Correction

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Correction for "Quantifying the hurricane risk to offshore wind turbines," by Stephen Rose, Paulina Jaramillo, Mitchell J. Small, Iris Grossmann, and Jay Apt, which appeared in issue 9, February 28, 2012, of *Proc Natl Acad Sci USA* (109:3247–3252; first published February 13, 2012; 10.1073/pnas.1111769109).

The authors note that on page 3251, right column, Equations **6** and **8** appeared incorrectly. The corrected equations appear below. These errors do not affect the conclusions of the article.

$$T_{ij}(y,n) = \lambda \text{ beta} - \text{binomial}(n-i+1,(n-i+1)-(n-j+1);\ \alpha_B,\beta_B) \quad j>i \qquad [6]$$

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

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Quantifying the hurricane risk to offshore wind turbines

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The U.S. Department of Energy has estimated that if the United States 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 United States. 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 United States. 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-y period. 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.

probabilistic analysis | wind energy | phase-type distribution | tropical cyclone

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 y, with U.S. wind power capacity increasing from 8.7 GW in 2005 to 39.1 GW 2010 (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 United States, 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 m 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 (2).

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 (Hurricane Database) database of the National Hurricane Center (4). In this 58-y period, only 15 y did not incur insured hurricane-related losses (5). 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. (6) 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 time scales, including the multidecadal (7, 8). Atlantic hurricane data show that hurricane seasons with very high activity levels occur with some regularity; for instance, since 1950, there have been 25 y with three or more intense hurricanes (Saffir-Simpson Category 3 or higher). There were two 2-y periods with 13 intense hurricanes: 1950–1951 and 2004–2005. 2004 and 2005 hurricanes were particularly damaging to the Florida and Gulf Coast regions (six hurricanes made landfall in those areas in 2004 and seven 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 (9). Numerous drilling rigs and hydrocarbon pipelines were also damaged. Similarly, hurricanes have damaged powers systems. Liu, et al. (10) 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 United States, 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 should 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 United States: Galveston County, TX; Dare County, NC; Atlantic County, NJ; and Dukes County, MA. Leases have been signed for wind farms off the coasts of Galveston (11) and Dukes County (12); projects off the coasts of New Jersey and North Carolina have been proposed (12).

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 (13) and several turbines in China were damaged by typhoon Dujuan (14). Here we consider only tower buckling, because blades are relatively easy to replace

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(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 turbine towers that buckle in a 50-turbine wind farm as a function of maximum sustained (10-min 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). Fig. 1 plots the median, fifth 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 (International Electrotechnical Commission) 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-min average wind speed with a 50-y return period of 50 m/s (97 knots) at hub height (15); we scale this wind speed from 90-m height to 10-m height assuming power-law wind shear with an exponent of 0.077 (16) because hurricane wind speeds are given for 10-m height.

A Category 2 hurricane (wind speeds of 45 m/s or higher) will buckle up to 6% of the turbine towers in a wind farm. Hurricane Ike in 2008, for example, had a maximum sustained wind speed of 95 knots (49 m/s) at 10-m 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 50% probability of buckling two or more towers and a 10% probability of buckling four or more turbine towers.

Higher-category hurricanes will destroy a significant number of turbines; a Category 3 (wind speeds of 50 m/s or higher) will buckle up to 46% of the towers. The damage caused by Category 3, 4, and 5 hurricanes is important for offshore wind development in the United States 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 (17).

Risk from Multiple Hurricanes. We calculate the cumulative distribution function (CDF) for the number of turbine towers that buckle in 20 y for wind farms at four different locations, assuming that buckled towers are not replaced after each storm. The distributions are modeled by a modified phase-type distribution described in *Materials and Methods*. Fig. 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 nonyawing 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 ±180° if no yaw backup power is available, though designers can assume the turbine points directly into the wind if 6 h of backup power is available for the yaw and control systems (15). 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 0.3°/sec, but Schroeder, et al. show that the wind direction of Hurricane Bob in 1991 changed 30° in approximately 60 s (0.5°/sec), as measured 55 km away from the center of the storm (18). The yawing case in Fig. 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 60% probability that at least one tower will buckle in 20 y and a 30% probability that more than half will buckle if the turbines cannot yaw; if they are able to yaw, there is still a 25% probability that at least one tower will buckle and a 10% probability that more than half will. In Dare County, NC, there is a 60% probability that at least one tower will buckle in 20 y and a 9% probability that more than half will buckle if the turbines cannot yaw; if they are able to yaw, there is a 15% probability that at least one tower will buckle and much less than 1% probability that more than half will.

