DOES NASA SMAP IMPROVE THE ACCURACY OF POWER OUTAGE MODELS?

Brent McRoberts, Texas A&M University
Steven Quiring, Ohio State University
Seth Guikema, University of Michigan

January 12, 2017

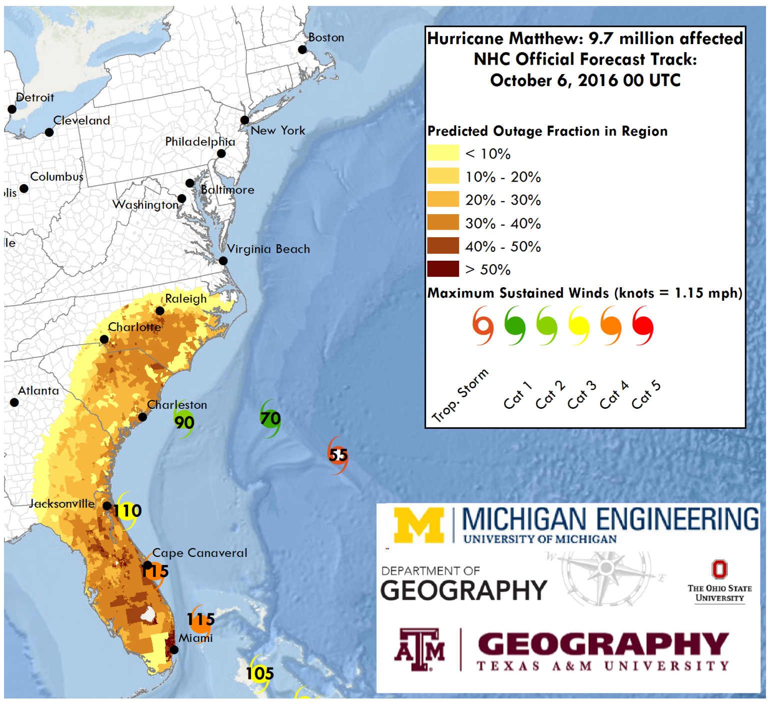
NASA SMAP: Hurricane Power Outage Prediction

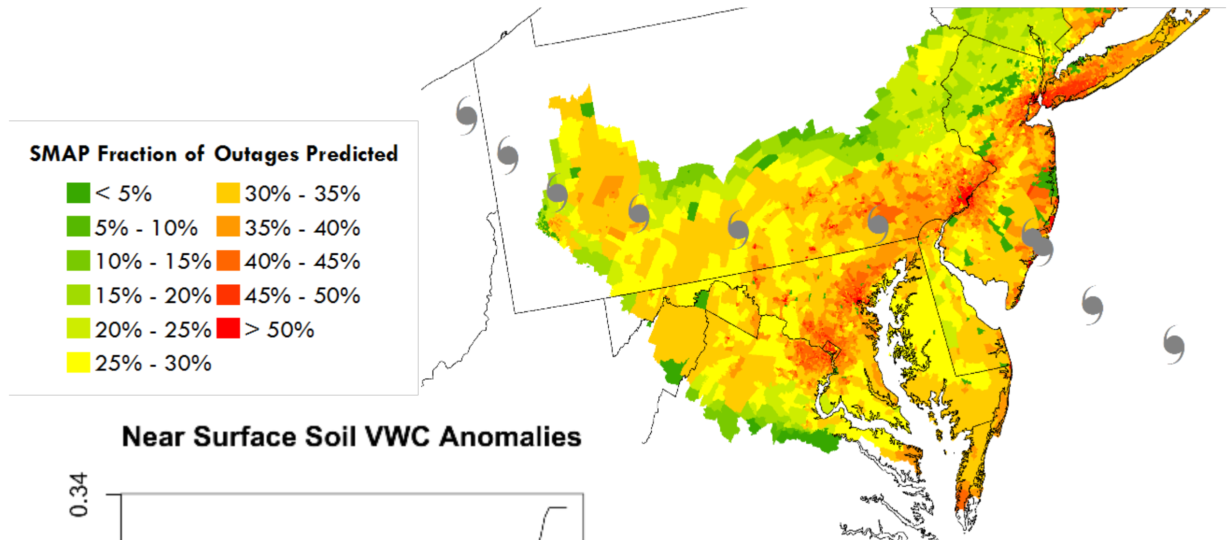
Brent McRoberts and Steven Quiring

<u>Research question</u>: Can SMAP data be used to improve power outage predictions?

