

1 Amplified threat of tropical cyclones to U.S.
2 offshore wind energy in a changing climate
3 Supplementary Information

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11 **Supplementary Note 1: Tropical Cyclone Model**
12 **Validation**

13 To establish confidence in the ability of RAFT (the Risk Analysis Framework for
14 Tropical Cyclones) to simulate tropical cyclones (TCs) under future climate condi-
15 tions, we validated RAFT-simulated peak TC intensities based on historical conditions
16 against observations from the International Best Track Archive for Climate Steward-
17 ship (IBTrACS). We evaluated RAFT's performance for 20-, 50-, and 100-year return
18 period (RP) storms within 200 km of the U.S. coast, finding that RAFT accurately
19 simulates maximum TC wind speeds with statistically significant pixel-wise Pearson
20 correlation coefficients of 0.74, 0.81, and 0.81, respectively (all p-values $\ll 0.001$).
21 RAFT aptly reproduces peak TC wind speeds in each case, exhibiting Mean Absolute
22 Errors (MAEs) of -1.5 , -2.2 , and 0.6 ms^{-1} for 20-, 50-, and 100-year RP storms. This
23 analysis was based on an ensemble of 450,000 RAFT-simulated TCs forced by nine
24 global climate models from Phase 6 of the Coupled Model Intercomparison Project

(CMIP6) [1] for the period 1980–2014. Observed TCs from 1970–2015 (2,322 events) in the IBTrACS dataset were used to validate RAFT’s performance at the basin scale.

Further validating RAFT’s performance, the analysis of landfall frequency shows that the mean percentage of landfalling TCs from RAFT ($26.8 \pm 2\%$) shows strong consistency with historical records (25.2%). Similar performance is exhibited when only considering Category 1–5 TCs, with RAFT simulations showing a mean landfall percentage of $14.1 \pm 1.3\%$ compared to the observed rate of 14%. Confidence intervals derived from the simulated multimodel ensemble data further reinforce RAFT’s capability to accurately simulate TC landfall across the U.S. coastline. For more details regarding our methodology for TC frequency analysis, see Methods.

Validation statistics for spatial Tropical Cyclone Frequency (TCF), calculated per event for each 0.5×0.5 degree region, indicate strong model performance across the Atlantic basin. The mean TCF from RAFT-simulated data is 4.16%, closely aligning with the observed mean TCF of 3.84%. Additionally, a strong TCF pixel-wise correlation coefficient of 0.86 coupled with an MAE of 0.015 reflect RAFT’s robust accuracy and reliability in simulating the occurrence of TCs across the Atlantic basin. The observed and simulated spatial TCF are illustrated in panels a and b of Figure S1.

We also compared key TC characteristics between RAFT simulations and IBTrACS observations across the Atlantic basin, specifically analyzing 6-hourly translation speed, lifetime maximum intensity, and seasonality. Each distribution consisting of basin-wide TC metrics is visualized in Figure S1. The 6-hourly translation speed exhibits a mean of 0.69 ms^{-1} for RAFT and 0.68 ms^{-1} for observations, with an MAE of 0.467 ms^{-1} . Regarding lifetime maximum intensity, RAFT simulations exhibit a mean of 38.2 ms^{-1} comparable to the observed mean of 37 ms^{-1} , along with an MAE of 7.92 ms^{-1} . For seasonality, the mean for the day of the year TCs occur in RAFT is approximately August 22nd, closely aligning with the observed mean of August 19th, accompanied by an MAE of 1.5 months. RAFT’s successful performance against observed historical data provides reasonable confidence in its use for future risk assessment based on simulated TCs under future climate scenarios. RAFT’s performance has additionally been validated against observations at the basin-scale based upon ERA5 reanalysis data [2].

Lastly, we evaluated the damage risk associated with modeled and observed TCs to validate RAFT’s ability to estimate the damage likelihood of offshore wind OSW turbines, as depicted in Figures S3 and S4. Significant pixel-wise correlations are attained for turbine damage risk in each case, with associated coefficients of 0.21 for 20-year TCs, 0.58 for 50-year TCs, and 0.71 for 100-year TCs. RAFT generally underestimates damage risk when compared to observations, exhibiting MAEs of -3.18% , -10.49% , and -1.13% for 20-, 50-, and 100-year TCs, respectively. Probability metrics are likely to exhibit greater variability compared to wind speeds due to the logistic nature of the fragility functions and the limited sample size of observations, which result in a smaller subset of TCs exceeding the damage threshold. Since return period events are computed pixel-wise, only TCs crossing through each subregion are used to estimate risk

for that subregion, a behavior most notably evident in Figure S3d. This point highlights the usefulness of RAFT for assessing risk, despite its tendencies to potentially underestimate damage probabilities, as it employs a larger set of TCs with statistical properties similar to those of observed TCs across the Atlantic basin (Figure S1).

