Pacific Hurricane Landfalls on Mexico and SST

TIMOTHY HALL
NASA Goddard Institute for Space Studies, New York, New York

MICHAEL K. TIPPETT
Department of Applied Physics and Applied Mathematics, Columbia University, New York, New York, and Center of Excellence for Climate Change Research, Department of Meteorology, King Abdulaziz University, Jeddah, Saudi Arabia

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ABSTRACT

A statistical model of northeastern Pacific Ocean tropical cyclones (TCs) is developed and used to estimate hurricane landfall rates along the coast of Mexico. Mean annual landfall rates for 1971–2014 are compared with mean rates for the extremely high northeastern Pacific sea surface temperature (SST) of 2015. Over the full coast, the mean rate and 5%–95% uncertainty range (in parentheses) for TCs that are category 1 and higher on the Saffir–Simpson scale (C1+ TCs) are 1.24 (1.05, 1.33) yr⁻¹ for 1971–2014 and 1.69 (0.89, 2.08) yr⁻¹ for 2015—a difference that is not significant. The increase for the most intense landfalls (category-5 TCs) is significant: 0.009 (0.006, 0.011) yr⁻¹ for 1971–2014 and 0.031 (0.016, 0.036) yr⁻¹ for 2015. The SST impact on the rate of category-5 TC landfalls is largest on the northern Mexican coast. The increased landfall rates for category-5 TCs are consistent with independent analysis showing that SST has its greatest impact on the formation rates of the most intense northeastern Pacific TCs. Landfall rates on Hawaii [0.033 (0.019, 0.045) yr⁻¹ for C1+ TCs and 0.010 (0.005, 0.016) yr⁻¹ for C3+ TCs for 1971–2014] show increases in the best estimates for 2015 conditions, but the changes are statistically insignificant.

1. Introduction

Landfalls of intense tropical cyclones (TCs) are among the most devastating natural catastrophes. Extensive work has been performed to estimate North Atlantic Ocean (NA) TC hazard on the U.S. Atlantic and Gulf of Mexico (the "Gulf") coasts and its relationship to climate change and variability (e.g., Emanuel 2011), which is understandable given the population and property that can potentially be affected. Less work has focused on the hazard that northeastern Pacific Ocean (NEPac) TCs pose for the Central and North American Pacific coasts, especially in Mexico. This gap exists despite the fact that the NEPac experiences more TCs annually than the NA and that the annual landfall rates for hurricanes are comparable: 1.3 yr⁻¹ from the Pacific and 2.3 yr⁻¹ from the Atlantic and Gulf, including 0.6 yr⁻¹ on the Caribbean Sea and Gulf coasts of Mexico (Jáuregui 2003). Sea surface temperature (SST) has been shown to influence NEPac TC activity (Irwin and Davis 1999; Camargo et al. 2008; Jien et al. 2015). There is evidence that SST has a stronger influence on the most intense TCs than on weaker TCs. Frank and Young (2007) found that the number of TCs in the NEPac that are category 3 and higher on the Saffir–Simpson scale (C3+) is more strongly correlated with the El Niño–Southern Oscillation (ENSO) SST signal than is the case for weaker TCs. This is consistent with the quantile-regression analyses of Elsner et al. (2008), which revealed the strongest dependence of maximum wind speed on SST for the most intense TCs. In a similar way, Martinez-Sanchez and Cavazos (2014) found higher NEPac C4+ TC occurrence and accumulated cyclone energy during El Niño (associated with higher NEPac SST) and neutral states of ENSO than during La Niña but no significant change for C1 + TC occurrence. Caron et al. (2015) noted that ENSO has a significant positive influence on TC counts only for C3+ TCs. In the context of a warming climate, trend analysis of TCs has shown that the greatest fractional increases occur at the highest
intensities (Elsner et al. 2008; Kossin et al. 2013), although Klotzbach and Landsea (2015) argue that sampling bias compromises the trends.

Given evidence for a link between SST and intense TCs, it is natural to look for a corresponding signal in landfall along the Pacific coast of Central and North America. (Because most, but not all, such landfalls occur on Mexico, we subsequently refer to this as Mexican Pacific landfall.) In fact, Farfán et al. (2013) pointed out that, of the 25 most intense Mexican Pacific landfall events, 10 occurred during El Niño and 10 occurred during neutral ENSO states but only 5 occurred during La Niña. This result is a clue that there may be a climate signal in Mexican landfalls, but on its own it does not provide a basis for a climate-dependent view of Mexican hurricane hazard. Our primary goal here is to explore further the relationship between SST and Mexican landfall, resolving the relationship regionally and by intensity and estimating uncertainty bounds.

