Climate Change Risk Analysis: From Simulation to Behavior

Seth Guikema and Allison Reilly, U. Michigan
Gina Tonn, Johns Hopkins University

Classic View of Infrastructure Interdependencies

- Physical interdependencies
- Geographic interdependencies
- Cyber interdependencies
- Logical interdependencies (i.e., “other”)

Decisions and Infrastructure

- Infrastructure users: effect system state through decisions of how to use the system services
- Infrastructure “antagonists”: effect system state through attacks
- Infrastructure operators: effect system state through decisions of how to respond to events and users in operating the system
- Infrastructure managers: effect system state through decisions about resource investments, both long and short-term
- Policy makers and regulatory agencies: effect system state through decisions about allowable actions, requirements, and incentives

Outline

- Potential for climate change induced changes in hurricane risk to coastal energy systems
- Behavior and the evolution of regional vulnerability in response to repeated hurricanes
- Flooding, behavior, and non-stationarity – evolving vulnerability

Long-Term Risk to Power Systems in a Changing Climate

Climatic Change
DOI 10.1007/s10584-014-1272-3

Simulation of tropical cyclone impacts to the U.S. power system under climate change scenarios

Andrea Staid · Seth D. Guikema · Roshanak Nateghi · Steven M. Quiring · Michael Z. Gao

Research Questions

- How would potential changes in hurricane hazards – intensity, frequency, location – influence wind-related power system risk?
- Which areas of U.S. coastline are most sensitive to changes in hurricane hazards?
- Can the possible changes be simulation in a way that will help support long-term utility hardening decision-making?

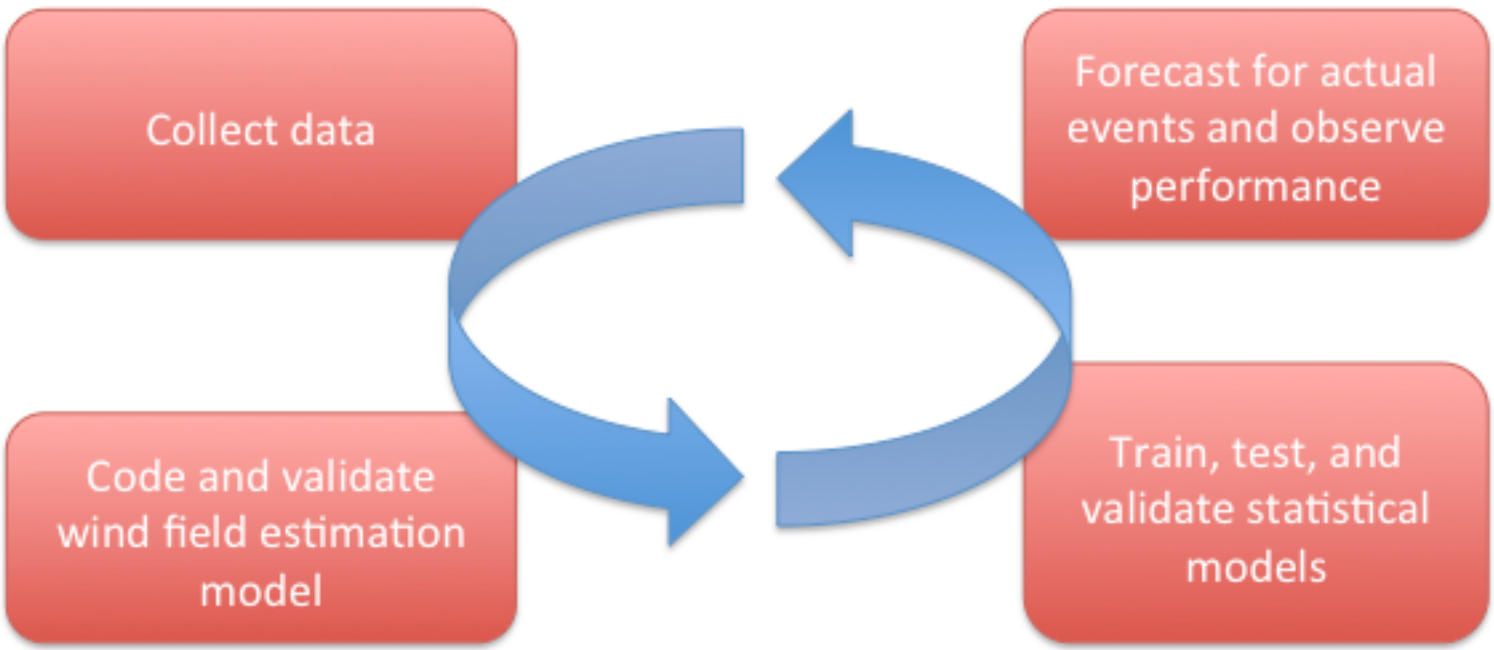
Goals & Data

- Goal: Accurately estimate power outages 4-6 days before landfall and update every 6 hours
- Unit of Analysis:
  - Utility-specific model: 12,000 ft. by 8,000 ft. grid cells
  - Spatially general model: census tracts
- Data:
  - Hurricane wind speeds & duration (wind field model)
  - Geographic data: LU/LC, soil type, topography, watersheds, etc.
  - Climatological: soil moisture, drought levels, long-term precip levels
  - Utility-specific: system inventory, tree-trimming

Model Development Process

10 hurricanes, 4-state area

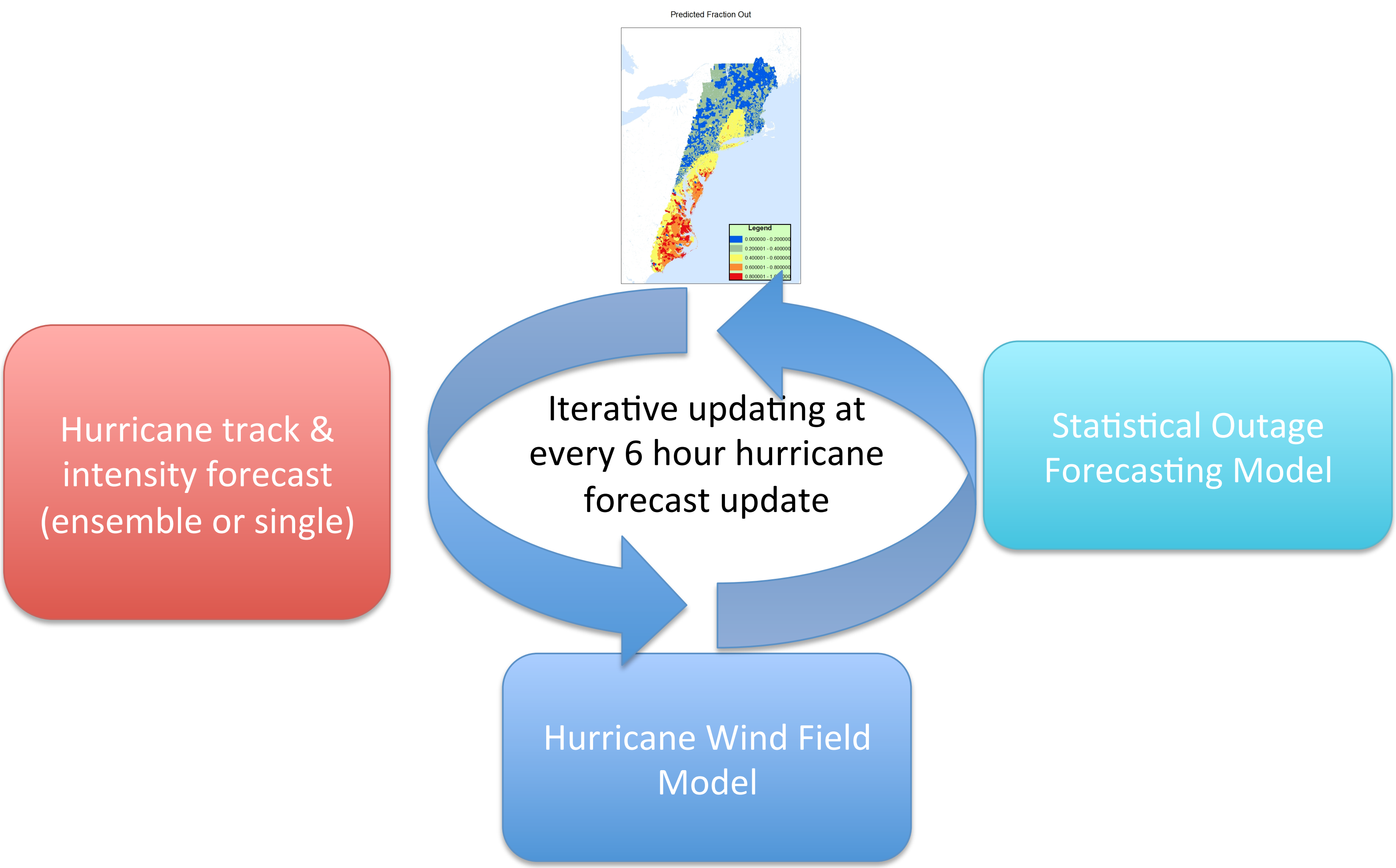
Have run model for 12(+) real storms



In-house Willougby-based model

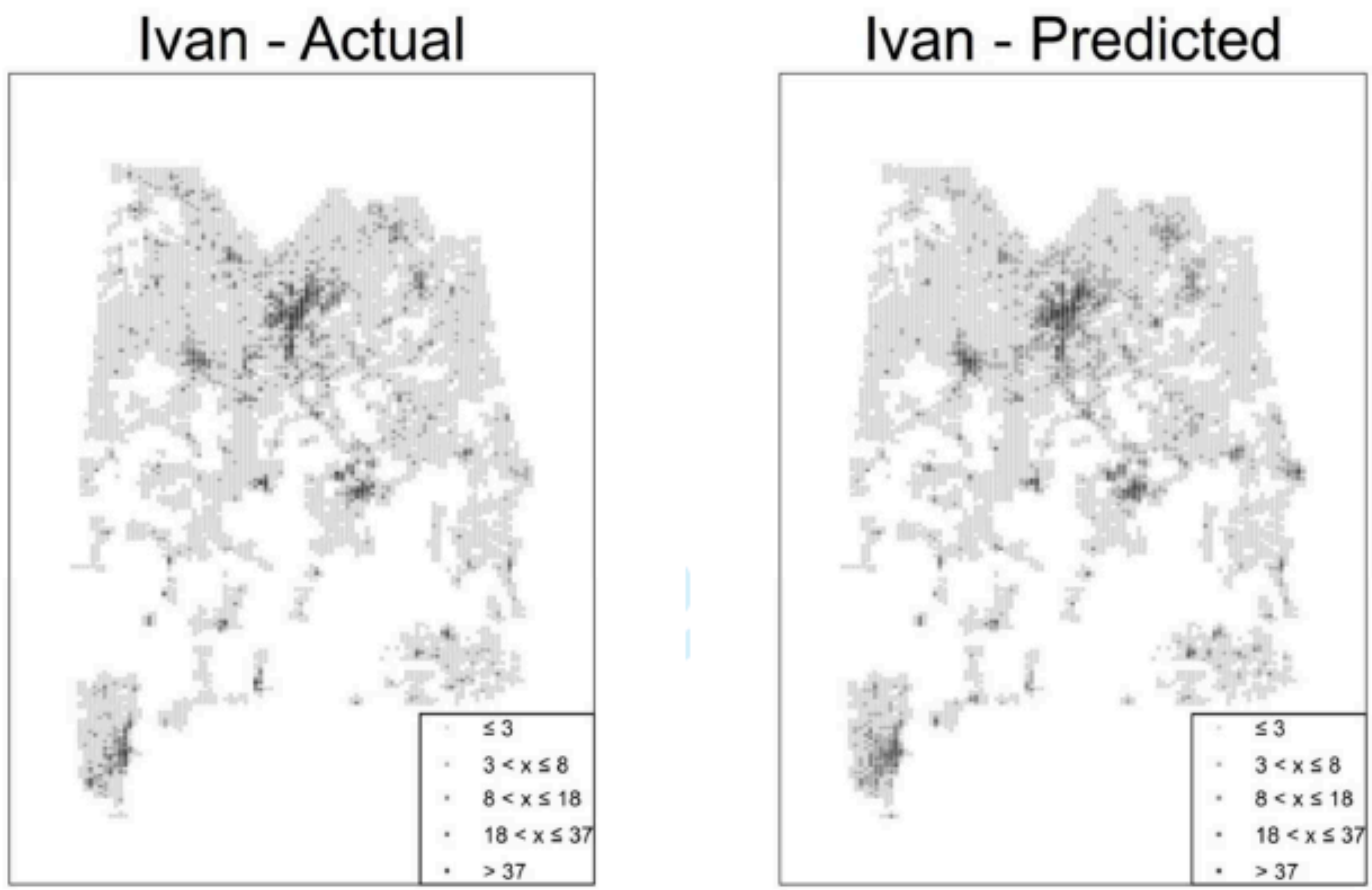
Use scenario storms to (a) answer policy-related queries and (b) gain Further confidence in the model

