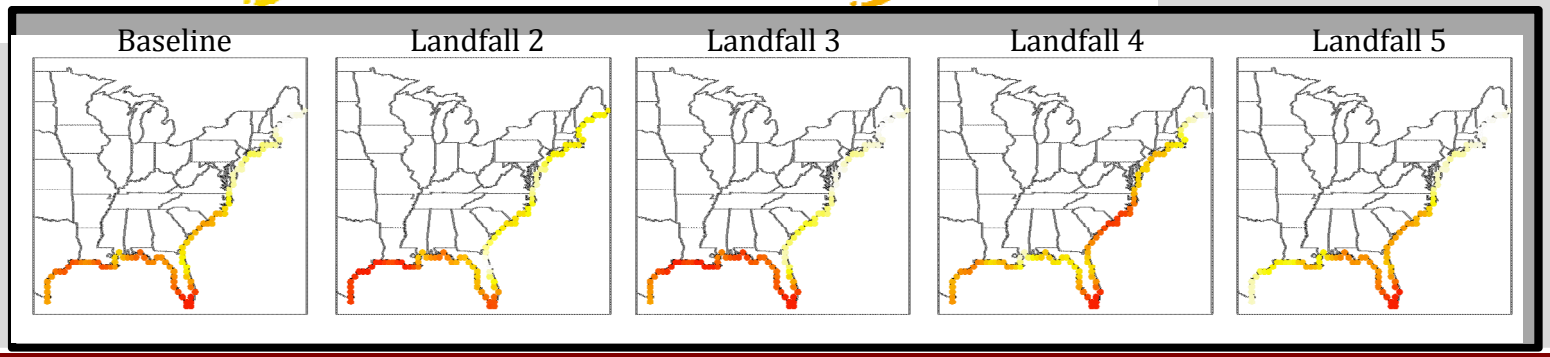




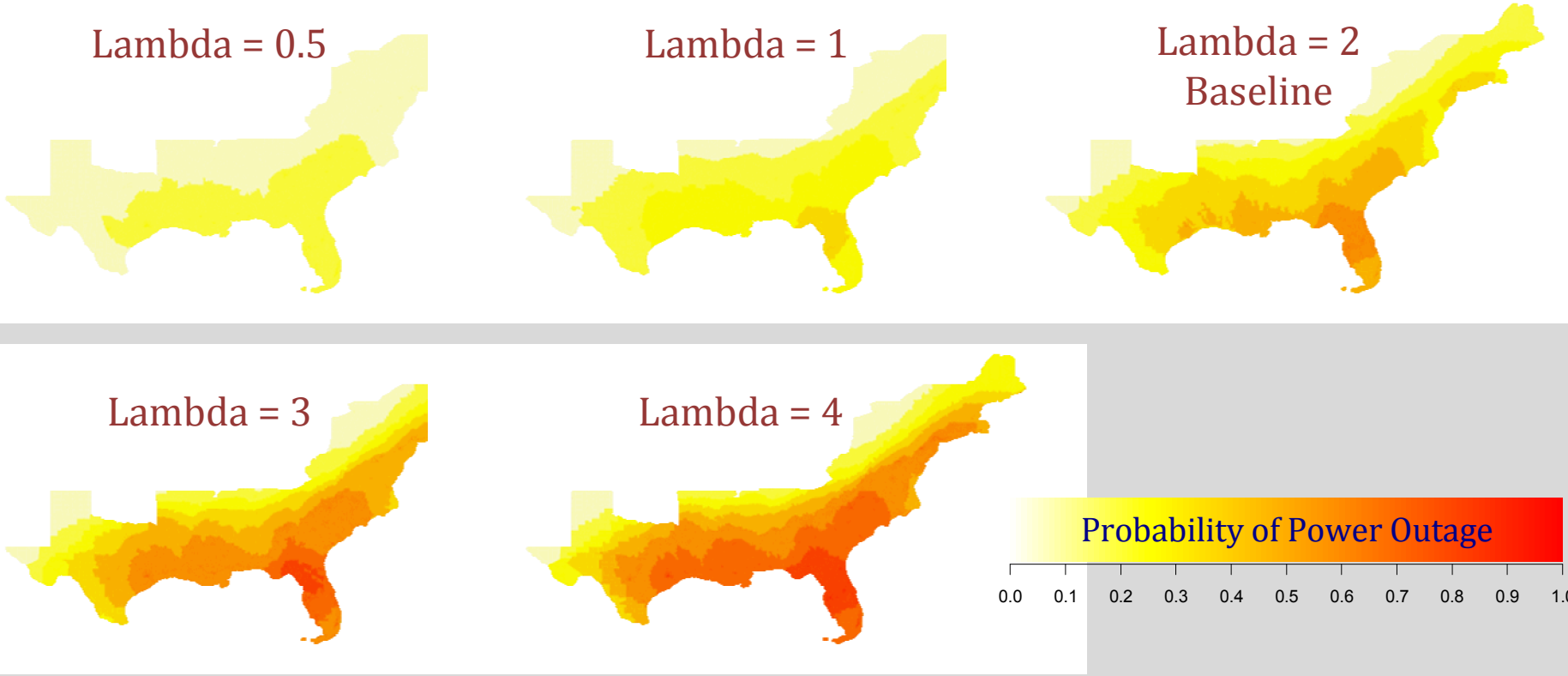






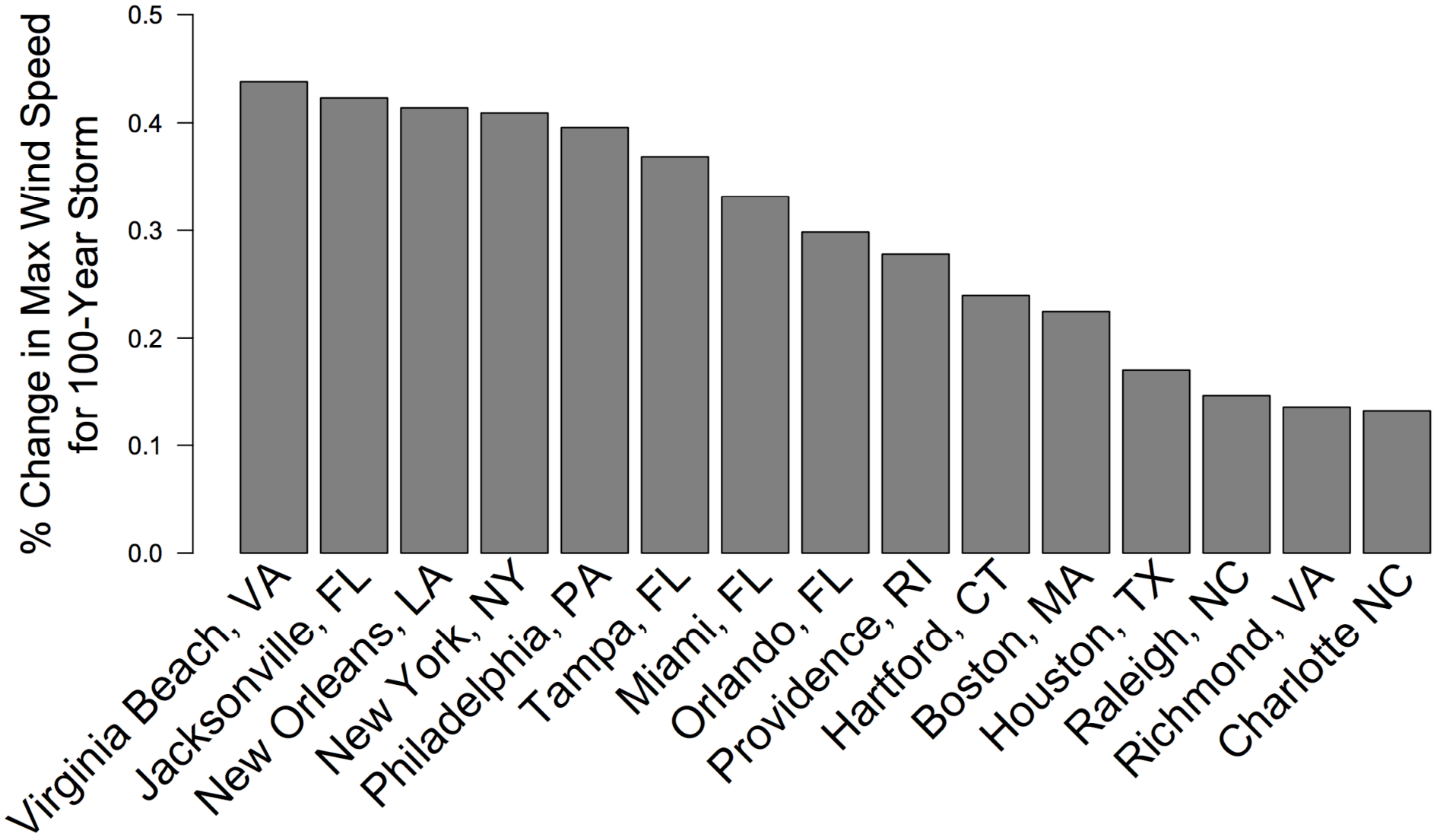


Annual Probability of Outage

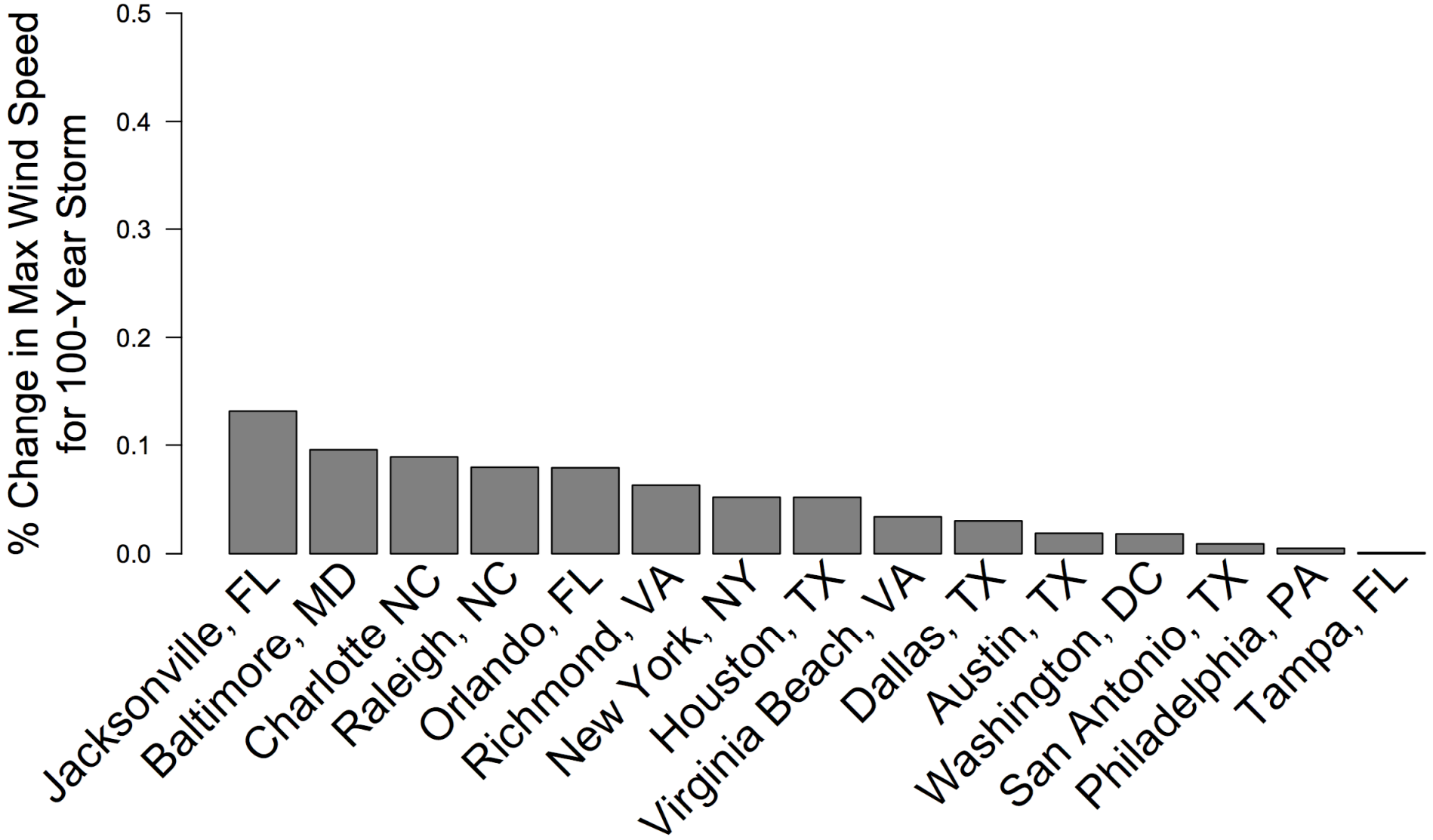


*The lambda value represents the average number of storms making landfall per year

