Quantifying the Hurricane Risk to Offshore Wind Turbines

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Abstract

The U.S. Department of Energy has estimated that if the U.S. is to generate 20% of its electricity from wind, over 50 GW will be required from shallow offshore turbines. Hurricanes are a potential risk to these turbines. Turbine tower buckling has been observed in typhoons, but no offshore wind turbines have yet been built in the U.S. We present a probabilistic model to estimate the number of turbines that would be destroyed by hurricanes in an offshore wind farm. We apply this model to estimate the risk to offshore wind farms in four representative locations in the Atlantic and Gulf Coastal waters of the U.S. In the most vulnerable areas now being actively considered by developers, nearly half the turbines in a farm are likely to be destroyed in a 20-year period. We show that adding a capability to yaw the turbine's nacelle fast enough to follow the wind direction changes in a hurricane significantly reduces the risk the turbine will be destroyed. Reasonable mitigation measures – increasing the design reference wind load, ensuring that the nacelle can be turned into rapidly changing winds, and building most wind plants in the areas with lower risk – can greatly enhance the probability that offshore wind can help to meet the United States' electricity needs.

As a result of state renewable portfolio standards and federal tax incentives, there is growing interest and investment in renewable sources of electricity in the United States. Wind is the renewable resource with the largest installed-capacity growth in the last 5 years, with U.S. wind power capacity increasing from 8.7 GW in 2005 to 33.5 GW 2009 (1). All of this development has occurred onshore. U.S. offshore wind resources may also prove to be a significant contribution to increasing the supply of renewable, low-carbon electricity. The National Renewable Energy Laboratory (NREL) estimates that offshore wind resources can be as high as four times the U.S. electricity generating capacity in 2010 (2). Although this estimate does not take into account siting, stakeholder, and regulatory constraints, it indicates that U.S. offshore wind resources are significant. Though no offshore wind projects have been developed in the U.S., there are 20 offshore wind projects in the planning process (with an estimated capacity of 2 GW) (2). The U.S. Department of Energy's 2008 report, *20% Wind by 2030* (3) envisions 54 GW of shallow offshore wind capacity to optimize delivered generation and transmission costs.

U.S. offshore resources are geographically distributed through the Atlantic, Pacific and Great Lake coasts. The most accessible shallow resources are located in the Atlantic and Gulf Coasts. Resources at depths shallower than 60 meters in the Atlantic coast, from Georgia to Maine, are estimated to be 920 GW; the estimate for these resources in the Gulf coast is 460 GW (4).

Offshore wind turbines in these areas will be at risk from Atlantic hurricanes. Between 1949 and 2006, 93 hurricanes struck the U.S. mainland according to the HURDAT database of the National Hurricane Center (5). In this 58-year period, only 15 years did not incur insured hurricane-related losses (3). The Texas region was affected by 35 hurricane events, while the southeast region (including the coasts of Florida, where no offshore resources have been estimated (2)) had 32 events.

Hurricane risks are quite variable, both geographically and temporally. Pielke *et al.* (4) note pronounced differences in the total hurricane damages (normalized to 2005) occurring each decade. Previous research has shown strong associations between North Atlantic hurricane activity and atmosphere-ocean variability on different timescales, including the multidecadal (6, 7). Atlantic hurricane data show that hurricane seasons with very high activity levels occur with some regularity; for instance, since 1950, there have been 25 years with three or more intense hurricanes (Saffir-Simpson Category 3 or higher). There were two 2-year periods with 13 intense hurricanes: 1950-1951 and 2004-2005. 2004 and 2005 hurricanes were particularly damaging to the Florida and Gulf Coast regions (6 hurricanes made landfall in those areas in 2004 and 7 the following year).

These hurricanes resulted in critical damages to energy infrastructure. Hurricane Katrina (2005), for example, was reported to have damaged 21 oil and gas producing platforms and completely destroyed 44 (8). Numerous drilling rigs and hydrocarbon pipelines were also damaged. Similarly, hurricanes have damaged powers systems. Liu *et al* (9), for example, reported that in 2003 Dominion Power had over 58,000 instances of the activation of safety devices in the electrical system to isolate damages as a result of Hurricane Isabel. Although no offshore wind turbines have been built in the U.S., there is no reason to believe that this infrastructure would be exempt from hurricane damages.

In order to successfully develop sustainable offshore resources, the risk from hurricanes to offshore wind turbines needs to be analyzed and understood. Here we present a probabilistic model to estimate the number of turbines that would be destroyed by hurricanes in an offshore wind farm. We apply this model to estimate the risk to offshore wind farms in four representative locations in the Atlantic and Gulf Coastal waters of the U.S.: Galveston County, TX; Dare County, NC; Atlantic County, NJ; and Dukes County, MA. As of the of 2010, leases have been signed for wind farms off the coasts of Galveston (10) and Dukes County (11); projects off the coasts of New Jersey and North Carolina have been proposed (11).

Results

Wind Farm Risk from a Single Hurricane

Wind turbines are vulnerable to hurricanes because the maximum wind speeds in those storms can exceed the design limits of wind turbines. Failure modes can include loss of blades and buckling of the supporting tower. In 2003, a wind farm of seven turbines in Okinawa, Japan was destroyed by typhoon Maemi (12) and several turbines in China were damaged by typhoon Dujuan (13). Here we consider only tower buckling, since blades are relatively easy to replace (although their loss can cause other structural damage). To illustrate the risk to a wind farm from hurricane force wind speeds, we calculate the expected number of turbines that buckle in a 50-turbine wind farm as a function of maximum sustained (10-minute mean) wind speed, assuming that turbines cannot yaw during the hurricane to track the wind direction (we later consider the case in which the nacelle can be yawed rapidly enough to track the wind direction of the hurricane). Figure 1 plots the median, 5th percentile, and 95th percentile of the number of turbine towers that buckle as a function of wind speed. The vertical dotted line shows the design reference wind speed for wind turbines in IEC Class 1 wind regimes, which includes the NREL 5-MW turbine we simulate, and nearly all offshore wind turbines currently in production. The IEC 61400-3 design standard for Class 1 wind regimes requires that a turbine survive a maximum 10-minute average wind speed with a 50-year return period of 50 m/s (97 knots) at hub height (14); we scale this wind speed from 80-m height to 10-m height assuming power-law wind shear with an exponent of 0.077 (15) because hurricane wind speeds are given for 10-meter height.

Higher-category hurricanes will destroy a significant number of turbines. A Category 2 hurricane (wind speeds of 45 m/s or higher) will buckle up to 17% of the turbines in a wind farm, and a Category 3 (wind speeds of 50 m/s or higher) will buckle up to 92%. The damage caused by Category 3, 4 and 5 hurricanes is important for offshore wind development in the U.S. because every state on the Gulf of Mexico coast and 9 of the 14 states on the Atlantic Coast have been struck by a Category 3 or higher hurricane between 1856 and 2008 (16). Hurricane Ike in 2008, for example, had a maximum sustained wind speed of 95 knots (49 m/s) at 10-meter height (Category 2) when it passed over the meteorological tower erected by the developers of the Galveston Offshore Wind project. If a 50-turbine wind farm had been located off the coast of Galveston when hurricane Ike struck, our model predicts that Hurricane Ike would have had a 90% probability of buckling between 1 and 7 turbines, with a median of 4 towers.

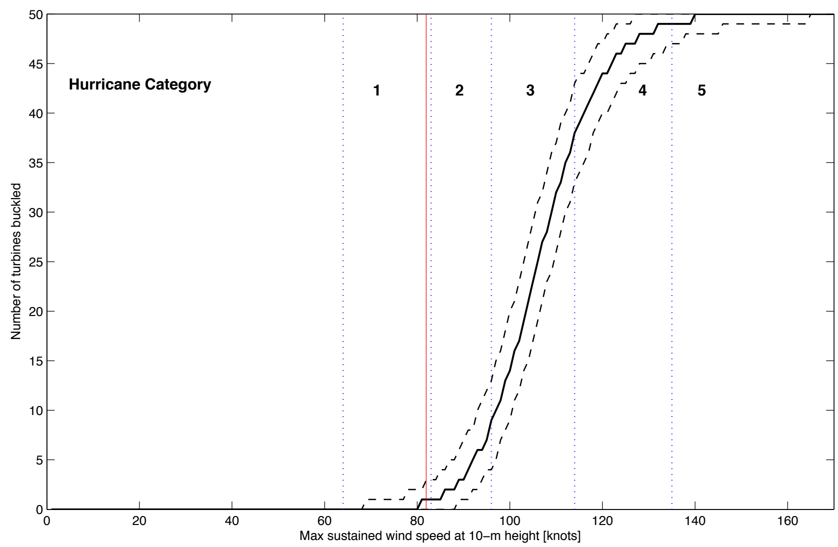

Figure 1: Cumulative distribution function of the expected number of turbine towers buckled by a single storm as a function of wind speed. This models a storm with a turbulence intensity of 14% in a 50-turbine wind farm of NREL 5-MW turbines (17) that cannot yaw to track the wind. The dashed lines plot the 5th and 95th percentile values and the solid vertical line shows V_{ref}, the design wind speed with a 50-year return period (14) scaled to 10-m height.