Prediction Process



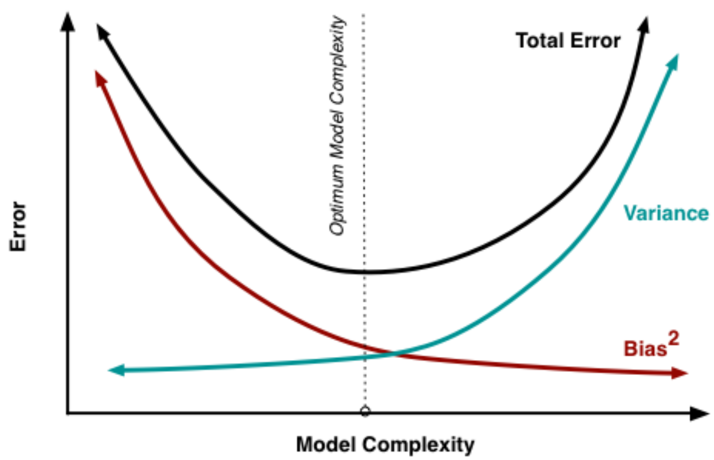
Current Generation Utility Model Prediction Example

Random forest model, reduced to 6 covariates (Nateghi et al., *Risk Analysis* 2013)



A Note On Validation

- Good fit ≠ Strong predictive accuracy in many cases
- Validation critical to balancing bias-variance tradeoff, *particularly for complex data mining models*



Source: Fortmann-Row

Our Validation Approach

1) Random hold-out validation
2) State-based holdout validation
3) Storm-based holdout validation
4) Hold-one-out validation

The Underlying Model

- A 500-member Random Forest, trained with 10 storms for 4 states, 30-fold 20% random selection cross-validation

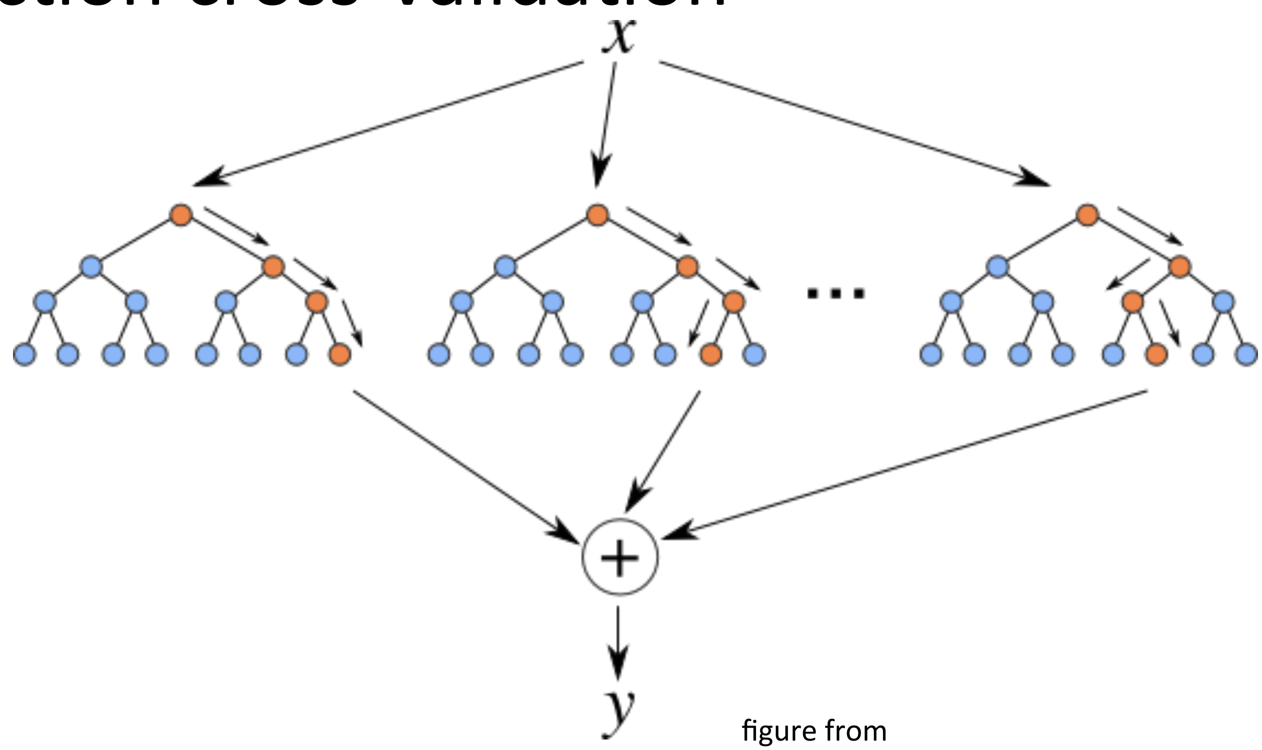
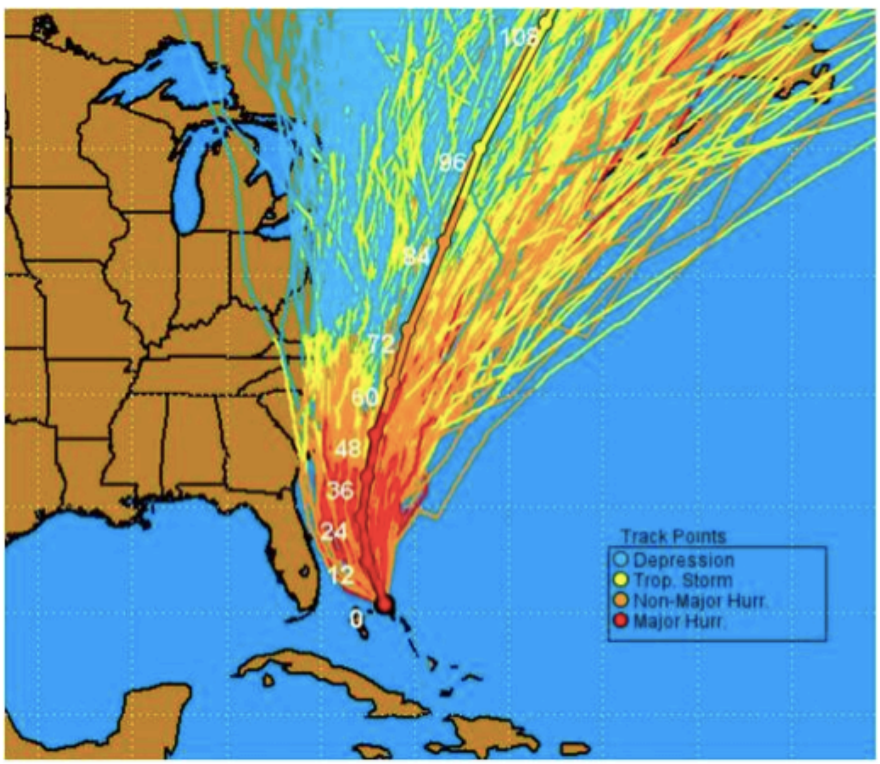


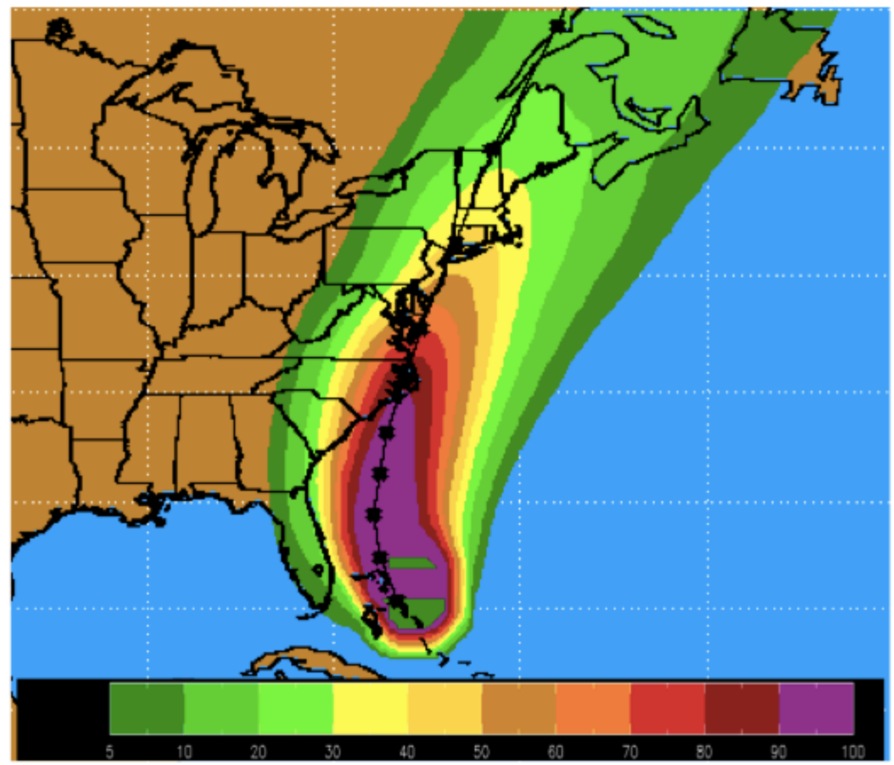
figure from
http://kazoo04.hatenablog.com/entry/2013/12/04/175402

Addressing Track Uncertainty

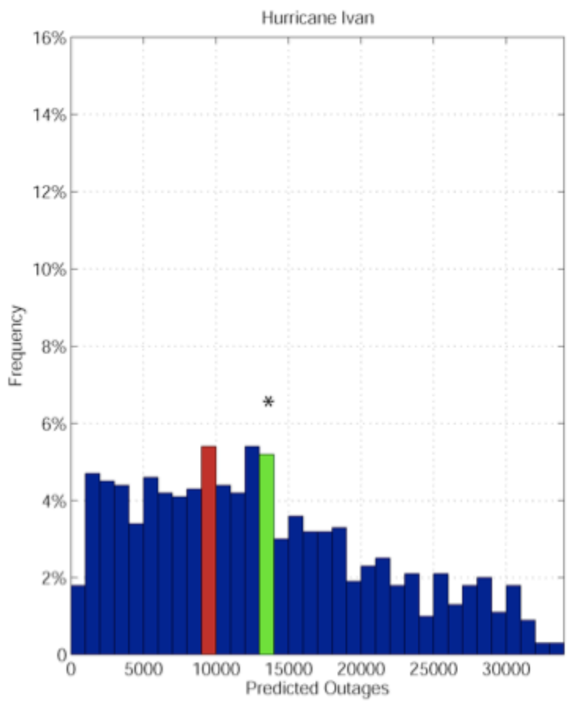
Quiring et al. (2013) Incorporating Hurricane Forecast Uncertainty into a Decision Support Application for Power Outage Modeling, *Bulletin of the American Meteorological Society*.