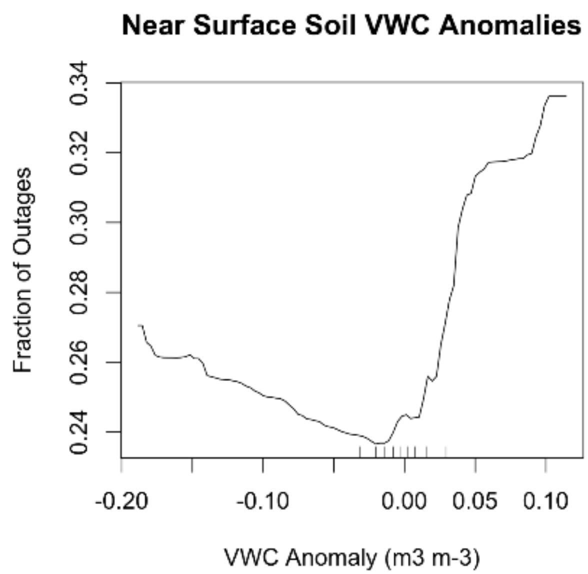
<u>Approach</u>: Sensitivity analysis was performed to compare outage predictions for 11 historical storms made using two different soil moisture datasets (SMAP and NLDAS-2)

<u>Results</u>: Outage predictions are sensitive to soil moisture; Using SMAP data has a significant impact





