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Pacific Hurricane Landfalls on Mexico and SST

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Abstract

A statistical model of Northeast Pacific 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 to mean rates for the extremely high Northeast Pacific sea-surface temperature (SST) of 2015. Over the full coast, the mean rate and 5%–95% uncertainty for Saffir-Simpson category one and higher TCs (category-1+ TCs) is $1.24^{1.33}_{1.05}\text{yr}^{-1}$ for 1971–2014 and $1.69^{2.08}_{0.89}\text{yr}^{-1}$ for 2015, a difference that is not significant. However, the increase for the most intense landfalls, category-5 TCs, is significant: $0.009^{0.011}_{0.006}\text{yr}^{-1}$ for 1971–2014 and $0.031^{0.036}_{0.016}\text{yr}^{-1}$ for 2015. The SST impact on the category-5 TC landfall rate is largest on the northern Mexican coast. The increased landfall rates for category-5 TCs is consistent with independent analysis showing that SST has its greatest impact on the formation rates of the most intense Northeast Pacific tropical cyclones. Landfall rates on Hawaii ($0.033^{0.045}_{0.019}\text{yr}^{-1}$ for category-1+ TCs and $0.010^{0.016}_{0.005}\text{yr}^{-1}$ for category-3+ TCs for 1971–2014) show increases in the best estimates for 2015 conditions, but the changes are insignificant according to our tests.

1. Introduction

Landfalls of intense tropical cyclones (TCs) are among the most devastating natural catastrophes. Extensive work has been performed to estimate North Atlantic (NA) TC hazard on the US Atlantic and Gulf coasts, and its relationship to climate change and variability (e.g., Emanuel, 2011), which is understandable, given the population and property in harm's way. Less work has focused on the hazard that Northeast Pacific (NEPac) TCs pose for the Central and North American Pacific coasts, specifically Mexico. This gap exists despite the fact that the NEPac experiences more TCs annually than the NA and that the annual hurricane landfall rates 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 Caribbean and Gulf coasts of Mexico (Jauregui, 2003).

Sea surface temperature (SST) has been shown to influence NEPac TC activity (Irwin et al., 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 NEPac Saffir-Simpson category three and higher (category-3+) TCs 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. Similarly, Martinez-Sanchez and Cavazos (2014) found higher NEPac category-4+ TC occurrence and accumulated cyclone energy during El Niño (associated with higher NEPac SST) and neutral states of ENSO than La Niña, but no significant change for category-1+ TC occurrence. Caron et al. (2015) noted that ENSO has a significant positive influence on TC counts only for category-3+ TCs. In the context of a warming climate, trend analysis of TCs has shown the greatest fractional increases at the highest intensities (Elsner et al., 2008; Kossin et al., 2013), though 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, though not all, such landfalls occur on Mexico, we subsequently refer to this as Mexican Pacific landfall.) In fact, Farfan et al (2013) pointed out that, of the 25 most intense Mexican Pacific landfall events, 10 occurred during El Niño and 10 during neutral ENSO states, but only 5 during La Niña. This result is a clue that there may be a climate signal in Mexican landfalls, but on its own is not 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 inter-annual climate variations. The statistical model exploits data from the entire basin to simulate the lifecycle 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 a such statistical model is to generate many realizations of a historical period in order 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 IBTrACS TC data (Knapp et al., 2010), 1971–2014 inclusive. There has been historically less aircraft reconnaissance in the NEPac than the NA, and the start date 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). Defining the NEPac to extend westward to the international dateline, there are 808 TCs, 411 TC that reach category-1+ intensity, and 57 TCs that make landfall at category-1+ intensity in the record 1971–2014 (Fig 1d). IBTrACS includes non-tropical stages in the evolution of TCs. We utilize complete IBTrACS tracks in model

construction, and consequently our computed landfall rates include a small contribution from non-tropical 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 HadISST (Hadley Centre) SST product (Rayner et al., 2003). An annual time series is generated by area-weighted spatial averaging of 160°W – 110°W , 2°N – 22°N and temporal averaging July–October. This SST index region overlaps ENSO Nino3.4, but is shifted northward and eastward. It is closely correlated with Nino3.4, but has a higher correlation with annual NEPac TC counts (0.45 compared to 0.27 for Nino3.4). Further shifts eastward towards North America did not appreciably affect the explained variance. Our choice of this index allow 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 ($V_{\max}$). (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, as the methodology is identical to the NA model described in Hall and Jewson (2007) and Hall and Yonekura (2013).

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.

Tracks

Once a TC is formed, it is propagated in six-hour steps. Given a TC at location $\mathbf{x}(t)$, its location $\mathbf{x}(t+6\text{hr})$ is determined by linear regression of the historical TC 6-hr displacements on the SST index and a six-hourly annual-cycle climatology of 500 mb NCEP winds weighted inversely with distance from $\mathbf{x}$. The errors about the mean are standardized and modeled as a lag-one autocorrelated process.