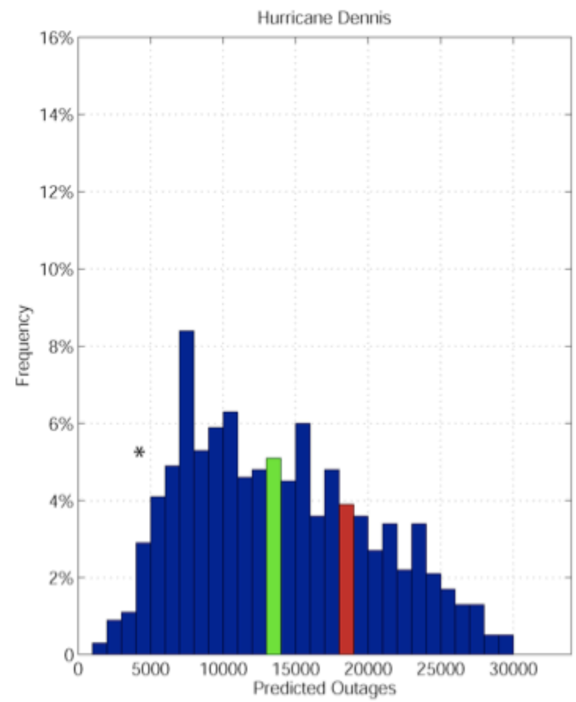
Use Monte Carlo Wind Speed Probability (MCWSP) model to simulate synthetic tracks. Example for Hurricane Irene:

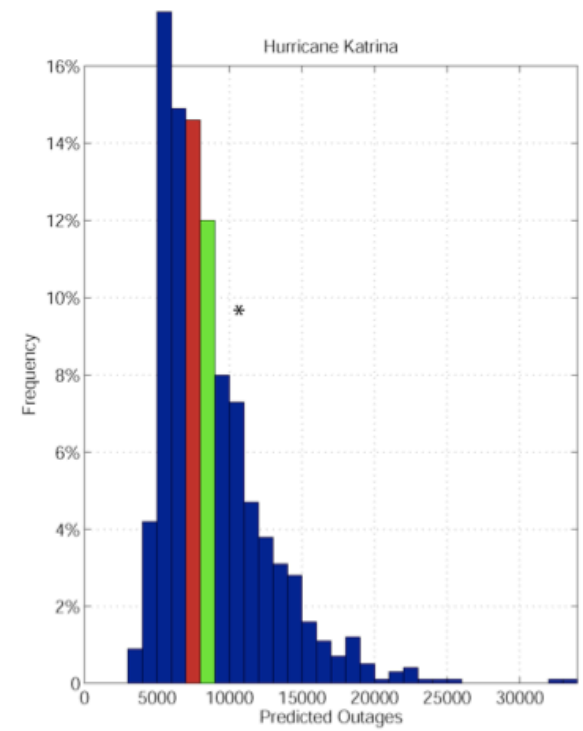




MCWSP-Based Estimates







24-Hour Ahead Forcasts

Green: Average of the MCWSP-based model (1000 replications)

Red: Best-track based

*: Realized (Actual) outages

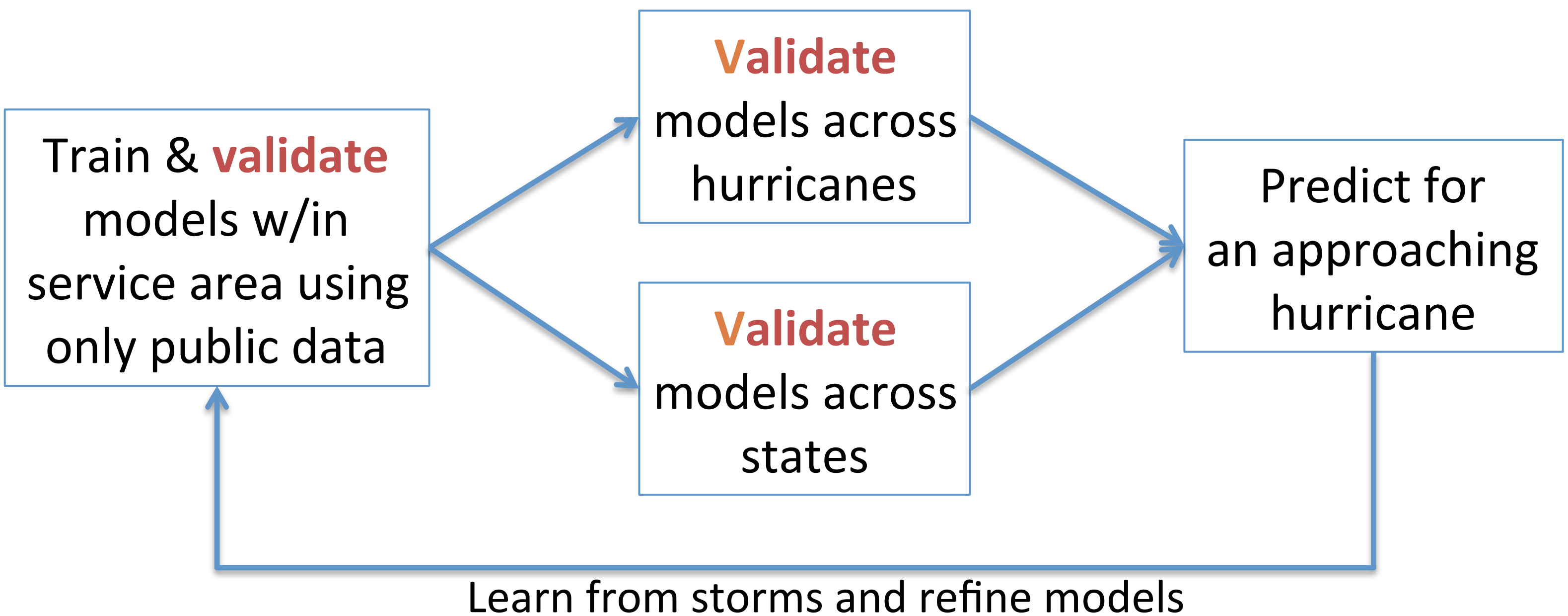
A Key Challenge:

All of the above models were specific to a utility service area and required privately held data.

Spatial Generalization

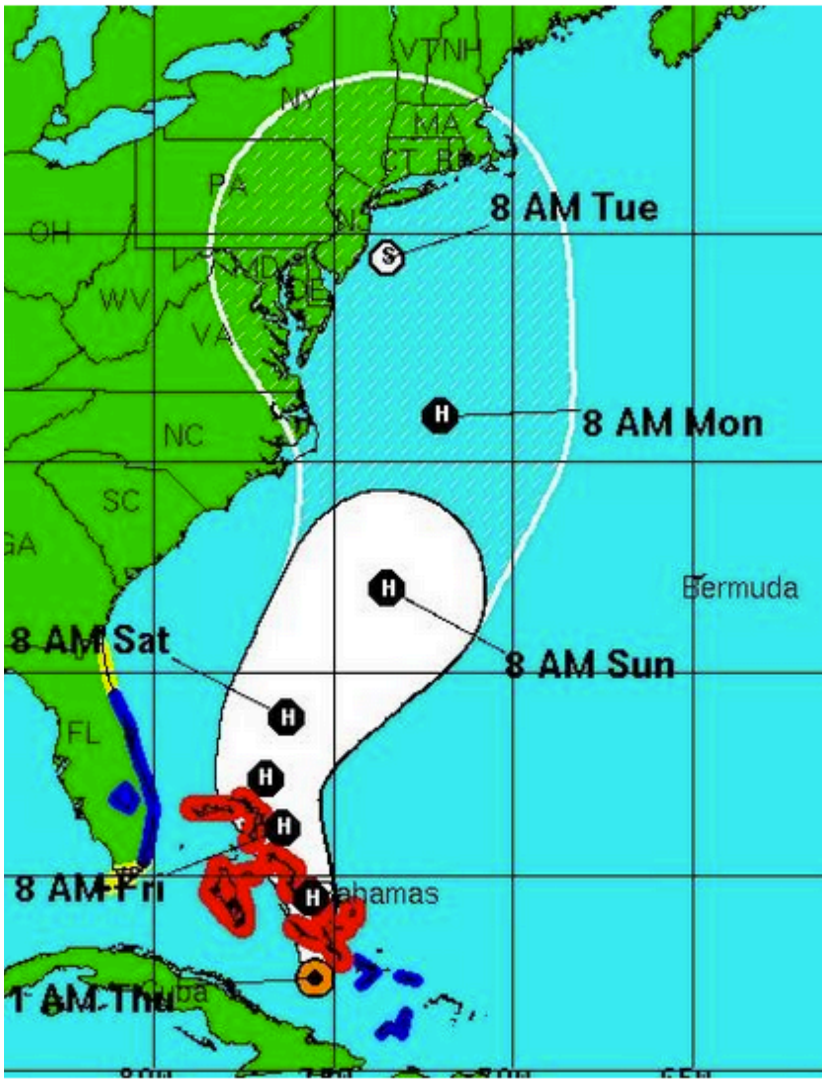
Can a model be developed that can be used for entire coast using only publicly available data while still maintaining accuracy?

Approach



Experience with Hurricane Sandy

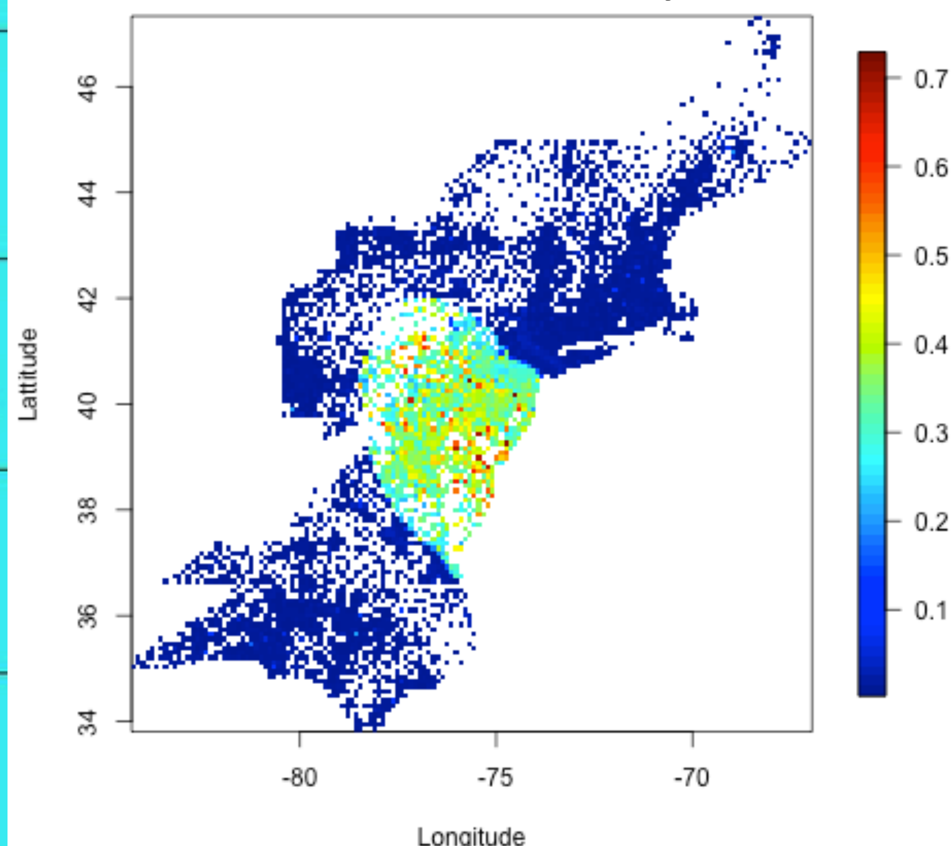
First Model Run: Oct 26, 5pm



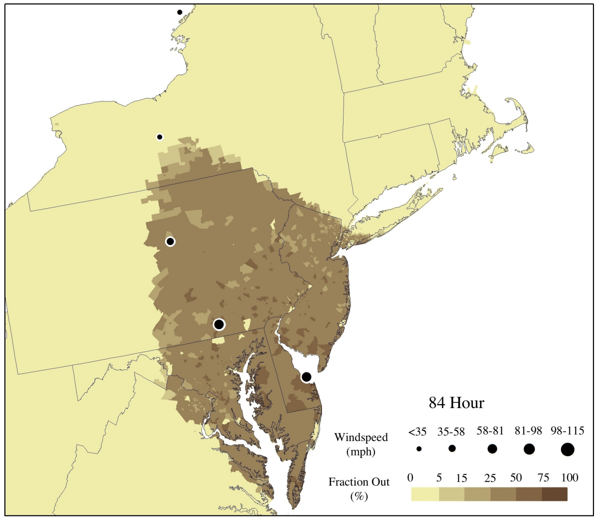
Our Forecast:

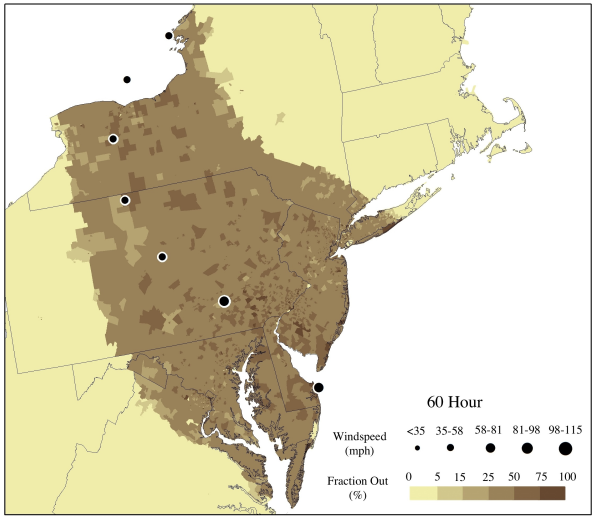
10 million without power

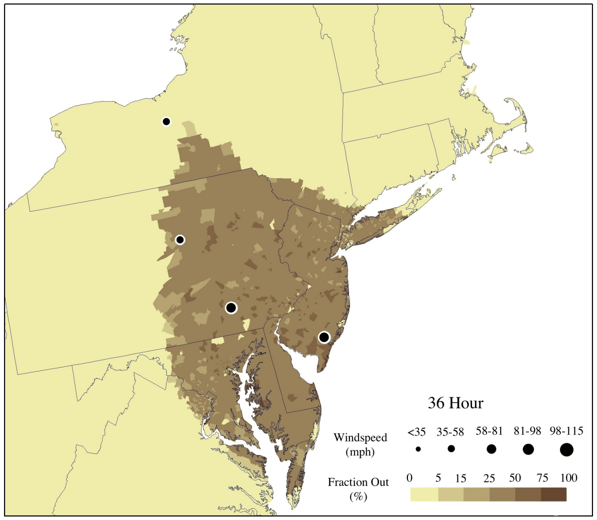
First Press Release by JHU

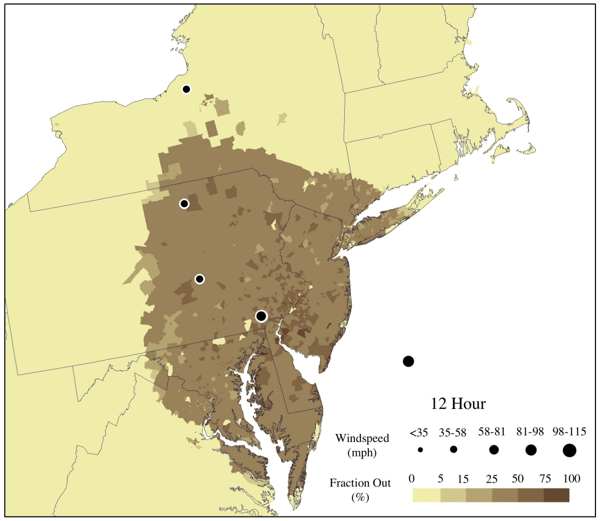


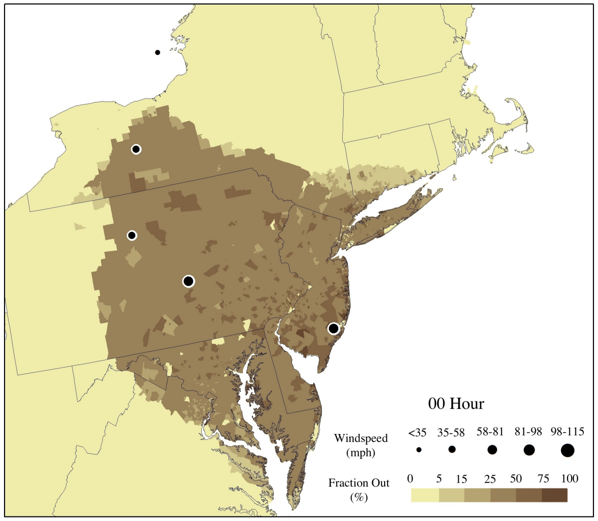
Progression of Hurricane Sandy Runs During the Event











Media Response:

- Substantial national coverage, some international coverage

  CNN, CNN International, Good Morning America, USA Today, Discovery Channel, CBC, Bloomberg TV, US New & World Report, WBAL, Punk Rock OR, etc.

- Focus of media interest:
  - Overall forecast
  - Limited to no interest in uncertainty in the forecasts

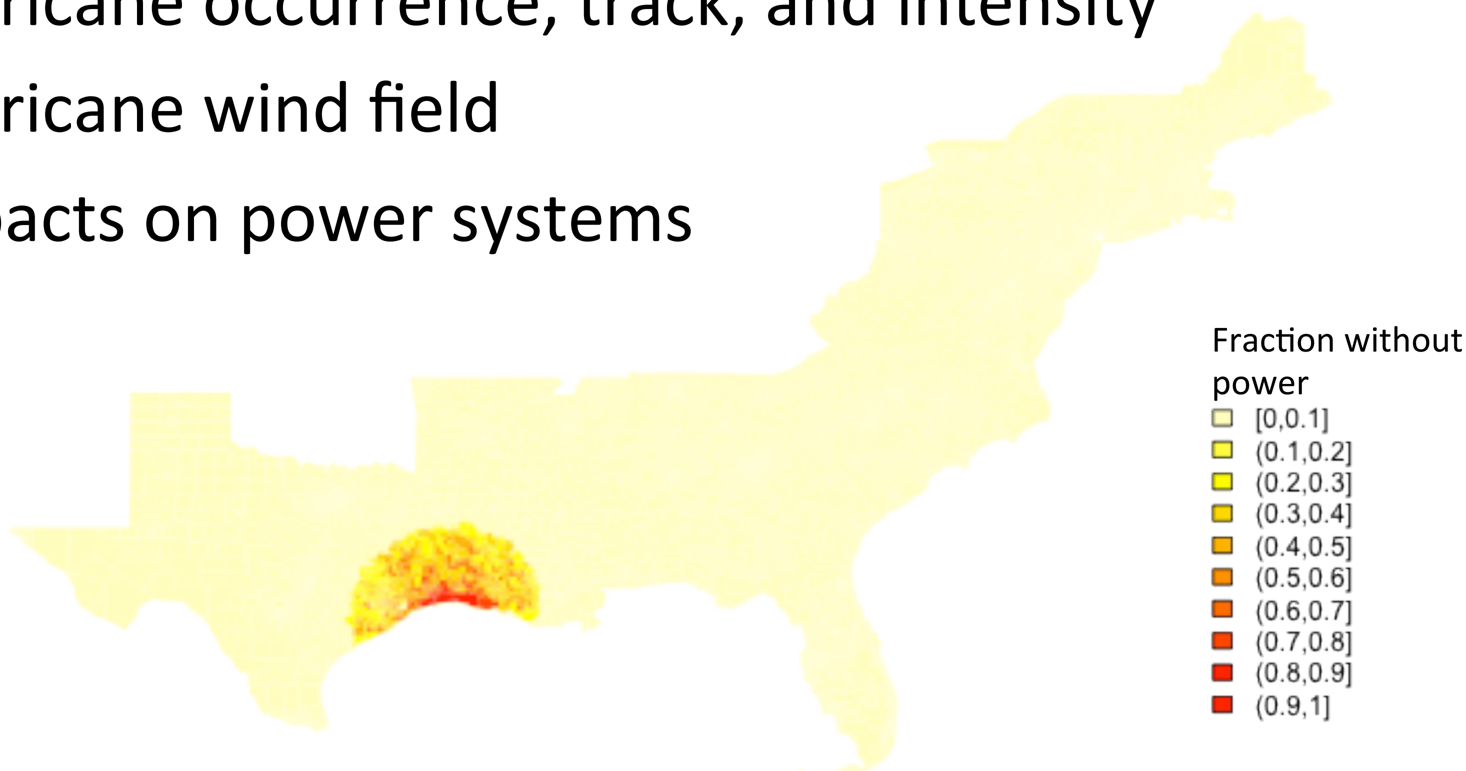
So How Did We Do?

- Important distinction: We predict cumulative outages, utilities generally report peak outages
- Important to realize: We cannot find a reliable source of actual outage data at the scale at which we are making predictions
- Results:
  - DOE estimated 8.5 million customers were out at peak
  - Our final estimate as the storm transited the mid-Atlantic was 8-10 million out
  - We were within 8% of DOE's estimates for NY, PA, MA, RI, VA
  - We overestimated outages for MD and DE
  - We underestimated outages for CT

Now Back to the Long-Term Question: Research Approach

Coupled, large-scale simulation of:

- Hurricane occurrence, track, and intensity
- Hurricane wind field
- Impacts on power systems



Existing Hurricane Climatology

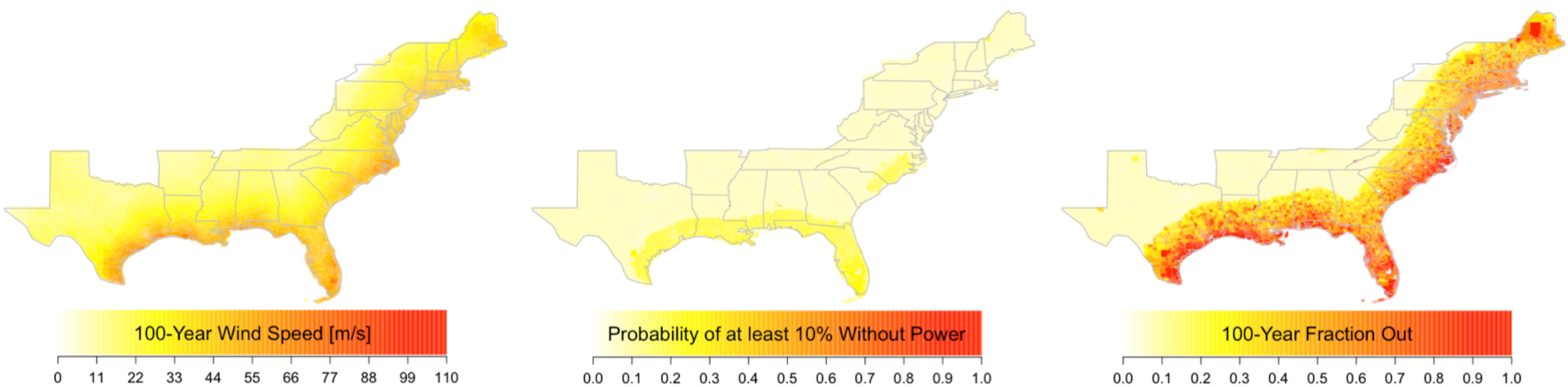


Figure 1: Baseline impacts of (a) 100-year wind speed, (b) annual probability of at least 10% of customers losing power, and (c) 100-year fraction of utility customers without power plotted for each census tract.