Risk from Multiple Hurricanes

We calculate the cumulative distribution function (CDF) for the number of turbines that buckle in 20 years for wind farms at four different locations, assuming that buckled turbines are not replaced after each storm. The distributions are modeled by a modified Phase-Type distribution described in the materials and methods section**.** Figure 2 shows the CDF for each location for two cases: turbines that can yaw to track wind direction (dashed line) and turbines that cannot yaw (solid line). The non-yawing case is a worst-case scenario, but it is realistic for two reasons. First, wind turbines typically do not have backup power for yaw motors and hurricanes often cause widespread power outages. Wind turbine design standards such as the IEC 61400-3 (Design Load Case 6.2) require turbine designers to assume a yaw misalignment up to ±180º if no yaw backup power is available, though designers can assume the turbine points directly into the wind if six hours of backup power is available for the yaw and control systems (14). Second, wind direction in a hurricane may change faster than a wind turbine can yaw. The NREL 5-MW turbine we model is designed to yaw at 0.3º/sec, but Schroeder, *et al* show that the wind direction of Hurricane Bob in 1991 changed 30º in approximately 60 seconds (0.5º/sec), as measured 55 km away from the center of the storm (18). The yawing case in Figure 2 illustrates how much the risk to a wind farm is reduced if the turbines can track the wind direction quickly and reliably as a hurricane passes.

Galveston County is the riskiest location to build a wind farm of the four locations examined, followed by Dare County, NC. In contrast, Atlantic County, NJ and Dukes County, MA are significantly less risky. In Galveston County, there is a 16% probability that no turbines will buckle in 20 years and a 46% probability that more than half will buckle if the turbines cannot yaw; if they are able to yaw, there is a 83% probability that none will buckle and a 7% probability that more than half will. In Dare County, NC, there is a 13% probability that no turbines will buckle in 20 years and a 33% probability that more than half will buckle if the turbines cannot yaw; if they are able to yaw, there is a 96% probability that none will buckle and much less than 1% probability that more than half will. In Atlantic County, NJ there is a 64% that no turbines will buckle in 20 years and a 4% probability that more than half will buckle. In Dukes County, MA, there is a 61% probability that no turbines will buckle in 20 years and less than 1% probability that more than half will buckle. If the turbines in Atlantic and Dukes counties are able to quickly yaw even when grid power is out, there is more than a 99% probability that none will buckle in 20 years.

The results in Figure 2 assume each hurricane has a turbulence intensity of 14%, where we define the turbulence intensity (TI) as the 10-minute standard deviation of wind speed divided by the 10-minute mean wind speed. The probability distributions in Figure 2 are sensitive to the chosen value of TI, especially for small numbers of turbines buckled. For example, the probabilities that no turbines are buckled in Galveston if the turbines are able to yaw are 76% and 89% for turbulence intensities of 12% and 16%, respectively. However, we believe a TI of 14% gives a low estimate of the number of turbines that buckle because much higher TI values are observed in hurricanes. Schroeder, *et al* recorded longitudinal (along-wind) turbulence intensities of 7 – 17% during the passage of Hurricane Bob in 1991 (18) and 12 – 42% during the passage of Hurricane Bonnie in 1998 (19).

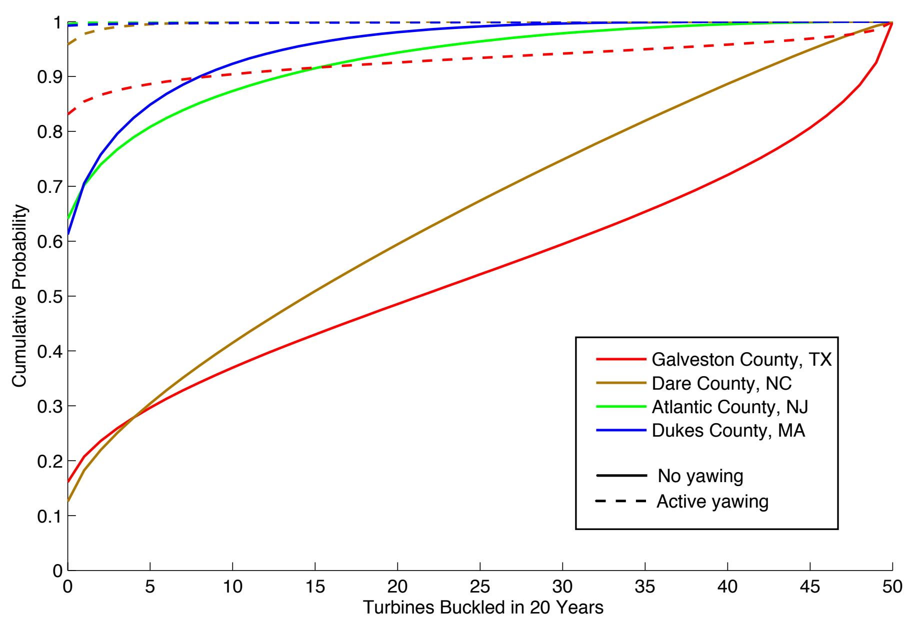

Figure 2: Cumulative distribution of the number of turbines in a 50-turbine wind farm buckled in 20 years if buckled turbines are not replaced. Dashed lines plot the distribution for the case that turbines can yaw to track the wind direction, and solid lines plot the distribution for the case that turbines cannot yaw.

If turbines are replaced after each storm, the cumulative probabilities for fewer than 35 turbines buckling in 20 years is within four percentage points of the distributions without replacement shown in Figure 2. However, there is a possibility that more than 50 turbines will buckle in 20 years. For example, there is a 33% probability in Galveston County and 22% probability in Dare County that more than 50 turbines will buckle if the turbines cannot yaw. The distributions with replacement are modeled as a compound Poisson distribution; the derivation of the distribution and a CDF plot of the results are given in the **Supporting Information**.

Distribution of Damage by Hurricane Intensity

The number of turbines that buckle in a wind farm during the farm's 20-year life is a function of the frequency of hurricane occurrence and the intensity of the hurricanes that occur. Higher-intensity storms buckle more turbines, but occur less frequently. To assess which categories of hurricanes cause the most expected damage, we use Monte Carlo simulation to calculate the expected value of the number of turbines that buckle in 20 years and the expected damage from each category of hurricane. The results are plotted in Figure 3. These results reflect damages averaged through 10,000 20-year periods—the results in any given 20-year period will be different, typically dominated by one or two hurricanes.

Figure 3 indicates that Category 3, 4 and 5 hurricanes cause most of the expected damage at each location: 89% in Galveston County, 80% in Dare County, 75% in Atlantic County, and 71% in Dukes County. However, no Category 4 and 5 hurricanes have made landfall in Dare, Atlantic, or Dukes counties since record keeping began in 1850. Analyses of U.S. hurricanes prior to 1850 report four landfalls in North Carolina that may have been category 4 (in 1815, 1827, 1842 and 1846) (20, 21) and one in 1821 that was likely either category 4 or 5 (21). This historic record indicates that hurricanes of intensity 4 or higher should be possible in Dare County. Category 4 hurricanes also appear possible in Atlantic county with sufficiently warm sea-surface temperatures such as during late August. Hurricane model projections (20) indicate that the Great Colonial Hurricane of August 1635 most likely retained category 4 intensity until reaching southern New Jersey. However, storms of category 4 intensity in coastal Massachusetts may be physically impossible in present climate conditions. Generalized Extreme Value distributions (GEV) fit to the maximum sustained wind speeds of hurricanes in the regions around Dare, Atlantic, and Dukes counties predict probabilities of 4%, 2%, and 2% , respectively, that a hurricane making landfall in those counties will be Category 4 or 5.

We test the sensitivity of our results in Figure 2 and Figure 3 to the occurrence of category 4 and 5 hurricanes by repeating the Monte Carlo simulation of 10,000 20-year periods but excluding periods that contain a category 4 or 5 hurricane. This analysis excludes 15% of total simulations for Dare County, 2% for Atlantic County, and 2% for Dukes County. The results for Dare County are the most sensitive to the occurrence of high-category hurricanes: the expected number of turbines that buckle in 20 years decreases from 19.3 to 13.4, the probability of no turbines buckling increases from 20% to 24% and the probability that less than half the turbines buckle increases from 68% to 80% when Category 4 and 5 hurricanes are excluded. The results for Atlantic and Dukes counties are less sensitive to the occurrence of high-category hurricanes: the expected number of turbines that buckle falls from 3.8 to 3.1 in Atlantic County and from 3.4 to 2.6 in Dukes County. In both Atlantic and Dukes counties, the probabilities of none of the turbines and less than half the turbines buckling increase approximately two percentage points. Plots of the CDF of number of turbines bucked with higher-category hurricanes excluded are given in the **Supporting Information**.

