Hurricane Risk to Offshore Wind Turbines Along the U.S. Coast

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Abstract

This paper applies the method developed by Rose, *et al.* to create a map of the hurricane risk to offshore wind farms along the Atlantic coast and Gulf coast of the U.S. The risk to offshore wind farms is lowest along the coast of Mid-Atlantic and New England regions. There is less than a 10% probability in those regions that hurricanes destroy more than 10% of a wind farm in 20 years in most counties. The risk to offshore wind farms is highest for counties along the Gulf of Mexico, in South Florida, and near Cape Hatteras, NC. There is greater than a 30% probability in those regions that hurricanes will destroy more than 10% of a wind farm in 20 years. The hurricane risk to offshore wind farms can be significantly decreased by adding backup power to ensure the turbines are able to rapidly yaw to point directly into the wind even when grid power has been lost.

This paper applies the method developed by Rose, *et al.* [1] to create a map of the hurricane risk to offshore wind farms along the Atlantic coast and Gulf coast of the U.S.

Results

There is significant geographical variation in the risk that hurricanes pose to offshore wind turbines. Hurricanes are 100 times more likely to destroy at least 10% of a wind farm in the riskiest county we studied (Miami-Dade, FL) than in the least risky county (Middlesex, NJ). In general, hurricanes pose less risk to offshore wind turbines in the Mid-Atlantic and New England states. In riskier areas, the probability of hurricanes destroying wind turbines can be reduced by providing turbines with backup power to they can yaw to track the wind direction even if grid power is knocked out by a hurricane.

Figure 1 maps the risk to wind farms if the wind turbines cannot yaw to track the wind direction. The case that the turbine cannot yaw represents a worst-case aerodynamic load on a turbine—the turbine is hit broadside by the wind because grid electric power required to yaw the turbine has been knocked out by the hurricane. The risks plotted in Figure 1 give the probability that more than 10% of a wind farm is destroyed by hurricanes in 20 years. Figure 4 in the Appendix plots the risk that more than 50% of the turbines in a wind farm are destroyed by hurricanes.

Wind farms along the Atlantic coast north of Maryland have the lowest risk—less than a 5% probability that more than 10% of the turbines are destroyed in 20 years. The lowest risk counties are in northern New Jersey and the New York City metro area. Counties along the Gulf of Mexico and in south Florida have the highest risk—higher than a 25% probability that more than 10% of the turbines are destroyed by hurricanes in 20 years. The highest risk counties are in the southern tip of Florida and the Mississippi River delta region of Louisiana.