In Atlantic County, NJ there is a 15% probability that at least one tower will buckle in 20 y and less than 1% probability that more than half will buckle. In Dukes County, MA, there is a 10% probability that at least one tower will buckle in 20 y 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 approximately a 99% probability that none will buckle in 20 y.

The results in Fig. 2 assume the TI of hurricanes is lognormally distributed with a mean of 9% and standard deviation of 1.5%, where we define the turbulence intensity (TI) as the 10-min standard deviation of wind speed divided by the 10-min mean wind speed. The TI distribution is fitted to data from tropical cyclones over water, as discussed in the *SI Text*. The probability distributions in Fig. 2 are sensitive to the chosen value of TI: higher turbulence intensities for a given mean wind speed means higher

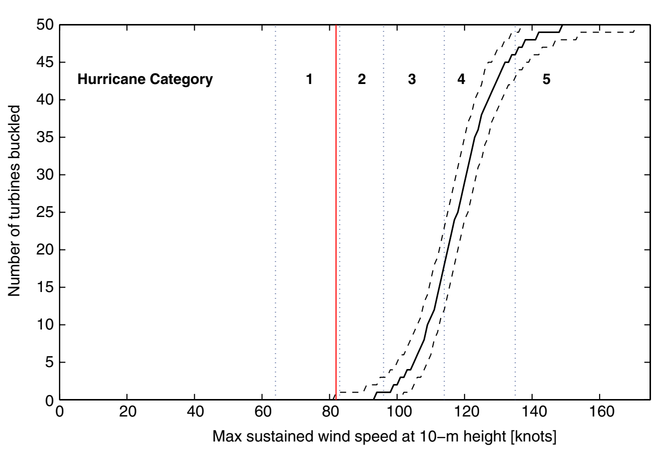

Fig. 1. Cumulative distribution function of the expected number of turbine towers buckled by a single storm as a function of wind speed. This models a hurricane with a TI of 9% in a 50-turbine wind farm of NREL 5-MW turbines (35) that cannot yaw to track the wind. The dashed lines plot the 5th and 95th percentile values and the solid vertical line shows V_{ref}, the design wind speed with a 50-yreturn period (15) scaled to 10-m height.

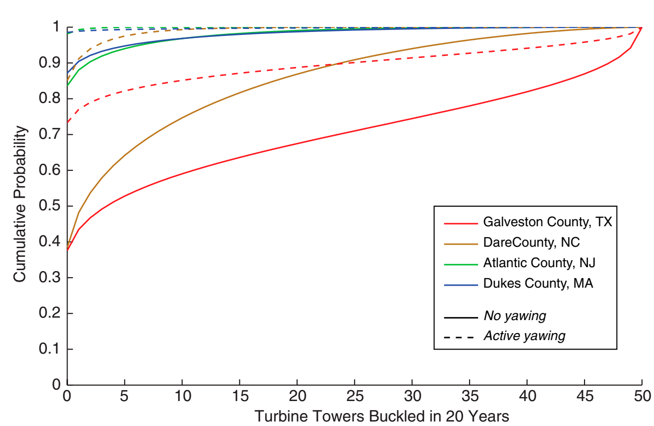

Fig. 2. Cumulative distribution of the number of turbine towers in a 50-turbine wind farm buckled in 20 y if buckled towers are not replaced. Dashed lines plot the distribution for the case that turbines can yaw to track the wind direction, and solid lines plot the distribution for the case that turbines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

peak wind speeds, which increase the probability of a turbine tower buckling.

If turbines are replaced after each hurricane, the cumulative probabilities for fewer than 35 turbine towers buckling in 20 y is within four percentage points of the distributions without replacement shown in Fig. 2. However, there is a possibility that more than 50 turbine towers will buckle in 20 y. For example, there is a 10% probability in Galveston County and 1% probability in Dare County that more than 50 turbine towers 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 *SI Text*.

Distribution of Damage by Hurricane Intensity. The number of turbine towers that buckle in a wind farm during the farm's 20-y life is a function of the frequency of hurricane occurrence and the intensity of the hurricanes that occur. Higher-intensity storms buckle more turbine towers, 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 y and the expected damage from each category of hurricane. The results are plotted in Fig. 3. These results reflect damages averaged through 10,000 simulated 20-y periods. The results in any given 20-y period will be different, typically dominated by one or two hurricanes.

Fig. 3 indicates that Category 3, 4, and 5 hurricanes are projected to cause most of the expected damage at each location: 98% in Galveston County, 95% in Dare County, 92% in Atlantic County, and 92% 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) (19, 20) and one in 1821 that was likely either Category 4 or 5 (20). 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 (19) 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.