Influence of Changes in Intensity

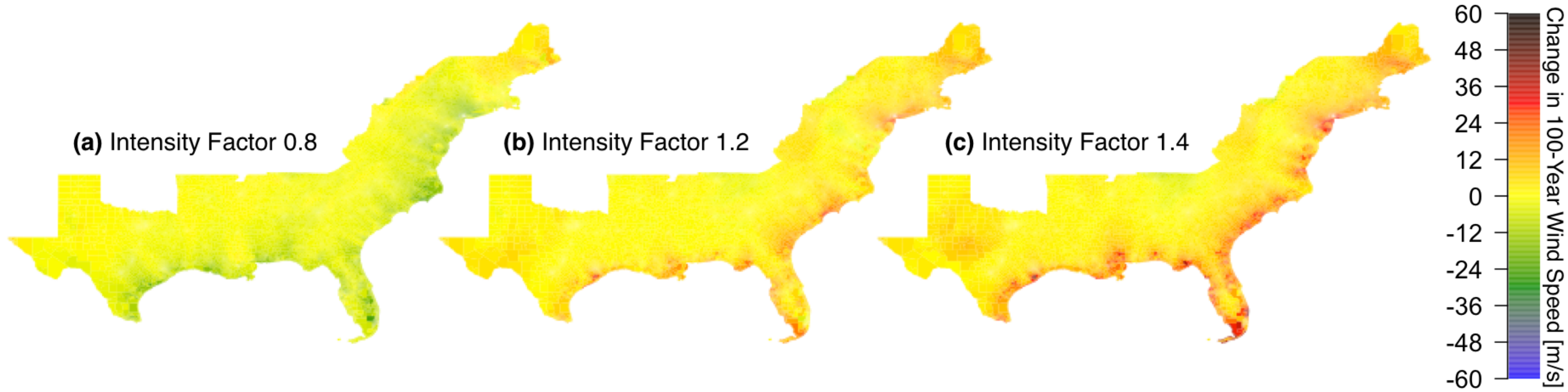


Figure 2: Changes in 100-year wind speeds for varying storm intensity away from baseline.

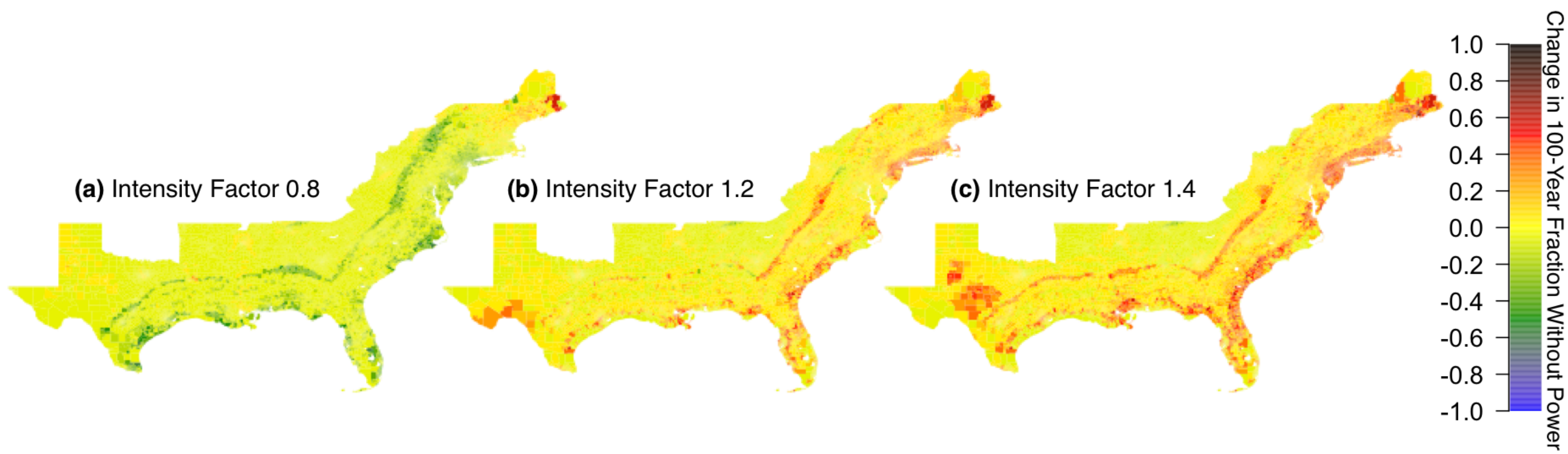


Figure 3: Changes in 100-year fraction of customers without power for varying storm intensity away from baseline.

Influence of Changes in Frequency

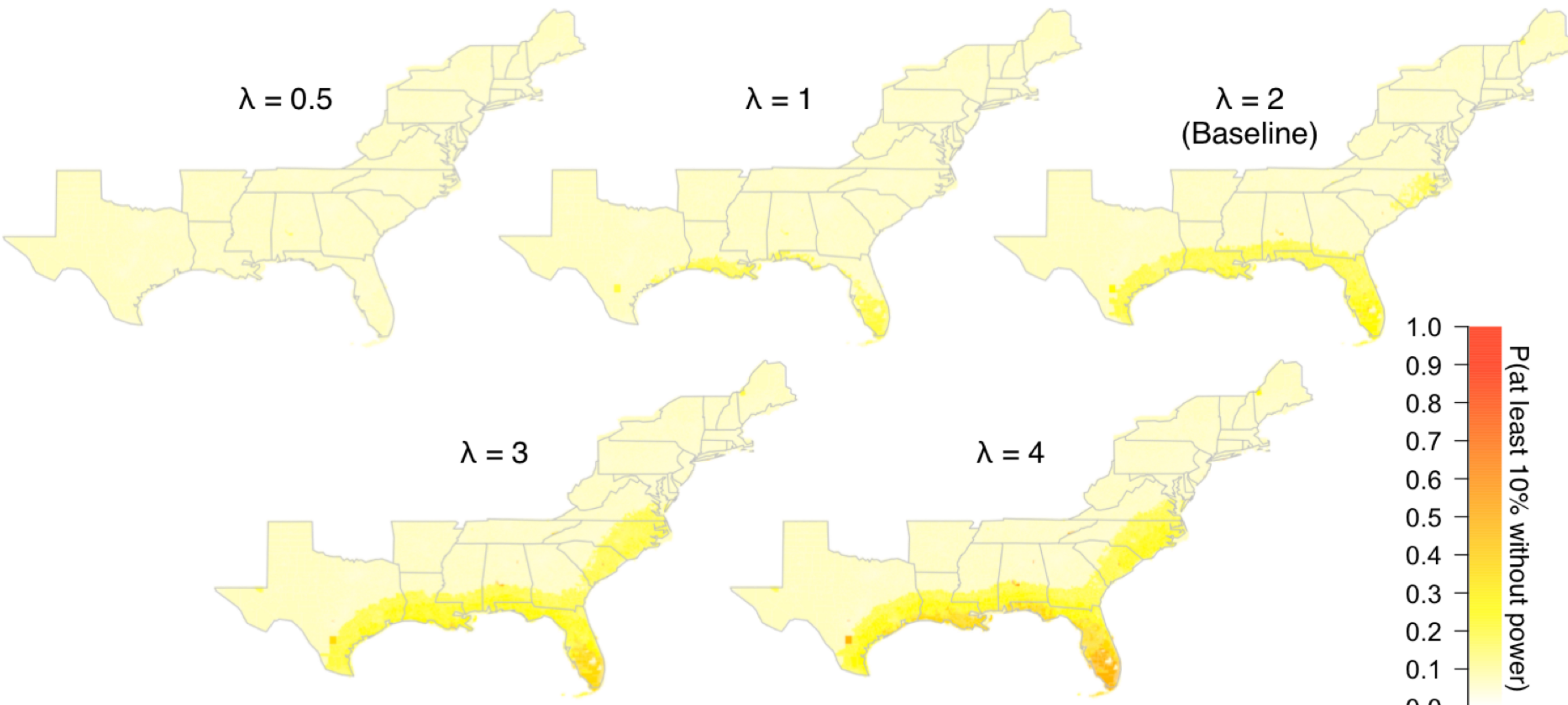


Figure 4: Changes in the probability of at least 10% of customers without power for varying storm frequencies.

Metropolitan Area Impacts: New York City vs. Washington, DC

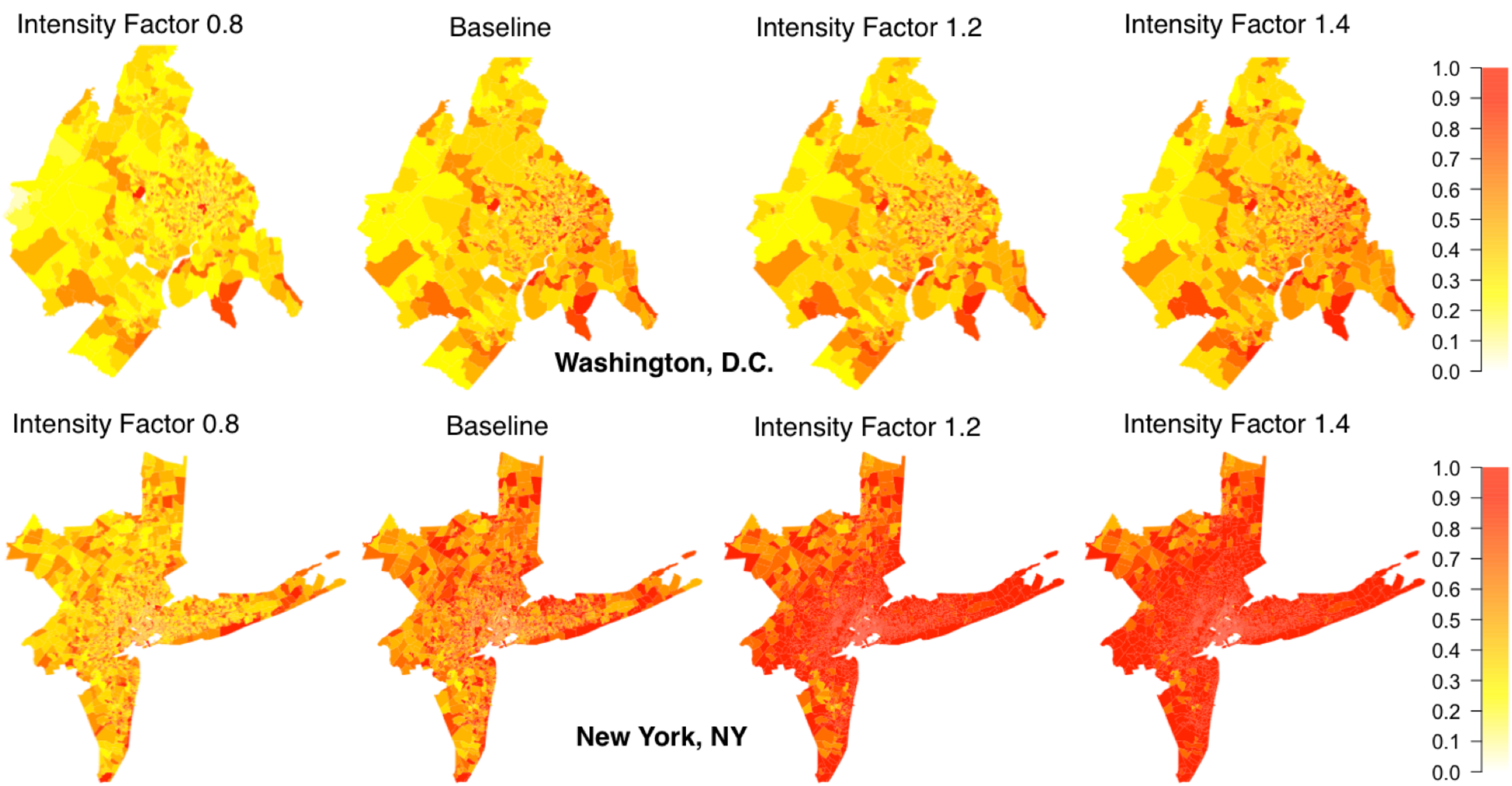
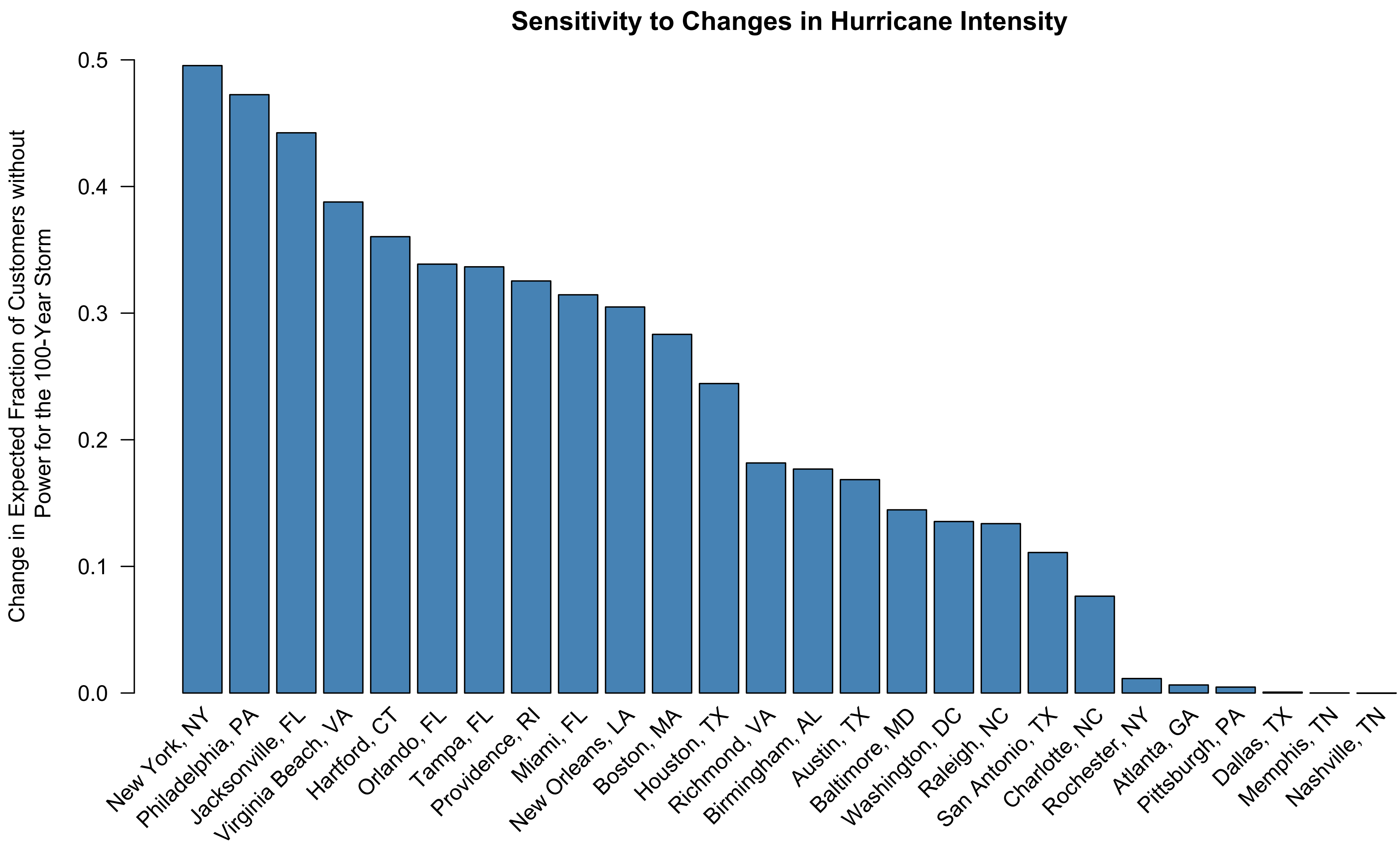