Here a statistical TC model for NEPac TCs is presented, with a focus on Pacific coast landfall and its dependence on interannual climate variations. The statistical model exploits data from the entire basin to simulate the life cycle of TCs from formation through dissipation. The stochastic nature of the model means that simulated TCs are distinct from each other and distinct from historical TCs, but their statistical properties match those of historical TCs. A key application of such a statistical model is to generate many realizations of a historical period to estimate mean landfall rates with greater precision than can be achieved using only historical landfall data (Hall and Jewson 2008). This approach is especially compelling when rates are being estimated on regions or scenarios for which there are few or no historical events. In effect, information from the entire basin is projected onto a region and scenario in question.

2. Data

The model is built on 44 years of International Best Track Archive for Climate Stewardship (IBTrACS) TC data (Knapp et al. 2010), 1971–2014 inclusive. In the past, there has been less aircraft reconnaissance in the NEPac than in the NA, and the start date of 1971 represents the beginning of satellite imagery of the region. Prior to 1971, frequency analysis suggests that significant numbers of TCs are missing from the record (Blake et al. 2009). If one defines the NEPac to extend westward to the international date line, there are 808 TCs, 411 TCs that reach C1+ intensity, and 57 TCs that make landfall at C1+ intensity in the 1971–2014 record (Fig. 1d). IBTrACS includes nontropical stages in the evolution of TCs. We utilize complete IBTrACS tracks in model construction, and therefore our computed landfall rates include a small contribution from nontropical storms that were once TCs.

The model uses a seasonal SST index of the NEPac main development region (MDR) as an independent variable derived from the monthly 1° gridded Hadley Centre Sea Ice and SST (HadISST) product (Rayner et al. 2003). An annual time series is generated by area-weighted spatial averaging of 160°–110°W and 2°–22°N and temporal averaging of July–October. This SST-index region overlaps ENSO Niño-3.4 but is shifted northward and eastward. It is closely correlated with Niño-3.4 but has a higher correlation with annual NEPac TC counts (0.45 as compared with 0.27 for Niño-3.4). Farther shifts eastward toward North America did not appreciably affect the explained variance. Our choice of this index allows us to make easier comparisons with ENSO–NEPac TC studies and to include part of the formation region extending eastward from 120°W to the North American coast. Caron et al. (2015) also found MDR seasonal SST to be a strong count predictor, and Jin et al. (2014) have established the direct thermal connection between ENSO and NEPac MDR SST and TCs.

3. Model

The model simulates NEPac TCs from formation through dissipation. The basic model sequence is formation, propagation, dissipation, and selection of an intensity time series. Each simulated TC consists of a 6-hourly time series of time and date, TC-center location, and maximum sustained wind speed $V_{\text{max}}$. (Central pressure and radius to maximum wind are also simulated but are not used in this study.) The model’s components are described only briefly here, because the method is identical to the NA model described in Hall and Jewson (2007) and Hall and Yonekura (2013).

a. Genesis

The spatial distribution of formation rates is determined by local Poisson regression of annual TC counts on the SST index. At each point on a 1° grid an annual count series is regressed on the SST index. Count contributions to the regression are weighted inversely with distance from the point, and the rate computed is scaled by area to 1° grid boxes. The resulting Poisson distributions are then sampled, producing simulations of the annual number and location of TC formation, depending on the SST-index value. The formation day of year is determined by sampling an annual-cycle space–time kernel density function.
b. Tracks

Once a TC is formed, it is propagated in 6-h steps. Given a TC at location \( x(t) \), its location \( x(t + 6h) \) is determined by linear regression of the historical TC 6-h displacements on the SST index and a 6-hourly annual-cycle “climatology” of 500-hPa National Centers for Environmental Prediction winds weighted inversely with distance from \( x \). The errors about the mean are standardized and modeled as a lag-1 autocorrelated process.