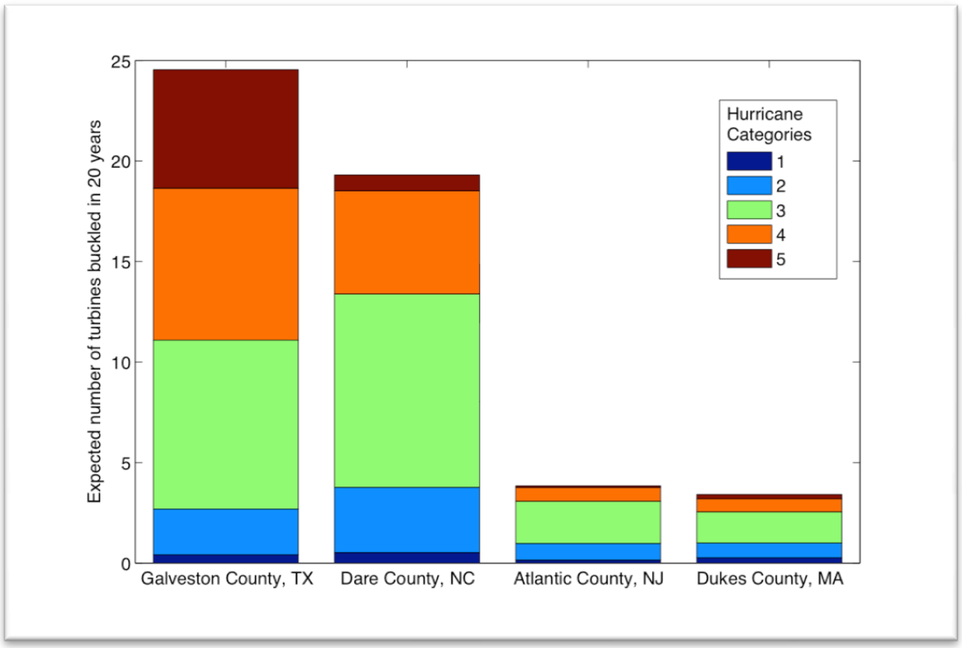

Figure 3: The expected number of turbines that buckle in a 50-turbine wind farm over 20 years for each location, subdivided by hurricane category.

Discussion

The 2008 DOE report (3) estimates that 54 GW of shallow offshore wind capacity will be required to bring the U.S. to 20% wind, and locates most of that capacity off the Gulf and East coasts. We find that hurricanes pose a significant risk to wind turbines off the U.S. Gulf and East coasts, even if they are designed to the most stringent current standard (IEC Class 1 winds). Now is an appropriate moment to consider mitigation strategies that can be incorporated to reduce risk to the grid and to operators, before large-scale offshore wind development is undertaken in the United States.

Engineered solutions can mitigate the risk of wind turbine damage as a result of hurricanes in the Eastern United States. Typically, wind turbines are designed based on engineering design codes for northern Europe and the North Sea, where nearly all the offshore and coastal wind turbines have been built. These codes specify maximum sustained wind speeds with a 50-year return period of 42.5 – 51.4 m/s (83 – 100 knots), lower than high intensity hurricanes (22). Asian countries have been interested in designing structurally stronger wind turbines that can survive typhoon-force winds (23). These authors have proposed changes in the characteristic values for the IEC 61400-3 design standard that would apply to turbines in areas exposed to tropical cyclones. Garciano, *et al* (24), also analyze data from the Philippines and propose increasing the design reference wind speed at hub height with a 50-year return period from 50 m/s to 58 m/s. Tarp-Johansen, Clausen, and others also analyze data from the Philippines and propose the design reference wind speed at hub height with a 50-year return period should be increased from 50 m/s to 67 m/s and the load safety factor should be increased from 1.35 to 1.7 to maintain the same level of reliability (13). Tarp-Johansen and Clausen estimate that the changes they propose to the design requirements increase the cost of each turbine 20 – 30% compared to conventional turbines (25). We have also demonstrated that wind turbines that have external power available to yaw can very substantially reduce the risk of being destroyed. Installing lead-acid batteries to allow a turbine to yaw without external power would add $70,000 - $100,000 to the price of a turbine and 4,000 - 7,000 kg to its weight, assuming 6 hours of backup power for yaw motors that draw 30 kW of power (26). In addition, the current yaw rate is 0.3 degrees per second. Further work is needed to determine the yaw rate appropriate for hurricanes. Backup power, robust wind direction indicators, and active controls may be cost-effective to reduce risk to the turbine.

There is ample warning of hurricanes, and supplemental generation reserves can be brought on line to cover for the wind plants that will be shut down for months to years that it may take to rebuild buckled towers. However, system operators must make it economical for the owners of such spare generation to stay in business even in years with no hurricane damage, and suitable capacity payment mechanisms will be required.

The probability of hurricane landfalls is not geographically uniform. Figure 4 plots the offshore wind resources within water shallower than 60 meters (2) and the annual rate of hurricane landfalls for states in the Eastern U.S. since 1900 (27). Information for Florida, Alabama, and Mississippi is not included in Figure 4. Though these states have moderate to high hurricane occurrence rates (0.44, 0.14, and 0.10 year^{-1} respectively), there are no offshore wind resource estimates available for them. The specific results shown in this paper are thus not representative of all the risk of hurricanes to all possible offshore wind farm locations. It is clear, however, that analysis of the type presented here should be performed as part of the wind farm siting analysis.

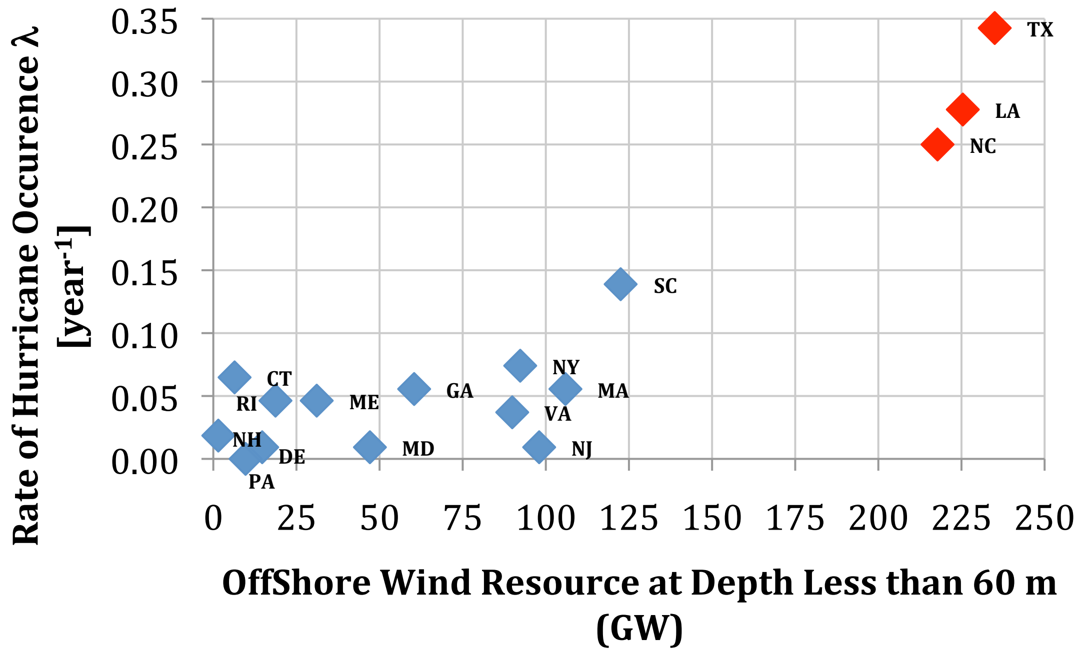

Figure 4: Resource vs. Hurricane Occurrence Rate λ [year-1]

Our analysis also assumed that historic wind speeds and historic rates of hurricanes occurrence are representative of future conditions. This may not be the case if climate change were to affect hurricane intensity or frequency. Detection of climate change effects on hurricanes is complicated by the very high sensitivity of hurricanes to variations in atmosphere-ocean conditions on multiple timescales, including the multidecadal (28); and by the short period over which hurricane observations are considered reliable (28, 29). Current high-resolution modeling studies project a relatively small increase in Atlantic hurricane intensity with increased global temperatures due to an increase in available thermal energy. These models also identify a possible decrease in Atlantic hurricane frequency, which may be attributable to the stabilization of the upper atmosphere (30). According to these projections, an increase in intensity due to climate change may not be noticeable for the next few decades (30-32). In line with this, Pielke *et al*. (33) report that no trends in normalized damages can be detected. On the other hand, a recent observational study (34) finds that there has been an increase in the intensity of the most intense hurricanes. Wind farm developers will invest and operate under the current uncertainties on the future development of Atlantic hurricane activity. The method developed here will support the decision process of wind turbine investors in hurricane-prone areas. Sensitivity analysis on models like the one presented here can allow investors and regulators to see how distribution parameters affect the risk.