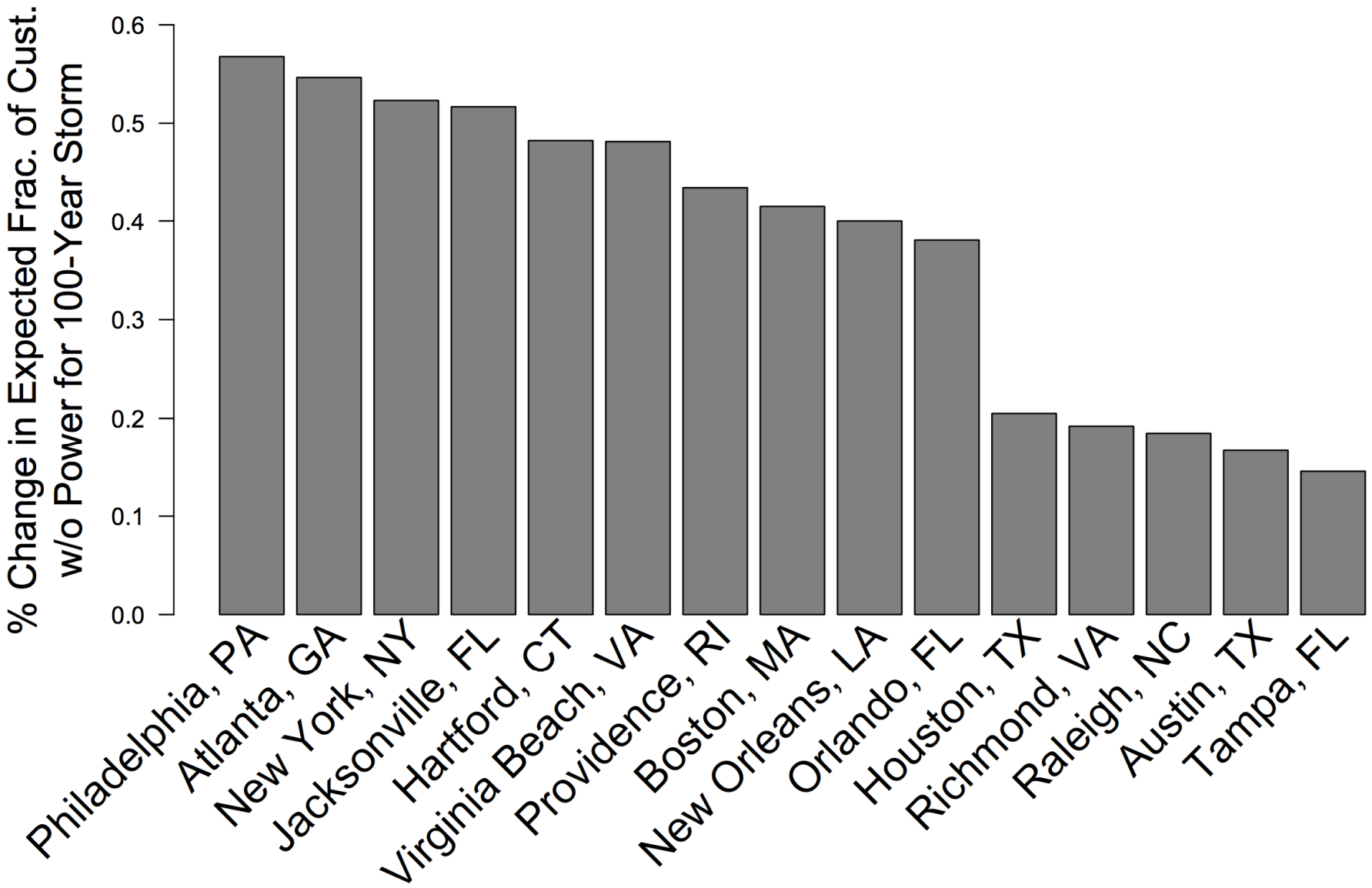
Max Wind – Sensitivity to Intensity



Max Wind – Sensitivity to Frequency



Fraction Out – Sensitivity to Intensity



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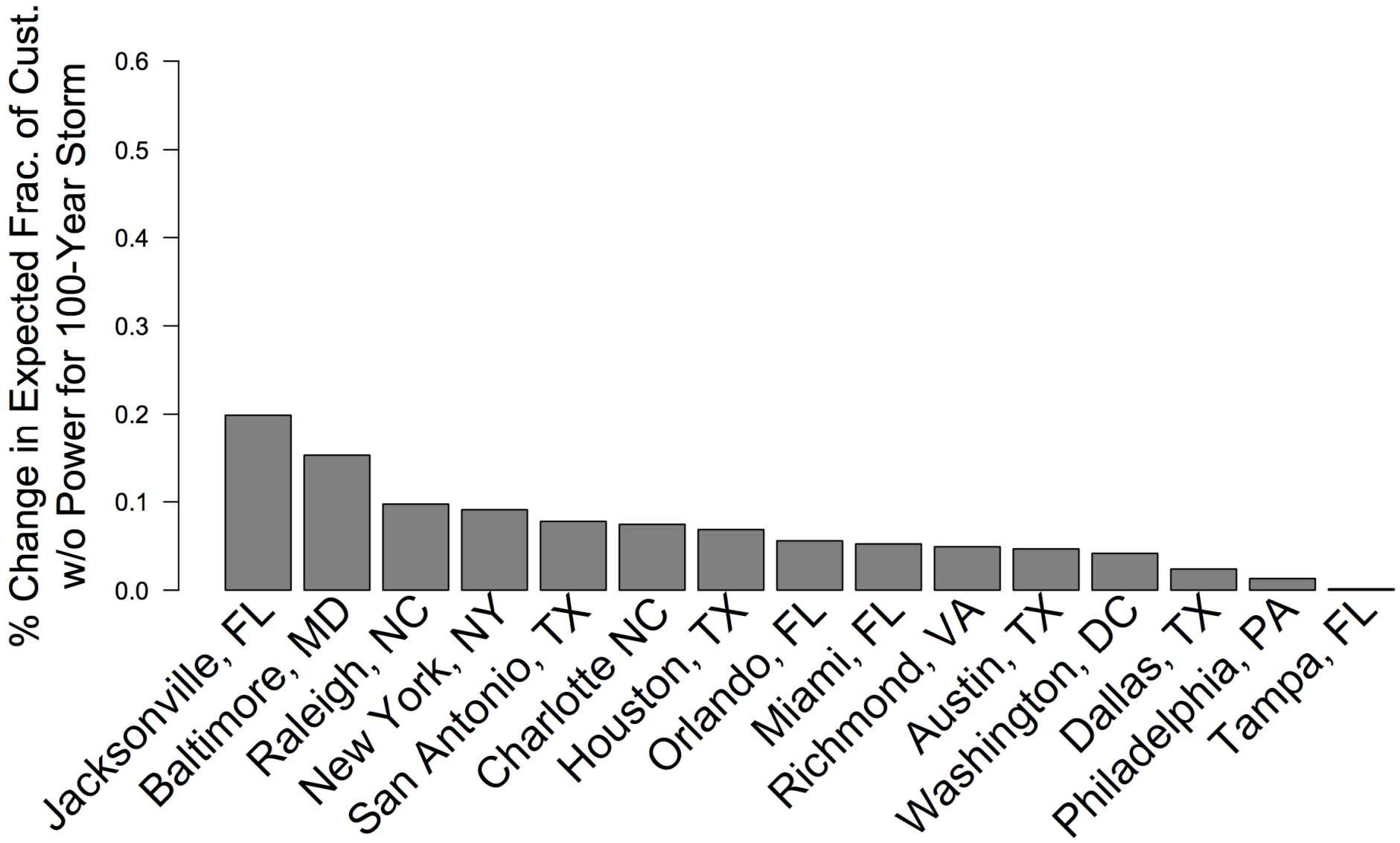
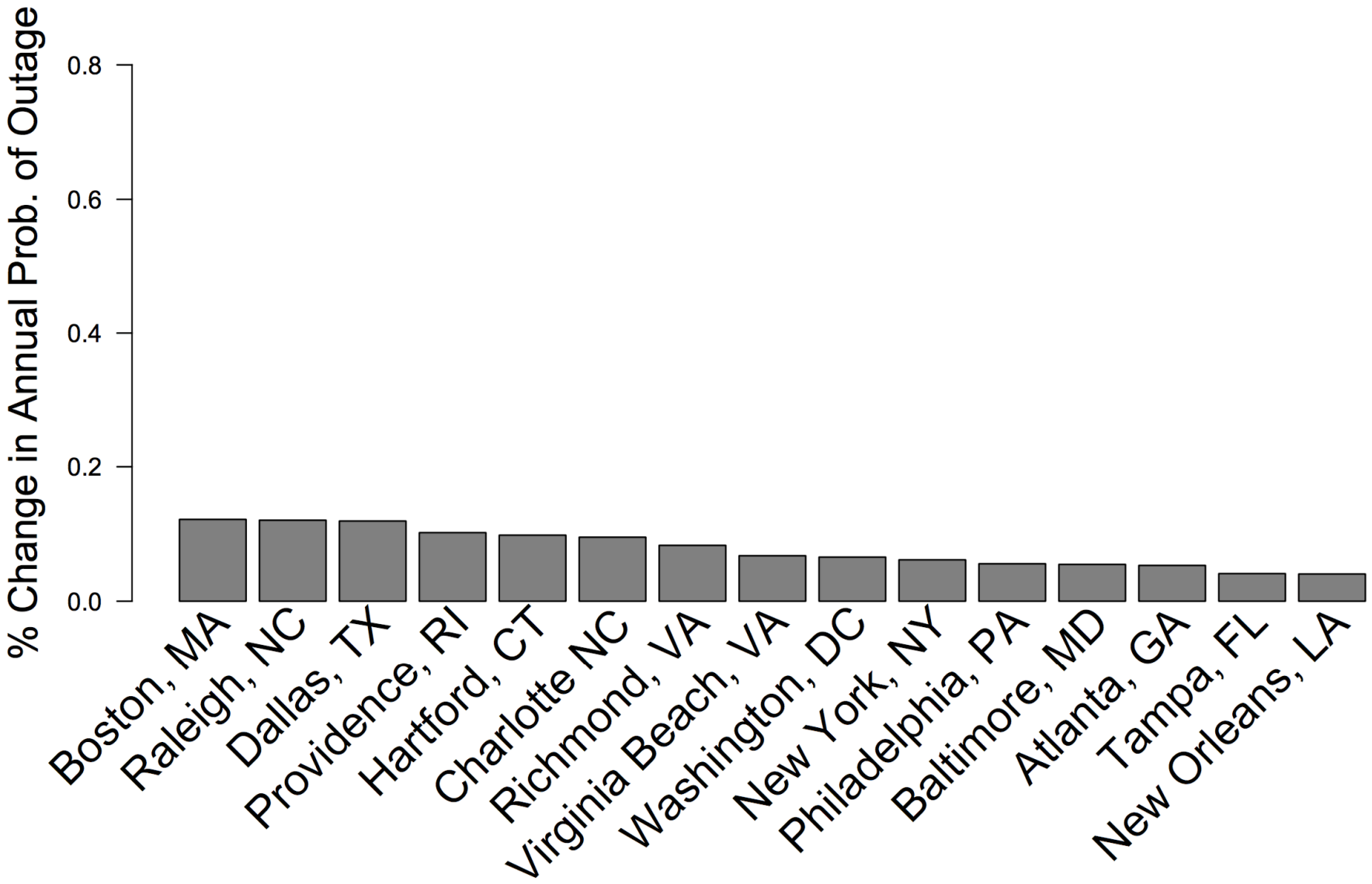
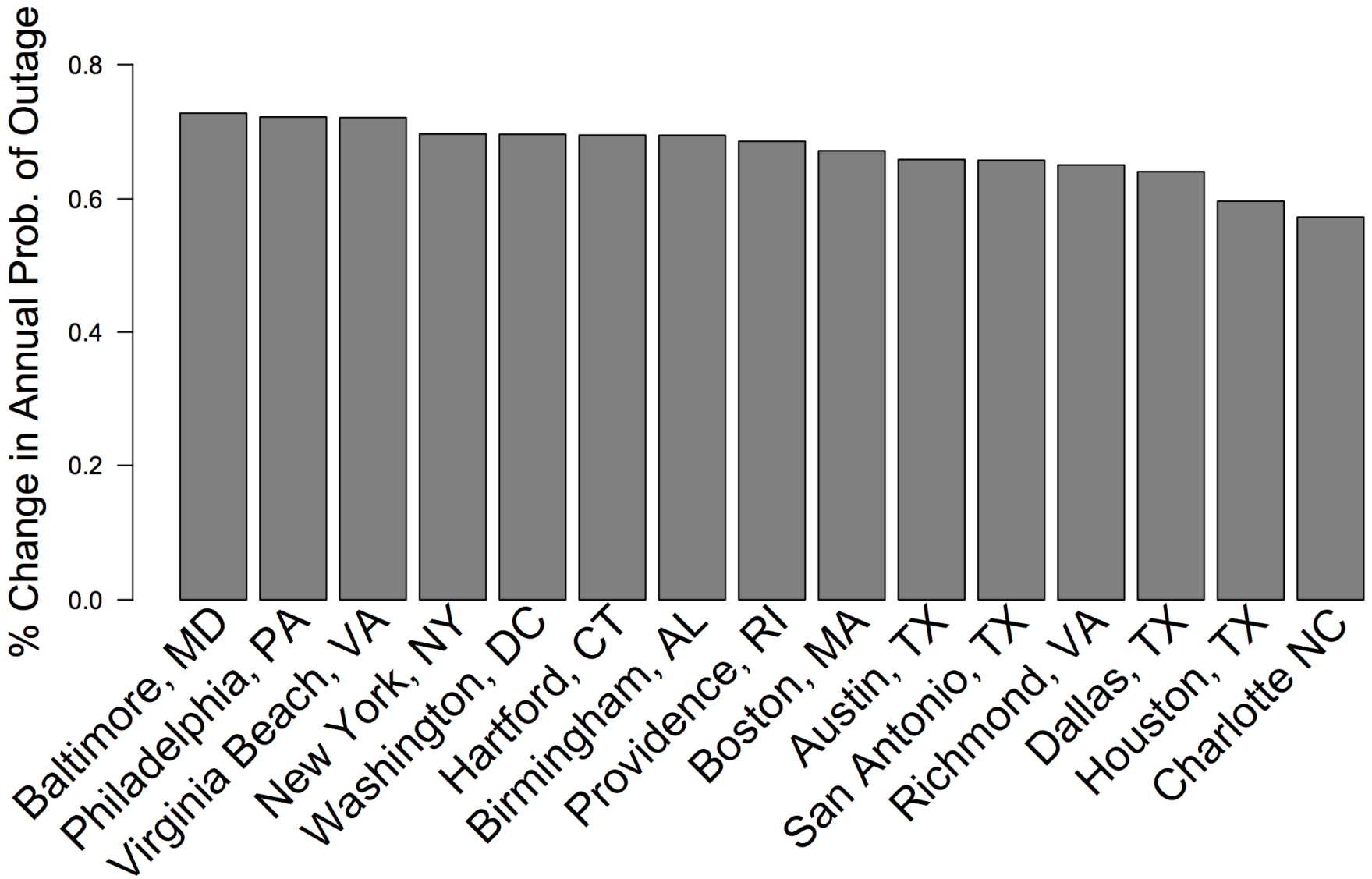