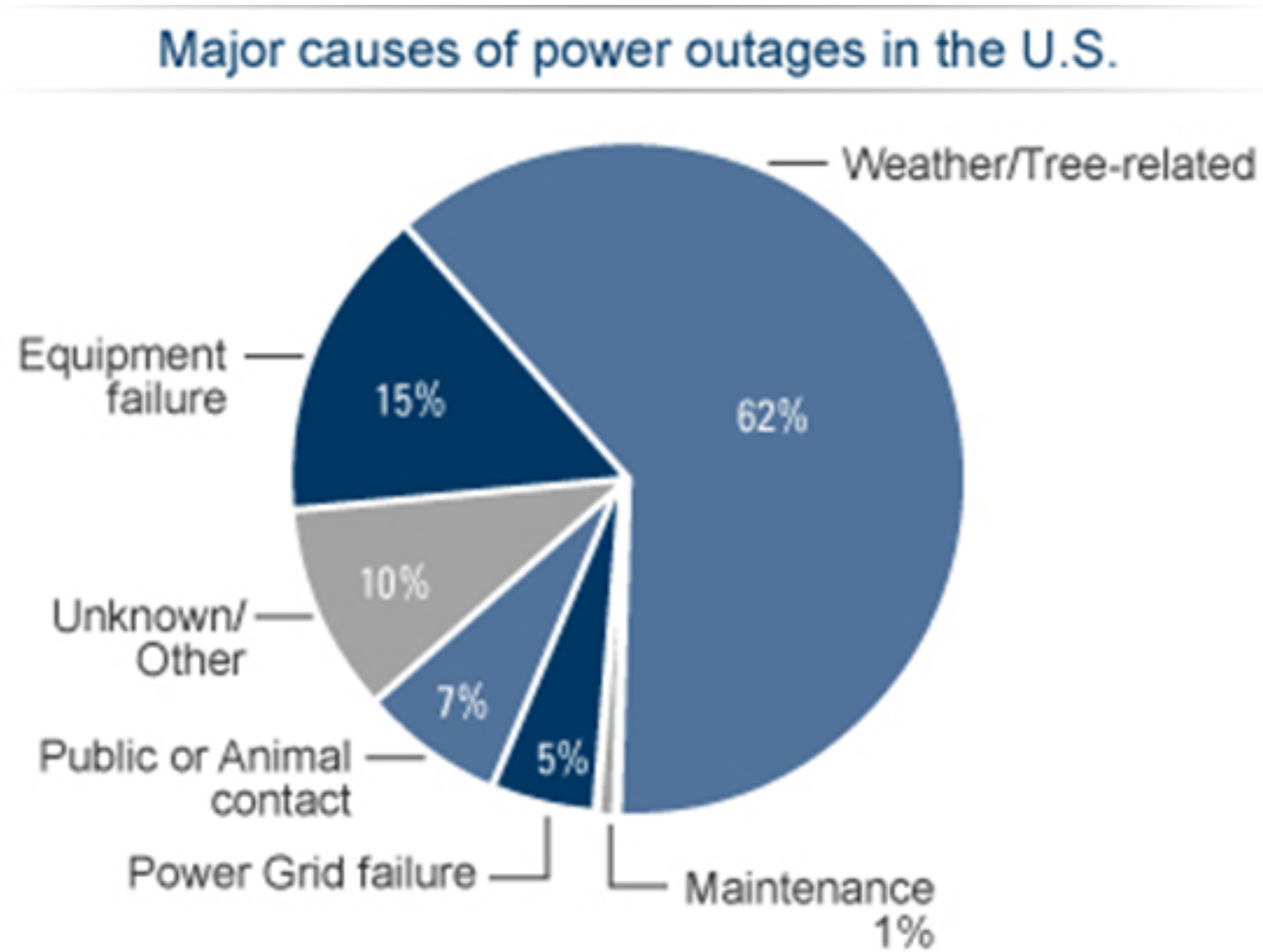
Hurricane Sandy



THE OHIO STATE UNIVERSITY

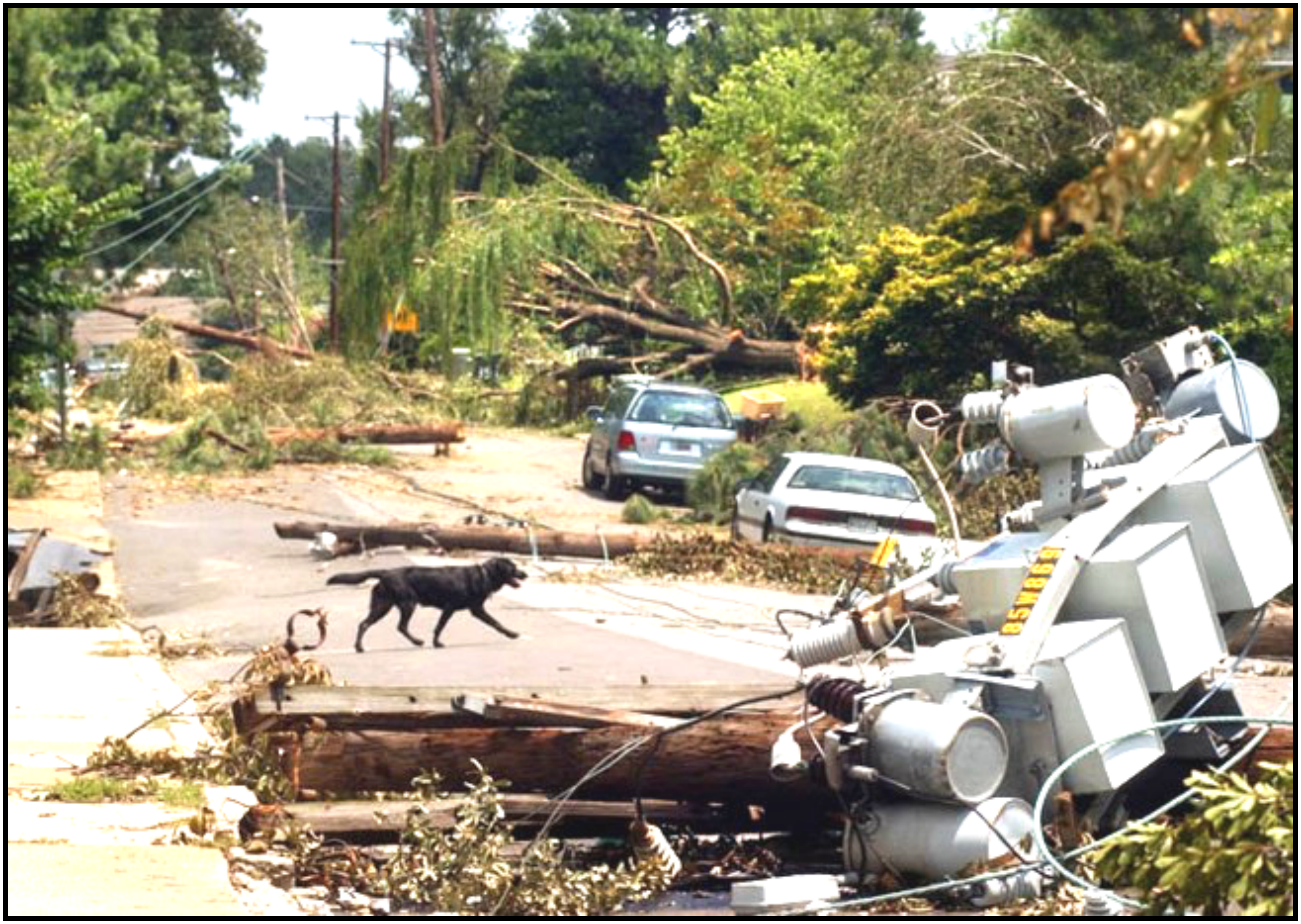
TEXAS A&M UNIVERSITY

Why study power outages?