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 $\mathbf{x}$ 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 $\mathbf{x}$. Over-ocean and over-land dissipation probabilities are strictly separated using a 0.1° land-ocean mask. Note that the complete tracking including dissipation is simulated before its $V_{\max}$ time series is determined. Such a separation of the track and $V_{\max}$ calculations is clearly not physical. However, as described below, the time series of $V_{\max}$ is chosen to match the characteristics of the track, and the relationship between dissipation events and low intensity is maintained.

Maximum Sustained Wind Speed

$V_{\max}$ time series are obtained for a track by weighted random sampling of historical time series. Once a track is simulated, time series of historical $V_{\max}$ 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. Additionally, and importantly, a preference is given to historical $V_{\max}$ series that come from a year whose 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, while 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 compared to the range of SST variability. Consequently, track similarity takes preference over SST similarity. However, given two comparable tracks 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 $V_{\max}$ time series except for the initial and final ones are suitably rescaled so that the simulated $V_{\max}$ 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. Finally, small differences between the durations of the selected $V_{\max}$ time series and the simulated track are removed by scaling the $V_{\max}$ series in time to fit the track.

4. Simulations

Two forms of simulations are performed: (i) 1000 simulations (ensembles) of the 44 year period 1971–2014 period; and (ii) a 44,000 year 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. Finally, the 5th and 95th percentile of the mean diagnostics are computed across 100 bootstrap samples.

5. Results

5.1. 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, 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 sub-regions 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 re-simulated. 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 thus 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 category-1+ and category-3+ 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 $0.38^{0.42}_{0.29}\text{yr}^{-1}$ for category 1+ TCs over a 400km stretch spanning the southern tip of the Baja peninsula and the opening of the Gulf of California. (Subscripts and superscripts on rates indicate the 5% and 95% uncertainty levels respectively from the bootstrap analysis.) There is a sharp minimum in between, 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 category-1–2 TC landfalls on southern California ($0.0010^{0.0034}_{0.0002}\text{yr}^{-1}$) and no category-3+ California TC landfalls in these simulations.

5.2. 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 to mean rates for the extremely warm 2015 season.

Figure 4 (top) shows the mean landfall rates (annual landfalls per gate) along the coast for category-1+ TCs and category-5 TCs for 1971–2014 and 2015. Category-1+ mean TC rates summed over the coast for 2015 are higher than 1971–2014 ($1.69^{2.08}_{0.89}\text{yr}^{-1}$ versus $1.24^{1.33}_{1.05}\text{yr}^{-1}$), but the increase is not significant, in the sense that the 5%–95% bootstrap ranges about the two means overlap. The basin-wide formation rate for all TCs in 2015 is $25.6^{32.4}_{20.6}\text{yr}^{-1}$ versus $17.6^{19.0}_{16.5}\text{yr}^{-1}$ for 1971–2014, which is a significant increase. However, for landfall, the formation rate increase is partially offset by a westward shift in TC formation in 2015 compared to 1971–2014 (Fig 5), a shift that has been noted by others with regard to El Niño (Irwin et al., 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 category-1+ landfalls rate over basin-wide TC formation) is slightly reduced, 0.066 for 2015 versus 0.070 for 1971–2014, though the difference is not significant.

For the most intense landfalls, category-5, the 2015 increase over 1971–2014 shown in Fig 4 (bottom) is significant: $0.031^{0.036}_{0.016}\text{yr}^{-1}$ for 2015 over the full coast versus $0.009^{0.011}_{0.006}\text{yr}^{-1}$ 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 $7.3^{32.0}_{2.8}$ times more likely for 2015 conditions than 1971–2014. At the site of Hurricane Patricia's near-category-5 2015 landfall the 2015 to 1971–2014 ratio is $1.48^{6.00}_{0.50}$, not a significant increase.

There are no category-5 Pacific-coast Mexican landfalls in the historic record, though Hurricane Patricia's landfall V_{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 category-5 landfall increase is driven by an increase in the model's formation rate of TCs whose LMI reaches category-5: $0.72^{0.97}_{0.52}\text{yr}^{-1}$ for 2015 conditions versus $0.28^{0.32}_{0.23}\text{yr}^{-1}$ for 1971–2014. Historically, there are 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_{max} time series and placing it on a track that makes landfall. The sampling is weighted towards years whose SST anomaly is close to the SST anomaly of the year being simulated, hence a greater (though 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 category-1+ and category-5 LMIs 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 category-1+ TCs shifts less than two degrees from 1971–2014 to 2015 (101.2°W, 13.3°N to 102.8°W, 13.5°N), while the mean genesis site for landfalling category-5 TCs shifts more than four degrees (101.0°W, 12.9°N to 105.0°W, 13.9°N). The mean category-1+ track has little change, while the category-5 mean track is further west and intersects the coast further north in 2015 than 1971–2014.

