

Estimating impacts of North Atlantic tropical cyclones using an index of damage potential

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Abstract An index of North Atlantic tropical cyclone (TC) damage potential due to winds and coastal surge is developed using seasonal climate variables of relative sea surface temperature and steering flow. These climate variables are proxies for the key damaging TC parameters of intensity, size, and forward speed that constitute an existing cyclone damage potential index. This climate-based approach has the advantage of sidestepping the need for data on individual TCs and explains 48 % of the variance in historical cyclone damage potential. The merit of the cyclone damage potential is in assessments relative to past events or past periods, and may be translated to actual damage using relationships between the damage potential index and specific exposure and vulnerability characteristics. Spread in the change in damage potential over the 21st century among climate simulations under representative concentration pathways 4.5, 6.0, and 8.5 is found to be less than the spread due to internal variability, as assessed using a climate model initial condition large ensemble. This study highlights the importance of accounting for internal climate variability in future climate impact assessments.

1 Introduction

Tropical Cyclones (TCs) dominate natural hazard losses, contributing 47 % of all U.S. billion-dollar natural hazard losses over the period 1980–2011 (Smith and Katz 2013). TC losses have increased substantially in recent decades (Pielke et al. 2008), driven largely by increased exposure (Pielke et al. 2008; Schmidt et al. 2010), and studies that isolate the hazard component by normalizing the losses for exposure find no linear long-term trend (Pielke

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et al. 2008; Miller et al. 2008; Bouwer 2011). Yet, normalization introduces unverified relationships between damage and the normalizing factor/s (Czajkowski and Done 2014), and climate change may have influenced TC activity over recent decades (Holland and Bruyère 2014). Moreover, Jagger et al. (2011) find climate signals in normalized total economic losses indicating a role for climate variability, and therefore potentially climate change, in compounding the effect of increasing exposure and vulnerability.

Projected future changes in TC activity (Knutson et al. 2010; Done et al. 2013; Knutson et al. 2013; Bacmeister et al., in prep.) have the potential to further exacerbate societal impacts. While there is consensus on future increases in maximum wind speeds and rainfall rates, future changes in frequency are less certain evidenced by the discord among recent studies (Knutson et al. 2008; Vecchi et al. 2008; Emanuel et al. 2008; Villarini and Vecchi 2012; Emanuel 2013; Camargo 2013; Wehner et al. 2014).

Studies that explore TC damage in future climate (Schmidt et al. 2010; Mendelsohn et al. 2012; Raible et al. 2012; Emanuel 2011) find the magnitude, and sometimes the sign, of the future change depends on the climate projection. A potential solution is to assess damage across a large number of climate projections. However, since global climate model data have been traditionally generated at spatial scales that do not adequately represent key damaging TC parameters (Shaevitz et al. 2014; Wehner et al. 2014), computationally expensive dynamical downscaling becomes necessary to explicitly simulate TCs (e.g., Done et al. 2013; Knutson et al. 2013), and this becomes prohibitive for large numbers of projections. A solution explored here relates large-scale climate variables directly to damage potential. This allows for a broad range of future damage potential scenarios that are based in the variables and scales where global climate models have skill, and provides estimates of uncertainty.

TCs can be related to damage through a function that describes how the exposure responds to the hazard. Such functions are commonly based on the maximum wind speed raised to the third power, representative of the power dissipated at the surface (Emanuel 2005).¹ Kantha (2006), Czajkowski and Done (2014), and Zhai and Jiang (2014) highlighted the importance of considering other wind field parameters in addition to the maximum wind speed. This concept was incorporated into the development of an index of Cyclone Damage Potential (CDP, Holland et al. 2015) formulated as:

$$CDP = 4 \frac{\left[\left(\frac{v_m}{65} \right)^3 + 5 \left(\frac{R_h}{50} \right) \right]}{v_t}, \quad (1)$$

where v_m is the maximum surface wind speed (knots), R_h is the radius of hurricane force winds (nautical miles) and v_t is the forward translation speed (knots). The CDP is applicable to offshore damage from wind, waves and currents and to onshore direct wind and coastal surge damage, but not necessarily to damage resulting from rainfall. The coefficient scales CDP from 0 to 10 to support effective communication. Note that damage is related to the duration of destructive winds (v_t^{-1}), not just their maximum value (v_m). This is consistent with Jain (2010) who found a strong relationship between duration of damaging winds and damage ratio (the ratio of the repair cost to the total exposed value). The CDP assesses damage ‘potential’ rather than actual damage which will depend on specific exposure and vulnerability² attributes.