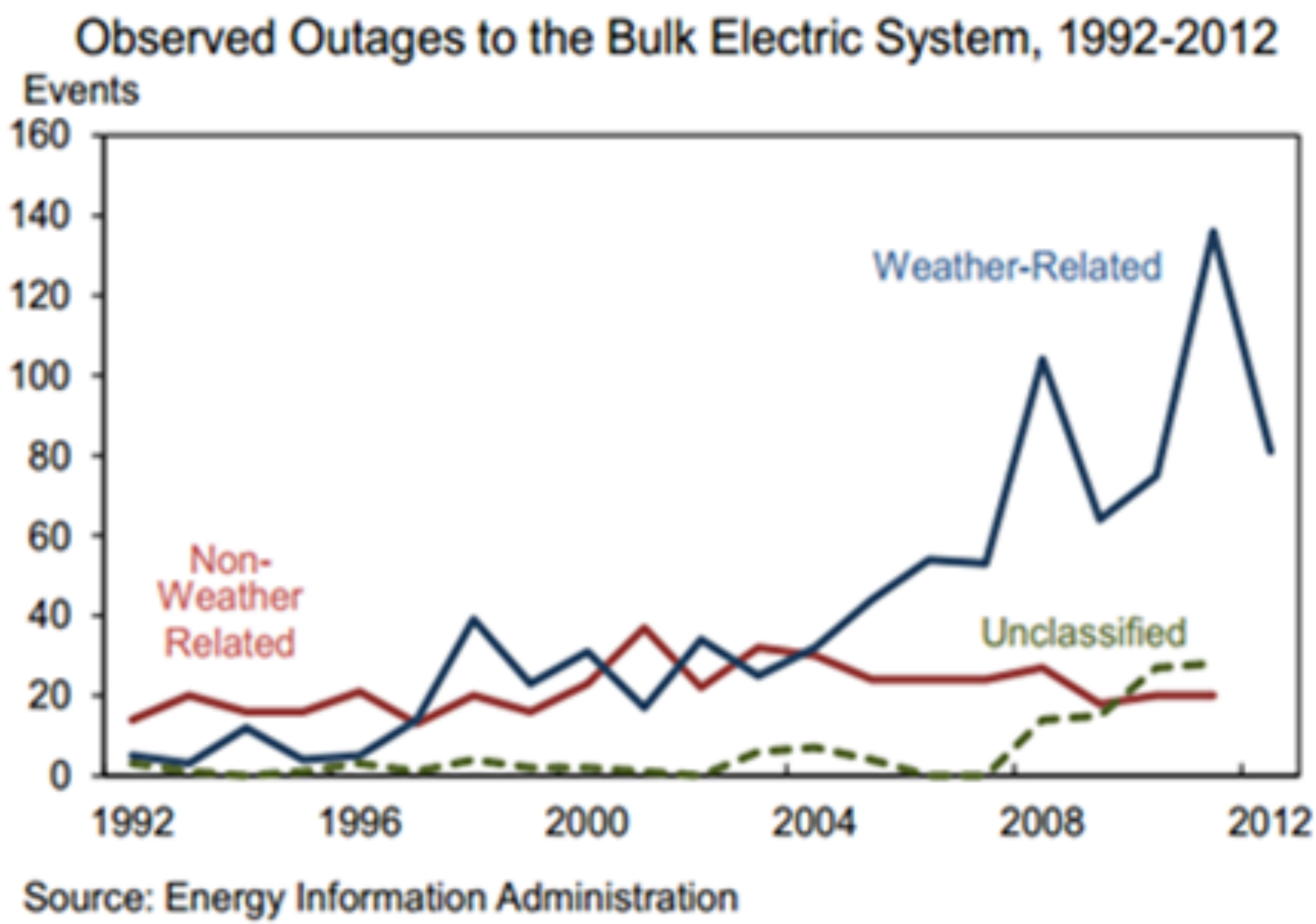
Campbell (2012) Congressional Research Service R42696

Typical Utility Pole Damage



Typical Utility Pole Damage

Why study power outages?



Campbell (2012) Congressional Research Service R42696

Why study power outages?