Supplementary Note 2: Ensemble Model

To capture a larger degree of climate variability in our analysis while reducing bias from individual models, we utilized an ensemble mean derived from the output of nine CMIP6 climate models. For each model, peak TC intensities are spatially illustrated for historical and future 20-year TCs in Figures S5-S6. Individual plots for 50-year TC intensity are omitted due to similar intermodel variability compared to 20-year TCs.

Historical simulations show relatively consistent results across models, with mean peak intensity standard deviations of $2 \pm 1.6 \text{ ms}^{-1}$ for 20-year TCs and $1.5 \pm 1.2 \text{ ms}^{-1}$ for 50-year TCs, and interquartile ranges (IQRs) of 2.2 ms^{-1} and 0.3 ms^{-1} , respectively. Future simulations display approximately 65–80% higher variability, reflecting uncertainty in global climate projections. This increased variability is observed with ensemble standard deviations of $3.3 \pm 2.7 \text{ ms}^{-1}$ and $2.7 \pm 2.2 \text{ ms}^{-1}$ for 20- and 50-year storms, along with IQRs of 3.8 ms^{-1} and 5.2 ms^{-1} under a future climate scenario.

Supplementary Note 3: Turbine Fragility Sensitivity Analysis

There are several approaches for estimating the probability of turbine damage in response to dynamic forcing. Our results in the main manuscript are based upon fragility curves developed for a widely modeled turbine, accounting for aerodynamic and sea wave loadings, making it well suited for modeling damage to an offshore wind turbine [3]. To assess the sensitivity of our choice of fragility function, we compare our results with the same analysis based on an alternative fragility function developed for an offshore wind turbine [4]. The fragility curves corresponding with each analysis are depicted in Figure S7.

The probability of turbine tower buckling using an alternative fragility function accounting for wind loadings is illustrated in Figure S8. The damage likelihood using this alternative model is overall lower in magnitude, while the locations with high risk remain consistent between the two models, exhibiting significant mean pixel-wise Pearson correlation coefficients of 0.3 for 20-year TCs and 0.55 for 50-year TCs. The lower damage probabilities exhibited by this alternative turbine model are likely due to the lack of wave loadings, compared to the model implemented in our study which includes both aerodynamic and hydrodynamic loadings [3].

Supplementary Note 4: Onshore Wind Turbine Damage Risk

In the main manuscript, we presented the probabilities of yielding and buckling for off-shore wind (OSW) turbines along the U.S. Atlantic and Gulf Coasts. Several coastal states also have substantial onshore wind farms, with Texas alone generating 26% of overall wind-sourced electricity in the U.S. in 2022, equating to over 40 GW of wind energy produced by more than 15,300 wind turbines [5]. Specifically within the U.S. coastal region, over 30 wind-related projects are operational within 150 km of the Texas Gulf Coast, with a total rated capacity exceeding 5 GW. Along the Atlantic Coast, wind projects span several states with a combined total rated capacity of over 1.3 GW [6]. While the remaining Gulf states currently lack utility-scale wind turbines, Louisiana has adopted a climate action plan aiming for 100% renewable or clean electricity by 2035 [7], and other Gulf states are offering incentives to encourage renewable energy adoption. Given the existing and potential development of onshore wind energy along the U.S. Atlantic and Gulf Coasts, extending hurricane risk assessments to coastal onshore wind energy infrastructure is essential.