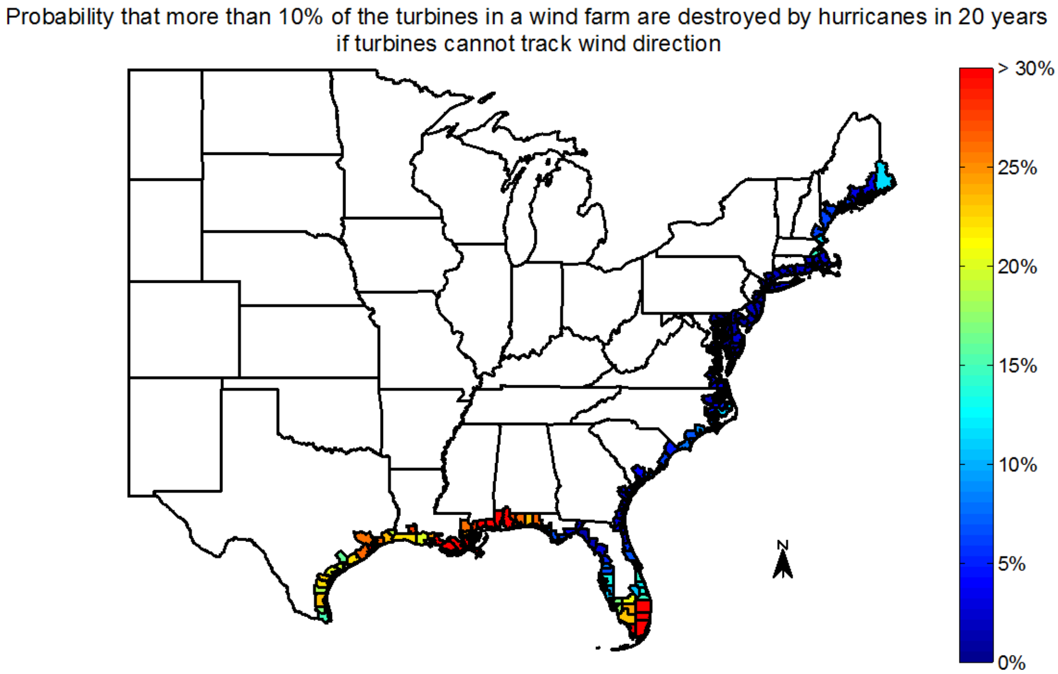

Figure 1: Probability that hurricanes destroy more than 10% of a wind farm in 20 years if the turbines cannot yaw to track the wind direction. Results for individual counties are listed in Table 3 in the column labeled "no yaw".

Figure 2 maps the risk to wind farms if the wind turbines can yaw at the rate recommended in Rose et al.[1] to track the wind direction, either because they have backup power for the yaw motors or because grid power has not been lost during the hurricane. The aerodynamic loads on turbines that can yaw to point directly into the wind are significantly lower, and the risk of buckling is correspondingly lower. The risks plotted in Figure 2 give the probability that more than 10% of a wind farm is destroyed by hurricanes in 20 years. Figure 5 in the Appendix plots the probability that more than 50% of a wind farm is destroyed by hurricanes.

Allowing the turbine to yaw to track the wind direction can reduce the risk by approximately 70% for the riskiest counties along the Gulf Coast and approximately 80% for the riskiest counties in Florida,.

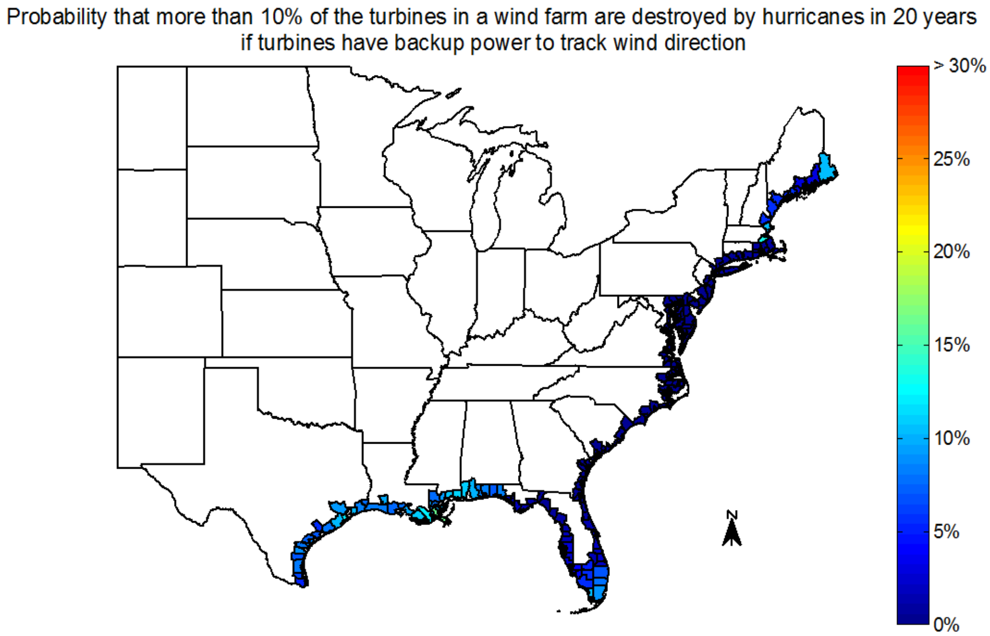

Figure 2: Probability that hurricanes destroy more than 10% of a wind farm in 20 years if the turbines have backup power for the yaw motors so they can track the wind direction. Results for individual counties are listed in Table 3 in the column labeled "yawing".