Hurricane	Economic Damage (Not Discounted)	Deaths*	Customers without Power
Katrina (2005)	~$125 billion	1833	~2.6 million^
Sandy (2012)	~$71 billion	286	~8.1 million
Ike (2008)	~$38 billion	195	~4-8 million
Wilma (2005)	~$29 billion	23	~3-4 million
Andrew (1992)	~$27 billion	65	~1.4 million
Irene (2011)	~$20 billion	56	~6 million

*Includes only direct deaths, not indirect increases in mortality rates
^Lots of uncertainty in this number

Weather-related power disruptions cost the U.S. economy $20B per year

Why does soil moisture matter?

- Stability: Saturated soils increase the likelihood of trees being uprooted or poles being blown over when subjected to strong winds

Why does soil moisture matter?

- Fragility: Drier soils can weaken trees, particularly in regions… This normally takes more time (e.g., drought)
- Currently a major problem in California

Why does soil moisture matter?

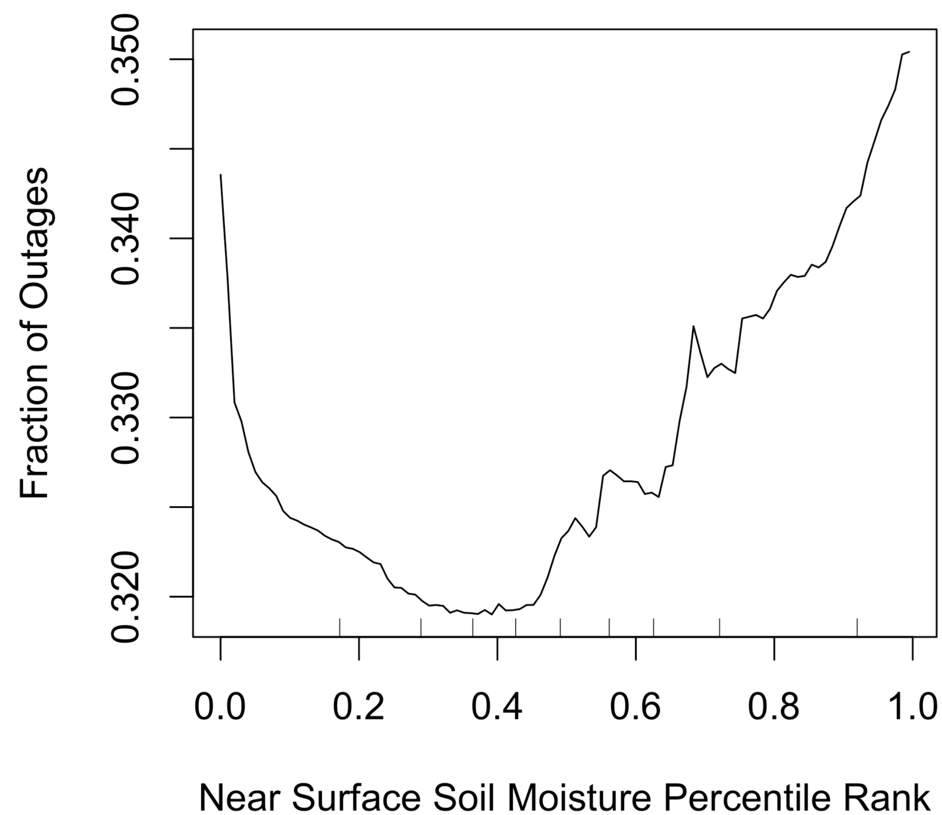
- Trees with shallow root systems are more susceptible
- Wetter precipitation climates → Shallower-rooted trees

Importance of Soil Moisture

- Random Forest statistical model allows quantitative influence of different individual variables

Table 1. Ranked list of variable importance in the Spatially Generalized Hurricane Outage Prediction Model (SGHOPM) by McRoberts et al. (in press).