There is a very substantial risk that Category 3 and higher hurricanes can destroy half or more of the turbines at some locations. By knowing the risks before building multiple GW of offshore wind plants, we can avoid precipitous policy decisions after the first big storm buckles a few turbines. Reasonable mitigation measures – increasing the design reference wind load, ensuring that the nacelle can be turned into the wind, and building most wind plants in the areas with lower risk – can greatly enhance the probability that offshore wind can help to meet the United States' electricity needs.

Materials and Methods

We model the distribution of the number of wind turbines buckled by hurricanes for two cases: (1) turbines are not replaced for the life of the wind farm, and (2) turbines are replaced after each hurricane. For each case, we calculate the distributions using two methods: an analytical probability distribution presented here and a Monte Carlo simulation discussed in the **Supporting Information**. All the analyses presented here model a wind farm of 50 NREL 5-MW wind turbines (17) for 20 years. We believe our results under-estimate the probability of loss because we model only buckling of the tower base but ignore damage to other components. Our results may also under-estimate the probability of tower buckling because we analyze the onshore version of the NREL 5-MW turbine, which has a simpler foundation structure and is not subjected to wave loads.

Analytical Distribution: Turbines Buckled without Replacement

We model $Y_{\text{no rep}}$, the number of turbines that buckle in T years without replacement as a modified Phase-Type distribution with six parameters: $Y_{\text{no rep}} \sim \text{PH}(\lambda, \mu, \sigma, \xi, \alpha, \beta)$. Figure 2 plots the results calculated with this method.

Hurricane occurrence is modeled as a Poisson process with rate parameter λ fitted to historical hurricane data. The probability that H, the number of hurricanes that occur in T years, equals a particular value h is:

$$\Pr(H = h) = \frac{(\lambda T)^h}{h!} e^{-\lambda T} \qquad [1]$$

The maximum 10-minute sustained wind speed of each hurricane at 10-meter height is modeled as a Generalized Extreme Value (GEV) distribution with a location parameter μ, a scale parameter σ, and a shape parameter ξ fitted to historical hurricane data. The probability density function for W, the maximum sustained wind speed, evaluated at particular value w is:

$$f_W(w) = \frac{1}{\sigma}\left(-\left(1+\xi\frac{w-u}{\sigma}\right)^{-\frac{1}{\xi}}\right)\left(1+\xi\frac{w-u}{\sigma}\right)^{-1-\frac{1}{\xi}} \qquad [2]$$

The probability that a single wind turbine is buckled by a 10-minute sustained hub-height wind speed u is modeled using a Log-Logistic function with a scale parameter α and a shape parameter β. The function is fitted to the results of simulations of stresses on a particular turbine design given a yaw direction relative to the wind, a wind turbulence intensity, and a sustained wind speed u. The Log-Logistic function is given by:

$$D(u) = \frac{\left(\beta/\alpha\right)\left(u/\alpha\right)^{\beta-1}}{\left(1+\left(u/\alpha\right)^{\beta}\right)^{2}} \quad [3]$$

The number of turbines buckled by a single hurricane in a wind farm of *n* turbines is modeled as a Beta Binomial distribution with parameters α_B and β_B. We derive the Beta Binomial distribution by fitting a Beta distribution with parameters α_B and β_B to the probability of buckling as a function of wind speed weighted by the probability of occurrence of each wind speed (a convolution of *D* and *W*) with a nonlinear least-squares fit. The wind speeds *W* are scaled to turbine hub height using the table of scaling values for hurricanes given by Franklin, *et al*. (15). Fitting the distribution simplifies the model by replacing the convolution of *D* and *W*, which together have five parameters, with a Beta distribution that has only two parameters. The Beta distribution gives the distribution of buckling probabilities for a single turbine given a hurricane with random (GEV) maximum wind speed. The corresponding Beta Binomial distribution with the same parameter values α_B and β_B gives the probability that *X*, the number of turbines that buckle out of *n* total, equals a particular value *x*:

$$\Pr(X = x) = \binom{n}{x}\frac{B(x-\alpha_B, n-x+\beta_B)}{B(\alpha_B,\beta_B)} \quad [4]$$

where B( ) is the Beta function.

The cumulative distribution of the number of turbines buckled in *T* or fewer years without replacement, $Y_{no\ rep}$, is modeled as a modified Phase-Type distribution:

$$\Pr(Y_{norep} \le y \mid \tau \le T) = \pi \exp\big(T\,\mathrm{T}(y,n)\big)e \quad [5]$$

where $\boldsymbol{\pi}$ is a row vector of initial state probabilities, **T** is a matrix of jump intensities for the transitions between states, and **e** is a column vector of ones. A Phase-Type distribution gives the distribution of times τ to reach the absorbing state of a Markov jump process (35, 36). In this application, each jump (state transition) represents a hurricane occurrence, each state represents a unique number or turbines buckled, and the absorbing state is when all *n* turbines in the wind farm have buckled. We modify the Phase-Type distribution to calculate the distribution of the number of turbines buckled $Y_{no\ rep}$ in a fixed time *T* by iteratively redefining the absorbing state to include cases where less than *n* turbines are bucked, as shown in Figure 5.

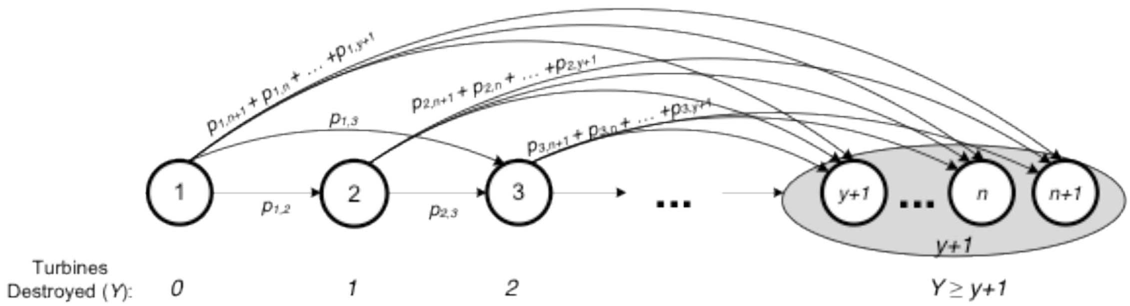

Figure 5: The Markov Chain used to calculate the probability that the number of turbines buckled is less than or equal to *y*. We define the absorbing state as all the states where $Y_{\text{no rep}} \geq y+1$.

This redefinition of the absorbing state makes the sizes of the vectors $\boldsymbol{\pi}$ and **e** a function of *y* and makes both the size and values of the matrix **T** a function of *y*. To calculate the probability that *y* or fewer turbines buckle, we define the absorbing state to include an integer number of turbines buckled from y+1 to *n*. There are y+1 total states; the $y+1^{st}$ state is the absorbing state. The term $\boldsymbol{\pi}$ in **[5]** is a y+1 element row vector of initial state probabilities; in this application $\boldsymbol{\pi} = [1\ 0\ \ldots\ 0]$ because the distribution begins in state 1 (no turbines buckled). The term **e** is a column vector of ones: $[1\ 1\ \ldots\ 1]^T$. The term **T** is a $(y+1)$ X $(y+1)$ matrix of jump intensities, where the jump intensity $\mathbf{T}_{ij}(y,n)$ from the i^{th} state to the j^{th} state is the product of λ, the rate of hurricane occurrence, and p_{ij}, the probability a hurricane causing a transition from state *i* to state *j* by buckling turbines. The off-diagonal elements of $\mathbf{T}(y,n)$ in the i^{th} row and j^{th} are calculated by:

$$\mathrm{T}_{ij}(y,n) = \lambda BetaBinomial(n-i+1, n-j+1; \alpha_B, \beta_B) \quad j \geq i \qquad [6]$$

and the diagonal elements are calculated by:

$$\mathrm{T}_{ii}(y,n) = -\left(t_i(y,n) + \sum_{j>i} \mathrm{T}_{ij}(y,n)\right) \qquad [7]$$

where **t** is the jump intensity for a hurricane that jumps directly to the absorbing state (i.e. destroys all remaining turbines):

$$t_i(y,n) = \lambda \sum_{m=0}^{n-y-1} BetaBinomial(n, n-m; \alpha_B, \beta_B) \qquad [8]$$

The off-diagonal elements of **T** do not sum to 1 along a row because some hurricanes do not cause a state transition (i.e. some hurricanes do not buckle any turbines).

Analytical Distribution: Turbines Buckled with Replacement

We model Y_{rep}, the number of turbines that buckle in T years with replacement as a compound Poisson distribution with six parameters: Y_{rep} ~ Compound Possion(λ, μ, σ, ξ, α, β). The compound Poisson distribution is a convolution of the Poisson distribution given in **[1]** for the number of hurricanes that occur in T years and the Beta Binomial distribution given in **[4]** for number of turbines buckled by each hurricane. No analytical expression exists for the PDF or CDF of a Compound Poisson distribution that contains a Beta Binomial distribution. We use Panjer's Recursion (37, 38), an iterative method, to approximate the PDF. The details are given in **Supporting Information**.