Method

We calculate the hurricane risk to an offshore wind farm near each county according to the method proposed by Rose, *et al.* assuming turbines are not replaced after they are buckled. [1] The hurricane risk to an offshore wind farm has three components: the probability that a hurricane occurs, the probability that the maximum wind speeds reach a certain level in a hurricane that occurs, and the probability that a wind turbine buckles at that wind speed.

We model the probability of a hurricane occurring as a Poisson distribution with the rate hurricane occurrence as a parameter. Table 3 lists the rate of hurricane occurrence for each coastal county in the eastern U.S. The rate of hurricane occurrence for a county is the number of hurricanes to directly or indirectly strike the county between 1900 and 2008 divided by 109 years. The number of hurricane strikes is taken from records compiled by the U.S. National Hurricane Center[2] updated from research by Jarrell, *et al.*[3]

We model the probability that the maximum sustained wind speed in a hurricane at 10-m height reaches a certain level as a Generalized Extreme Value (GEV) distribution. We fit a GEV distribution to the maximum sustained wind speeds of all hurricanes (with a 1-min averaging period) in each region shown in Figure 3. The fitted parameters, the number of hurricanes, and the latitude and longitude ranges of each region are given in Table 1. We convert the 1-min maximum sustained wind speeds drawn from the GEV distribution to the 10-min maximum sustained wind speed needed to calculate turbine damage by dividing by 1.12, a relationship proposed in equation 6 in a paper by Powell, *et al.*[4]

Table 1: Distribution parameters for the GEV distribution of maximum sustained wind speed in a hurricane (1-min averaging period).

Region	Max sustained wind speed: GEV distribution [knots]	Number of hurricanes (1900-2008)	Geographic range of hurricanes modeled (lat/long)
A	μ = 78.6, σ = 12.2, ξ = 0.269	80	25.5°N-30.5°N 92°W-99°W
B	μ = 82.1, σ = 15.3, ξ = 0.127	109	25.5°N-31°N 86°W-92°W
C	μ = 74.1, σ = 7.66, ξ = 0.231	45	28°N-31°N 82.7°W-86°W
D	μ = 79.1, σ = 15.0, ξ = 0.0444	78	24°N-29°N 81°W-84°W
E	μ = 86.6, σ = 17.6, ξ = -0.0861	59	24°N-27°N 78°W-81°W
F	μ = 78.1, σ = 11.7, ξ = 0.0427	86	27°N-32.5°N 78°W-82°W
G	μ = 77.3, σ = 11.8, ξ = -0.0288	179	32°N-36.5°N 71°W-81°W
H	μ = 76.4, σ = 10.3, ξ = -0.000974	82	36°N-41°N 71°W-77.5°W
I	μ = 71.5, σ = 6.59, ξ = 0.249	52	40.3°N-42°N 66°W-74.5°W
J	μ = 65.1, σ =0.238, ξ = 4.01	25	42°N-47°N 66°W-71.5°W