¹ Murnane and Elsner (2012), however, found an exponential relationship between maximum wind speed and loss.

² The term vulnerability is used very broadly here to cover socio-economic and physical characteristics.

However, CDP explains variance in historical losses to the offshore energy industry in the Gulf of Mexico, for which spatial exposure and vulnerability may be assumed homogeneous (Holland et al. 2015). The merit of the index is in its ability to make relative comparisons to historical events, and, on longer timescales, to historical climate.

Building on the CDP, a new damage potential index is developed here using known relationships between TC parameters and their large-scale environment (Bruyère et al. 2012; Menkes et al. 2012; Emanuel 1986; Holland 1983; Gray 1979). This new index assesses damage potential of the entire hurricane season, irrespective of whether any TCs make landfall. Such an index is applicable to any large-scale climate dataset, and is used here to assess the importance of internal climate variability in future damage potential assessments.

Specifically, three future damage potential scenarios are generated under different Representative Concentration Pathways (RCPs); 4.5, 6.0 and 8.5 (van Vuuren et al. 2011) to characterize the spread in the future change in damage potential resulting from different anthropogenic forcing. This spread is then compared to the spread due to internal climate variability assessed using a 30-member initial condition climate model ensemble under RCP 8.5. This paper is part of a larger project on the Benefits of Reducing Anthropogenic Climate change (BRACE; O'Neill and Gettelman, in prep.) that characterizes the difference in impacts driven by climate outcomes resulting from the forcing associated with RCPs 8.5 and 4.5. The projections of cyclone damage potential developed here compliment the detailed TC projections of Bacmeister et al. (in prep) and damage projections of Gettelman et al. (in prep) by sampling a broader range of future scenarios.

The next section outlines the experimental approach and summarizes data sources. Section 3 describes index development. Section 4 presents the spread in future damage potential scenarios. Finally, section 5 presents a concluding discussion.

2 Methods and data

Using historical data over the North Atlantic, empirical relationships are identified between large-scale climate variables and the TC input parameters of the CDP (v_m , R_h , and v_r) by calculating linear correlations. These relationships then form the basis of an index of cyclone damage potential based solely on large-scale data.

Historical TC data for the period 1988–2009 are sourced from The Tropical Cyclone Extended Best Track Dataset (EBTrACS, Demuth et al. 2006), available every 6 h. Historical large-scale climate data are sourced from; the Climate Forecast System Reanalysis (CFSR, Saha et al. 2010), a global coupled atmosphere–ocean–land surface–sea ice system, and Reynolds SST analysis (Reynolds et al. 2007), also available every 6 h.

To assess the anthropogenically forced change in TC damage potential the new index is applied to three climate projections, each under a different RCP (Section 5.1). Specifically, we use Community Earth System Model version 1 (CESM1) climate data from phase 5 of the Coupled Model Intercomparison Experiment (CMIP5) (Monaghan et al. 2014). These data are at approximately one-degree grid spacing and available for a 20th Century period (1951–2005) and for the period 2006–2100 under RCP forcing scenarios 4.5, 6.0, and 8.5.

To assess the spread in the forced change in TC damage potential relative to spread due to unforced internal climate variability, the index is additionally applied to a 30-member initial condition CESM1 ensemble at approximately one-degree grid spacing, referred to hereafter as the CESM Large Ensemble (CESM-LE, Kay et al. 2014). CESM-LE used small initial

condition differences (round-off order 10^{-14} K differences in air temperature) to generate 30 realizations of the period 1920–2100 under historical and future RCP8.5 climate forcing. Damage scenarios are developed for time slices for which 6-hourly data are available (1990–2005, 2026–2035, and 2071–2080) (Section 5.2). Although a 15-member initial condition ensemble was generated under RCP4.5 as part of the BRACE project, 6-hourly temporal outputs were not saved thereby precluding its use in this study.