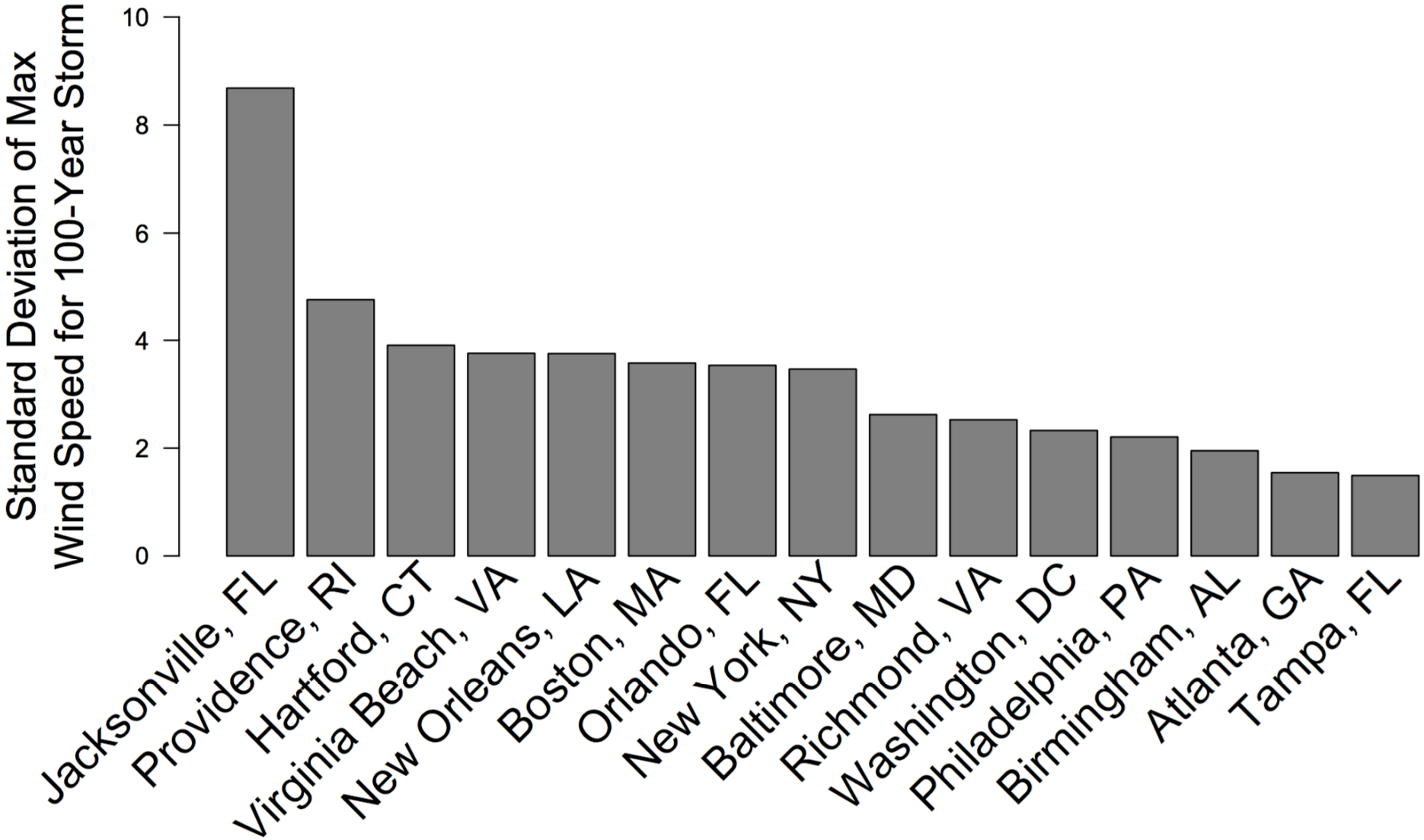
P(outage) – Sensitivity to Intensity



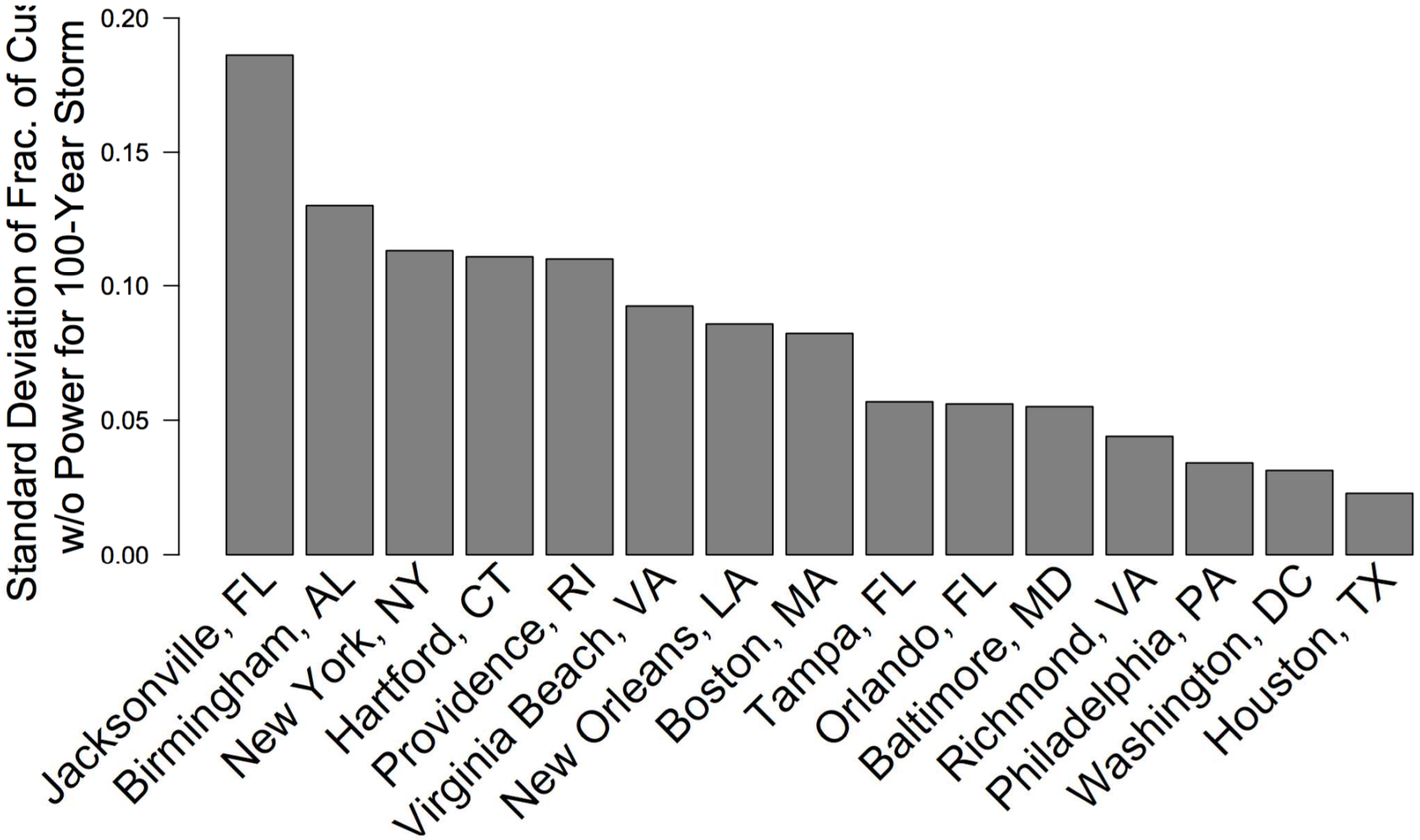
P(outage) – Sensitivity to Frequency



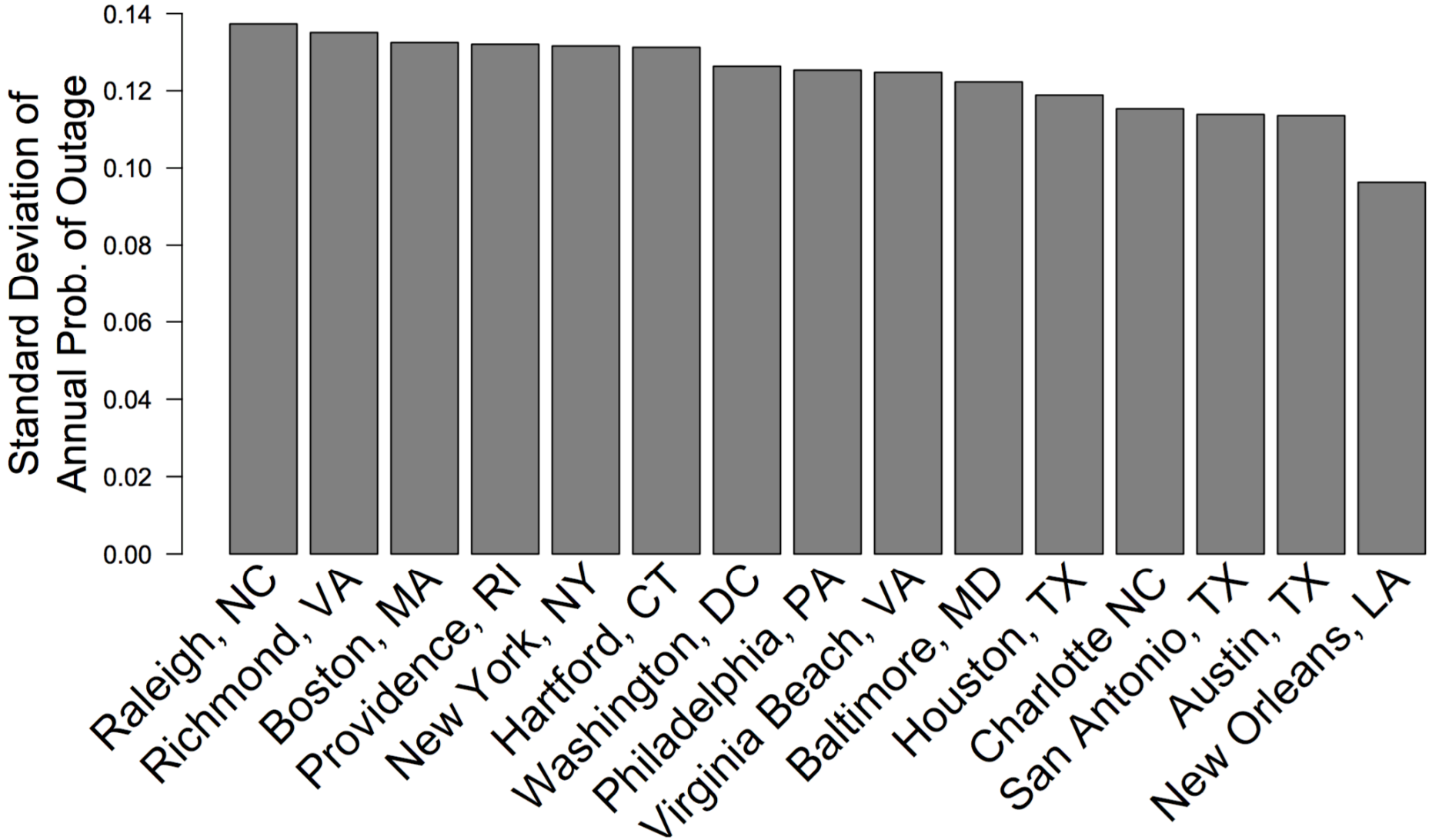
Max Wind – Sensitivity to Location



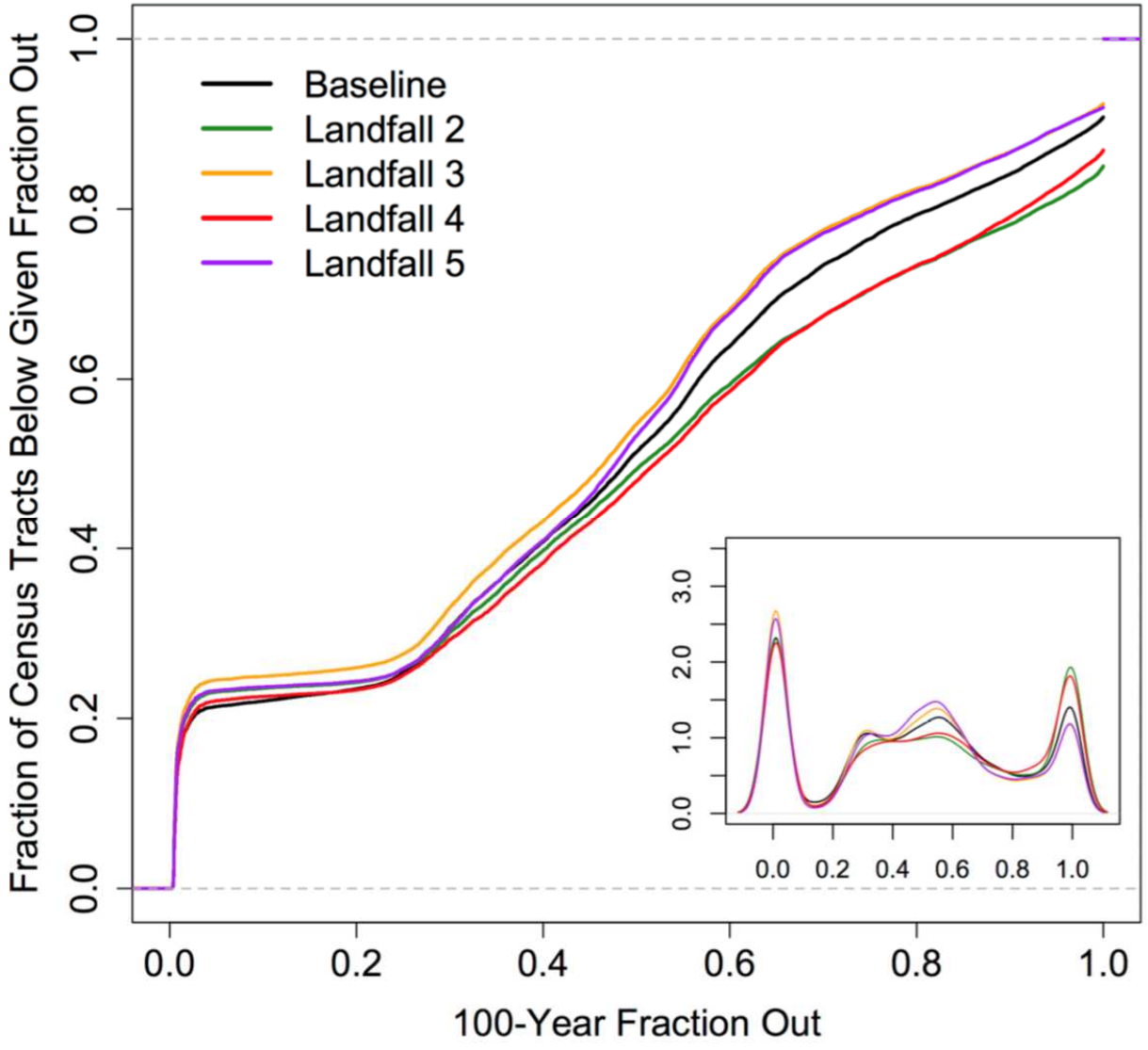
Fraction Out – Sensitivity to Location