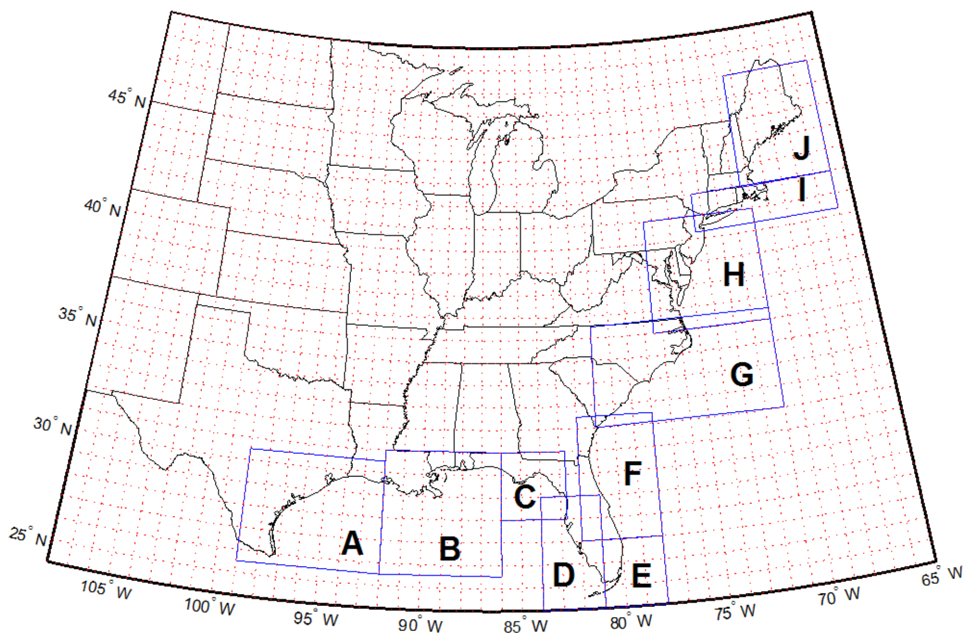

Figure 3: Geographic range of hurricanes used to fit a GEV distribution to maximum sustained wind speeds.

We model the probability that a wind turbine buckles at a given sustained (10-min average) hub-height wind speed as a log-logistic function. Table 2 gives the parameters of the log-logistic function for two cases: the case that a turbine can yaw to point into the wind and the case that the turbine cannot yaw. These cases distinguish between a turbine that has backup power for its yaw motors and can track the wind direction even if a power outage occurs, and turbines that do not have backup power for yaw motors. We fit the parameters for the log-logistic function to the results of dynamic load simulations of the NREL 5-MW offshore wind turbine[5] in the FAST simulations software[6]. The simulations model a given mean wind speed with a lognormal-distributed turbulence intensity with a mean of 9% and standard deviation of 1.5%.

Table 2: Parameters of log-logistic functions for probability of tower buckling as a function of sustained wind speed at hub height [knots]

	Turbine pointed into wind (Active Yawing)	Turbine pointed perpendicular to wind (Not Yawing)
Damage function parameters (log-logistic function)	$\alpha = 174, \beta = 19.3$	$\alpha = 140, \beta = 18.6$

The parameters in Table 1 for GEV distribution give the distribution of maximum sustained wind speed at 10-m height, but the log-logistic function for the probability of a turbine buckling considers the wind speed at hub height (90 m). We scale hurricane wind speeds from 10-m height to 90-m hub height using a relationship given by Franklin, *et al.*[7] The parameters in Table 1 are fit to sustained wind speeds averaged over a 1-minute period, so we also scale the hurricane wind speeds to a 10-min averaging period by dividing by 1.12. The scaling factor to convert 1-min average hurricane wind speeds to 10-min average wind speeds is calculated using equation 6 in a paper by Powell, *et al.*[4]

Table 3: Rates of hurricane occurrence and the numerical results plotted in Figure 1 ("no yaw") and Figure 2 ("yawing").

	Rate of hurricane occurrence [hurricanes/year]
Cameron County, TX	0.08
Willacy County, TX	0.09
Kenedy County, TX	0.13
Kleberg County, TX	0.10
Nueces County, TX	0.13
San Patricio County, TX	0.13
Aransas County, TX	0.12
Refugio County, TX	0.12
Calhoun County, TX	0.11
Jackson County, TX	0.08
Matagorda County, TX	0.13
Brazoria County, TX	0.15
Galveston County, TX	0.19
Harris County, TX	0.15
Chambers County, TX	0.15
Jefferson County, TX	0.14
Orange County, TX	0.11