The mean annual cycle of all climate data are bias corrected following Bruyère et al. (2013) using the code available from Bruyère et al. (2015). For the CESM1 simulations, a long-term mean annual cycle, taken over 1981–2005, is replaced with that from the European Centre for Medium-Range Weather Forecasts (ECMWF) Interim Reanalysis (Simmons et al. 2006). For the CESM-LE, a long-term mean annual cycle, taken over 1990–2005, is replaced with that from CFSR. A stationary bias is therefore assumed, and may conflate with the climate change. However, Bruyère et al. (2013) show bias has been approximately stationary over the past few decades. This procedure corrects the mean annual cycle, and also improves the shape of the distribution of the 6-hourly data (not shown). The differences in averaging periods and reanalysis sources used for CESM1 and CESM-LE arises from availability of datasets from previous work, and are unlikely to affect our conclusions.

3 Index development

3.1 Climate forcing of tropical cyclone damage potential

Whereas the CDP index of Holland et al. (2015) relates damage to characteristics of individual cyclones, the index developed here relates seasonal and basin-wide damage potential directly to the large-scale climate. To establish a foundation for this approach, linear correlations between late summer (August–September–October, ASO) and basin mean CDP input parameters (v_m , R_h , and v_t) and ASO and area mean climate variables are calculated over the period 1988–2009. Climate variables known to influence TC activity are explored: Sea Surface Temperature (SST, Emanuel 1986), relative SST (Vecchi et al. 2008), potential intensity (PI, Emanuel 1995), vertical wind shear

Table 1 Correlation between summer, basin mean TC parameters, and summer, area mean climate variables using an averaging area of (5°–20°N, 60°–15°W). Maximum wind speed (v_m), radius to hurricane force winds (R_h), and forward translation speed (v_t), Sea Surface Temperature (SST), relative sea surface temperature ($SST_{relative}$), Potential Intensity (PI), vertical wind shear (VWS), entropy deficit (χ), ventilation index (Λ), and steering flow (v_{steer}). *Bold* indicates correlations are significant at 95 % using a standard two-sided *t*-test

r^2	v_t	v_m	R_h	SST	$SST_{relative}$	PI	VWS	χ	Λ	v_{steer}
v_t	1.00	.01	.06	.00	.01	.00	.04	0.02	0.01	.04
v_m		1.00	.86	.28	.53	.27	.26	0.12	0.30	.00
R_h			1.00	.26	.40	.22	.25	0.14	0.27	.01
SST				1.00	.56	.82	.31	0.05	0.56	.05
$SST_{relative}$					1.00	.56	.55	0.11	0.69	.00
PI						1.00	.30	0.06	0.61	.06
VWS							1.00	0.16	0.86	.01
χ								1.0	0.05	0.01
Λ									1.0	0.00
v_{steer}										1.00

(VWS, e.g., McBride and Zehr 1981), entropy deficit (χ , Emanuel 2010; 2013), ventilation index (Λ , Tang and Emanuel 2012), and steering flow (e.g., Galameau and Davis 2013). Statistical significance of the correlations is evaluated using a standard two-sided t -test. For validation, the predictive skill was tested using cross-validation, in which (i) one data point is removed, (ii) the regression is fit to the remaining data points, and (iii) the fitted regression is used to predict the withheld point. This is repeated for each point in the dataset and R^2 is computed.

On season and basin scales, v_m and R_h are significantly and highly correlated with a variance explained of 0.86 (Table 1). These two TC parameters are also significantly correlated with five of the climate variables considered here; SST, relative SST, PI, VWS and Λ (Table 1). The highest correlations ($R^2=0.40$ for R_h ; $R^2=0.53$ for v_m) are with relative SST. Relative SST is calculated here as the difference between SST averaged over the main development region of the North Atlantic ($5^\circ\text{--}20^\circ\text{N}$, $60^\circ\text{--}15^\circ\text{W}$, Bruyère et al. 2012) and SST averaged over a tropical belt between $\pm 15^\circ$ latitude. While local SST warming can destabilize the atmosphere locally, changes in tropical mean SST can change upper-tropospheric temperature anomalies leading to a remote control on local TC activity (Vecchi and Soden 2007).