c. Dissipation

We define dissipation in the IBTrACS data to occur at the last 6-hourly point of a track. At every 6-hourly simulated TC position \( x \) there is a probability that the track dissipates. This probability is determined by logistic regression of historical dissipation events on the SST index weighted inversely with distance from \( x \). Overocean and overland dissipation probabilities are strictly separated using a 0.1° land–ocean mask. Note that the complete tracking including dissipation is simulated before its \( V_{\text{max}} \) time series is determined. Such a separation of the track and \( V_{\text{max}} \) calculations is clearly not physical, but, as described below, the time series of \( V_{\text{max}} \) is chosen to match the characteristics of the track, and the relationship between dissipation events and low intensity is maintained.

d. Maximum sustained wind speed

The \( V_{\text{max}} \) time series are obtained for a track by weighted random sampling of historical time series. Once a track is simulated, time series of historical \( V_{\text{max}} \) are sampled and placed on the simulated track, with a preference for series whose historical tracks are similar to the simulated track. Similarity is defined by inverse weights on differences in genesis location, dissipation location, and duration of track. In addition and important, a preference is given to historical \( V_{\text{max}} \) series that come from a year for which the SST-index value is similar to the SST index of the simulation year. The weighting kernels are Gaussian: the SST kernel bandwidth is 1.0 in standardized SST-anomaly units, the genesis- and dissipation-site bandwidths are 300 km, and the duration bandwidth is 0.1 in units of fractional duration difference. The bandwidths in genesis location, dissipation location, and track duration are much smaller fractions of the range of these quantities than is the SST bandwidth in comparison with the range of SST.
variability. As a consequence, track similarity takes preference over SST similarity. Given two comparable tracks, however, the scheme will preferentially sample a similar SST state. Once the weighted random sampling is performed, the lifetime maximum intensity (LMI) receives a small random perturbation and all points of the \( V_{\text{max}} \) time series except the initial and final ones are suitably rescaled so that the simulated \( V_{\text{max}} \) series are not limited to historical values. The perturbations are drawn from a generalized extreme-value fit of the historical LMIs (Hall and Yonekura 2013) to ensure that the distribution of the perturbed set conforms closely to that of the unperturbed set. Small differences between the durations of the selected \( V_{\text{max}} \) time series and the simulated track are then removed by scaling the \( V_{\text{max}} \) series in time to fit the track.

4. Simulations

Two forms of simulations are performed: 1) 1000 simulations (ensembles) of the 44-yr period 1971–2014 and 2) a 44 000-yr simulation with the SST index held to the 2015 value. The 1971–2014 “historical” simulations, driven by the historical SST-index series, are used to evaluate the model and to make best estimates of long-term landfall rates. The 2015 simulations are used to estimate the effect of an extreme SST-index value on NEPac TC characteristics. (The 2015 SST index was 2.8 standard deviations above the 1971–2014 mean.) For both the 1971–2014 and 2015 simulations, bootstrap analysis is performed to estimate uncertainties on the ensemble-mean rates generated by the model and to determine the statistical significance of differences between 1971–2014 and 2015 mean rates. In each bootstrap sample, the model is completely reconstructed using data drawn with replacement from the available 44 years. For each reconstructed model, the 1971–2014 and 2015 simulation ensembles are generated (1000 simulations of 1971–2014 and 44 000 simulations of 2015), and the mean diagnostics are computed across the ensembles. Last, the 5th percentile and 95th percentile of the mean diagnostics are computed across 100 bootstrap samples.

5. Results

a. Long-term landfall rates

The 1971–2014 simulations are used to estimate long-term landfall rates and to evaluate the model’s landfall characteristics. Landfall is calculated across a series of 29 segments, or “gates,” each 200 km in length, that line the coast from Central America through California. The model is unbiased if the historical rate over 1971–2014 is a typical member of the set of rates from the 1000 simulations of 1971–2014. Initially there was found to be a low landfall bias on the Baja Peninsula. The formation and track model components are optimized individually to maximize out-of-sample likelihoods accumulated over the entire basin, but this does not preclude the possibility of bias on subregions of the basin or on diagnostics such as landfall that depend on the coupling of model components (Bonazzi et al. 2014). To correct this bias, 20% of the TCs that do not make landfall on the Baja Peninsula are resimulated. This preferential sampling rate causes the historical rate to fall within the 5%–95% range of regional simulated landfall rates. This correction is applied identically to both 1971–2014 and 2015 simulations and therefore has little impact on comparisons. This approach to landfall adjustment is similar to the simulated-track accept–reject procedure described by Kriesche et al. (2014).