Cameron Parish, LA	0.13
Vermilion Parish, LA	0.12
Iberia Parish, LA	0.11
Saint Mary Parish, LA	0.15
Terrebonne Parish, LA	0.17
Lafourche Parish, LA	0.17
Jefferson Parish, LA	0.15
Plaquemines Parish, LA	0.23
Saint Bernard Parish, LA	0.15
Orleans Parish, LA	0.11
Saint Tammany Parish, LA	0.11
Hancock County, MS	0.13
Harrison County, MS	0.15
Jackson County, MS	0.16
Mobile County, AL	0.15
Baldwin County, AL	0.15
Escambia County, FL	0.13
Santa Rosa County, FL	0.12
Okaloosa County, FL	0.10
Walton County, FL	0.12
Bay County, FL	0.13
Gulf County, FL	0.11
Franklin County, FL	0.10
Wakulla County, FL	0.06
Jefferson County, FL	0.03
Taylor County, FL	0.02
Dixie County, FL	0.03
Levy County, FL	0.05
Citrus County, FL	0.03
Hernando County, FL	0.05
Pasco County, FL	0.04
Pinellas County, FL	0.07
Hillsborough County, FL	0.07
Manatee County, FL	0.05
Sarasota County, FL	0.06
Charlotte County, FL	0.10
Lee County, FL	0.11
Collier County, FL	0.15
Monroe County, FL	0.29

Miami-Dade County, FL	0.23
Broward County, FL	0.20
Palm Beach County, FL	0.16
Hendry County, FL	0.15
Glades County, FL	0.13
Okeechobee County, FL	0.11
Martin County, FL	0.15
Saint Lucie County, FL	0.15
Indian River County, FL	0.13
Brevard County, FL	0.15
Volusia County, FL	0.07
Flagler County, FL	0.05
Saint Johns County, FL	0.04
Duval County, FL	0.04
Nassau County, FL	0.03
Camden County, GA	0.02
Glynn County, GA	0.01
Mcintosh County, GA	0.01
Liberty County, GA	0.02
Bryan County, GA	0.02
Chatham County, GA	0.05
Beaufort County, SC	0.07
Colleton County, SC	0.06
Charleston County, SC	0.13
Georgetown County, SC	0.10
Horry County, SC	0.08
Brunswick County, NC	0.13
New Hanover County, NC	0.12
Pender County, NC	0.11
Onslow County, NC	0.15
Carteret County, NC	0.20
Pamlico County, NC	0.13
Beaufort County, NC	0.07
Hyde County, NC	0.19
Dare County, NC	0.21
Tyrrell County, NC	0.09
Washington County, NC	0.05
Bertie County, NC	0.03
Chowan County, NC	0.05

Perquimans County, NC	0.07
Pasquotank County, NC	0.07
Camden County, NC	0.08
Currituck County, NC	0.14
Virginia Beach County, VA	0.12
Chesapeake County, VA	0.09
Suffolk County, VA	0.06
Isle Of Wight County, VA	0.05
Surry County, VA	0.05
James City County, VA	0.05
York County, VA	0.05
Gloucester County, VA	0.05
Mathews County, VA	0.04
Middlesex County, VA	0.04
Lancaster County, VA	0.04
Northumberland County, VA	0.03
Westmoreland County, VA	0.03
Northampton County, VA	0.06
Accomack County, VA	0.05
Worcester County, MD	0.03
Somerset County, MD	0.02
Saint Mary'S County, MD	0.03
Calvert County, MD	0.03
Anne Arundel County, MD	0.03
Baltimore County, MD	0.03
Harford County, MD	0.02
Cecil County, MD	0.02
Kent County, MD	0.02
Queen Anne'S County, MD	0.02
Talbot County, MD	0.02
Caroline County, MD	0.02
Dorchester County, MD	0.02
Wicomico County, MD	0.02
Sussex County, DE	0.05
Kent County, DE	0.02
New Castle County, DE	0.02
Salem County, NJ	0.01
Cumberland County, NJ	0.02
Cape May County, NJ	0.05