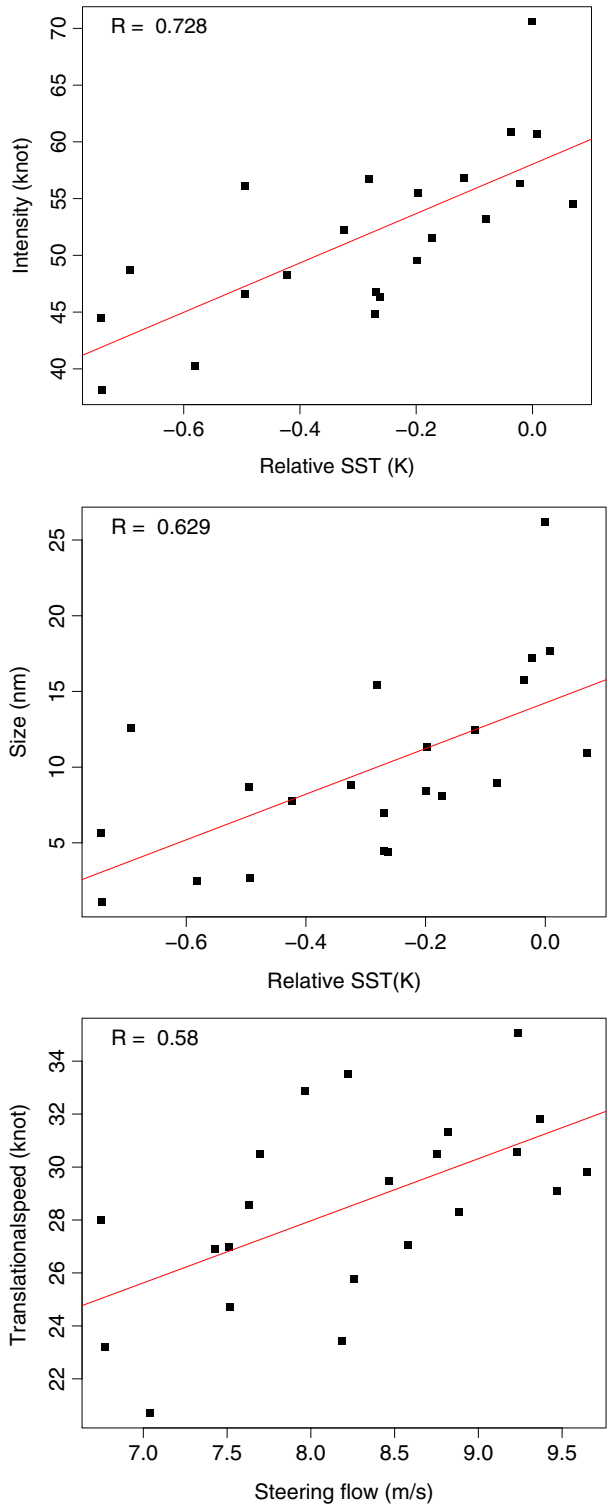
The climate forcing of TC intensity is well documented (Emanuel et al. 2004; Wing et al. 2007; Kossin and Vimont 2007), but climate forcing of TC size is less well understood. Synoptic variability and internal cyclone factors may also strongly control TC size (Liu and Chan 2002; Maclay et al. 2008). The results are consistent with Quiring et al. (2011) who found the strongest predictor of seasonal R_{34} (radius to 34knot winds) is v_m (positively correlated), with large scales playing a secondary role. This agrees with Kossin et al. (2007) who found most of the variance in R_{34} is explained by v_m at the individual cyclone level, explained through expansion of the outer skirt of winds as the storm intensifies.