Here, we present similar results for the case of onshore wind turbines subjected to the aerodynamic forcings of 20- and 50-year TCs, using fragility functions developed for onshore turbines as shown in Figure S7 alongside OSW turbine fragility curves. The damage state assessed for onshore turbines is associated with the degree of tower deflection that could result in permanent displacement, based on a 2.5 MW tower with a hub height of 80 meters [8]. Similar to OSW energy risk, damage probabilities from a 20-year TC are roughly 5 – 10× higher on average for the Gulf states compared to the Atlantic states. The risk of damage from a 20-year TC is expected to increase by a factor of 2.5, rising to nearly 8% along the Atlantic Coast and 42% along the Gulf Coast. The most pronounced risks are expected in New England, North Carolina, Florida, Louisiana, and parts of Texas for a 20-year storm (Fig. S9a,b,c). Substantially higher damage probabilities are anticipated for 50-year TCs affecting the Gulf and Atlantic Coasts, indicating that wind speeds associated with such storms are virtually guaranteed to induce severe turbine degradation. The likelihood of damage is projected to extend further inland for a 50-year storm, while coastal regions may experience near 100% damage likelihood even with historical TC intensities (Fig. S9d,e,f).

We further aim to enrich our onshore wind energy risk assessment by including Puerto Rico, renowned for its susceptibility to weather extremes such as TCs. This focus is underscored by the region's centralized energy grid, making the potential for impacts more pervasive, as highlighted by Hurricane Maria in 2017 [9, 10]. As of 2023, Puerto Rico hosts two large-scale onshore wind farms with a combined total rated capacity of 124.6 MW [6], and further wind energy development has been proposed to strengthen the region's grid architecture [9].

Historically, 20-year storms affecting Puerto Rico have corresponded with Category 1 TCs. However, these storms are projected to intensify significantly under future climate conditions, reaching Category 4 levels with nearly a 20 ms^{-1} increase in peak intensity (Fig. S10a). Similarly, 50-year TCs are expected to strengthen from Category

145 3 to Category 5. This amplification translates to a stark increase in turbine risk, with
 146 the mean probability of TC-induced tower buckling projected to rise from nearly 0%
 147 to 27% for a 20-year TC, and from nearly 5% to 69% for a 50-year TC (Fig. S10b).
 148 Recognizing the potential catastrophic impacts of TCs on Puerto Rico's vulnerable
 149 energy grid, along with projected increases in TC effects, our analysis underscores the
 150 necessity for targeted strategies to bolster the resilience and reliability of the region's
 151 power system.

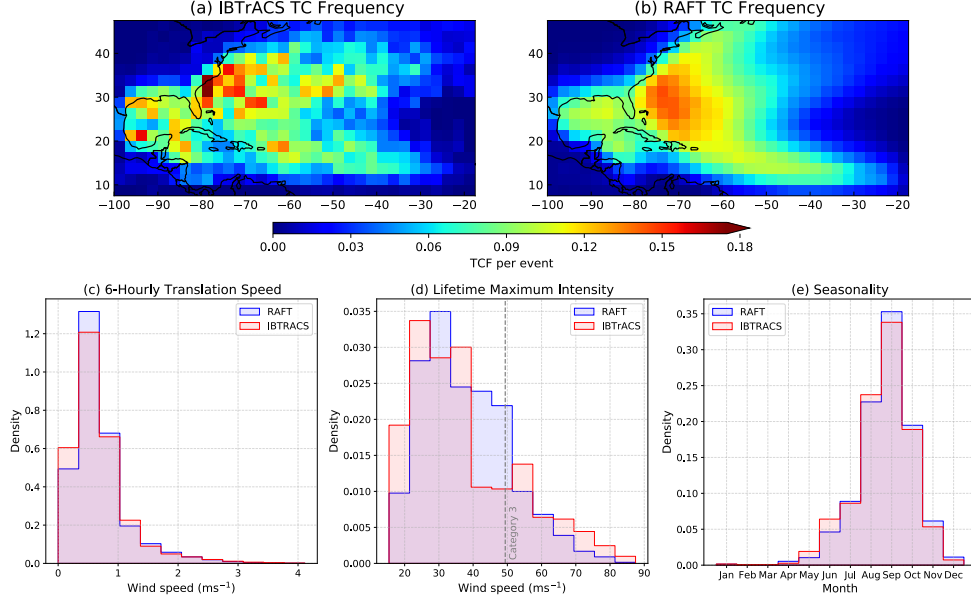


Fig. S1 RAFT model validation for Atlantic tropical cyclones. Basin-scale comparison of (a,b) spatial tropical cyclone (TC) frequency, (c) 6-hourly translation speed, (d) lifetime maximum intensity, and (e) seasonality for historical RAFT-simulated TCs against observations via IBTrACS. TC frequency is computed as the total number of 6-hourly TC track positions within each 2.5-degree square grid, and normalized by the total number of TC events. Observations are included from 1970 and thereafter. Simulated TCs persisting at least one day are included, resulting in over 437,000 simulated TCs.