Atlantic County, NJ	0.05
Burlington County, NJ	0.05
Ocean County, NJ	0.05
Monmouth County, NJ	0.03
Middlesex County, NJ	0.01
Hudson County, NJ	0.01
Bergen County, NJ	0.01
Richmond County, NY	0.00
New York County, NY	0.02
Kings County, NY	0.02
Queens County, NY	0.03
Nassau County, NY	0.05
Suffolk County, NY	0.06
Bronx County, NY	0.02
Westchester County, NY	0.02
New London County, CT	0.05
Middlesex County, CT	0.05
New Haven County, CT	0.05
Fairfield County, CT	0.05
Newport County, RI	0.05
Bristol County, RI	0.05
Providence County, RI	0.05
Kent County, RI	0.05
Washington County, RI	0.05
Bristol County, MA	0.05
Dukes County, MA	0.07
Nantucket County, MA	0.07
Barnstable County, MA	0.07
Plymouth County, MA	0.06
Norfolk County, MA	0.05
Suffolk County, MA	0.05
Essex County, MA	0.04
Rockingham County, NH	0.02
York County, ME	0.02
Cumberland County, ME	0.02
Sagadahoc County, ME	0.02
Lincoln County, ME	0.02
Knox County, ME	0.01
Waldo County, ME	0.01

Hancock County, ME	0.01
Washington County, ME	0.04

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4. Powell, M. D., Houston, S. H. & Reinhold, T. A. Hurricane Andrew's Landfall in South Florida. Part I: Standardizing Measurements for Documentation of Surface Wind Fields. *Weather and Forecasting* **11**, 304–328 (1996).
5. Jonkman, J., Butterfield, S., Musial, W. & Scott, G. *Definition of a 5-MW reference wind turbine for offshore system development*. (National Renewable Energy Laboratory: Golden, CO, 2009).
6. Jonkman, J. M. & Buhl, M. L. J. *FAST User's Guide*. 1–143 (National Renewable Energy Laboratory: Golden, CO, 2005).
7. Franklin, J., Black, M. & Valde, K. GPS Dropwindsonde Wind Profiles in Hurricanes and Their Operational Implications. *Weather and Forecasting* **18**, 32–44 (2003).

Appendix

Figure 4 and Figure 5 plot the probability that more than 50% of the turbines in a wind farm are destroyed by hurricanes in a 20-year period. These results are similar to the results plotted in Figure 1 and Figure 2, but show the probability of greater damage.