Figure 2 shows the resulting landfall rates over the full coast expressed as landfalls per 1971–2014 period in the following six intensity categories: tropical storm and the Saffir–Simpson hurricane categories 1–5. (We subsequently refer to tropical-storm intensity as “category 0.”) Historical 1971–2014 rates and model ensemble-mean rates over the 1000 1971–2014 simulations are shown, as are the inner 50% and 90% of the distribution of model rates from the 1000 simulations. In all categories, the historical rate falls within the inner 90% of the simulations, and in all but one it falls within the inner 50%.
Figure 3 shows the coastal gates and the 1971–2014 mean landfall rates for C1+ and C3+ TCs expressed as landfalls per 100 years accumulated over pairs of successive gates. Rates are maximal just north and south of the Gulf of California, peaking at 0.38 (0.29, 0.42) yr$^{-1}$ for C1+ TCs over a 400-km stretch that spans the southern tip of the Baja Peninsula and the opening of the Gulf of California. (The first and second values in the parentheses indicate the 5% and 95% uncertainty levels, respectively, for the rates from the bootstrap analysis.) There is a sharp minimum between those two points, where the coast curves away from the oncoming mean track. To the north, SST drops rapidly and TCs are not easily sustained. There is a low rate of C1–2 TC landfalls on southern California [0.0010 (0.0002, 0.0034) yr$^{-1}$] and no C3+ California TC landfalls in these simulations.

b. High SST state

SST influences TC activity in the NEPac (e.g., Camargo et al. 2008). Our goal is to estimate the impact of SST on landfall rates. To this end, long-term mean (1971–2014) landfall rates are compared with mean rates for the extremely warm 2015 season.

Figure 4 (top panel) shows the mean landfall rates (annual landfalls per gate) along the coast for C1+ TCs and category-5 TCs for 1971–2014 and 2015. Category-1+ mean TC rates summed over the coast for 2015 are higher than for 1971–2014 [1.69 (0.89, 2.08) yr$^{-1}$ vs 1.24 (1.05, 1.33) yr$^{-1}$], but the increase is not significant, in the sense that the 5%–95% bootstrap ranges about the two means overlap. The basinwide formation rate for all TCs in 2015 is 25.6 (20.6, 32.4) yr$^{-1}$ versus 17.6 (16.5, 19.0) yr$^{-1}$ for 1971–2014, which is a significant increase. For landfall, the formation-rate increase is partially offset by a westward shift in TC formation in 2015 when compared with 1971–2014 (Fig. 5), a shift that has been noted by others with regard to El Niño (Irwin and Davis 1999; Camargo et al. 2008; Jien et al. 2015). Other factors being equal, this shift reduces the fraction of TCs making landfall. Consistent with this picture, the mean category-1 landfall fraction (best-estimate C1+ landfall rate over basinwide TC formation) is slightly reduced to 0.066 for 2015 versus the 0.070 for 1971–2014, although the difference is not significant.

For the most intense landfalls, category 5, the 2015 increase over 1971–2014 shown in Fig. 4 (bottom panel) is significant: 0.031 (0.016, 0.036) yr$^{-1}$ for 2015 over the full coast versus 0.009 (0.006, 0.011) yr$^{-1}$ for 1971–2014. The SST category-5 impact is especially large on the northern Mexican coast. The impact peaks on the southern tip of the Baja Peninsula, where category-5 landfalls are 7.3 (2.8, 32.0) times as likely for 2015.
conditions as for 1971–2014. At the site of Hurricane Patricia’s near-category-5 2015 landfall, the ratio for 2015 to 1971–2014 is 1.48 (0.50, 6.00), which is not a significant increase.

There are no category-5 Pacific coast Mexican landfalls in the historical record, although Hurricane Patricia’s landfall $V_{\text{max}}$ was within observational uncertainty of category 5. We are making a statement about an increased rate for an event that may not have happened in the well-documented historical record, and it is worthwhile exploring in detail the factors driving the increase. The increase in category-5 landfalls is driven by an increase in the model’s formation rate of TCs whose LMI reaches category 5: 0.72 (0.52, 0.97) yr$^{-1}$ for 2015 conditions versus 0.28 (0.23, 0.32) yr$^{-1}$ for 1971–2014.