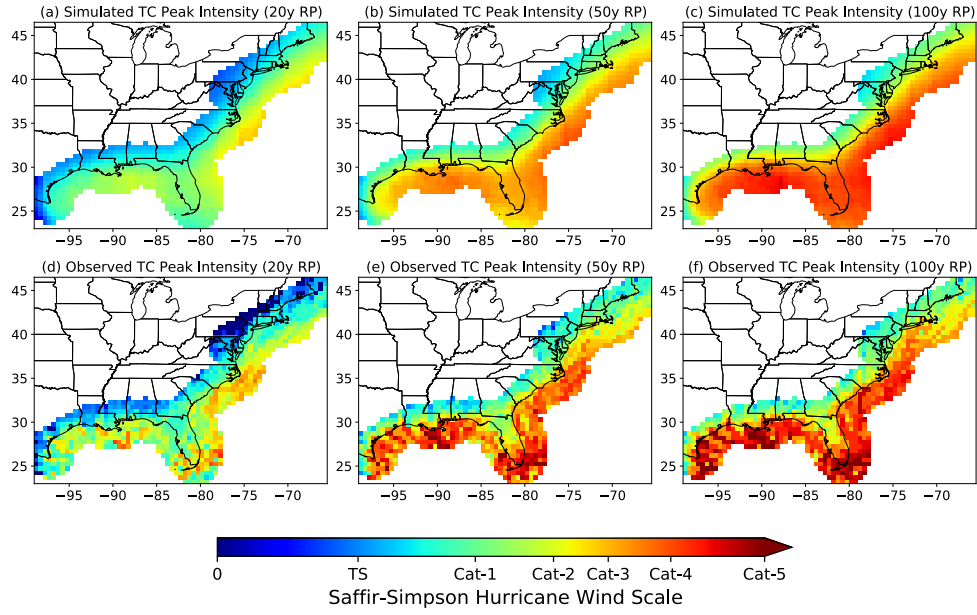


Fig. S2 Peak TC intensity for RAFT simulations and IBTrACS observations. Maximum sustained (10-minute) wind speeds at hub height (90 m) are used to compare simulated vs observed 20-year (a,d), 50-year (b,e), and 100-year (c,f) return period storms.

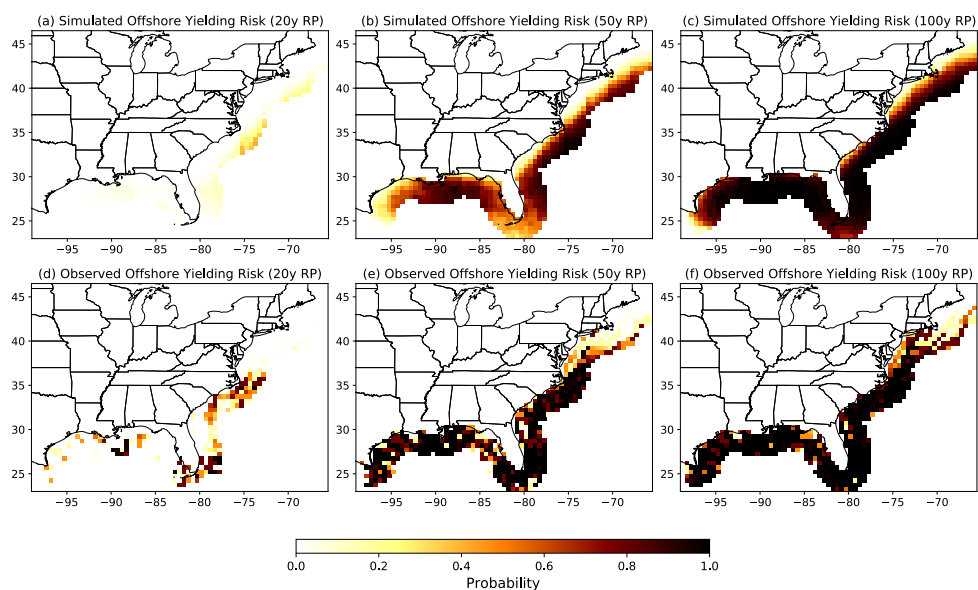


Fig. S3 Turbine yielding probability for RAFT simulations and IBTrACS observations. Probabilities represent the chance of tower yielding from exposure to TC-force winds, assuming no tower repair or replacement for the historical period (1980 – 2014).