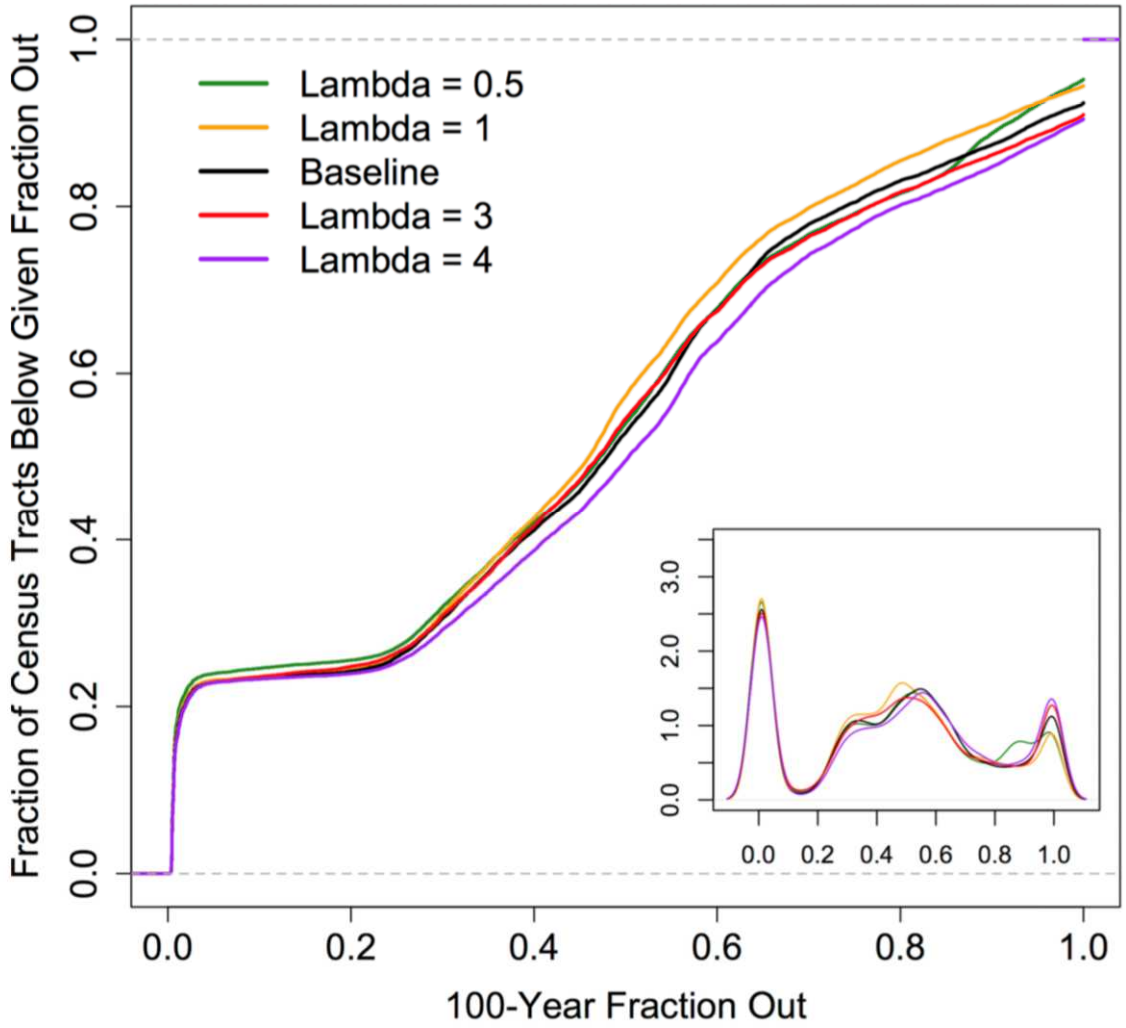
P(outage) – Sensitivity to Location



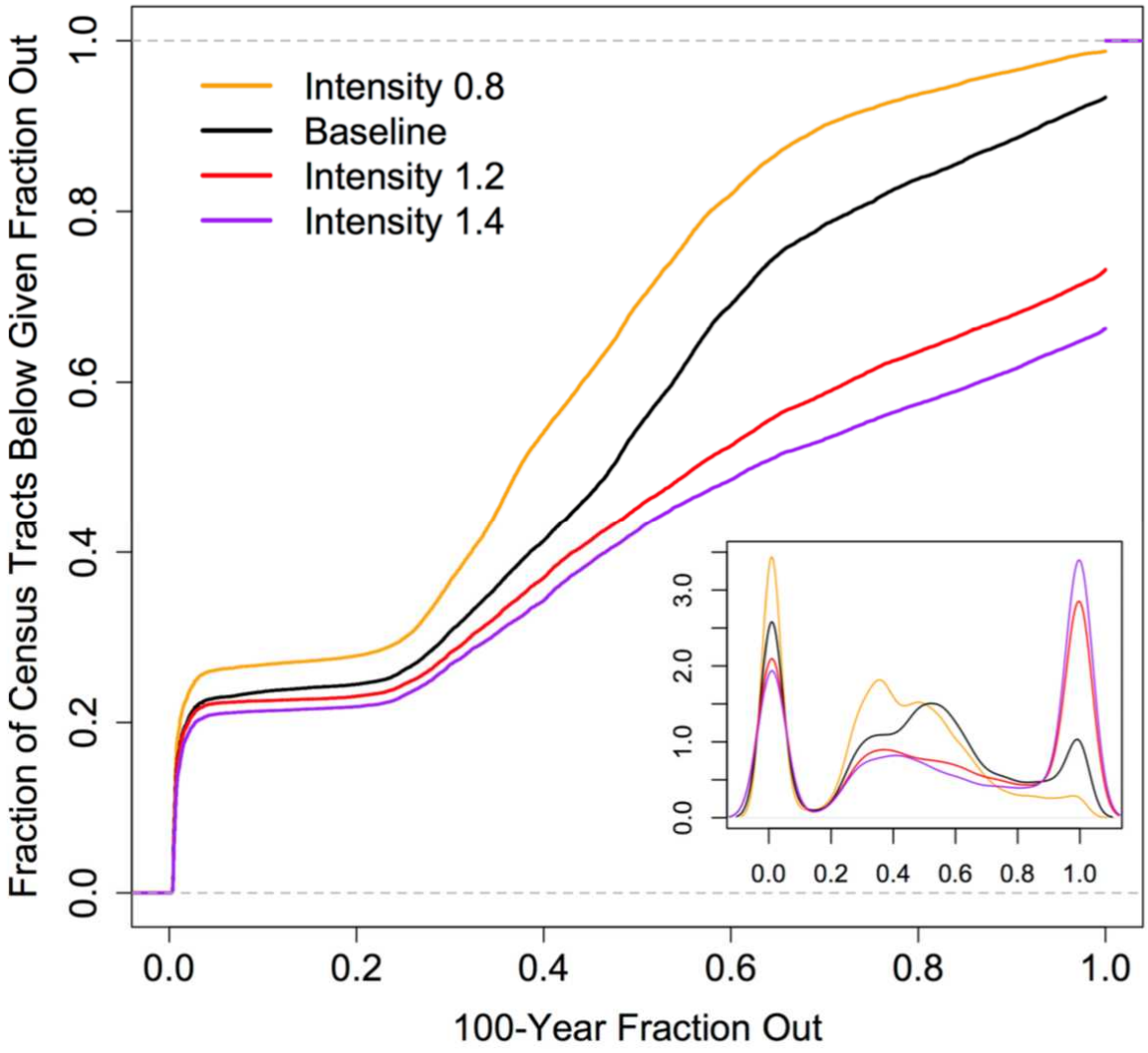
Fraction Out - Landfall Sensitivity



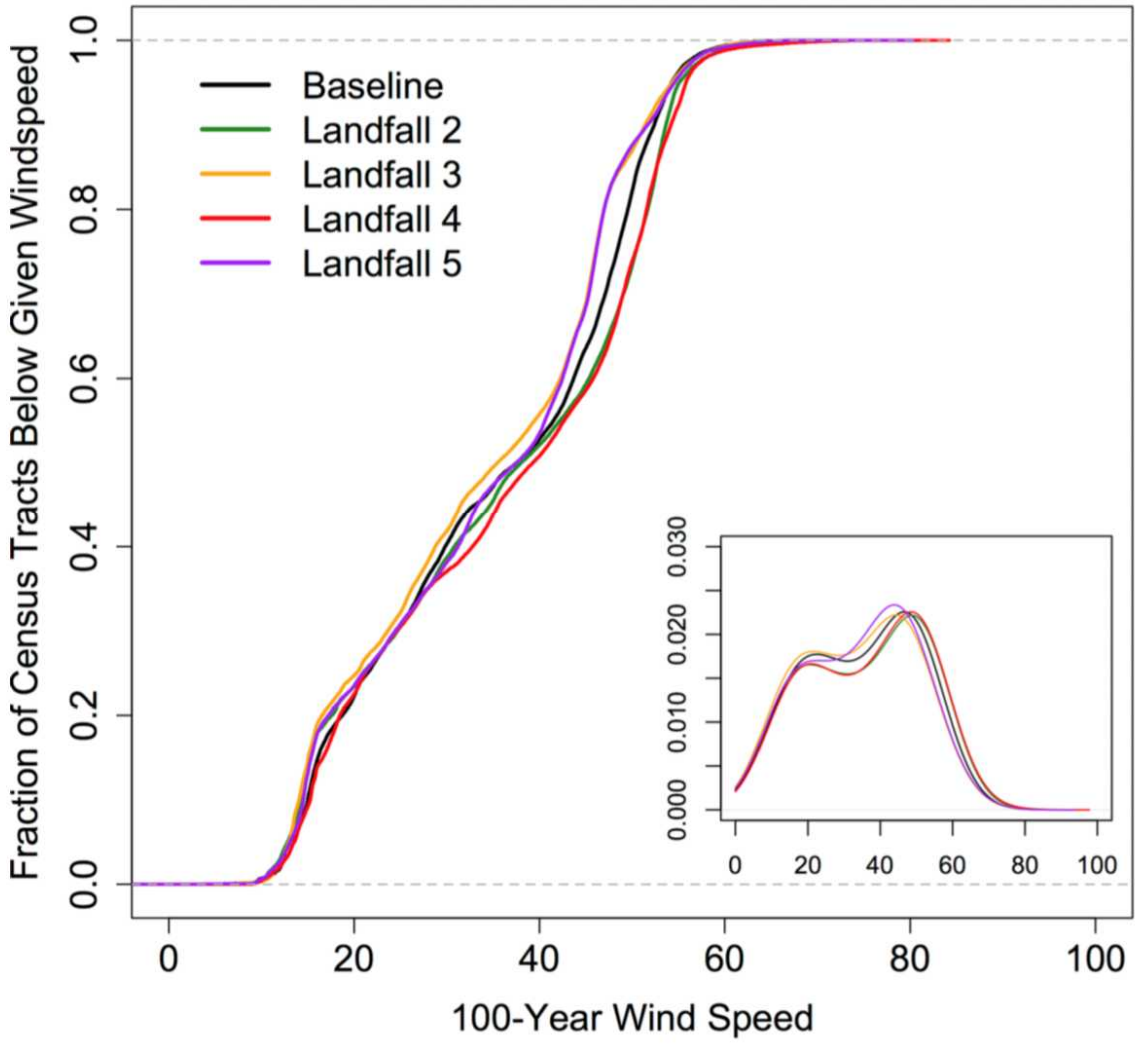
Fraction Out - Frequency Sensitivity



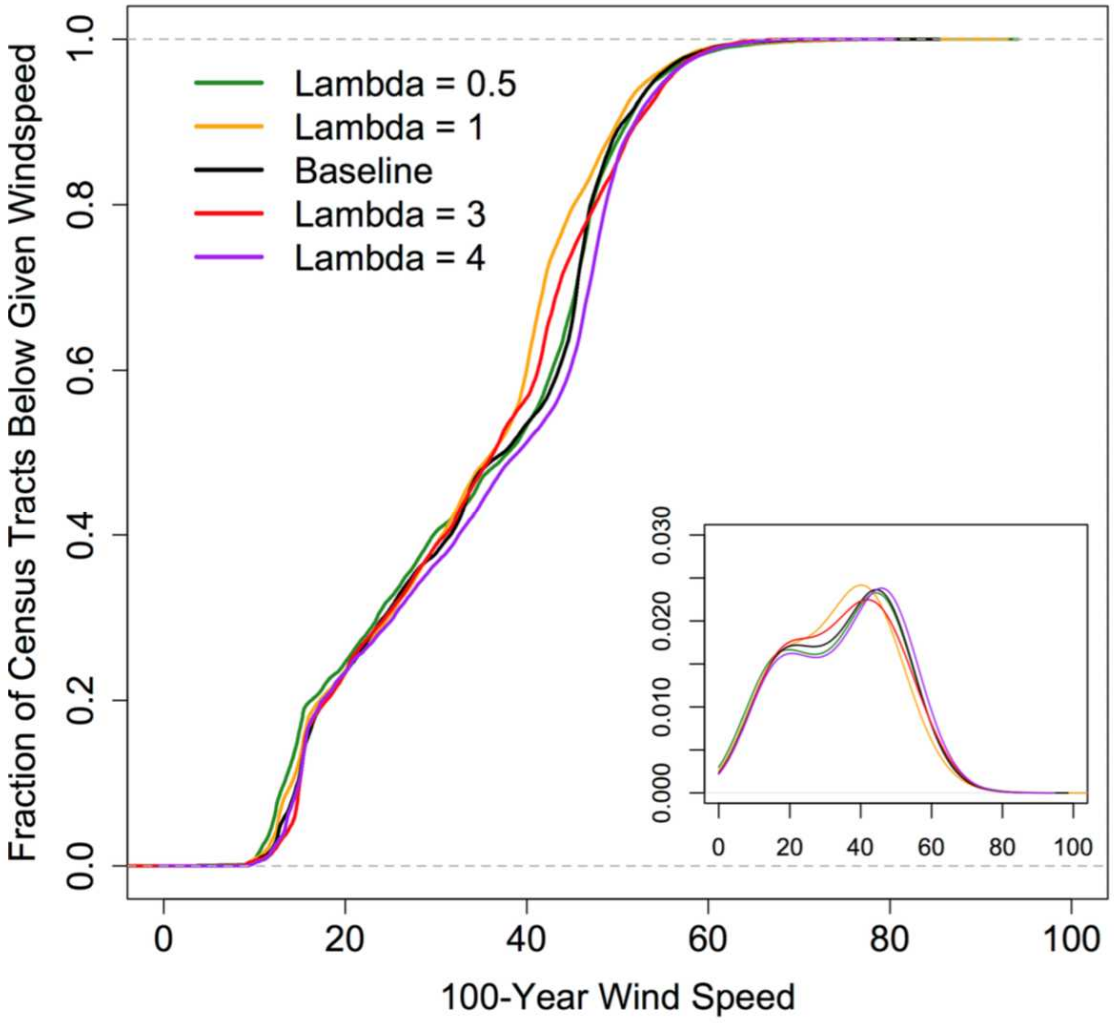