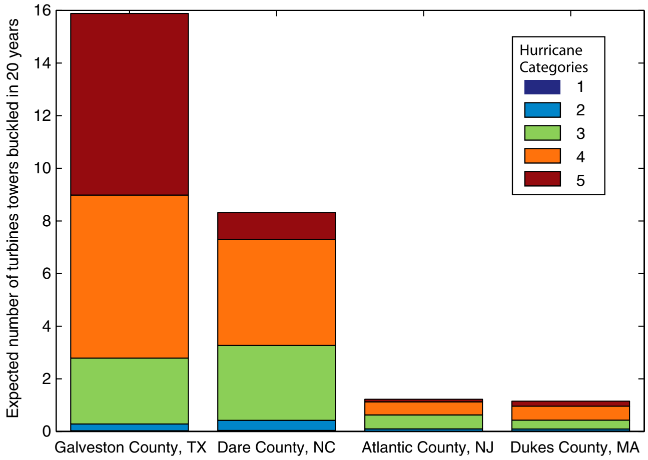

Fig. 3. The expected number of turbine towers that buckle in a 50-turbine wind farm over 20 y for each location, subdivided by hurricane category.

We test the sensitivity of our results in Fig. 2 and Fig. 3 to the occurrence of Category 4 and 5 hurricanes by repeating the Monte Carlo simulation of 10,000 20-y periods but excluding periods that contain a Category 4 or 5 hurricane. This analysis excludes 16% 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 turbine towers that buckle in 20 y decreases from 8.3 to 3.2, the probability of no turbine towers buckling increases from 33% to 39%, and the probability that less than half the turbine towers buckle increases from 89% to more than 99% when Category 4 and 5 hurricanes are excluded. The results for Atlantic and Dukes counties show a similar trend: the expected number of turbine towers that buckle falls from 1.3 to 0.6 in Atlantic County and from 1.2 to 0.5 in Dukes County. In both Atlantic and Dukes counties, the probabilities of none of the turbine towers and less than half the turbine towers buckling increase approximately two percentage points. Plots of the CDF of number of turbine towers bucked with higher-category hurricanes excluded are given in *SI Text*.

Discussion

The 2008 DOE (Department of Energy) report (3) estimates that 54 GW of shallow offshore wind capacity will be required to bring the United States 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-y return period of 42.5–51.4 m/s (83–100 knots), lower than high intensity hurricanes (21). Several authors have studied extreme winds in areas prone to tropical cyclones. Garciano, et al. (22), propose increasing the 50-y design reference wind speed for the Philippines from 50 m/s to 58 m/s at hub height, Clausen, et al. (23), propose 55–75 m/s (at 10-m height) for parts of the Philippines and southern Japan, and Ott proposes a model of extreme wind speeds in the western Pacific (24). Some authors analyze the design codes in the context of tropical cyclones. A study by Jha, et al., sponsored by a Joint Industry Project that included two wind turbine manufacturers (GE Energy and Clipper Wind), compares the reliability levels of an offshore wind turbine designed to IEC 61400-3 and API RP-2A standards operating in several hurricane prone U.S. locations (15, 25, 26). Clausen, et al. (14), recommend increasing the design load safety factor, currently 1.35, to 1.7 in order to maintain the same level of reliability in tropical cyclone areas. Clausen, et al. estimate increasing the safety factor will increase the cost of an onshore turbine 20–30%. The percentage cost increase to strengthen an offshore turbine, like the one we model in this paper, for tropical cyclones is likely to be smaller because a significant portion of the cost of offshore turbines is in the logistics of transporting, installing, and maintaining them.

We have also demonstrated that wind turbines that have external power available to yaw can have a substantially reduced risk of being destroyed. Installing lead-acid batteries to allow a turbine to yaw without external power would add $30,000–$40,000 (2010 prices) to the price of a turbine and 1,400–2,400 kg to its weight, assuming 6 h of backup power for yaw motors that draw 12 kW of power (27). The yaw rate of the turbine we model is 0.3 ° per second. Further work is needed to determine the yaw

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rate that is appropriate for hurricanes. Backup power, robust wind direction indicators, and active controls may be a low cost way to reduce risk to the turbine.

A main concern with losing wind turbines during hurricanes is the implication this will have for grid reliability, and more work is needed on this issue. We hypothesize, however, that 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 the 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. Fig. 4 plots the offshore wind resources within water shallower than 60 m (2) and the annual rate of hurricane landfalls for states in the eastern United States since 1900 (28). Information for Florida, Alabama, and Mississippi is not included in Fig. 4. Though these states have moderate to high hurricane occurrence rates (0.44, 0.14, and 0.10 y^{-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.