The physical control of TC motion by the environment is well known and the Beta-Advection model is a very good representation of the large-scale control on hurricane motion (Holland 1983; Galameau and Davis 2013). In spite of this, v_t is not significantly correlated with any of the climate variables considered here (Table 1). This is because the relationship only holds locally in time and space, and synoptic variability causes local steering flows to deviate strongly from the summer and area mean. Rather than taking an area mean, weighting the averaging area according to the likelihood of TC occurrence should provide a better estimate of the steering flow that controls seasonal v_t . The likelihood of TC occurrence is determined by randomly seeding 50,000 passive tracers in the 6-hourly large-scale flow. The historical genesis density determines the likelihood the tracers survive over the period 1988–2009. We choose to assume stationary genesis density. An alternative approach would be to use genesis indices but these can be poor predictors of the spatial distribution of genesis (Bruyère et al. 2012). Subsequent tracks follow the 6-hourly steering flow, first filtered to remove signatures of TC-like vortices in the large-scale data. The resulting track density thereby provides the spatial likelihood of TC occurrence and is used to weight the steering flow. The result of weighting the steering flow is to increase the correlation between v_t and steering flow from 0.04 to 0.58.

3.2 Index formulation

Relative SST alone is linearly related to v_m and R_h (Fig. 1), with significant and high correlations of 0.73 and 0.69 respectively, and weighted steering flow alone is linearly related to v_t (Fig. 1) with a significant and medium correlation of 0.58. These medium to high correlations are encouraging, particularly given that internal variability dictates an upper limit on the portion of TC activity that can be inferred from large-scale data (Done et al. 2014).

Fig. 1 Scatter plots of season, basin mean TC parameters and their large-scale predictors for the period 1988–2009. (*top*) Maximum wind speed vs. relative SST, (*middle*) radius to hurricane force winds vs. relative SST, and (*bottom*) forward translation speed vs. weighted steering flow. Linear correlation coefficients are significant at 99 % using a two-sided *t*-test



The new index is formulated by combining relative SST and the weighted steering flow into a form that echoes the original CDP equation and is consistent with the underlying physical mechanisms of wind damage (i.e., retaining emphasis on the duration of damaging winds). The new index uses the ratio of the relative SST to the weighted steering flow as the predictor variable, and a linear regression is fit between accumulated CDP for each season (ASO) and the predictor ratio for 1988–2009. The new index is formulated as:

$$CDP_{climate} = 67 \frac{SST_{relative}}{STR_w} + 6, \quad (2)$$

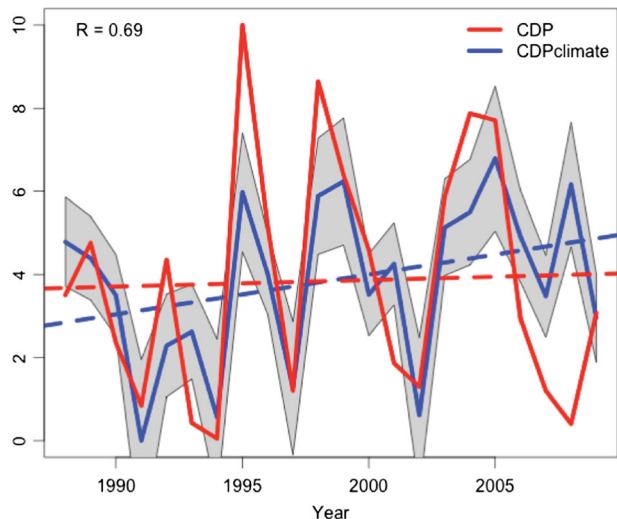
where $SST_{relative}$ is the relative SST, STR_w is the weighted steering flow, and the coefficients are estimated to minimize the root mean square errors (Helsel and Hirsch 1995). Before fitting, accumulated CDP is normalized between 0 and 10 by dividing by the maximum accumulated CDP (the maximum occurred in 1995, Fig. 2) and multiplying by ten. Any values greater than ten may be interpreted as having a greater damage potential than has occurred in the historical record.

4 Current climate damage potential

$CDP_{climate}$ is evaluated first against historical observed seasonal CDP to quantify how much of the variance in a weather-based assessment of damage potential is captured by a climate-based assessment. Historical losses are then used to evaluate the relative merits of the weather versus climate approach. Finally, $CDP_{climate}$ distributions are compared among reanalysis-driven and climate model-driven distributions to evaluate simulated current climate damage potential.

$CDP_{climate}$ explains 48 % of the variance of historical CDP over the period 1988–2009, which is statistically significant at the 99.9 % confidence level (Fig. 2). In cross-validated mode, 37 % of the variance is explained. This is an encouraging result given the potentially large component of damage potential that will never be predictable by the large-scales due to the internal variability of TCs, as discussed in Done et al. (2014). A climate based damage potential assessment is therefore a reasonable approach in the absence of detailed TC information.