Fraction Out - Intensity Sensitivity



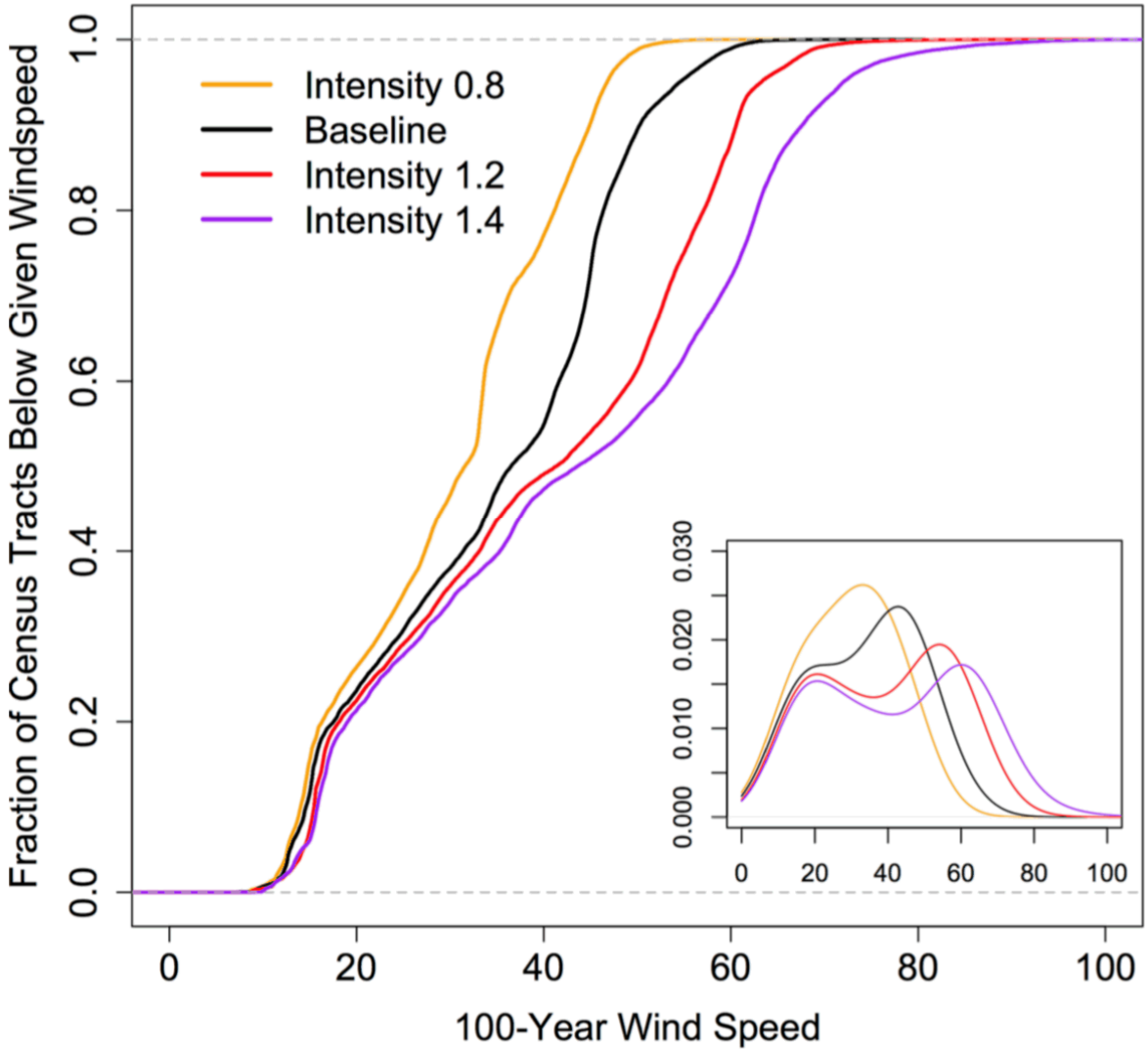
Wind Speed – Landfall Sensitivity

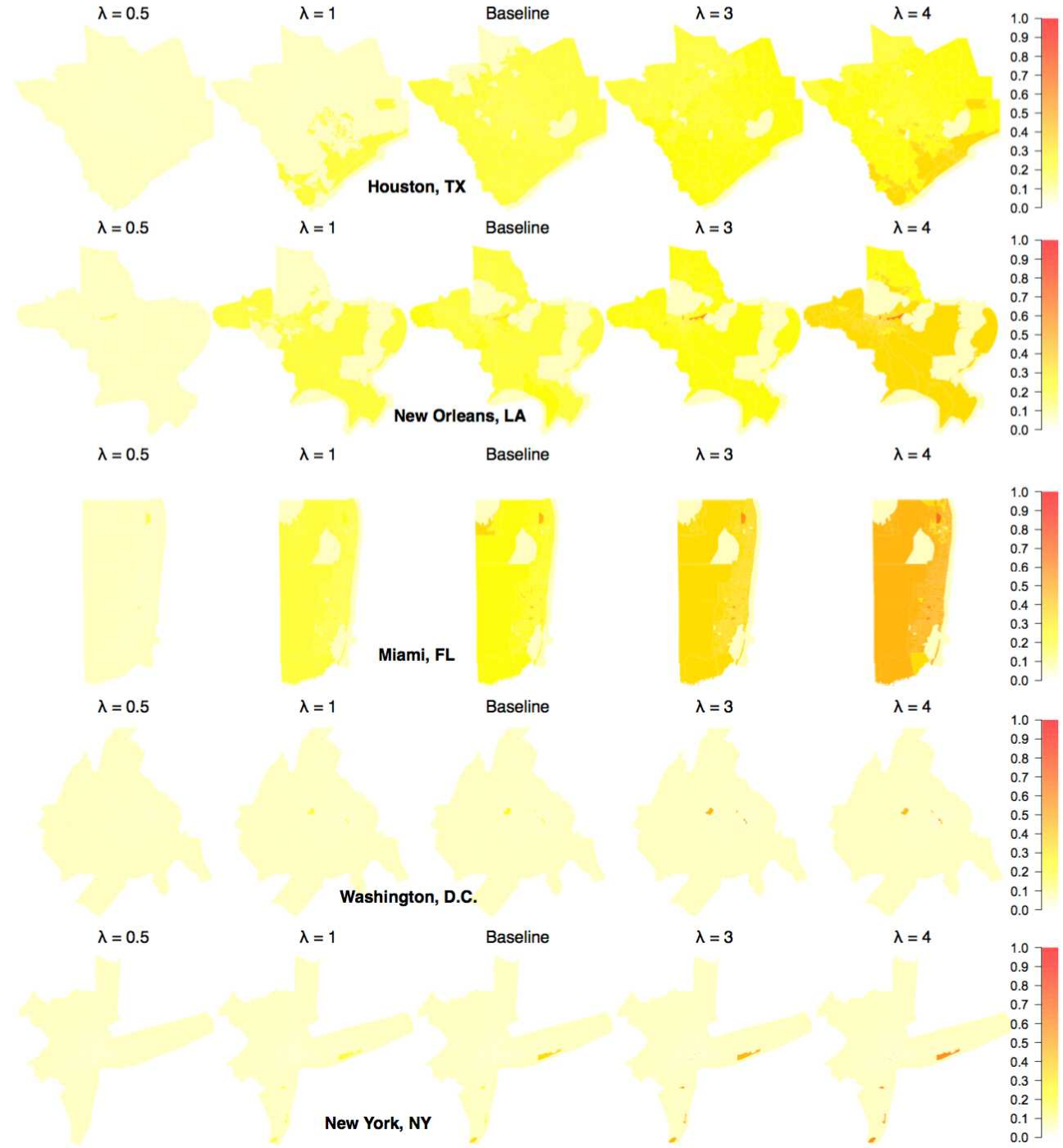


Wind Speed – Frequency Sensitivity

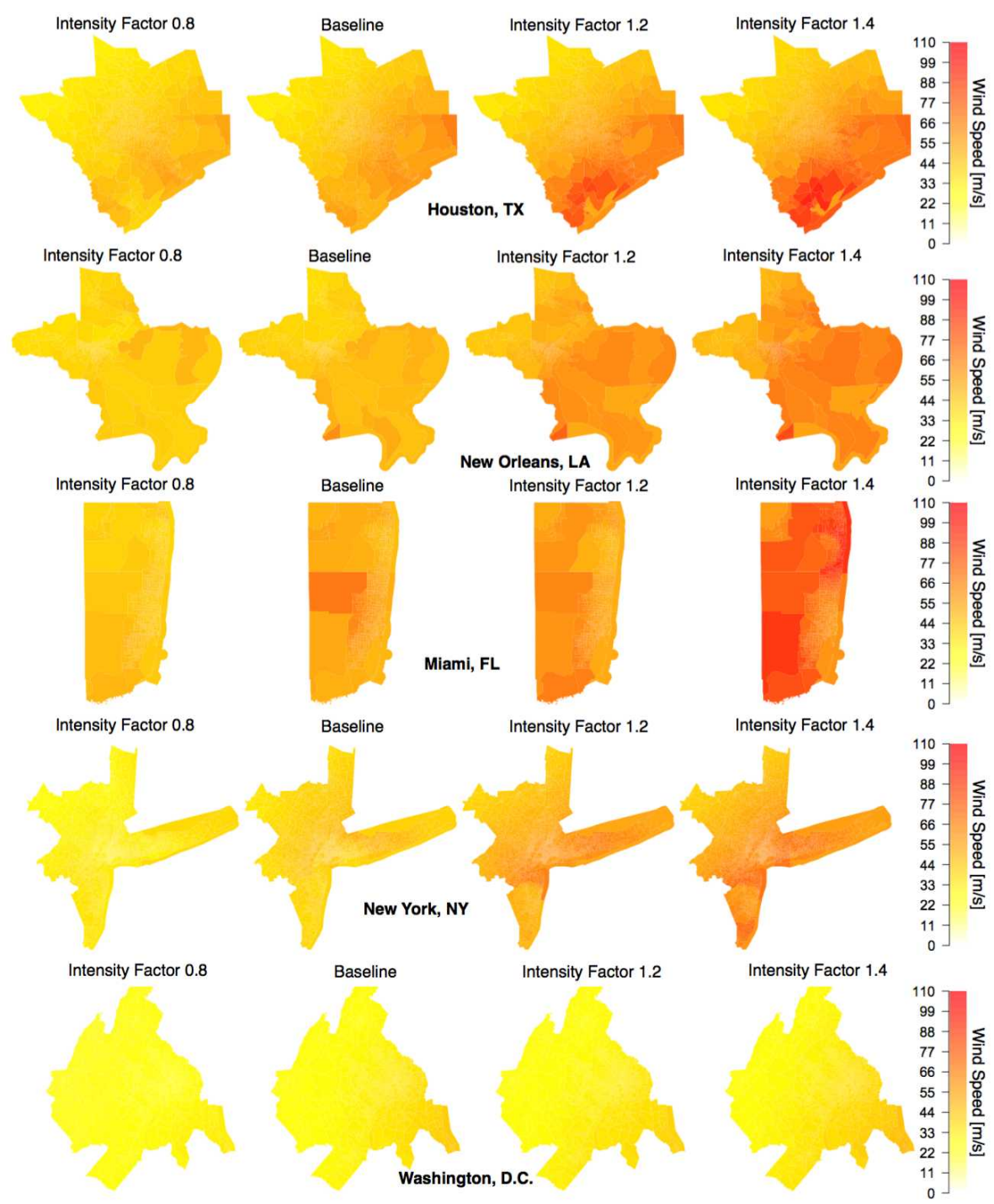


Wind Speed – Intensity Sensitivity

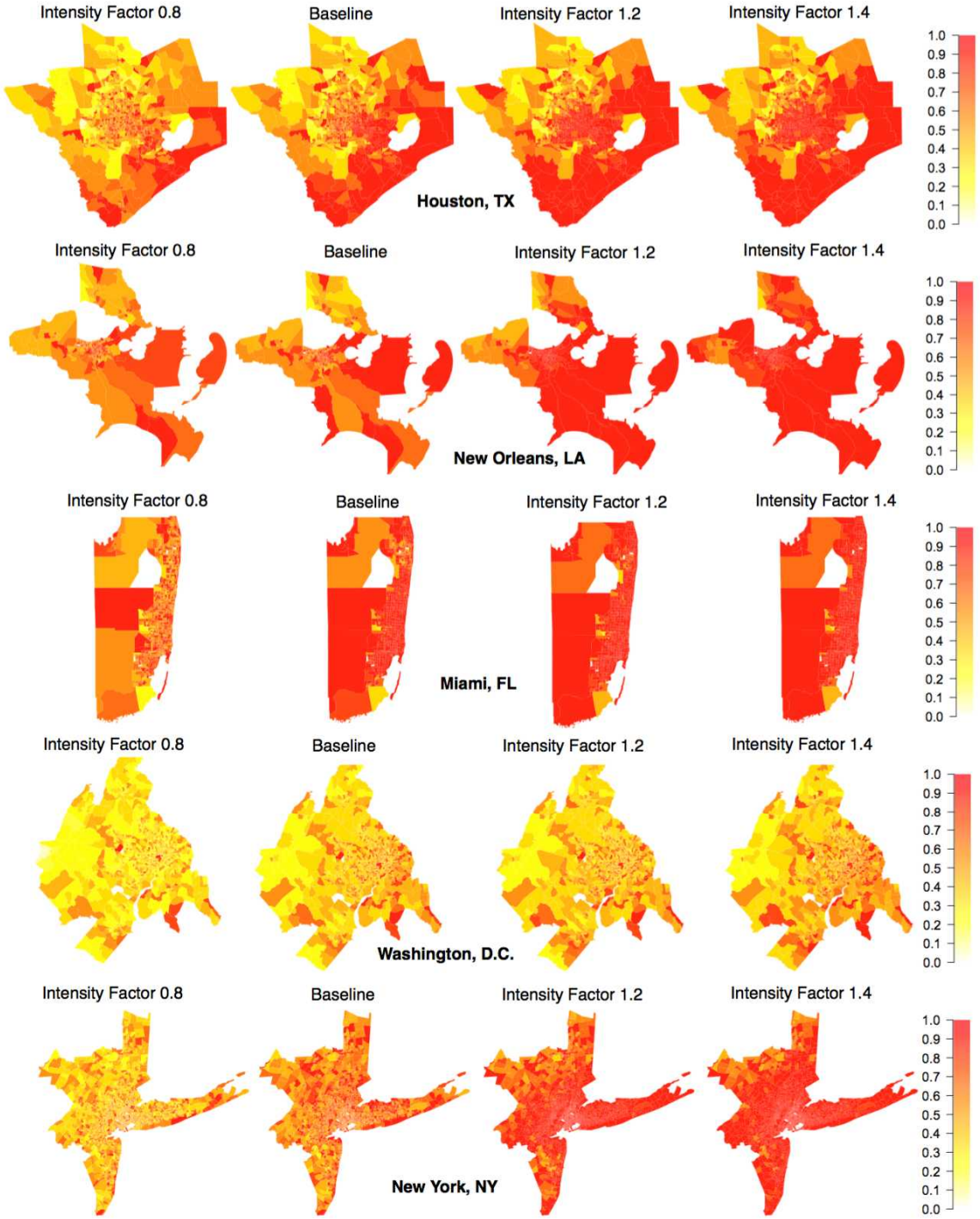