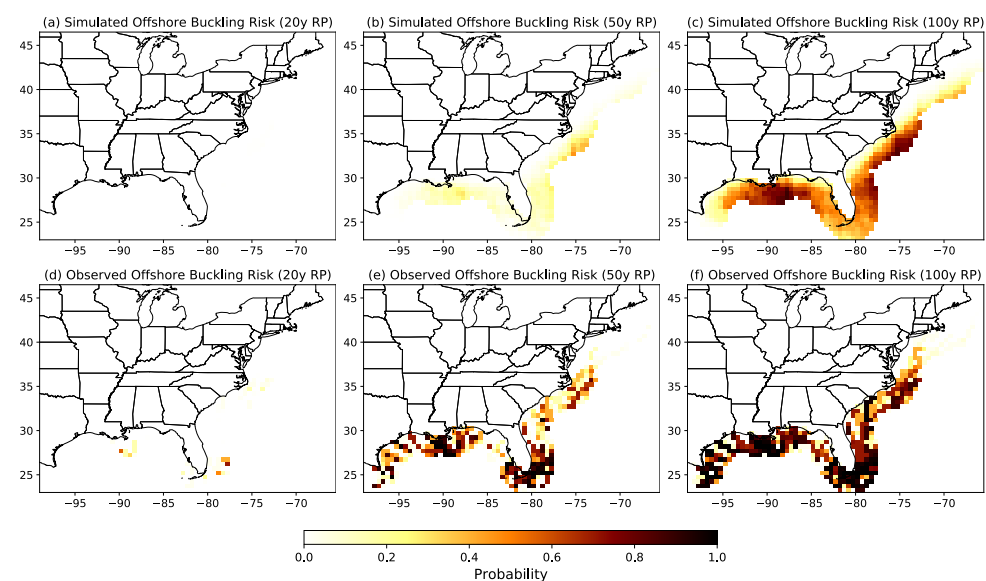


Fig. S4 Turbine buckling probability for RAFT simulations and IBTrACS observations. Probabilities represent the chance of tower buckling from exposure to TC-force winds, assuming no tower repair or replacement for the historical period (1980 – 2014).