From a historical perspective, there were 13 TCs with category-5 LMI in 1971–2014, and their occurrence is heavily weighted to years of high SST. The model exploits the existence of these intense TCs and their relationship to SST: the model’s intensity scheme has a small probability of sampling a category-5 $V_{\text{max}}$ time series and placing it on a track that makes landfall. The sampling is weighted toward years for which the SST anomaly is close to the SST anomaly of the year being simulated; hence there is a greater (although still small) chance for category-5 landfall in years with high SST.

The 2015 increase in category-5 landfall occurs on the northern Mexican coast, north of Puerto Vallarta. This northern signature is consistent with a westward shift in formation of category-5 LMI TCs. Figure 6 shows the formation-rate distributions for TCs that reach $\text{C1}+$ and for category-5 LMI for 1971–2014 and 2015 conditions. The westward shift in 2015 is more marked for category-5 LMI and includes a second western lobe. Tracks emanating from more-western genesis sites are less likely to make landfall along the southern Mexican coast, and thus the landfall signature of additional category-5 TCs is concentrated on the northern coast. This is borne out in the mean tracks of landfalling TCs, also plotted in Fig. 6. The mean genesis site of landfalling $\text{C1}+$ TCs shifts by less than 2$^\circ$ from 1971–2014 to 2015 (from 13.3$^\circ$N, 101.2$^\circ$W to 13.5$^\circ$N, 102.8$^\circ$W), whereas the mean genesis site for landfalling category-5 TCs shifts by more than 4$^\circ$ (from 12.9$^\circ$N, 101.0$^\circ$W to 13.9$^\circ$N, 105.0$^\circ$W). The mean $\text{C1}+$ track has little change, and the category-5 mean track is farther west and intersects the coast farther north in 2015 than in 1971–2014.

We now examine the relationship of basinwide LMI with SST in a manner that is independent of the model to bolster the model’s category-5 landfall result. How does LMI differ between years with below-average SST (cold) and years with above-average SST (warm)? Fig. 7 (top panel) shows the distributions of 1971–2014 TC counts by LMI bin for cold and warm years. There are more TCs in warm years than in cold years in all of the LMI bins. [In the past, of the 13 TCs that reach $V_{\text{max}} \geq$
250 km h$^{-1}$ (category 5), 11 occur in the 23 warm years and 2 occur in the 21 cold years.] To test the significance of the SST sensitivity, a permutation test is employed, given the null hypothesis that there is no TC LMI–SST relationship. We randomly assign years to the TCs 1000 times, compute the occurrence rate in warm and cold years for each random assignment, and take the ratio of the warm-to-cold rates. The historical ratio of warm to cold rate is significantly different than unity if it falls outside the random 5%–95% range. Figure 7 (bottom panel) shows the results of the permutation test: the distribution of category-1–4 TC LMIs is not significantly associated with SST, but the rate of category-5 TC LMI is significantly higher in warm years than in cold years.

Klotzbach and Landsea (2015) have raised the importance of sampling issues in the pre-1990 data that cause positive biases in C4+ occurrence trends. To test the robustness of our results, we repeat the analysis on the 25 years from 1990 to 2014. This shorter period actually shows an increased association between category-5 LMI and SST. Of the 13 category-5 TCs during 1971–2014, 12 occur in 1990–2014. Among these 12 category-5 TCs, 11 occur in the 13 warm years and 1 in the 12 cold years, where the SST mean is now taken with respect to 1990–2014. Figure 8 (top panel) shows the number distribution, and Fig. 8 (bottom panel) shows the results of the permutation test. Category-4 rates and category-5 rates are both significantly higher in warm years than in cold years. Note also that there is considerable uncertainty on $V_{\text{max}}$ observational estimates (Torn and Snyder 2012; Landsea and Franklin 2013). To assess the impact of this uncertainty we repeat the 1971–2014 and 1990–2014 permutation tests 1000 times, adding to each TC’s LMI a random normal deviation of zero mean and 9 km h$^{-1}$ standard deviation [i.e., a 10-kt (1 kt = 0.51 m s$^{-1}$) two-sided width]. Of the 1000 cases, the
historical warm-to-cold-year category-5 LMI ratio is greater than the random-permutation 95% level 991 times for 1971–2014 and 999 times for 1990–2014. In other words, the significance of the category-5-SST relationship is robust to observational uncertainty. These LMI occurrence analyses buttress the model result that category-5 landfall rates on Mexico are significantly higher than the long-term mean in a warm year such as 2015.