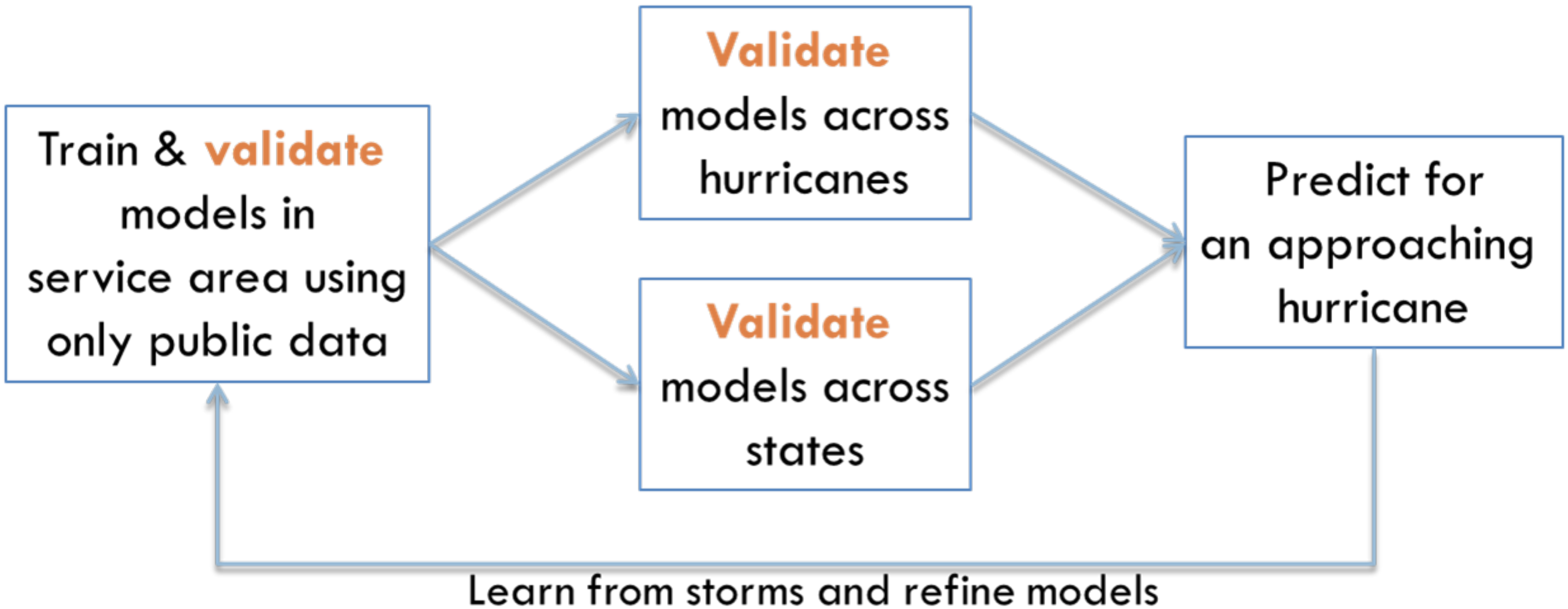
Rank	Type	Variable	VI
1	Baseline	Max wind speed	100.00
2	Baseline	Strong winds duration	87.45
3	SPI	SPI12	70.16
4	Baseline	Population density	41.05
5	Soil moisture	Soil CDF 2	38.54
6	Soil moisture	Soil CDF 1	38.42
7	SPI	SPI3	37.75
8	SPI	SPI24	35.69
9	SPI	SPI6	33.33
10	Tree	Average wood density	33.01
11	Soil moisture	Soil CDF 3	30.38
12	SPI	SPI1	30.32
13	Land cover	Wetlands land cover	28.69
14	Elevation	Max elevation	27.63
15	Tree	Percentage deep	26.83
16	Tree	Percentage taproot	26.83
17	Root zone depth	Root zone mean depth	26.58
18	Tree	Average Janka hardness	26.20
19	Tree	Average max tree height	25.73
20	Land cover	Forest land cover	24.52
21	Tree	Percentage treed	23.64
22	Land cover	Grassland land cover	22.89
23	Elevation	Median elevation	22.19
24	Tree	Average crushing strength	22.14
25	Tree	Average maximum DBH	6.76



McRoberts et al.: Does NASA SMAP Improve the Accuracy of Power Outage Models?

Spatially Generalized Model (SGHOPM)

- Spatially Generalized Hurricane Outage Prediction Model



- Three standard variables in SGHOPM:
  - Population density
  - Maximum wind speed
  - Duration of strong winds

SGHOPM

1) Binary Classification (BC) model step

- Determine if the outage will occur

2) Non-zero outage (NOZE) model step

- Determine non-zero fractional outage

Additional Variables

Land Surface Characteristics (Static)	Soil Moisture Characteristics (Dynamic)
• Topography	• ***<u>Soil Moisture (Volumetric Water Content)</u>***
• Land Cover Type	• Precipitation
• Root Zone Type	
• Trees	