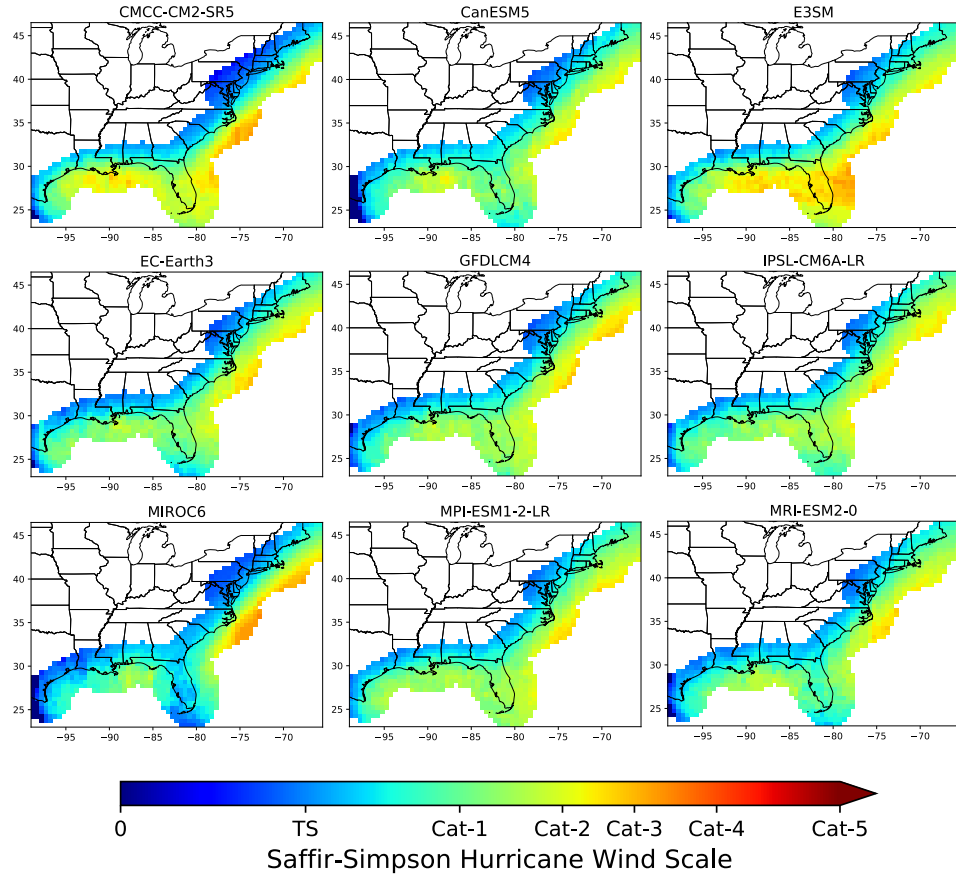


Fig. S5 Individual model output for peak TC intensities associated with 20-year RP storms representative of a historical climate (1980 – 2014). TC wind speeds are simulated using the RAFT TC model forced by each of nine CMIP6 global climate models. Spatially averaged 5th and 95th percentile wind speeds associated with the coastal region for the ensemble are 28.5 ms^{-1} and 34 ms^{-1} , respectively.

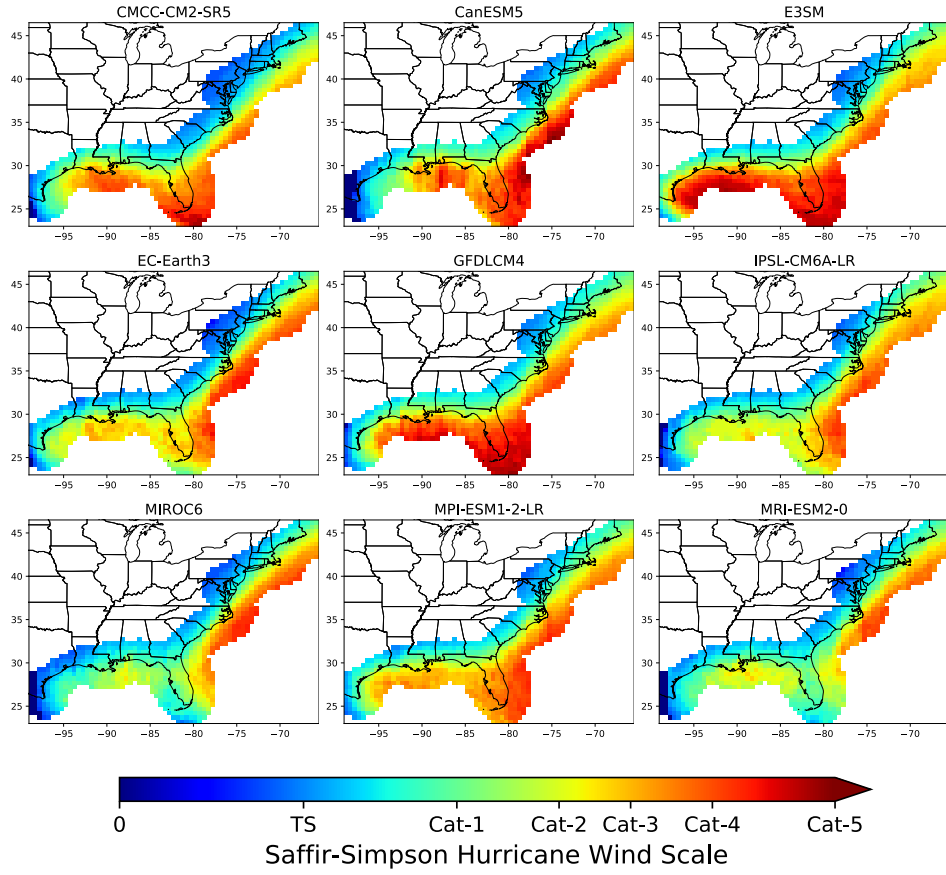


Fig. S6 Individual model output for peak TC intensities associated with 20-year RP storms representative of a future climate (2066 – 2100). TC wind speeds are simulated using the RAFT TC model forced by each of nine CMIP6 global climate models. Spatially averaged 5th and 95th percentile wind speeds associated with the coastal region for the ensemble are 33.4 ms^{-1} and 43 ms^{-1} , respectively.