Application to Specific Locations

The rate of hurricane occurrence parameter λ for the Poisson distribution given in **[1]** is calculated as the number of hurricanes to make landfall in each county between 1900 and 2007 (16), divided by the length of the time period. The calculated values for the locations we investigate are given in Table 1. The parameters for the Generalized Extreme Value distribution given in **[2]** are fit to historical data for the maximum 10-minute sustained wind speed at 10-meter height for all hurricanes to pass through the geographic ranges of interest (described in the fourth column of Table 1) between 1851 and 2008.

Table 1: Distribution Parameters for Poisson and Generalized Extreme Value Distributions.

	Rate of hurricane occurrence [events/year]	Max. Sustained hurricane wind speed: GEV distribution [knots]	Geographic range of hurricanes modeled (lat/long)
Galveston County, TX	λ = 0.19	μ = 78.7, σ = 12.1, ξ = 0.251	25.5ºN - 30ºN 92ºW – 99ºW
Dare County, NC	λ = 0.21	μ = 77.6, σ = 11.9, ξ = -0.0366	32º - 36.5ºN 71º - 81ºW
Atlantic County, NJ	λ = 0.047	μ = 77.2, σ = 10.6, ξ = -0.0544	36º - 41ºN 71º - 77.5ºW
Dukes County, MA	λ = 0.075	μ = 73.2, σ = 6.99, ξ = -0.139	40.3º - 42ºN 66º - 74.5ºW

The parameters for the Log-Logistic function given in **[3]** are fit to probabilities of turbine tower buckling calculated by comparing the results of simulations of the 5-MW Offshore wind turbine designed by the U.S. National Renewable Energy Laboratory (17) to the stochastic resistance to buckling proposed by Sørensen, *et al* (39). The fitted parameters for different levels of wind turbulence intensity and for turbines that can and cannot yaw to track wind direction are given in Table 2. More extensive details are given in the **Supporting Information**.

Table 2: Parameters for Log-Logistic Distribution

Turbulence intensity	Pointed into wind (active yawing)	Pointed perpendicular to wind (not yawing)
16% (Class A)	$\alpha = 5.18$, $\beta = 0.051$	$\alpha = 4.83$, $\beta = 0.045$
14% (Class B)	$\alpha = 5.24$, $\beta = 0.047$	$\alpha = 4.84$, $\beta = 0.064$
12% (Class C)	$\alpha = 5.29$, $\beta = 0.032$	$\alpha = 4.84$, $\beta = 0.059$

Acknowledgements

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Quantifying the Hurricane Risk to Offshore Wind Turbines
Supporting Information

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Risk From Multiple Hurricanes with Replacement

In the main body of the paper, Figure 2 present CDF plots for the number of turbines destroyed in 20 years if buckled turbines are not replaced. Here we present similar results for the case that buckled turbines are replaced after each storm. Figure S1 plots the CDF for each location for two cases: turbines that can yaw to track wind direction (dashed lines) and turbines that cannot yaw (solid lines).

In this scenario, damaged turbines are replaced after each storm so there is no limit to the maximum number of turbines that buckle. There is a 23% probability that more than 50 turbines will buckle in Galveston County and a 12% probability that more than 50 will buckle in Dare County.

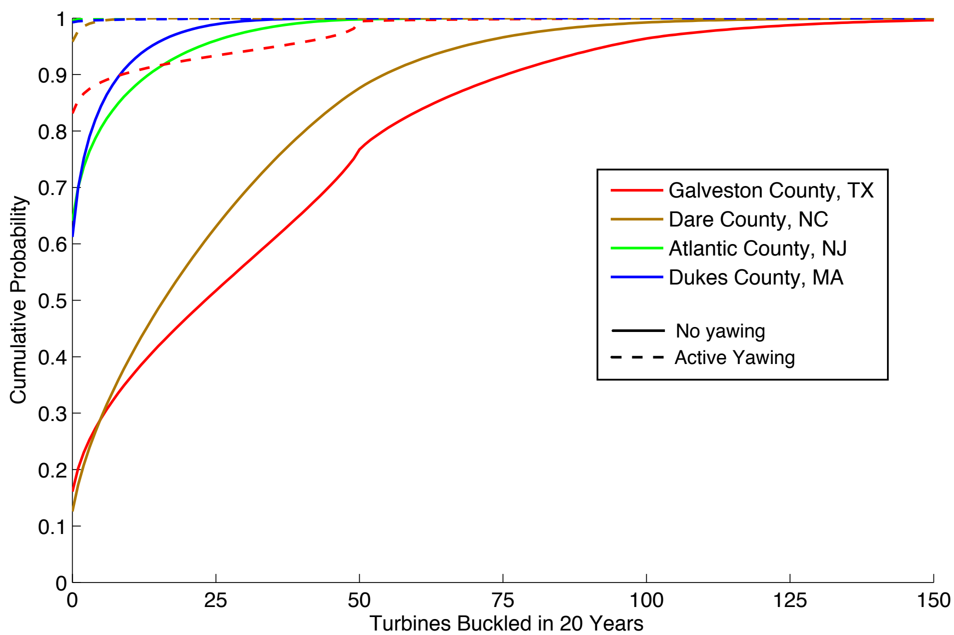

Figure S1: Cumulative distribution of the number of turbines in a 50-turbine wind farm buckled in 20 years if buckled turbines are replaced after each storm if they buckle. Dashed lines plot the distribution for the case that turbines can yaw to track the wind direction, and solid lines plot the distribution for the case that turbines cannot yaw.

Risk From Multiple Hurricanes, Cat. 4 and 5 Hurricanes Excluded

To illustrate the effect of excluding category 4 and 5 hurricanes for Dare, Atlantic, and Dukes counties, we plot the CDF of the number of turbines damaged with and without those higher-category hurricanes. The results for the case that turbines cannot yaw to track the wind direction are shown in Figure S2, where solid lines plot the results for all hurricanes and dotted lines plot the results excluding category 4 and 5 turbines. Similarly, the results for the case that turbines can actively yaw are shown in Figure S3, where solid lines plot the results for all hurricanes and dotted lines plot the results excluding category 4 and 5 turbines.

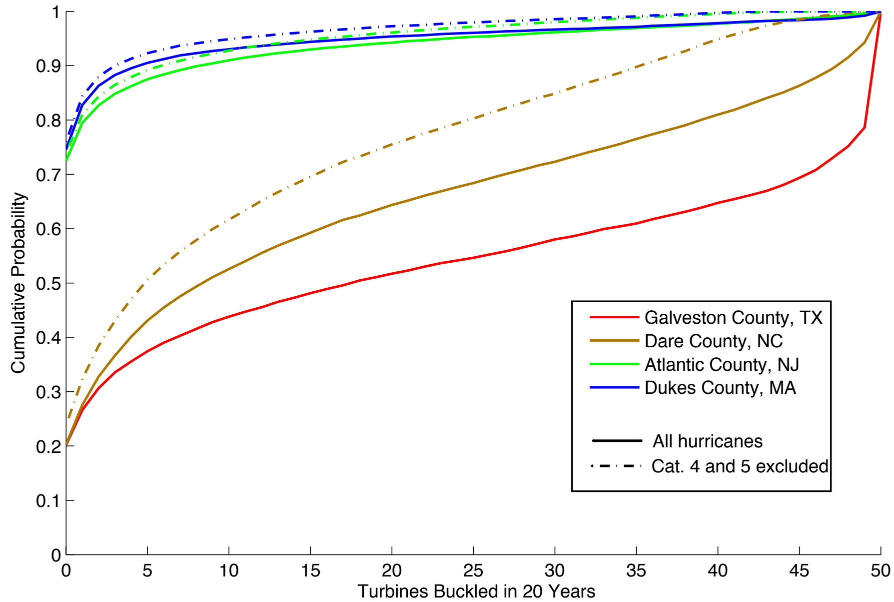

Figure S2: CDF of the number of turbines buckled in 20 years without replacement; turbines cannot yaw to track the wind. Solid lines plot the distribution including all hurricanes, and dotted lines plot the distribution with category 4 and 5 hurricanes excluded.