Fig. 2 Seasonal, basin accumulated CDP, scaled between 0 and 10, and $CDP_{climate}$ for the historical period 1988–2009, using the Demuth et al. (2006) extended best track dataset for CDP and CFSR data for $CDP_{climate}$. Dashed lines indicate the linear trend. Grey shading represents the 95 % confidence interval for $CDP_{climate}$ estimate



Assessing damage potential using large-scale data removes the need for information on the TCs themselves, and may afford benefits by removing uncertainties in seasonal TC activity. Using ensemble simulation, Done et al. (2014) quantified uncertainty in seasonal TC count due to internal variability of small-scale processes, and produced a range of 6 to 12 TCs for a given large-scale environment. Villarini and Vecchi (2012) found a similarly high internal variability of TCs using a statistical TC model. Individual realizations of the hurricane season would therefore have a very different seasonal damage potential, meaning the value of $CDP_{climate}$, based on large-scale data, represents the less volatile mean of a distribution of damage potential. For a given year then, $CDP_{climate}$ may be more closely related to actual damage than using information from a single realization of seasonal TC activity.

This potential benefit is evaluated by correlating $CDP_{climate}$ and a number of other measures of seasonal TC activity to season total historical TC losses. Total US economic loss data are available over the period 1988–2009 that have been adjusted to 2015 US dollars by accounting for inflation, population, and wealth from Pielke et al. (2008) for the period 1988–2005, and from ICAT (<http://www.icatdamageestimator.com>) for years after 2005. Despite a strong dependency of losses on the impacted vulnerability, correlations with measures of the hazard presents useful insights on the relative value of climate-scale versus weather-scale damage potential indices. Using data for the ASO, the correlation between losses and $CDP_{climate}$ of 0.35, although low, is higher than correlations with Accumulated Cyclone Energy³ of 0.23 and Power Dissipation Index⁴ of 0.26. Furthermore, the correlations with ACE and PDI represent upper limits available from free-running seasonal TC simulations since these simulations do not reproduce one-to-one correspondence with observed storms. Eliminating the need for information on individual TCs, and thus eliminating the internal variability of TCs from the index, may therefore afford benefits to damage potential assessments,

Application of $CDP_{climate}$ to reanalysis and current climate global climate model data allows exploration of the current climate distribution of damage potential, and also identification of climate model bias in damage potential. Specifically, distributions are assessed for a 22-year period of CFSR data (1988–2009) and the 10-year current climate time-slice of the CESM-LE for which 6-hourly data are available (1990–1999). The distribution mean $CDP_{climate}$ using CFSR of 3.2 is not significantly different from the mean $CDP_{climate}$ of the CESM-LE of 2.6, using a one-sided *t*-test (*p*-value=0.39), as expected since the CESM-LE data are bias corrected. Interannual variability is also very similar with a Coefficient of Variation (CV)⁵ of 0.86 for CFSR and 0.98 for the mean of the CESM-LE. The CESM-LE produces a maximum of 11.9, 1.7 times higher than the maximum from CFSR of 6.9, and likely due to the increased sample size (30 realizations) and may be a more accurate assessment of the maximum $CDP_{climate}$ possible in current climate. In summary, CESM-LE adequately captures the statistics of $CDP_{climate}$ for current climate.