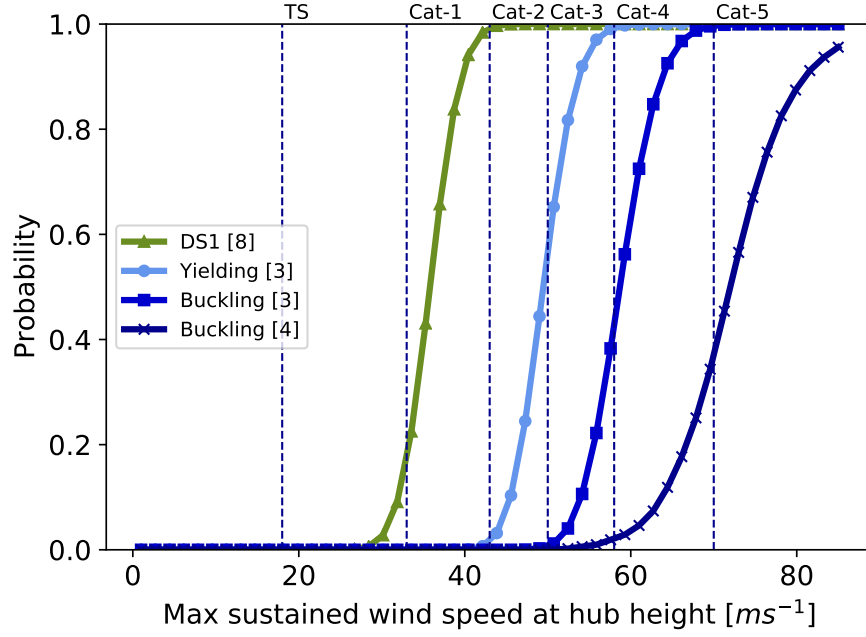


Fig. S7 Fragility functions for wind turbine tower damage probability as a function of hub height peak sustained wind speed (ms^{-1}). The y-axis represents the probability of structural deformation corresponding to a specified damage state, namely yielding or buckling for offshore turbines and DS1 for onshore turbines. Fragility curves for offshore turbines (blue) [3, 4] are developed to estimate structural behaviors for the NREL 5 MW reference turbine with a 90 m hub height [11], whereas the onshore damage function (green) [8] is based upon a 2.5 MW turbine with an 80 m hub height. [4, 8] assume a rigid foundation and no ocean wave loads, whereas [3] additionally accounts for sea wave loadings.

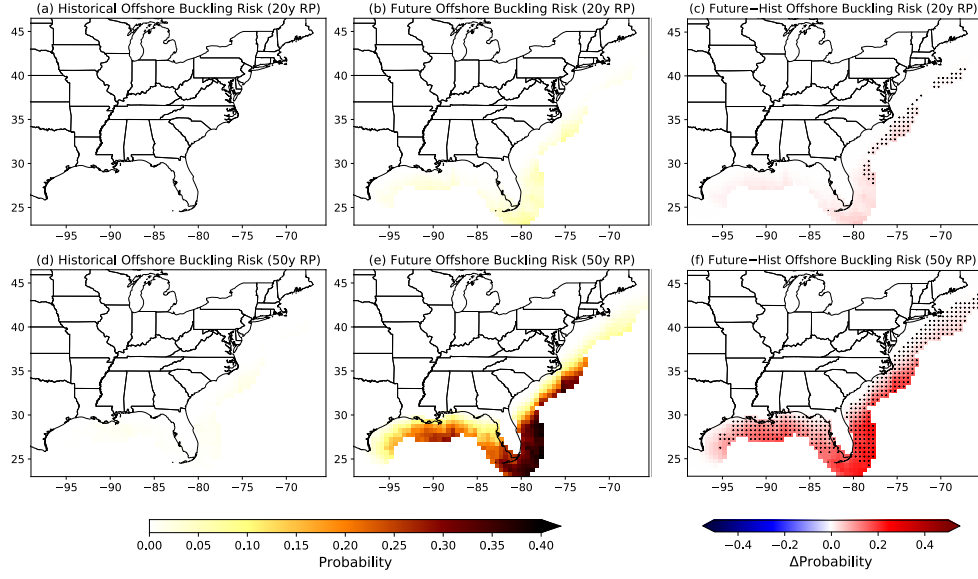


Fig. S8 Offshore turbine tower buckling probabilities resulting from exposure to (a,b) 20-year and (d,e) 50-year TCs simulated using historical (1980 – 2014) and future (2066 – 2100) climatic conditions. Damage probabilities are based upon a fragility analysis for the NREL 5 MW reference turbine [11] without a yaw control system exposed to aerodynamic loadings [4]. The rightmost panels indicate the change in buckling risk to wind turbines. Black markers denote regions where at least 8 out of 9 models agree on the sign of the difference.