Although the main focus of our work is landfall on the Pacific North American coast, Hawaii is also impacted from TCs forming in the NEPac. The TC occurrence near Hawaii is related to El Niño (Chu and Wang 1997) as well as to other modes of natural variability (Murakami et al. 2015). We have calculated landfall rates on Hawaii, where for this purpose a TC is considered to make “landfall” if it crosses one of eight 200-km gates surrounding the islands (Fig. 9, left panel). The mean rates for TCs above the Saffir–Simpson thresholds are shown in Fig. 9 (right panel), along with the 5%–95% confidence range from the bootstrap analysis. For C1+ the annual rate is 0.033 (0.019, 0.045) yr⁻¹ for 1971–2014 and 0.056 (0.027, 0.093) yr⁻¹ for 2015. For C3+ the respective values are 0.010 (0.005, 0.016) yr⁻¹ and 0.018 (0.007, 0.036) yr⁻¹. The best-estimate rates are higher in 2015 than in 1971–2014 for all category thresholds, but confidence ranges overlap. The ratio of the best-estimate rates is highest for category 5, but the uncertainty range is also largest. In fact, bootstrap examination of the rate ratios for different categories indicates that only C0+ TCs (tropical-storm intensity and higher), with a rate ratio for 2015 to 1971–2014 of 1.86 (1.10, 3.18), exhibits a significant increase. By comparison, the category-5 ratio is 2.89 (0.25, 16.0).

6. Conclusions

A statistical model of NEPac TCs is presented and is used to estimate long-term landfall rates on Mexico as well as rates under the extremely warm 2015 SST conditions. Over the full coast the mean rate for C1+ is 1.24 (1.05, 1.33) yr⁻¹ for 1971–2014 and 1.69 (0.89, 2.08) yr⁻¹ for 2015—a difference that is not statistically significant. The increase in category-5 landfalls, however, is significant: 0.009 (0.006, 0.011) yr⁻¹ for 1971–2014 and 0.031 (0.016, 0.036) yr⁻¹ for 2015. The SST category-5 impact is especially large on the northern section of coast, peaking on the southern tip of the Baja Peninsula, where category-5 landfalls are 7.3 (2.8, 32.0) times as likely for 2015-like SST conditions.

These SST–landfall findings are broadly consistent with past NEPac TC analysis and the few previous studies on Mexican landfall. Martínez-Sánchez and Cavazos (2014) found higher NEPac C4+ occurrence
and accumulated cyclone energy during El Niño and neutral states of ENSO than during La Niña but no significant change for C1+. In their analysis of various NEPac activity predictors, Caron et al. (2015) found that ENSO has a significant positive influence on TC counts only for major hurricanes. Farfán et al. (2013) found that of the 25 “top” Mexican Pacific landfall events, 20 occurred during El Niño and neutral ENSO states (10 each) but only 5 occurred during La Niña. Our results are consistent with these but go well beyond by providing geographic resolution along the coast and an analysis of statistical significance.

It is worthwhile to ask why the model’s category-5 landfall rate is significantly higher in 2015 but the C1+ rate is not. Intensity in the model depends on SST by preferential sampling of \( V_{\text{max}} \) time series from years for which SST anomaly is close to the anomaly of the simulation year. The impact of SST on the sampling is only apparent for the most intense TCs; that is, only the frequency of the most intense TCs shows a dependence on SST. This is consistent with the quantile regression analyses of Elsner et al. (2008), which revealed the strongest dependence of maximum wind speed on SST for the most intense TCs, and with Kossin et al. (2013) and Elsner et al. (2008), which found the largest fractional increases at the highest intensities. In a similar way, Frank and Young (2007) found that NEPac C3+ TCs display significantly more dependence on ENSO than do weaker TCs. The physical mechanisms for this effect remain unclear, but arguments that are based on LMI distributions and potential intensity (PI) may be relevant (Sobel et al. 2016): Other factors being equal, the PI of TCs increases with SST (Bister and Emanuel 2002). In addition, a TC has an intensity that is approximately uniformly distributed between a lower threshold and the local PI (Emanuel 2000). As a consequence, increases in PI (in this case via SST) stretch the intensity distribution, causing the largest fractional increase to occur at the highest intensities.

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REFERENCES