Sensitivity Analysis on Past Storms

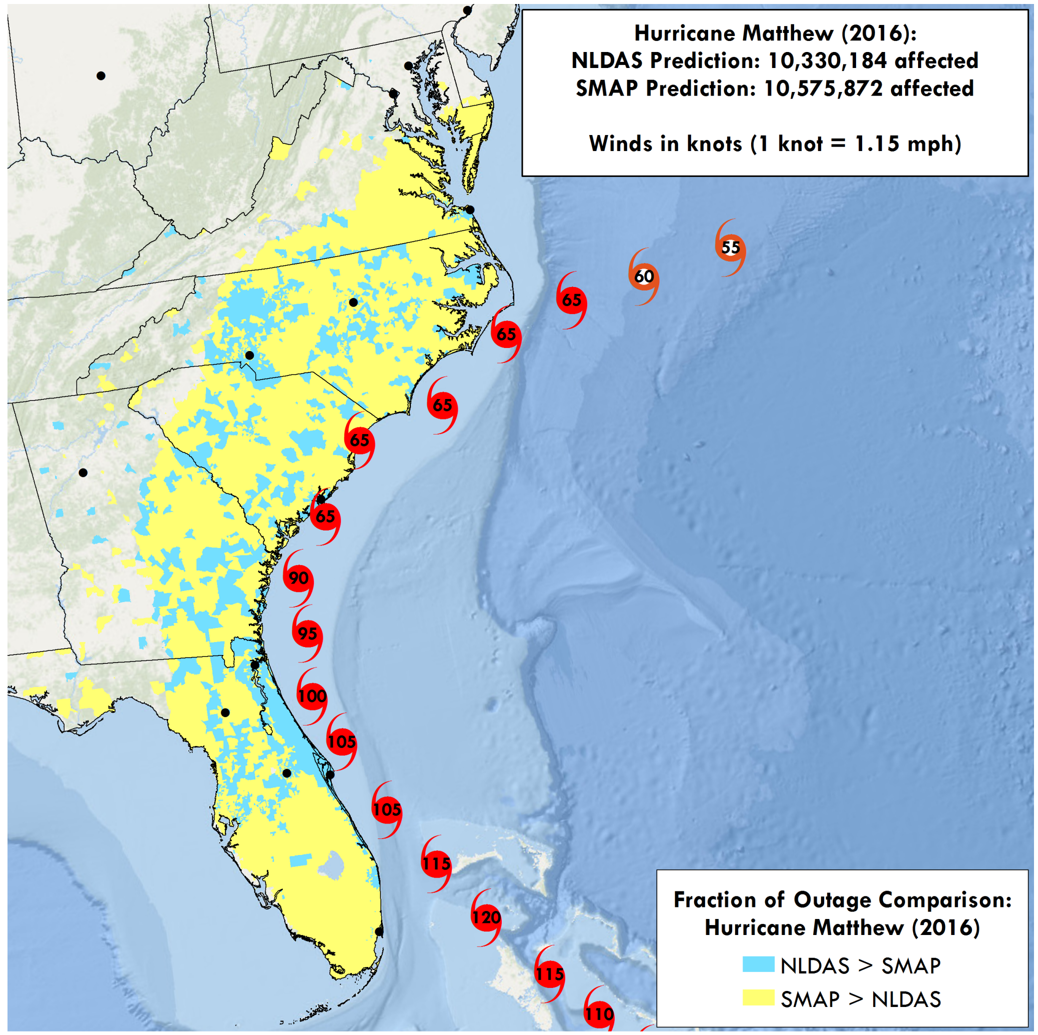
- Storm wind field
- 2015 soil moisture

Storm	Population in Region	Soil Moisture Anomalies			Pct Population Affected		
		NLDAS	SMAP	Difference	NLDAS	SMAP	Difference
Alicia	8,671,312	-0.01	0.11	**0.13**	39.90%	40.40%	0.50%
Allison	226,577	-0.02	-0.09	**0.07**	28.14%	28.41%	0.28%
Andrew	14,402,010	-0.01	0.04	0.05	42.50%	42.93%	0.42%
Camille	8,979,162	0.02	0.06	0.04	36.09%	36.44%	0.35%
Fay	18,027,058	-0.02	0.09	**0.11**	38.95%	39.05%	0.10%
Galveston	19,508,683	-0.02	-0.05	0.03	37.57%	38.04%	0.47%
Gilbert	384,751	0.02	0.14	**0.12**	33.81%	37.93%	**4.12%**
Hugo	7,314,585	-0.02	0.06	**0.08**	26.20%	29.70%	**3.50%**
Jeanne	16,188,388	-0.01	0.00	0.01	39.31%	39.46%	0.14%
Josephine	1,650,997	0.01	0.01	0.00	22.89%	22.47%	0.41%
Sandy	44,286,296	-0.06	-0.04	0.01	36.10%	36.87%	0.76%

Hurricane Matthew

Differences between the model-predicted fraction of the population without power for Hurricane Matthew. Blue (yellow) census tracts are locations where the predicted outages from NLDAS were greater (less) than SMAP.