5 Future climate damage potential

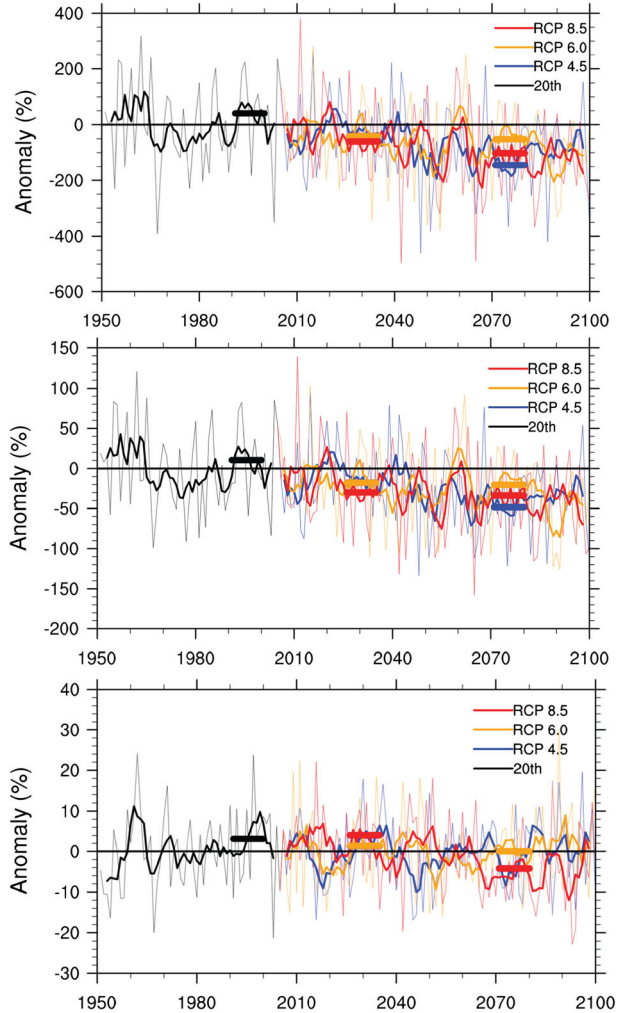
To assess the spread in future damage potential, $CDP_{climate}$ is applied to three climate projections, each under a different RCP. The strength of this forced signal is then assessed

³ sum of the squares of the 6-hourly maximum wind speed.

⁴ sum of the cubes of the 6-hourly maximum wind speed (Emanuel 2005).

⁵ The Coefficient of Variability is the standard deviation divided by the mean.

Fig. 3 Timeseries of bias corrected CESM1 climate simulations under 20th Century emissions for the period 1950–2005, branching to RCPs 4.5 (blue lines), 6.0 (orange lines), and 8.5 (red lines) from 2005 to 2100. Thicker lines are the 5-year running average, and horizontal lines indicate 10-year means for the periods 1990–1999, 2026–2035, and 2071–2080. Note that the 10-year mean for RCP4.5 for 2026–2035 cannot be seen because it lies beneath the 10-year mean for RCP6.0. Percent anomaly is relative to the reference period 1950–2005. *Top panel shows CDP_{climate}, middle panel shows relative SST, and bottom panel shows weighted steering flow*

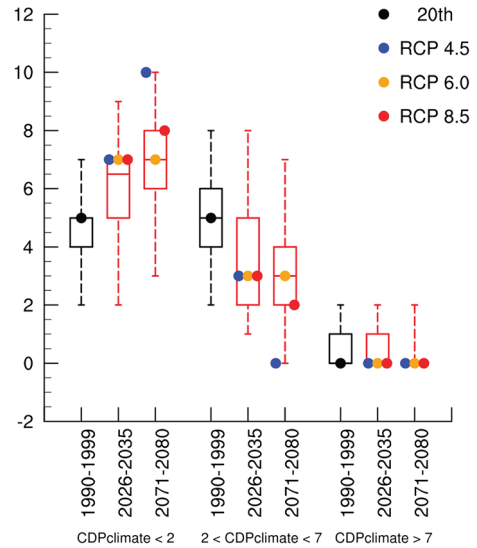


relative to internal climate variability by application of CDP_{climate} to an ensemble climate projection under a single RCP.

5.1 Forced response

Application to the three CESM1 scenarios under RCPs 4.5, 6.0, and 8.5 (Fig. 3) produces a future reduction in damage potential relative to current climate. A future relative SST cooling (i.e., the tropical mean SST warms faster than the local Atlantic SST, Fig. 3) drives the decrease in damage potential. Steering flow shows no statistically significant trend (Fig. 3). Linear trends in damage potential over the period 2005–2100 of $-1.66 \times 10^{-2}/\text{year}$ for RCP4.5, $-1.15 \times 10^{-2}/\text{year}$ for RCP6.0, and $-2.48 \times 10^{-2}/\text{year}$ for RCP8.5 are significantly different from zero but not significantly different among the RCPs suggesting a strong role for internal climate variability.