P(outage) - Sensitivity to Frequency

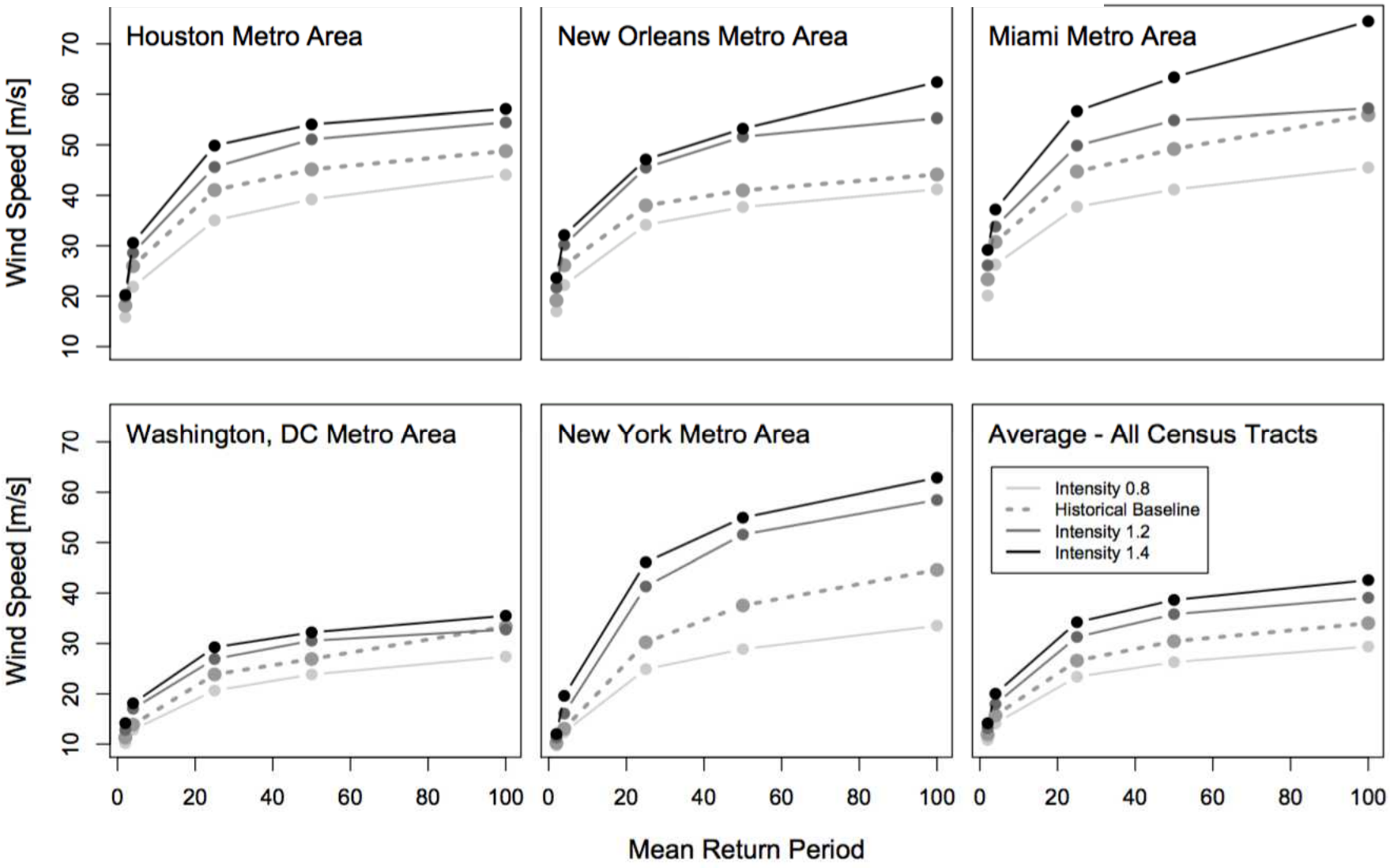


Wind Speed - Sensitivity to Intensity

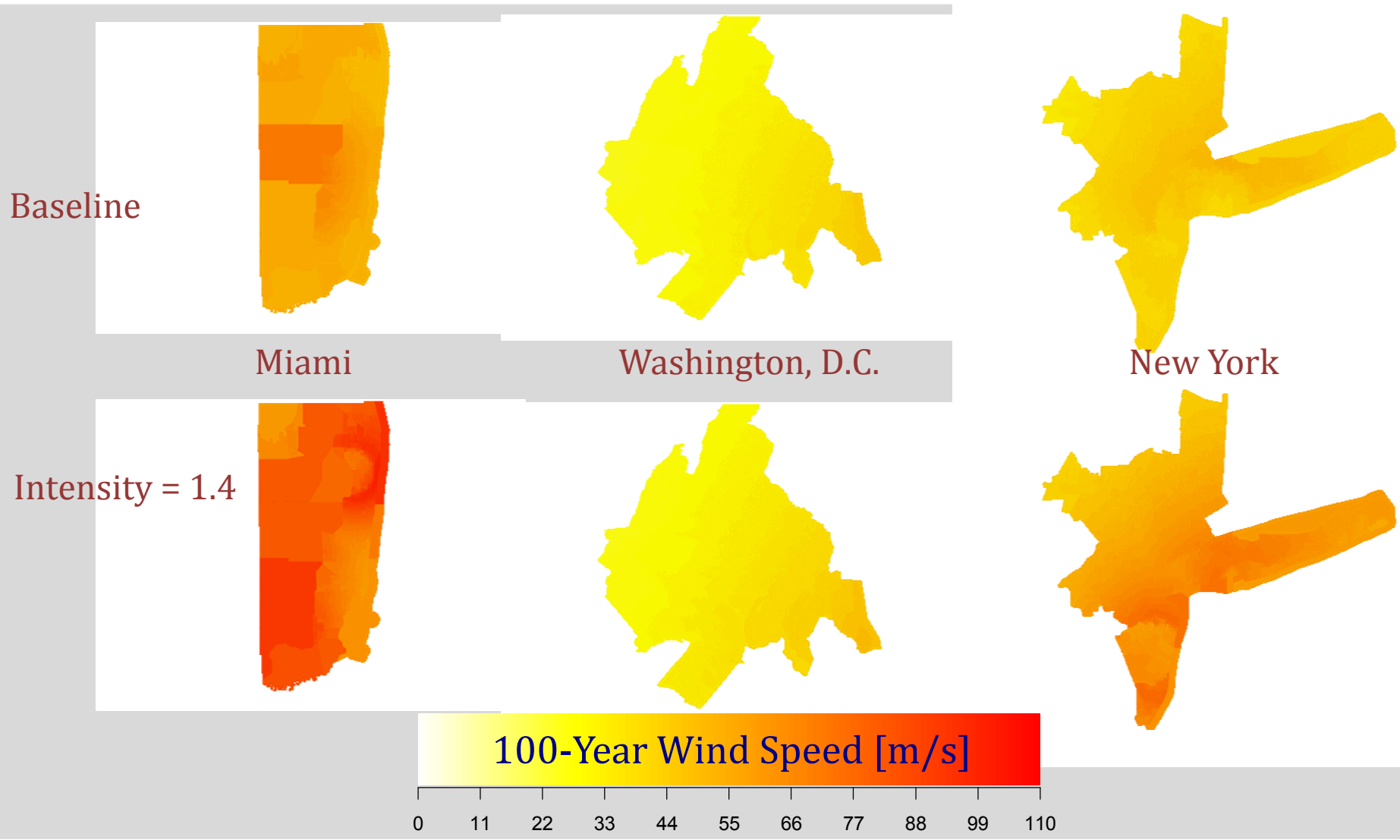


Fraction Out - Sensitivity to Intensity

Figure 5.6: Mean return periods for the fraction of customers without power as intensity varies, plotting the