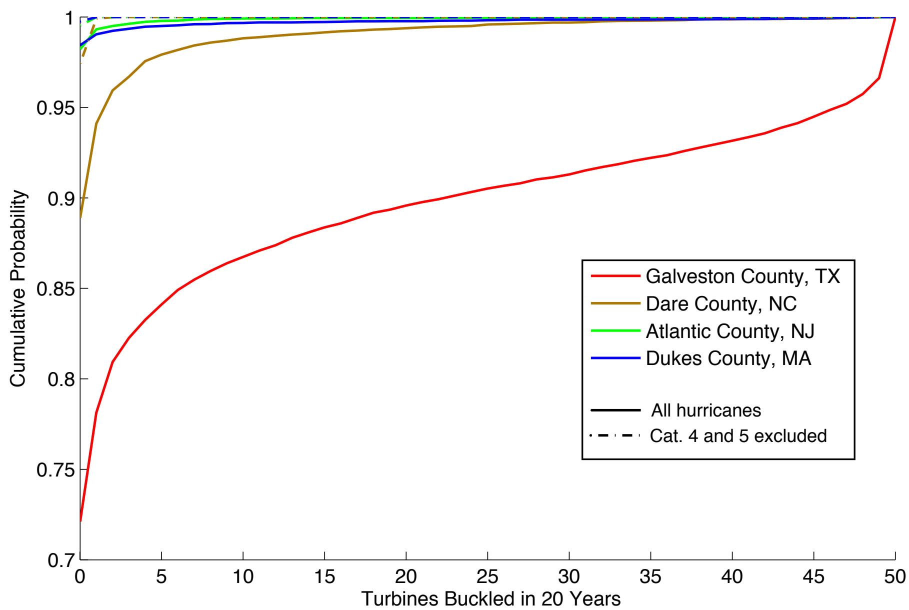

Figure S3: CDF of the number of turbines buckled in 20 years without replacement; turbines can actively yaw to track the wind. Solid lines plot the distribution including all hurricanes, and dotted lines plot the distribution with category 4 and 5 hurricanes excluded.

Analytical Distribution: Turbines Buckled with Replacement

As described in the main document, we use a Compound Poisson distribution to model Y_{rep}, the total number of turbines destroyed in T years in a wind farm of n turbines if turbines are immediately replaced after they are destroyed by a hurricane. The Compound Poisson distribution is a function of six parameters: λT, μ, σ, ξ, α, and β.

$$Y_{rep} \sim \text{Compound Poisson}(\lambda T, \mu, \sigma, \xi, \alpha, \beta) \quad \text{[A1]}$$

No analytical expression exists for the PDF or CDF of a Compound Poisson distribution that contains a Beta Binomial distribution. We use Panjer's Recursion (1, 2), an iterative method, to compute the exact pdf:

$$\Pr(Y_{rep} = y) = g_y = \sum_{j=1}^{y}\left(a + \frac{bj}{y}\right) f_j g_{y-j} \quad \text{[A2]}$$

where

$$f_j = \begin{cases} \Pr(X_i = j) & j \le n \\ 0 & j > n \end{cases} \quad \text{[A3]}$$

The value of f_j is zero for $j > n$ in equation A2 because the Beta Binomial distribution for the number of turbines damaged in the ith hurricane X_i is not defined for $x > n$, i.e. the number of turbines damaged in one hurricane cannot be larger than the number of turbines in the wind farm. Panjer defines a and b for a Poisson distribution (1).

$$a = 0$$
$$b = \lambda T$$

The initial value of f is:

$$f_0 = \Pr(X_i = 0) = \binom{n}{0}\frac{\mathrm{B}(0 + \alpha_B, n - 0 + \beta_B)}{\mathrm{B}(\alpha_B, \beta_B)} = \frac{\mathrm{B}(\alpha_B, n + \beta_B)}{\mathrm{B}(\alpha_B, \beta_B)} \quad \text{[A4]}$$

and the initial value g_0, from (3), gives the probability that no turbines are buckled by hurricanes in T years as the probability that no hurricanes occur ($H = 0$) plus the probability that a positive number of hurricanes occur but cause no damage:

$$\begin{aligned} g_0 &= \Pr(H=0) + \Pr(Y = 0 \mid H > 0) \\ &= \frac{(\lambda T)^0}{0!}e^{-\lambda T} + \sum_{i=1}^{\infty}\left(\Pr(X=0)\right)^i \Pr(H=i) \\ &= e^{-\lambda T} + \sum_{i=1}^{\infty}\left(\binom{n}{0}\frac{\mathrm{B}(0+\alpha_B, n-0+\beta)}{\mathrm{B}(\alpha,\beta)}\right)^i \frac{(\lambda T)^i}{i!}e^{-\lambda T} \\ &= e^{-\lambda T} + \sum_{i=1}^{\infty}\left(\frac{\mathrm{B}(\alpha_B, n-\beta)}{\mathrm{B}(\alpha,\beta)}\right)^i \frac{(\lambda T)^i}{i!}e^{-\lambda T} \end{aligned} \quad \text{[A5]}$$

where B(α, β) is the Beta function:

$$B(\alpha,\beta) = \frac{\Gamma(\alpha-1)\Gamma(\beta-1)}{\Gamma(\alpha+\beta-1)} = \frac{(\alpha-1)!(\beta-1)!}{(\alpha+\beta-1)!} \quad \text{[A6]}$$

and Γ() is the Gamma function.

Monte Carlo Distribution: Turbines Buckled with Replacement

To check the Compound Poisson distribution described above, we use Monte Carlo simulations to calculate Y_{rep}, the distribution of the total number of turbines buckled in *T* years in a wind farm of *n* turbines if turbines are replaced after each hurricane. We simulate 10,000 20-year periods using the same distributions used in the Compound Poisson distribution: *H* for the frequency of hurricane occurrence, *W* for the maximum sustained wind speed, and *D* for the probability of buckling as a function of wind speed.

For each simulated 20-year period in a given location, we calculate the total number of turbines that buckle according to the following procedure:

1. Draw number of hurricanes from Poisson distribution *H* described in Hurricane Frequency.
2. Draw maximum sustained wind speed for each hurricane from Generalized Extreme Value distribution *W* described in Hurricane Intensity (*W*.
3. Scale maximum sustained wind speed to hub height (4) and calculate probability of a single turbine buckling at that wind speed using the Log-Logistic damage function described in Wind Turbine Damage Function (*D*).
4. Calculate the number of turbines buckled in each hurricane using a Binomial distribution with the probability of buckling calculated in step 3 and *n* turbines.

A comparison of the distributions calculated with the compound Poisson distribution and the Monte Carlo simulation is shown in Figure S4.

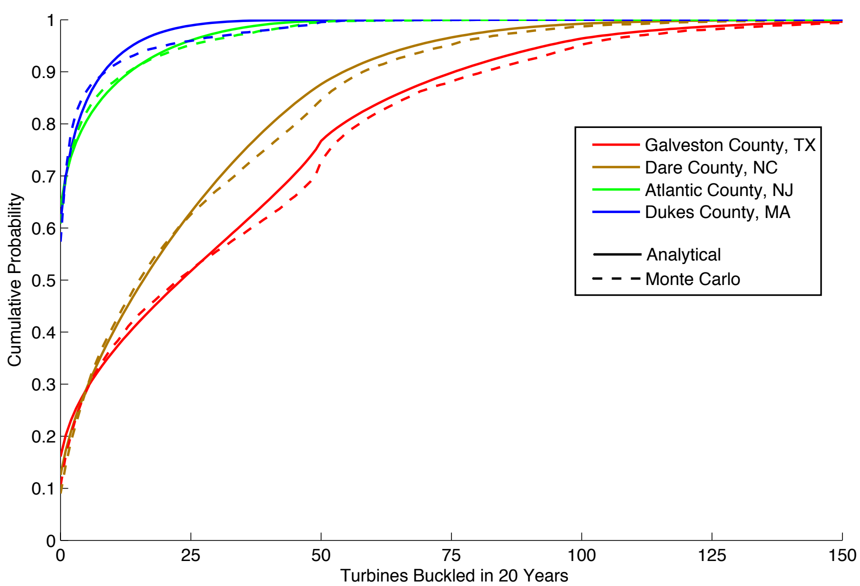

Figure S4: A comparison of the cumulative probability distributions of number of turbines buckled in 20 years for the case where turbines are replaced after each storm if they buckle. Results calculated with Monte Carlo simulation are plotted as dashed lines and results calculated with a compound Poisson distribution are plotted as solid lines.

Monte Carlo Distribution: Turbines Buckled without Replacement

To check the Phase-Type distribution described in the main paper, we use Monte Carlo simulations to calculate $Y_{\text{no rep}}$, the distribution of the total number of turbines buckled in T years in a wind farm of n turbines if turbines are not replaced after they are destroyed. We simulate 10,000 20-year periods using the same distributions used in the Phase-Type distribution: H for the frequency of hurricane occurrence, W for the maximum sustained wind speed, and D for the probability of buckling as a function of wind speed.

For each simulated 20-year period in a given location, we calculate the total number of turbines buckled according to the following procedure:

1. Draw number of hurricanes from Poisson distribution H described in Hurricane Frequency.
2. Draw maximum sustained wind speed for each hurricane from Generalized Extreme Value distribution W described in Hurricane Intensity (W.
3. Scale maximum sustained wind speed to hub height (4) and calculate probability of a single turbine buckling at that wind speed using the Log-Logistic damage function described in Wind Turbine Damage Function (D).
4. Calculate the number of remaining turbines buckled in each hurricane using a Binomial distribution with the probability of buckling calculated in step 3 and the number of turbines remaining after all the previous hurricanes.

A comparison of the distributions calculated with the Phase-Type distribution given in the main paper and the Monte Carlo simulation described above is shown in Figure S5.