Figure 5: 100-year fraction of customers without power for metropolitan areas for scenarios of varying storm intensity.

Metro Area Sensitivity



Insights

- Not all areas of the country are equally sensitive to changes in hurricane hazard
- Even without probabilistic climate model based projections of hurricane hazards we can gain understanding into differing degrees of sensitivity
- A validated predictive model of storm impacts is of critical importance

The evolving resilience of communities facing repeated hurricanes

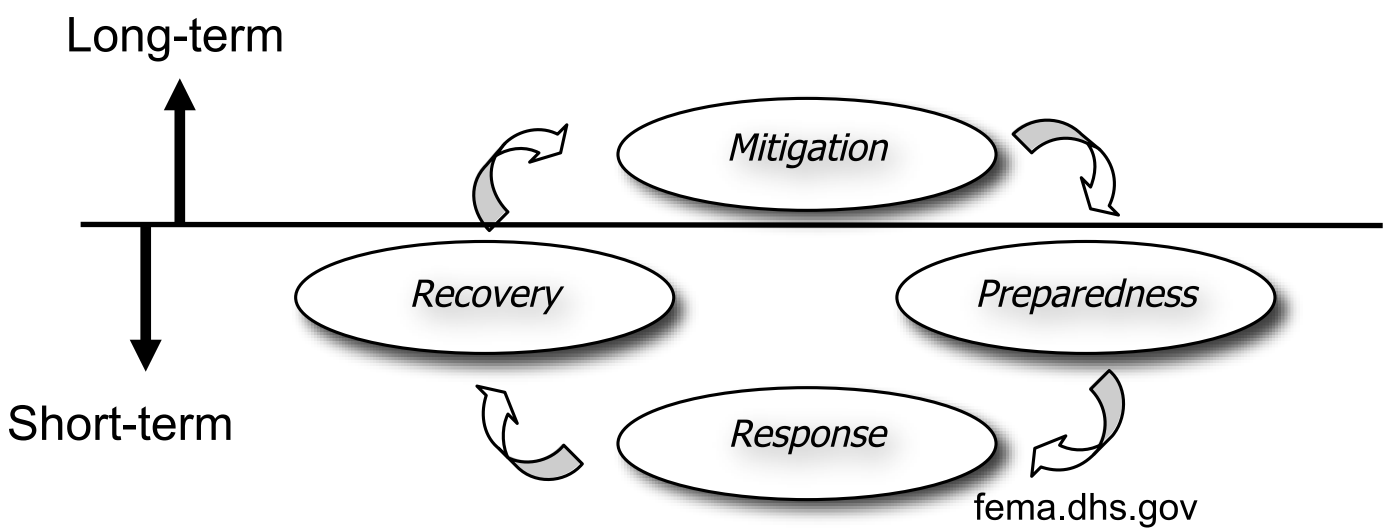
Allison C. Reilly
University of Michigan

Laiyin Zhu
Western Michigan University

Tak Igusa
Johns Hopkins University

Seth D. Guikema
University of Michigan

Four Phases of Emergency Management



Hazard SEES: Individual response and community resilience to repeated hurricanes

Our perspective is distinct from prior literature examining impacts of hurricanes, which include:

- Structural responses to wind and storm surge
- Evacuation and other “preparedness” actions
- System functionality during “response” phase
- Optimize investments for mitigation

<u>Approach</u> Build an ABM framework to simulate the impacts of

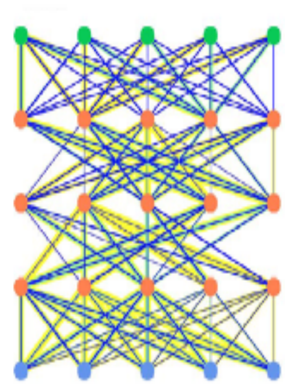
- Different hurricane environments
- Damage caused by these hurricanes
- How individuals make decisions about mitigation and land use change

Agent-Based Models

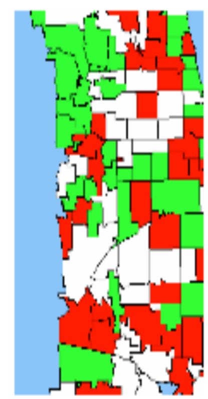
- Include decision-making entities (agents) in addition to stochastic elements.
- Agents have learning rules and decision rules
- Allows for agent heterogeneity
- Widely used to examine situations in which individual behavior is an important driver of collective outcomes (public health, natural hazard response)
- Typically run many simulations. Observe averages, outliers.

Euclidean Space: *2D, 3D*

Grid: *von Neumann neighborhood*



Network



GIS: Geographic Information System

http://www.mcs.anl.gov/~leyffer/listn/slides-06/MacalNorth.pdf

ABM Overview for Evolution of community Resilience to Repeated Hurricanes

<u>**Hurricane History** (historic or synthetic storm tracks)</u>

<u>Parcel Risk</u>

<u>Threat</u>

Wind speed (WMU)

Storm Surge (GMU/ JHU)

<u>Vulnerability</u>

via HAZUS fragility curves

<u>Consequence</u>

Damage, measured on a 0 – 4 scale

Damage State	
0	No damage
1	Minor damage
2	Some damage
3	Severe damage
4	Total destruction

<u>Community-level Losses</u>

including spatial patterns and by building stock type

<u>Government Policy/Information Sharing</u> for heightened resilience

<u>Individual learning and decision making</u>

Parcel hardening (UM, GU)

Land use change (RFF)

Modeling Agent Decision-Making

Prescriptive decision models (i.e., agents make *the best* decision)

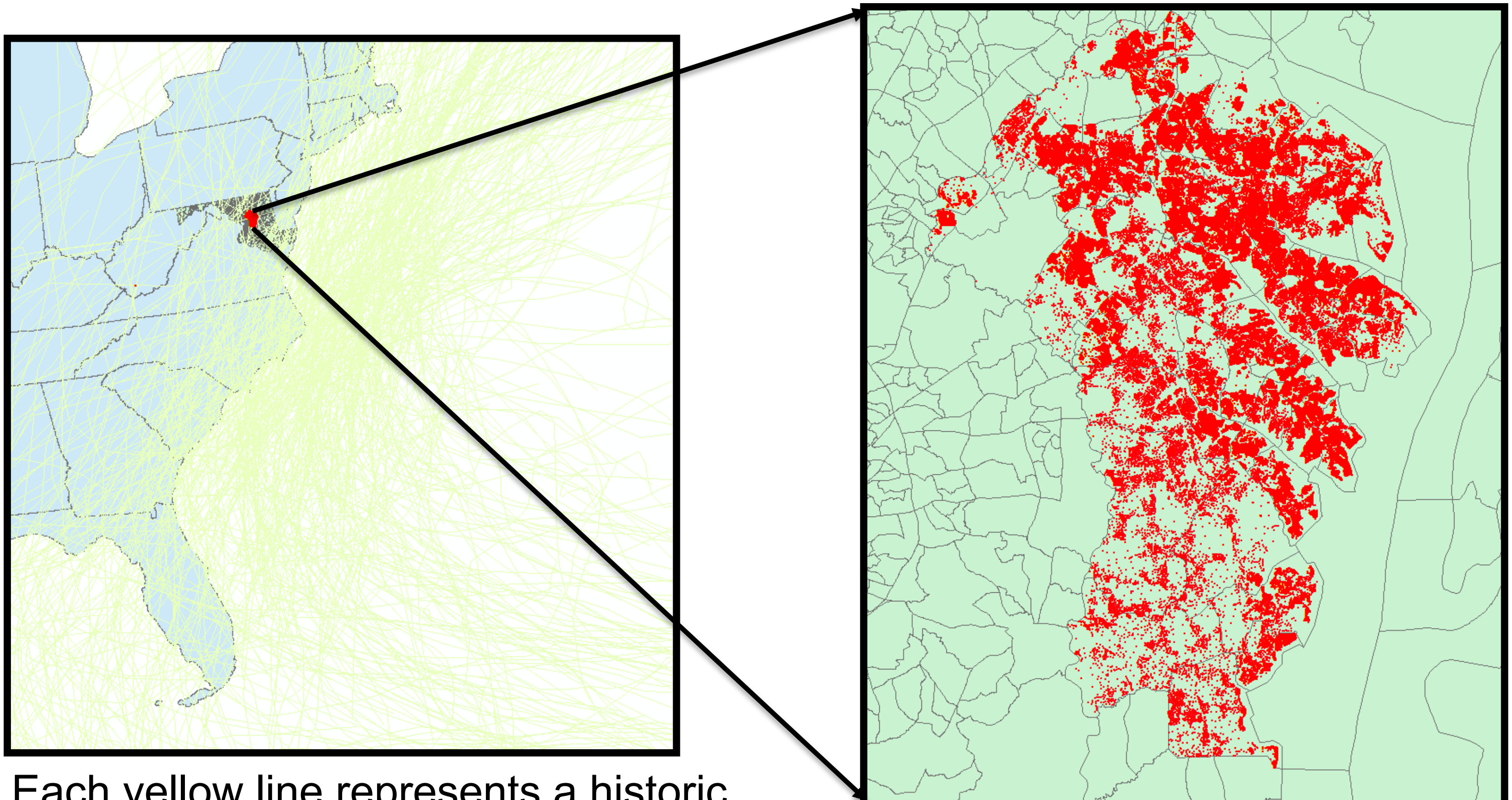
- Utility Theory: maximize expected net benefit