Our analysis also assumed that historic wind speeds and historic rates of hurricane occurrence are representative of future conditions. Historic conditions may be poor predictors 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 time scales, including the multidecadal (29), and by the short period over which hurricane observations are considered reliable (29, 30). 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. Some of these models also identify a possible decrease in Atlantic hurricane frequency, which may be attributable to the stabilization of the upper atmosphere (31). According to these projections, an increase in intensity due to climate change may not be noticeable for the next few decades (30–33). In line with this, Pielke, et al. (6) 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.

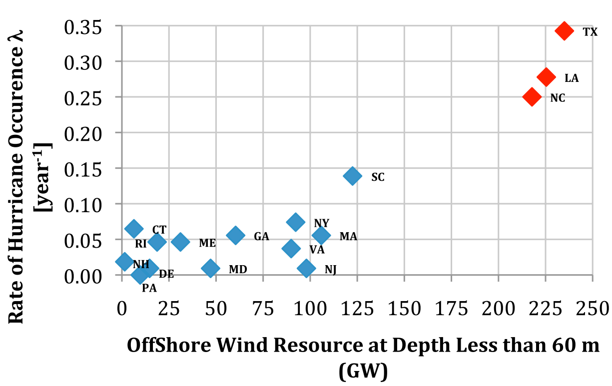

Fig. 4. Resource vs. Hurricane Occurrence Rate λ [year^{-1}].

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 turbine towers. 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 turbine towers buckled by hurricanes for two cases: (*i*) turbines are not replaced for the life of the wind farm, and (*ii*) 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 *SI Text*. All the analyses presented here model a wind farm of 50 NREL 5-MW wind turbines (35) for 20 y. The turbines are shut down with their blades feathered to 90° because hurricane wind speeds are much higher than the maximum operating limit of wind turbines. We believe our results underestimate the probability of loss because we model only buckling of the tower base but ignore damage to other components. Our results may also underestimate the probability of tower buckling because we analyze the onshore version of the NREL 5-MW turbine, which has a rigid foundation structure and is not subjected to wave loads; Jha, et al. (25) develop a more detailed model the NREL 5-MW turbine that includes foundation compliance and wave loads.

Analytical Distribution: Turbine Towers Buckled without Replacement. We model $Y_{\text{no rep}}$, the number of turbine towers that buckle in T-years without replacement as a modified phase-type distribution with six parameters: $Y_{\text{no rep}} \sim \text{PH}(\lambda, \mu, \sigma, \xi, \alpha, \beta)$, where λ is the hurricane occurrence rate; μ, σ, and ξ are the three parameters of the GEV distribution for event maximum wind speed; and α and β are the two parameters of the log-logistic wind speed-turbine buckling probability relationship. We use a phase-type distribution because it models a series of events (storms) that occur randomly with a certain rate, and each buckles an integer number of turbine towers; it gives the distribution for the distribution of time until all towers have been buckled. Fig. 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-min sustained wind speed of each hurricane at 10-m height is modeled as a 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:

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

The probability that a single wind turbine tower is buckled by a 10-min sustained hub-height wind speed u is modeled using a log-logistic function with a scale parameter α and a shape parameter β. The parameters for turbines that can and cannot yaw to track wind direction are given in Table 1. These parameters are fit to probabilities of turbine tower buckling calculated by comparing the results of simulations of the 5-MW offshore wind turbine

Table 1. Parameters of log-logistic Functions for Probability of Tower Buckling

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

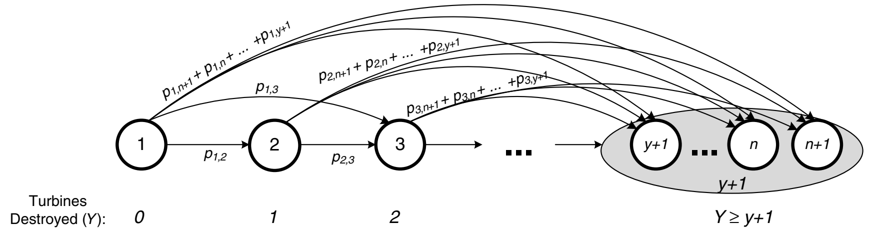

Fig. 5. The Markov Chain used to calculate the probability that the number of turbine towers buckled is less than or equal to y. We define the absorbing state as all the states where $Y_{\text{no rep}} \geq y+1$.

designed by the NREL (35) to the stochastic resistance to buckling proposed by Sørensen, et al. (36). More extensive details are given in *SI Text*.