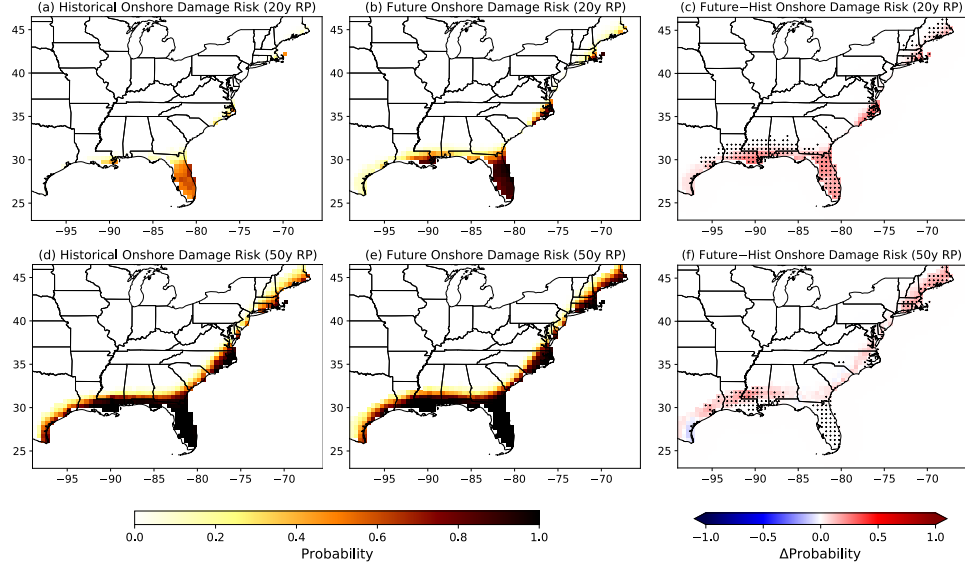


Fig. S9 Onshore turbine tower damage probabilities resulting from exposure to (a,b) 20-year; (d,e) 50-year TCs simulated using historical (1980 – 2014) and future (2066 – 2100) climatic conditions. The damage state represented here is associated with a displacement of 1.25% of the tower height [8]. Rightmost panels indicate the change in damage risk to onshore wind turbines. Black markers denote regions where at least 8 out of 9 models agree on the sign of the difference.

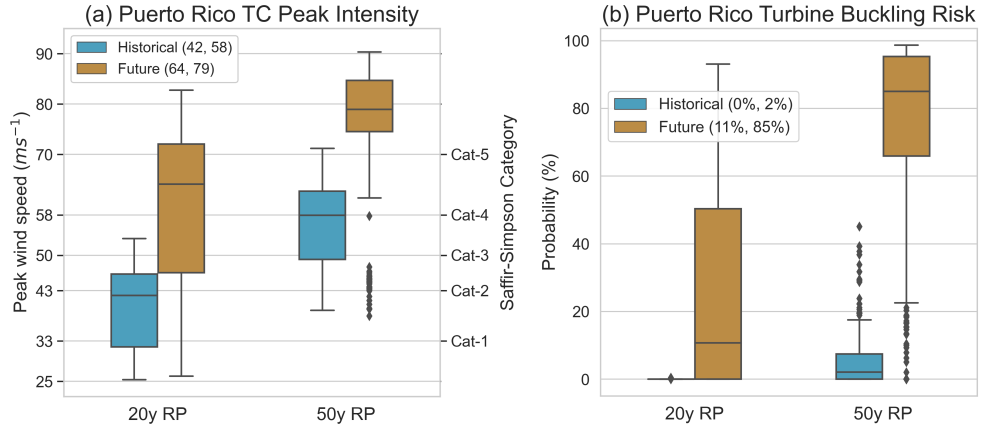


Fig. S10 Distributions for (a) maximum sustained 1-minute hub height (90 m) TC wind speeds for 20- and 50-year TCs and (b) associated onshore turbine tower buckling probabilities simulated using historical (1980 – 2014) and future (2066 – 2100) climatic conditions. 50th percentile values are provided in the legend for 20- and 50-year TCs, respectively. All reported changes for Puerto Rico were found to be statistically significant at the 95th percent confidence level.

Supplementary References

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