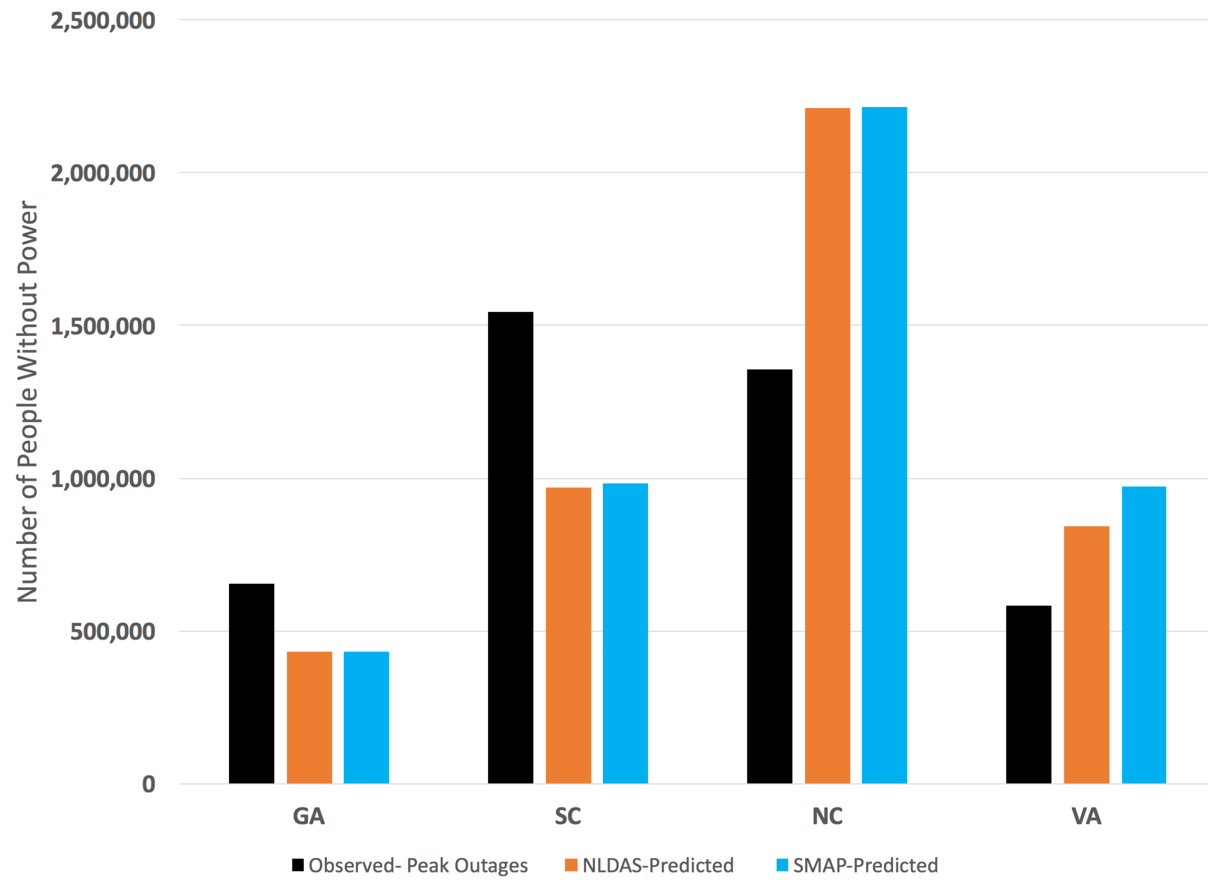
- More accurate soil moisture data has the potential to enhance the accuracy of power outage forecasts.
- Results from Hurricane Matthew showed that the performance of SMAP and NLDAS-2 was similar.



Hurricane Matthew

Preliminary accuracy assessment of power outage predictions for Matthew. Black bars represent the observed peak number of people without power by state. Outage data from DOE Situation reports are converted to number of people using a ratio of people/meter that varies from state to state. Blue (orange) bar is the model-predicted number of people without power using SMAP (NLDAS) data.

We forecast five days ahead of time that 4.5 million people would be without power in Georgia, North Carolina, South Carolina and Virginia. The actual number worked out to be around 4.1 million, so we overestimated outages by around 9 percent.



Future Research

- Detailed analysis of model performance for Hurricane Matthew at the county level
- Examine the spatial variations in model performance and causes of these variations
- Improve SGHOPM using outage data from additional hurricanes
- Quantify model improvement due to SMAP and assess economic value of improved predictions
- Seek funding to support these research activities