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 TI, and a sustained wind speed u, described in further detail in *SI Text*. The log-logistic function is given by:

$$D(u) = \frac{(u/\alpha)^{\beta}}{1 + (u/\alpha)^{\beta}}. \qquad [3]$$

The number of turbine towers 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. (16). 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 tower 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 turbine towers that buckle out of n total, equals a particular value x:

$$\Pr(X = x) = \binom{n}{x} \frac{\mathrm{B}(x + \alpha_{\mathrm{B}}, n - x + \beta_{\mathrm{B}})}{\mathrm{B}(\alpha_{\mathrm{B}}, \beta_{\mathrm{B}})}, \qquad [4]$$

where B() is the beta function.

The cumulative distribution of the number of turbine towers buckled in T or fewer years without replacement, $Y_{\text{no rep}}$, is modeled as a modified phase-type distribution:

$$\Pr(Y_{\text{no rep}} \leq y | \tau \leq T) = \boldsymbol{\pi} \exp(T\mathbf{T}(y,n))\mathbf{e}, \qquad [5]$$

where π is a row vector of initial state probabilities, $\mathbf{T}$ is a matrix of jump intensities for the transitions between states, and $\mathbf{e}$ 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 (37, 38). 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 turbine towers in the wind farm have buckled. We modify the phase-type distribution to calculate the distribution of the number of turbine towers buckled $Y_{\text{no rep}}$ in a fixed time T by iteratively redefining the absorbing state to include cases where less than n turbine towers are bucked, as shown in Fig. 5.

This redefinition of the absorbing state makes the sizes of the vectors π and $\mathbf{e}$ a function of y and makes both the size and values of the matrix $\mathbf{T}$ a function of y. To calculate the probability that y or fewer turbine towers buckle, we define the absorbing state to include an integer number of turbine towers buckled from $y+1$ to n. There are $y+1$ total states; the $y+1^{\text{st}}$ state is the absorbing state. The term π in **[5]** is a $y+1$ element row vector of initial state probabilities; in this application $\pi = [1\ 0 \ldots 0]$ because the distribution begins in state 1 (no turbine towers buckled). The term $\mathbf{e}$ is a column vector of ones: $[1\ 1 \ldots 1]^T$. The term $\mathbf{T}$ is a $(y+1) \times (y+1)$ 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 turbine towers. The off-diagonal elements of $\mathbf{T}(y,n)$ in the i th row and j th are calculated by:

$$T_{ij}(y,n) = \lambda \text{ beta-binomial}(n - i + 1, n - j + 1; \alpha_B, \beta_B) \qquad j \geq i \qquad [6]$$

and the diagonal elements are calculated by:

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

where $\mathbf{t}$ is the jump intensity for a hurricane that jumps directly to the absorbing state (i.e., destroys all remaining turbines):

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

The off-diagonal elements of $\mathbf{T}$ 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 turbine towers).

Analytical Distribution: Turbine Towers Buckled with Replacement. We model Y_{rep}, the number of turbine towers that buckle in T-years with replacement as a compound Poisson distribution with six parameters: $Y_{\text{rep}} \sim$ Compound Possion (λ, μ, σ, ξ, α, β). We use a compound Poisson distribution because it models the distribution of the sum of independent identically distributed events (hurricanes buckling wind turbines, in this case) that occur as a Poisson process. 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 turbine towers buckled by each hurricane. No analytical expression exists for the PDF (probability density function) or CDF (cumulative distribution function) of a compound Poisson distribution that contains a beta-binomial distribution. We use Panjer's recursion (39, 40), an iterative method, to approximate the PDF. The details are given in *SI Text*.

Table 2. Distribution Parameters for Poisson and GEV 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	$\lambda = 0.19$	$\mu = 78.7$, $\sigma = 12.1$, $\xi = 0.251$	25.5°N–30°N 92°W–99°W
Dare County, NC	$\lambda = 0.21$	$\mu = 77.6$, $\sigma = 11.9$, $\xi = -0.0366$	32°–36.5°N 71°–81°W
Atlantic County, NJ	$\lambda = 0.047$	$\mu = 77.2$, $\sigma = 10.6$, $\xi = -0.0544$	36°–41°N 71°–77.5°W
Dukes County, MA	$\lambda = 0.075$	$\mu = 73.2$, $\sigma = 6.99$, $\xi = -0.139$	40.3°–42°N 66°–74.5°W

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 (direct and indirect strikes) in each county between 1900 and 2007 (17), divided by the length of the time period. The calculated values for the locations we investigate are given in Table 2. The parameters for the GEV distribution given in **[2]** are fit to historical data for the maximum 10-min sustained wind speed at 10-m height for all hurricanes to pass through the geographic ranges of interest (described in the fourth column of Table 2) between 1851 and 2008.

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