Descriptive decision models (i.e., what agents *actually* do)

- Bounded Rationality and satisficing
  - Prospect theory
  - Luce's choice axiom
- Theory of Reasoned Action
  - Behavioral Intention = f(beliefs, subjective norms)
- Near-misses

Case Study: Anne Arundel County, MD

Illustrate framework using simple decision rules



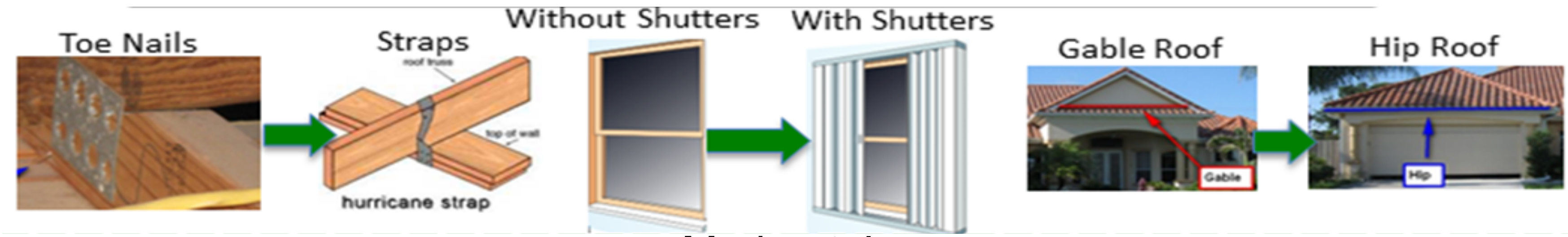
Each yellow line represents a historic hurricane track; 15 have impacted Anne Arundel County since 1860

Each red dot represents one of ~162,000 residential parcels

Case Study: Anne Arundel County, MD

Illustrate framework using simple decision rules

Mitigation options



Inexpensive

Moderately expensive

Expensive

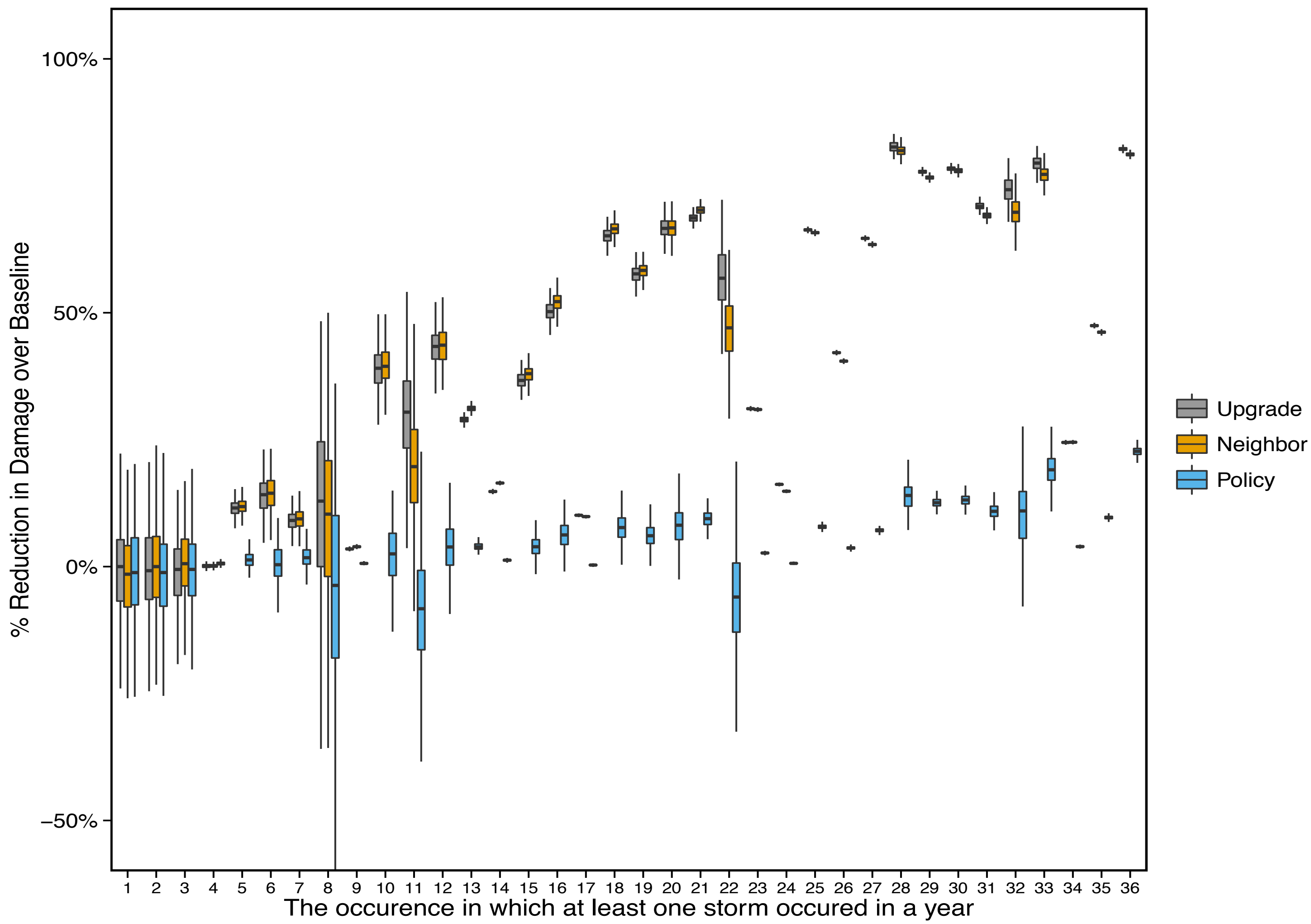
Simple decision rules

1. **Baseline:** Parcels return to same resistance level
2. Upgrade with some probability, conditioned on extent of damage
3. Upgrade with some probability, conditioned on extent of damage AND the neighbor's damage
4. Government subsidy for upgrade given to some percentage homes

Hazard

1. Historic hurricane record from Anne Arundel County, Miami, and Boston

Reduction in damage over baseline for 3 decision rules: Miami historical storm record



Reduction in damage over "do nothing case" for 4 decision rules

Mitigation decisions impact community vulnerability

Regulatory/policy

- Incentives that get people to mitigate must be targeted and vetted to be effective

Engineering

- What we assume about how people mitigate really matters
- Community vulnerability and resilience is a dynamic principle that is impacted by an array of factors

Evolving Community Flood Risk

Gina Tonn

Seth Guikema

Evolving Community Flood Risk

- Improve understanding of temporal changes in community flood risk through combined analysis of behavioral, engineering, and physical hazard aspects
- Interactions of community actions, engineering measures, and individual behavior may result in unanticipated changes to flood vulnerability that aren't captured by standard models
- Components
  - Base model: Simulate risk (flood damage and population at risk) over time. How does risk vary based on differing stochastic elements?
  - Mitigation alternatives: How do community interventions impact flood risk over time?
  - Climate change: How does risk change based on climate change scenarios?

Simulation Steps

Repeat Simulation - Next Year

Annual Flood

- Sampled from historic flood data (also adjusted or simulated data)
- Damage tallied
- Population at-risk tallied

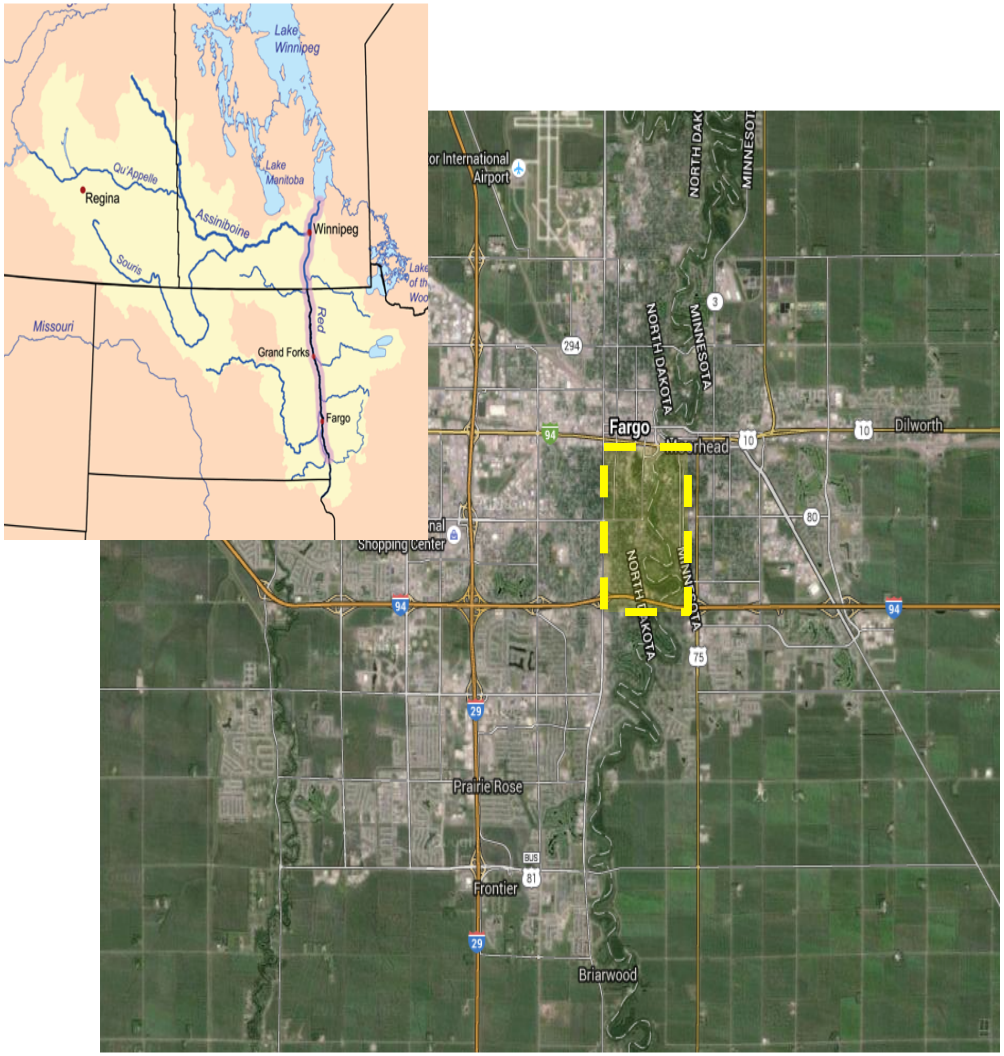
Agent Action

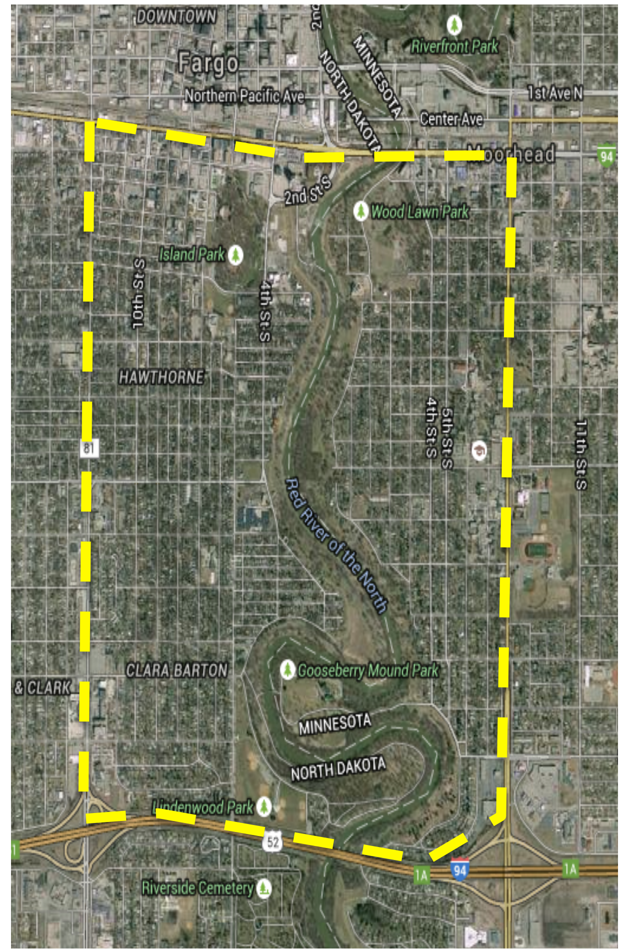
- Options: do nothing; complain; elevate mechanical equipment; elevate home; move out
- Decision based on risk perception, coping perception, utility (all recalculated each year)