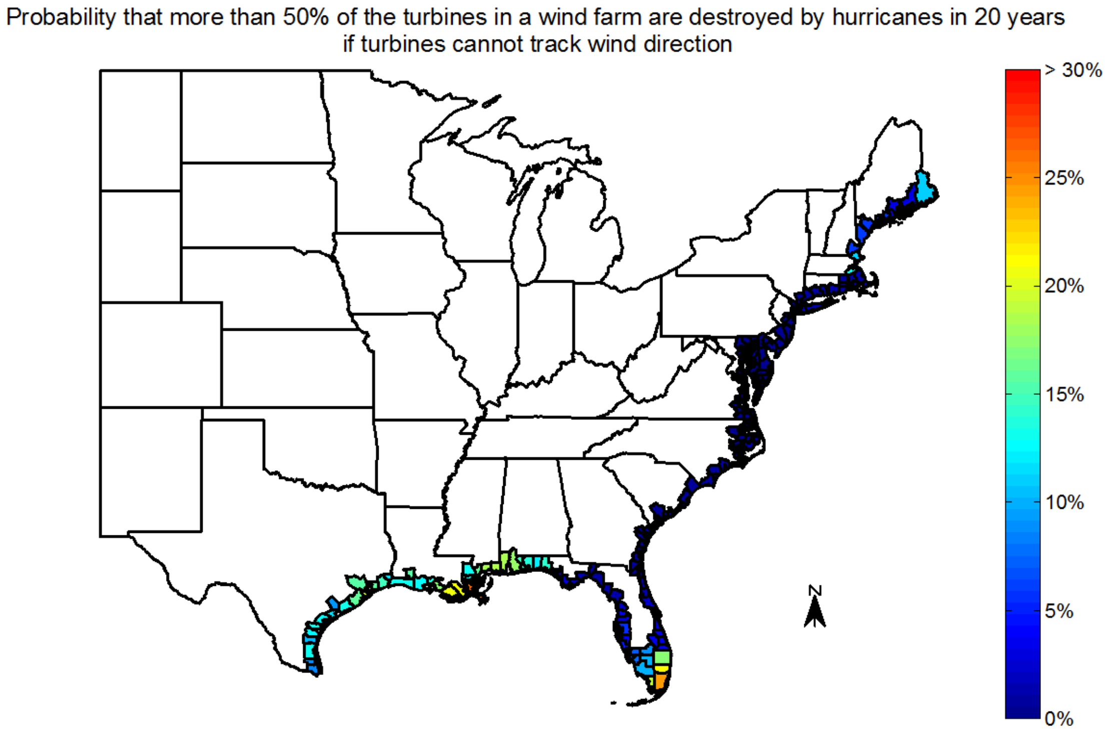

Figure 4: Probability that hurricanes destroy more than 50% of a wind farm in 20 years if the turbines cannot yaw to track the wind direction. These results are similar to the results in Figure 1, but show the probability that of higher damage to the wind farm.

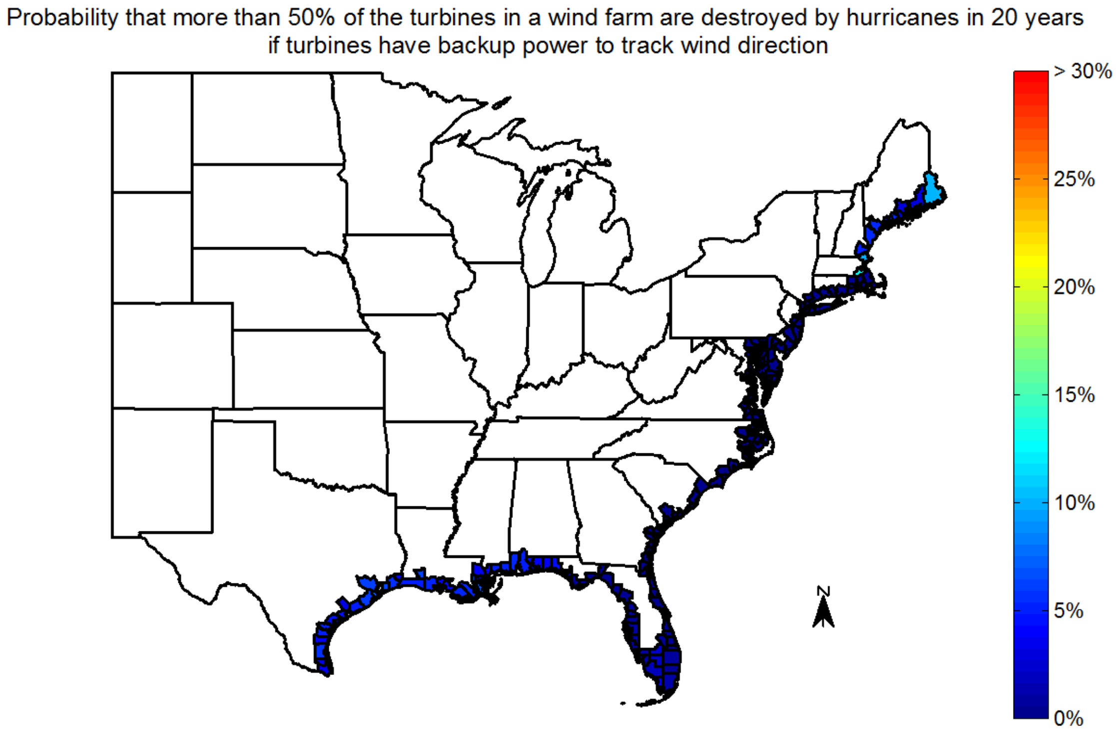

Figure 5: Probability that hurricanes destroy more than 50% of a wind farm in 20 years if the turbines have backup power for the yaw motors so they can track the wind direction. These results are similar to the results in Figure 2, but show the probability that of higher damage to the wind farm.