Fig. 4 Number of years of low, moderate and high damage potential for each decadal timeslice; 1990–1999, 2026–2035, and 2071–2080. *Dots* indicate the CESM1 simulations under 20th century emissions and RCPs 4.5, 6.0, and 8.5. *Box plots* show the distributions from the CESM-LE under RCP8.5



5.2 Strength of the forced response

The strength of the anthropogenic signal in damage potential may be quantified by comparison with estimates of variability due to internal climate variability. To aid interpretation, this comparison is presented in terms of three categories of damage potential: low (index values <2), moderate (values between 2 and 7) and high (values >7). The delineation of categories is arbitrary and does not affect the conclusions. This categorical approach enables relative comparisons to historical events since each category has a number of historical analogs. Figure 4 shows the future shift towards lower damage potential categories under all RCPs (4.5, 6.0, and 8.5).

Figure 4 also shows the spread in the distribution across the categories due to internal climate variability, as estimated from the 30-member CESM-LE under RCP8.5. The CESM-LE mean shows a future shift towards lower damage potential categories, in agreement with the three projections under different RCPs. This shift is driven by an ensemble mean relative SST cooling of 27 % by the period 2026–2035 and 65 % by the 2070s (not shown). The slowing steering flow of 1–2 % is insufficient to offset the cooling relative SST. Importantly, the distributions from the three simulations under RCPs 4.5, 6.0, and 8.5 lie within the estimated range of the distribution due to internal climate variability (Fig. 4), meaning internal variability dominates the forced response. Spread among the RCPs does not emerge above internal variability during the 21st century.

6 Concluding discussion

An index of TC damage potential has been developed that enables rapid assessments of damage potential directly from large-scale climate data. Key damaging TC parameters (intensity, size, and forward speed) identified and incorporated into a weather-based Cyclone Damage Potential (CDP) index by Holland et al. (2015), were related to relative SST and a measure of the large-scale steering flow. A climate-based index of damage potential was then

formulated using these relationships, and referred to as CDP_{climate} . Consideration of historical losses showed that this climate-based approach affords benefits by eliminating uncertainty due to the internal variability of TCs, thereby representing a mean of a damage potential distribution. Stakeholders may translate damage potential to actual damage using relationships between the damage potential index and their specific exposure and vulnerability characteristics.

Reanalysis-driven and bias corrected climate model-driven distributions of CDP_{climate} showed good agreement for current climate. Projections of future damage potential over the 21st century using three climate simulations under representative concentration pathways 4.5, 6.0, and 8.5 do not differ significantly. Indeed, their spread is found to be less than estimates of spread due to internal climate variability using a 30-member climate model initial condition ensemble. Differences in damage potential driven by climate outcomes resulting from different anthropogenic forcings are therefore overwhelmed by differences due to internal climate variability.

These results are critically dependent on the choice of predictors of damage potential. Although relative SST has the highest correlation with v_m and R_h for 22-year historical period considered here, an alternative model of damage potential could be based on local SST or the ventilation index (Table 1). A local SST-based index would project increasing damage potential (compared to the decreasing damage potential projected here using relative SST) and reversed dominance of anthropogenic forcing versus internal climate variability (not shown). The use of relative quantities rather than climate-invariant thresholds is appropriate for climate change simulations, as suggested by Emanuel (2013) for entropy deficit, and Tang and Emanuel (2012) for the ventilation index. In this spirit, relative SST was chosen here and is as a balance between statistical correlation and physical robustness. Support that relative SST is a valid choice is provided by high-resolution modeling studies that show that measures of TC activity track changes in relative rather than local SST (Vecchi et al. 2008; Done et al. 2013; Knutson et al. 2013), and theoretical arguments for a limit on TC intensity (Vecchi and Soden 2007).

The projected future reduction in TC damage potential found here is model dependent, evidenced by the lack of agreement in relative SST change (Villarini and Vecchi 2012) or North Atlantic TC activity (Camargo 2013) across the CMIP5 ensemble. However, the dominance of internal climate variability over forced signals in relative quantities such as relative SST is likely to be model independent. Improving understanding of spatial SST change may therefore be key to understanding future change in TC damage potential. More generally, this study highlights the importance of accounting for internal climate variability in future climate impact assessments.

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