Community Action

- Options: do nothing; information campaign; mitigation project
- Decision based on percentage of agents that complain, percentage of houses damaged, and utility

Case study location: Fargo, ND





Annual Flood

- Elevation
  - Sampled from historic annual peak elevations at stream gage within study area
  - Adjusted sample sets for:
    - Community mitigation
    - Climate change scenarios
- Flood Depth
  - Estimated for each agent based on flood elevation and GIS topographic data
- Damage
  - Calculated for each agent based on structure type, property value, flood depth, HAZUS depth-damage curve
- Population at-risk
  - Count number of agents in study area each year (non-vacant parcels)

Agent Action

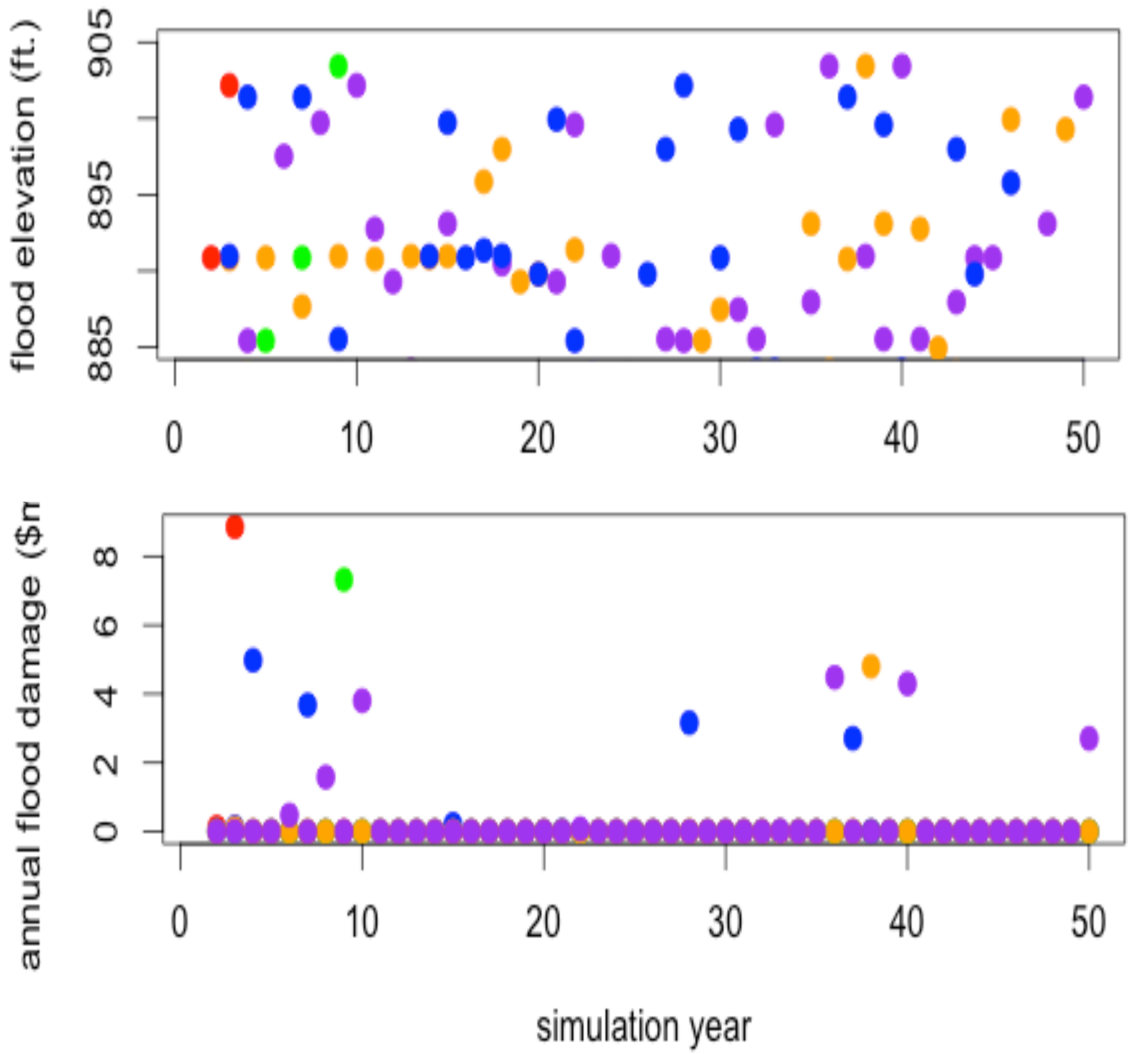
- Perceived Risk (Lindell 2008, Dillon 2008)
  - Based on:
    - Agent's flood experience
    - Agent's near-miss experience
    - Neighbors' flood and near-miss experience
    - Agent's mitigation measures
    - Community mitigation measures
    - Information dissemination by community
- Perceived Coping Ability (Poussin 2014, Bubeck 2013)
  - Agents' confidence in their ability to take action
  - Based on:
    - Home value (proxy)
    - Previous agent mitigation action
    - Previous neighbor mitigation action
    - Information dissemination by community

- Possible Agent Actions
  - Do nothing
  - Complain to community
  - Elevate mechanical equipment
  - Elevate home
  - Move

Community Action

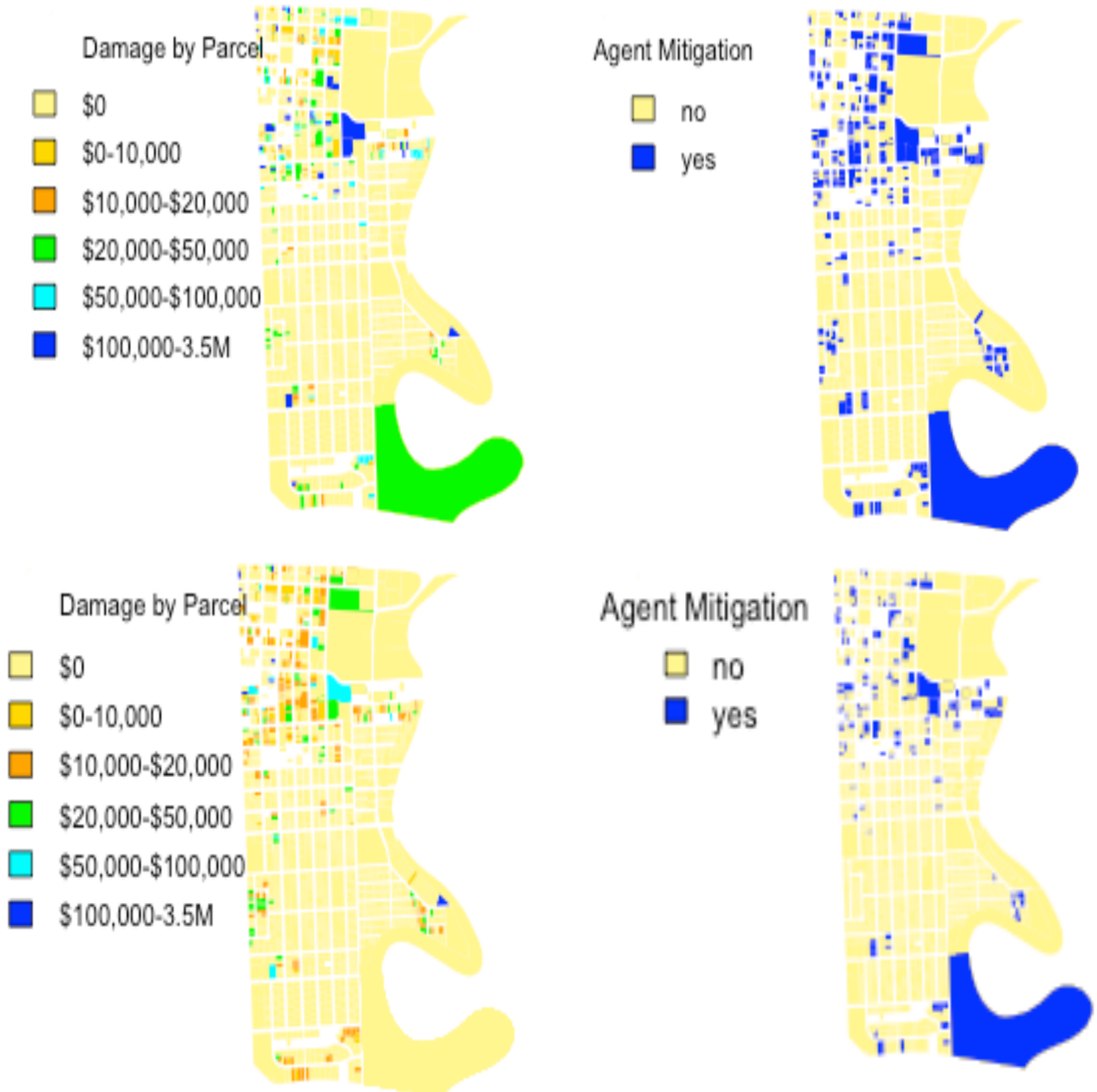
- Actions based on:
  - Agent complaints vs. complaint threshold
  - Community damage vs. damage threshold
- Possible actions:
  - Information campaign
  - Mitigation project
    - Levee
    - Diversion
    - Floodplain restoration

Base model results



Simulation	Total Damages	Agent Mit. (number)	Comm. Mit.
1 (purple)	$17.4M	355	No
2 (orange)	$4.9M	332	No
3 (blue)	$14.9M	342	No
4 (red)	$9.0M	65	Yes (yr 3)
5 (green)	$7.3M	168	Yes (yr 9)

Example Simulation Results



Findings and additional work

- Findings
  - ABM is a useful tool to simulate flood risk evolution based on many interacting stochastic factors and decisions
  - Sensitivity analysis is necessary and useful
- Additional work:
  - Compare community mitigation alternatives
  - Climate sensitivity analysis

Concluding Thoughts

- Behavior can effect vulnerability over time – need to think beyond engineered protective measures and consider behavioral response to protective measures in coastal risk analyses
- Not all areas of the country are equally sensitive to climate change induced changes in hurricane hazards – need to consider both sensitivity to change and likelihood of the change in the long run

Ackknowlegements

- NSF – CMMI (IMEE, CIS), SEES programs
- DOE – BER and OIMA
- Army Corps for data