average for five metropolitan areas and for all census tracts (bottom right) evaluated.



Metropolitan Area Impacts



Metropolitan Area Impacts

Sandia National Laboratories

Baseline

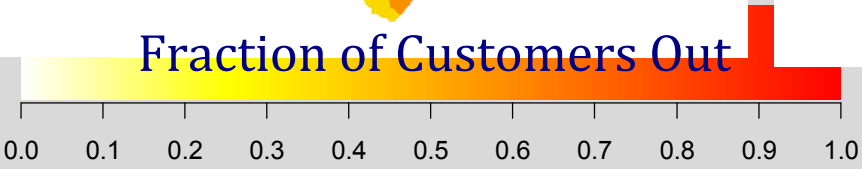
Intensity = 1.4

Miami

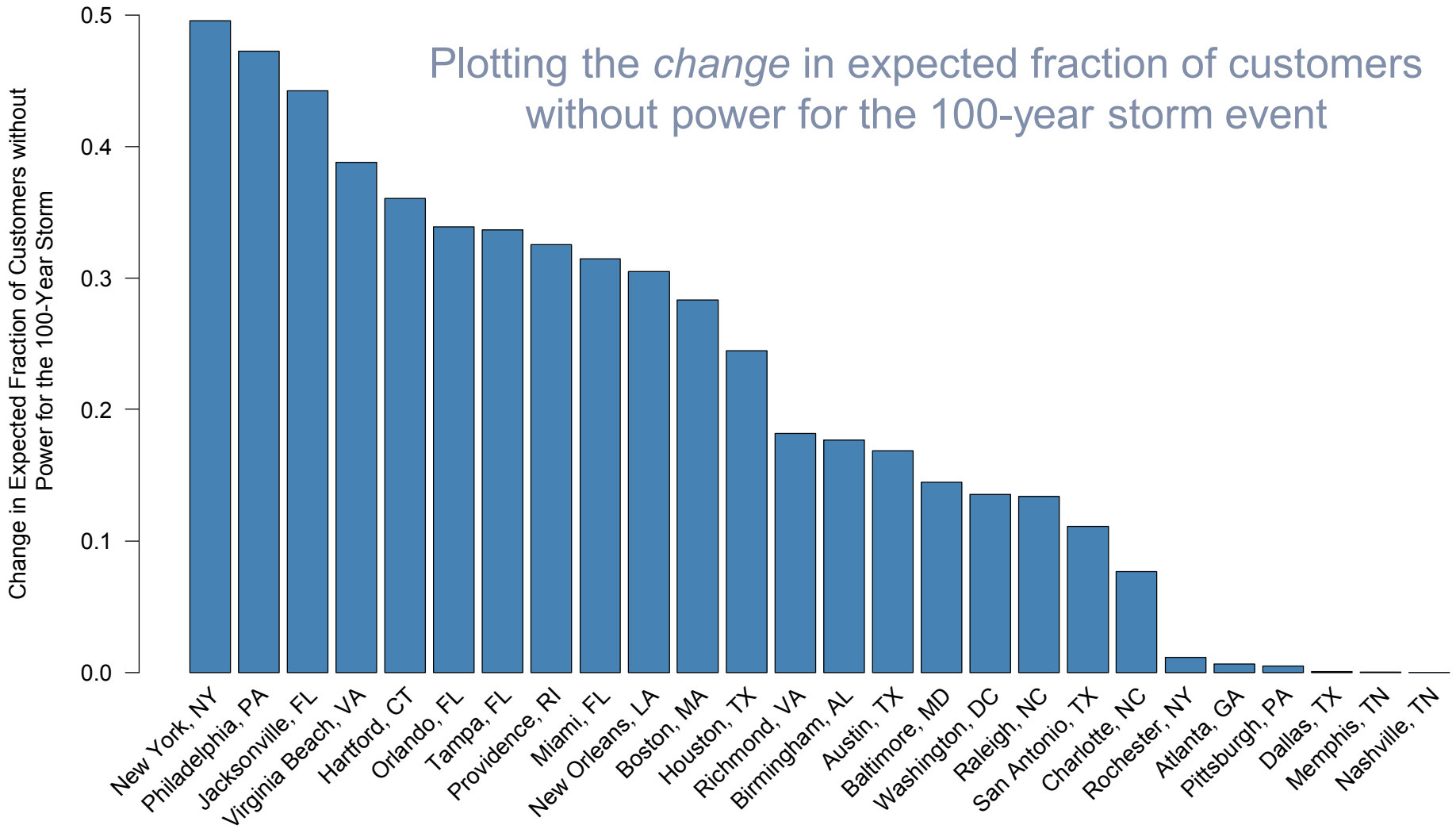
Washington, D.C.