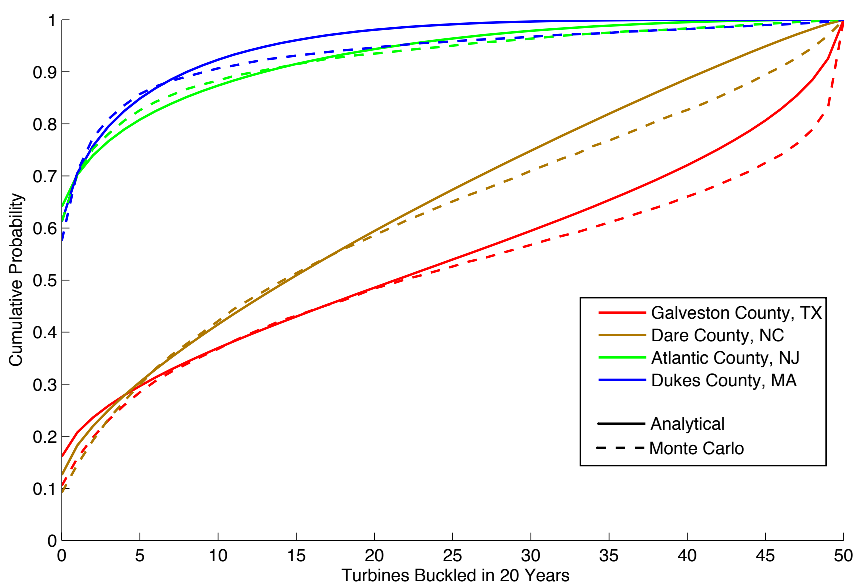

Figure S5: A comparison of the cumulative probability distributions of number of turbines buckled in 20 years for the case where turbines are not replaced if they buckle. Results calculated with Monte Carlo simulation are plotted as dashed lines and results calculated with a Phase-Type distribution are plotted as solid lines.

Hurricane Frequency (*H*)

We fit a Poisson distribution to the rate of hurricane occurrence in a particular county by dividing the number of hurricanes to make landfall in that county from 1900 to 2006 by the number of years (5). Table 1 in the main document lists the resulting rate of hurricane occurrence values λ for the four counties we examine. This method of calculating the rate of hurricane occurrence assumes that the rate is constant and equal to the average rate. However, previous research has shown strong associations between North Atlantic hurricane activity and atmosphere-ocean variability on different timescales, including the multidecadal (6, 7).

Hurricane Intensity (*W*)

We fit a Generalized Extreme Value distribution (GEV) to the maximum 10-minute sustained wind speed at 10-meter height of hurricanes that pass through a region around the counties we examine. Table 2 in the main paper gives the parameters of the fitted GEV distributions for each location and the latitude and longitude limits of the regions around those locations. Figure S6 compares the empirical and fitted CDFs for the maximum sustained wind speed at each location.

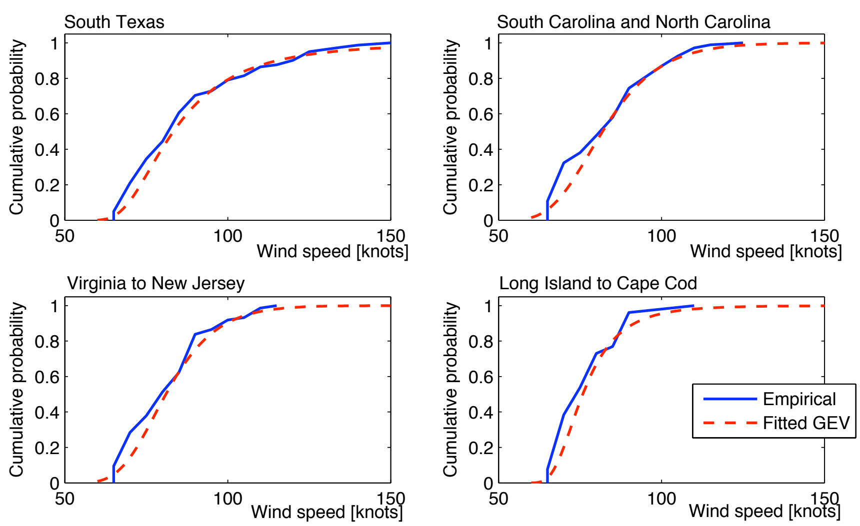

Figure S6: Comparison of empirical CDFs for maximum hurricane wind speed in the regions we examine and the GEV distributions fitted to those data.

Wind Turbine Damage Function (*D*)

We fit a Log-Logistic distribution to the probability of a wind turbine tower buckling as a function of 10-minute sustained wind speed at hub height. The probability of the turbine tower buckling at a given wind speed is calculated by simulating tower bending moments of a 5-MW NREL turbine and comparing them to the stochastic resistance to buckling of the turbine tower. In our analysis, we model the 5-MW wind turbine design created by the U.S. National Renewable Energy Laboratory (NREL) for two load cases (active yawing and not yawing) and three turbulence intensity values (12%, 14%, and 16%). Turbulence intensity I is calculated as the quotient of the 10-minute mean wind speed u and the 10-minute standard deviation σ: $I = u_{10\ min}/\sigma_{10\ min}$.

We calculate separate damage functions for the "active yawing" and "not yawing" load cases because those are the best- and worst-case wind load conditions for an idling wind turbine. The active-yawing case assumes the grid power is available to the turbine or the turbine has a backup power source for the yaw motors and control system; the not-yawing case assumes the turbine does not have a backup power source and grid power has been lost, a typical occurrence in hurricanes (8). The current design standards for wind turbines given by the IEC (9) and Germanischer-Lloyd (10) require that an idling wind turbine be able to survive 10-minute sustained wind with 50-year recurrence period (load case 6.2). If backup power is not available for the yaw and control systems, the IEC standard requires the turbine must be able to survive a yaw misalignment of ±180º and the Germanischer-Lloyd standard specifies ±30º. The "active yawing" case we simulate assumes backup power for the yaw system, and the "not yawing" case assumes a yaw misalignment of 90º. The probability of buckling as a function of wind speed for each turbulence intensity value and yawing/not yawing are plotted in Figure 7.

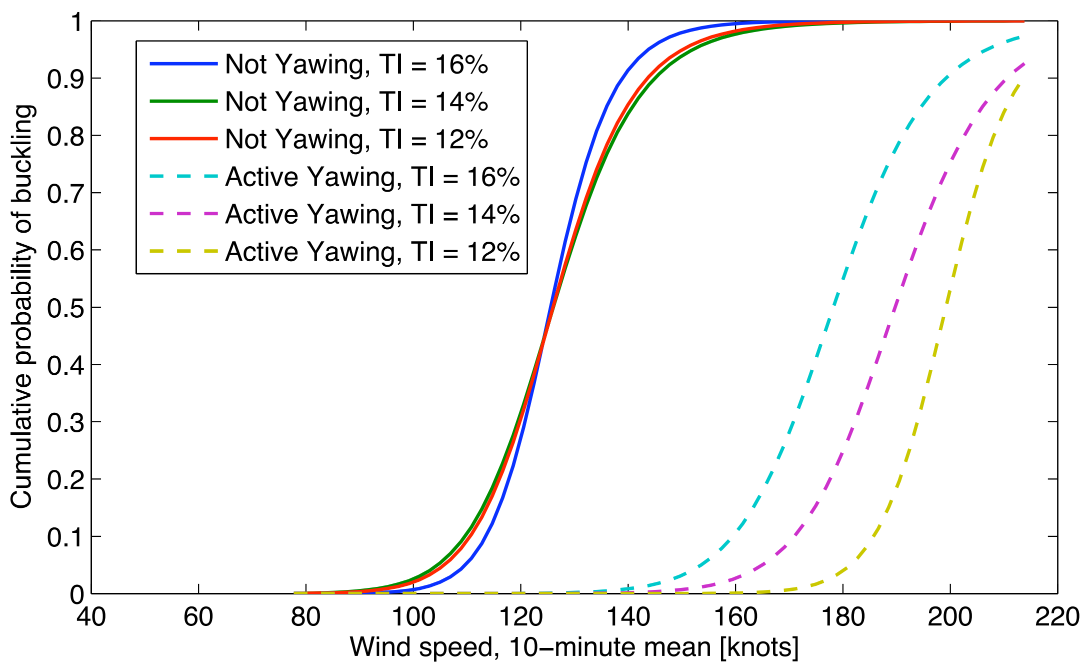

Figure 7: Comparison of the probability of buckling as a function of wind speed (damage function). TI = turbulence intensity.

Bending moment simulation

We calculate a range of maximum tower bending moments by simulating the mechanical loads on an NREL 5-MW turbine (11) for mean hub-height wind speeds from 40 to 110 m/s (78 – 214 knots). These wind speeds are significantly higher than the wind speeds at which wind turbines shut down to avoid damage (typically 25 m/s), so the simulations assume the turbine is idling with its blades feathered to 90º. To simplify the simulations, we simulate the land-based version of the NREL 5-MW turbine instead of the offshore version so we don't need to model the effects of waves; as a result, the damage function we derive should under-predict the probability of an offshore turbine buckling at a given wind speed. For each mean wind speed u (in 1 m/s increments), we run 10 10-minute dynamic simulations of the wind turbine using FAST version 7.00.01a-bjj (12). We use TurbSim version 1.50 (13) to generate a three-dimensional wind field with a different random seed for each simulation. The turbulent wind fields are generated using the Normal Turbulence

Model (NTM) given in the IEC 61400-3 standard (9). That IEC standard specifies that the Extreme Wind speed Model (EWM) should be used to test the effect of extreme winds on an idling turbine (load case 6.2), but we use the NTM instead because it generates wind time series with larger standard deviations. Schroeder, et al found the longitudinal turbulence intensity of wind speed ranges from 7 – 17% during the passage of Hurricane Bob in 1991 (14) and 12 – 42% in the passage of Hurricane Bonnie in 1998 (15). We test the sensitivity of our results to different turbulence intensities by calculating separate damage functions for turbulence intensities of 12%, 14%, and 16%.

We analyze the FAST simulation results by calculating the magnitude of the tower bending moment and finding its maximum value. FAST calculates the x-component (`TwrBsMxt`) and y-component (`TwrBsMyt`) of the bending moment at the tower base. We calculate the magnitude as $M = \sqrt{\mathtt{TwrBsMxt}^2 + \mathtt{TwrBsMyt}^2}$ and choose the maximum value from each simulation.

We were warned that FAST simulations might be unstable for large yaw mis-alignments (16) and we found the maximum tower bending moments in some simulations of the not-yawing case (90º wind direction) were much higher (several orders of magnitude) than the rest of the simulation results. To exclude these anomalous results, we fit a line to the maximum bending moment as a function of 10-minute mean wind speed using a robust linear least-squares with bi-square weights and exclude any data points more than 1.5 times or less than 0.5 times the best-fit line. The data and the exclusion limits are illustrated in Figure S8. This method does not exclude any model results from the active-yawing case (0º) wind, which we expected because the FAST simulation is believed to be reliable for small yaw misalignments.

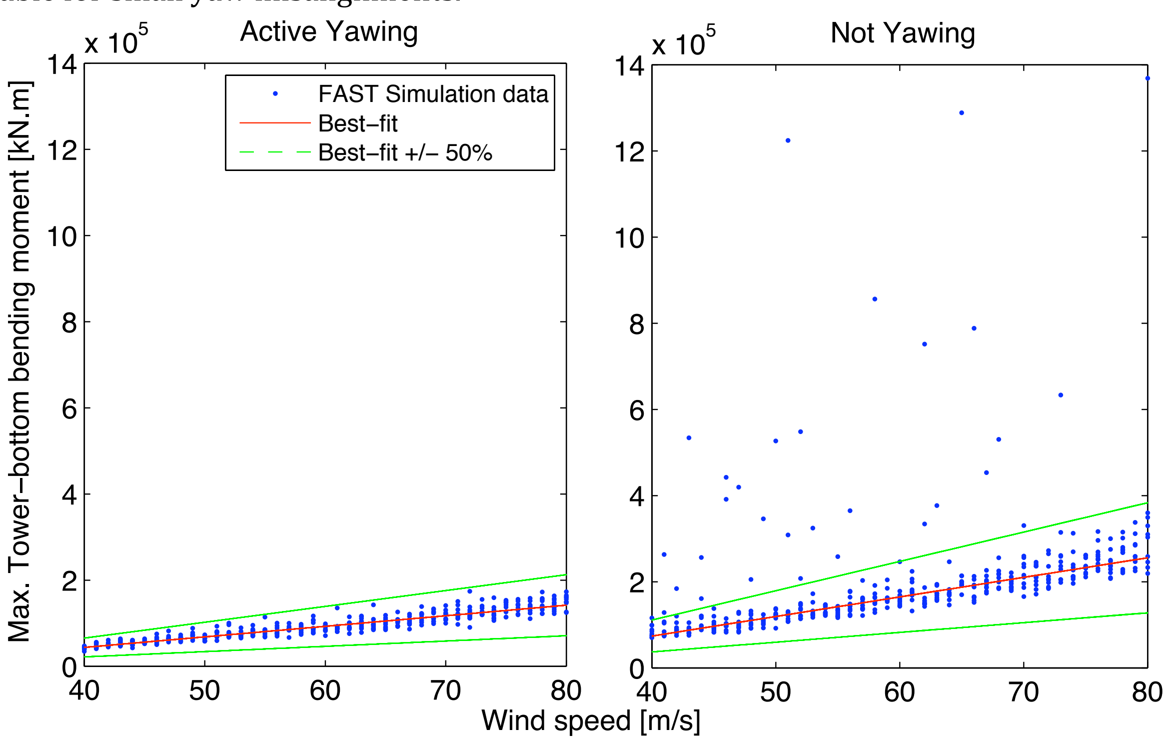

Figure S8: The method for excluding anomalous simulation results for maximum tower bending moment. The red line is a robust linear best-fit to the data and the green dashed lines are 0.5 and 1.5 times the best-fit line. Data outside the green dashed lines are excluded.

Calculation of buckling probability

Given the maximum tower bending moments M calculated above, we calculate the probability of a turbine tower buckling by comparing the simulated bending moments to a random variable for the resistance of a tower to buckling.

For each combination of mean wind speed u, turbulence intensity I, and yaw status A, we create 1000 bending moment values by repeatedly sampling the simulation results with equal probability. If no anomalous values were excluded, there are 10 simulation values to sample from; there are fewer if some were excluded.

We create 1000 resistance to buckling values by sampling from M_{cr}, the resistance to buckling of a thin-walled cylinder (17):

$$M_{cr} = \tfrac{1}{6}\left(1 - 0.84\frac{D}{t}\frac{X_{y,ss}F_y}{X_{E,ss}E}\right)\left(D^3 - (D-2t)^3\right)X_{y,ss}X_{cr}F_y \quad [A7]$$

with the parameters given in Table S1:

Table S1: Parameters of resistance to buckling at the base of a NREL 5-MW turbine tower. LN = log-normal distribution, COV = coefficient of variance. Adapted from [Søresnen 2005]

Variable	Description	Distribution Type	Expected Value	COV
D	Tower diameter (base)	-	6 m	-
t	Tower thickness (base)	-	0.027 m	-
E	Young's modulus	-	210 GPa	-
F_y	Yield stress	LN	1	0.05
$X_{y,ss}$	Model uncertainties due to scale effects: yield stress	LN	1	0.05
$X_{E,ss}$	Model uncertainties due to scale effects: Young's modulus	LN	1	0.02
X_{cr}	Critical load capacity	LN	1	0.10

The damage function D is calculated by comparing all the sampled bending moment values to the sampled resistance-to-buckling values to find the probability of buckling for each 10-minute mean wind speed u, turbulence intensity I, and yaw status A:

$$D(u; I, A) = \Pr\left(M_{cr} \le M(u; I, A)\right) \quad [A7]$$

Nomenclature

T = time period to investigate
n = number of turbines in the wind farm
u = 10-min avg. hub-height wind speed

λ = rate parameter for occurrence of hurricanes
μ = location parameter for distribution of wind speed in a hurricane
σ= scale parameter for distribution of wind speed in a hurricane
ξ = shape parameter for distribution of wind speed in a hurricane
α = scale parameter for the log-logistic distribution of the probability of a turbine buckling at a 10-minute average wind speed u
β = shape parameter for the log-logistic distribution of the probability of a turbine buckling at a 10-minute average wind speed u
α_B, β_B = parameters of the Beta Binomial distribution for the distribution of turbines buckled in a single hurricane (parameters are derived by fitting a Beta distribution to the damage function weighted by the probability of occurrence of wind speed)

W = random variable for the maximum sustained (10-minute) wind speed of a hurricane
w = a wind speed drawn from W
D = random variable for the probability of turbine damage for a given wind speed w
d = a damage probability drawn from D
X = random variable for the number of turbines damaged in 1 hurricane
x = a number of damaged turbines drawn from X
H = random variable for the number of hurricanes in T years
h = a number of hurricanes drawn from H
Y_{rep} = random variable for the number of turbines damaged in T years, with replacement
$Y_{no\ rep}$ = random variable for the number of turbines damaged in T years, no replacement
y = a number of turbines damaged drawn from Y

a = constant for alternative description of the Poisson distribution used in Panjer recursion from (18)
b = constant for alternative description of the Poisson distribution used in Panjer recursion from (18)

T = transition matrix for phase-type distributions
τ = the time to destroy all turbines (or reach an absorbing state) if turbines are not replaced

z = number of Monte Carlo simulations

T = matrix of state transition intensities. The values T_{ij} are the probabilities of transition from state i to state j. There are n+1 states, where the n+1 state is the absorbing state
t =
$\boldsymbol{\pi}$= starting probabilities for each state
k = number of turbines in absorbing state
m = just an index for summation

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