New York

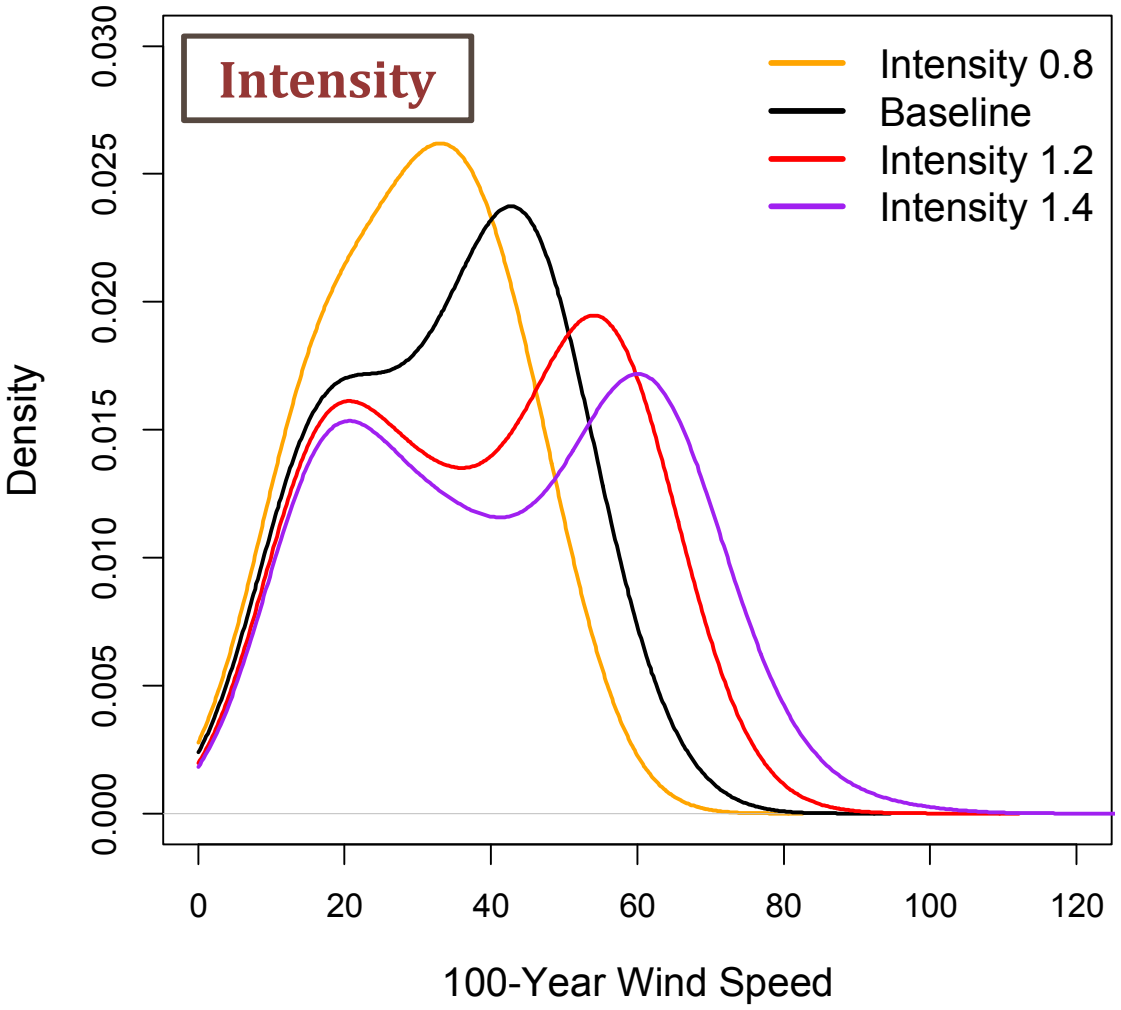
Fraction of Customers Out

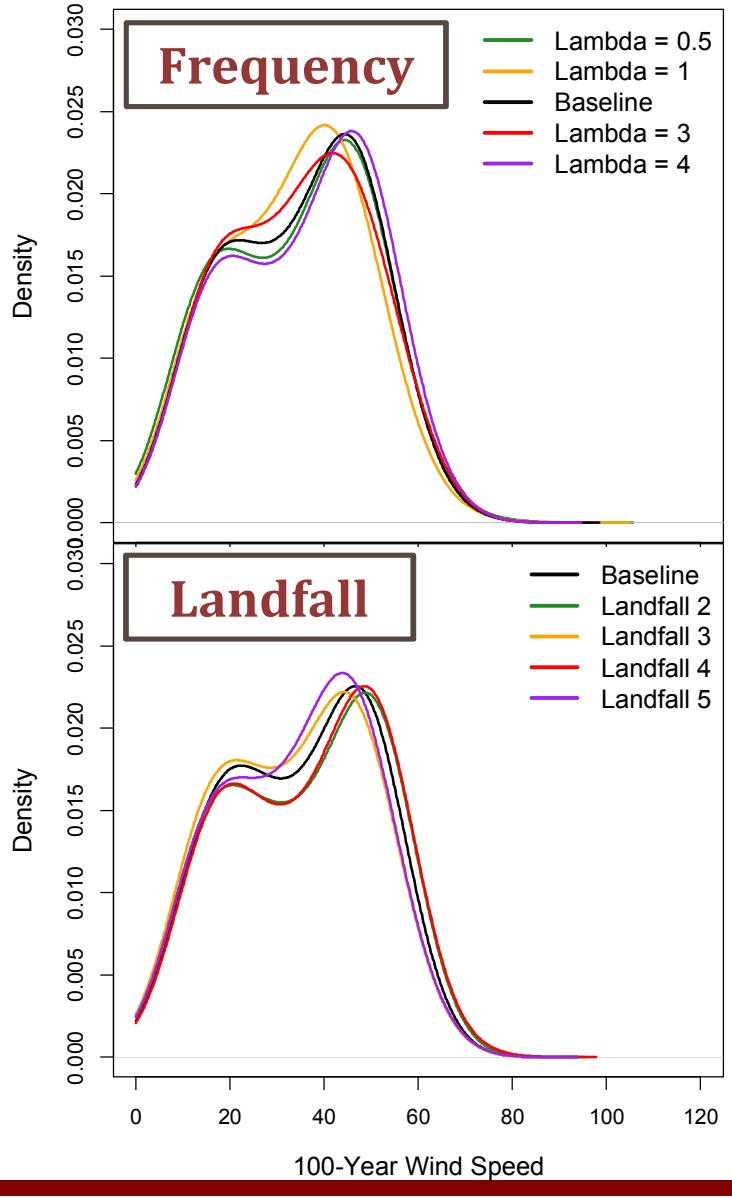


Sensitivity to Hurricane Intensity



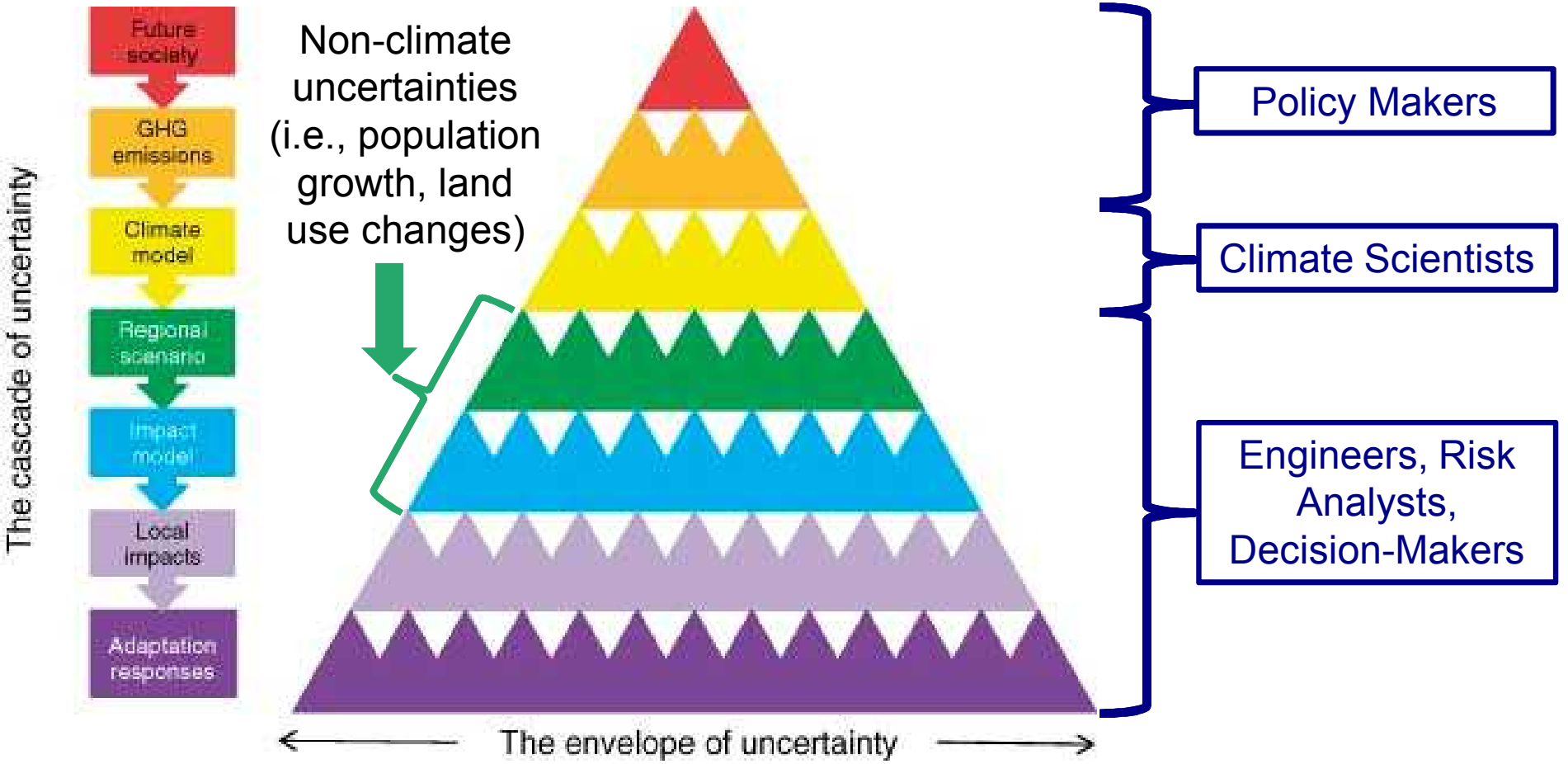
Scenario Risk Sensitivity





Staid, A., Guikema, S.D., Nateghi, R., Quiring, S.M. and Gao, M.Z., 2014. Simulation of tropical cyclone impacts to the US power system under climate change scenarios. *Climatic change*, *127*(3-4), pp.535-546.

Layers of Climate Uncertainty



Weather Volume 65, Issue 7, pages 180-185, 29 JUN 2010 DOI: 10.1002/wea.543
http://onlinelibrary.wiley.com/doi/10.1002/wea.543/full#fig1

Questions?

Sandia National Laboratories

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