We now examine the relationship of basin-wide LMI to SST in a manner independent of the model in order 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) shows the distributions of 1971–2014 TC counts by LMI bin for cold and warm years. There are more TCs in warm years than cold in all the LMI bins. (Historically, of the 13 TCs that reach $V_{\max} \geq 250$ km/hr (category-5), 11 occur in the 23 warm years and 2 in the 21 cold years.) To test 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 warm-to-cold rate ratio is significantly different than unity if it falls outside the random 5%–95% range. Fig 7 (bottom) 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 category-4+ occurrence trends. To test 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. Fig 8 (top) shows the number distribution and 8 (bottom) shows the results of the permutation test. Both category-4 and category-5 rates are significantly higher in warm years than cold. Finally, we note that there is considerable uncertainty on $V_{\max}$ 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/hr standard deviation (i. e., a 10kt 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. TC occurrence near Hawaii is related to El Nino (Chu and Wang, 1997) as well as other modes of natural variability (Murakami et al. 2015a). 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). The mean rates for TCs above the Saffir-Simpson thresholds are shown in Fig 9 (center), along with the 5%–95% confidence range from the bootstrap analysis. For category-1+ the annual rate is $0.033^{0.045}_{0.019}\text{yr}^{-1}$ for 1971–2014 and $0.056^{0.093}_{0.027}\text{yr}^{-1}$ for 2015. For category-3+ the respective values are $0.010^{0.016}_{0.005}\text{yr}^{-1}$ and $0.018^{0.036}_{0.007}\text{yr}^{-1}$. The best-estimate rates are higher in 2015 compared to 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 category-0+ TCs (tropical storm intensity and higher), with a 2015 to 1971–2014 rate ratio of $1.86^{3.18}_{1.10}$, exhibits a significant increase. By comparison, the category-5 ratio is $2.89^{16.0}_{0.25}$.

6. Conclusions

A statistical model of NEPac TCs is presented and 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 category-1+ is $1.24^{1.33}_{1.05}\text{yr}^{-1}$ for 1971–2014 and $1.69^{2.08}_{0.89}\text{yr}^{-1}$ for 2015, a difference that is not statistically significant. The increase in category-5 landfalls, however, is significant: $0.009^{0.011}_{0.006}\text{yr}^{-1}$ for 1971–2014 and $0.031^{0.036}_{0.016}\text{yr}^{-1}$ 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 $7.3^{32.0}_{2.8}$ times more 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. Martinez-Sanchez and Cavazos (2014) found higher NEPac category-4+ occurrence and accumulated cyclone energy during El Nino and neutral states of ENSO than La Nina but no significant change for category-1+. 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. Farfan et al. (2013) found that of the 25 “top” Mexican Pacific landfall events, 20 occurred during El Nino and neutral ENSO states (10 each), but only 5 during La Nina. 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, while the category-1+ rate is not. Intensity in the model depends on SST by

preferential sampling of $V_{\max}$ time series from years whose SST anomaly is close to the anomaly of the simulation year. However, 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 Kossin et al. (2013) and Elsner et al. (2008), which found the largest fractional increases at highest intensities. Similarly Frank and Young (2007) found that NEPac category-3+ TCs display significantly more dependence on ENSO than weaker TCs. The physical mechanisms for this effect remain unclear. However, arguments based on LMI distributions and potential intensity (PI) may be relevant (Sobel et al., 2016): Other factors 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). Consequently, 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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Fig 1.

Tracks from three sample simulations of (a, b, c) 1971–2014 and (d) IBTrACS for the same period. Colors indicate intensity level: category-0+ (blue), category-1+ (yellow), category-3+ (orange), and category-5 (red).

Fig 2.

Landfall counts accumulated from 1971–2014 over all mainland gates at intensities category-0+, category-1+, etc. Shown are means over the 1000-member ensemble of simulations (red), inner 90% across the simulations (yellow), inner 50% (orange), and historical counts (blue). There are zero historical category-5 TC landfalls, which lies inside the inner 50% of the simulation range.

Fig 3.
Landfall rates per 100 yr every 400km along the coast for category-1+ TCs (blue) and category-3+ TCs (red). The subscripts and superscripts indicate the 5% and 95% confidence interval determined by a bootstrap analysis (see text).

Fig 4. Ensemble mean annual landfall rates per gate along the coast for category-1+ TCs (top) and category-5 TCs (bottom) for 1971–2014 (dark blue) and 2015 SST conditions (red). The shaded regions are the inner 90% confidence on the means determined from a bootstrap analysis. Vertical dashed lines are milestone markers along the coast as labeled at top and in Fig 3.

Fig 5. Mean annual TC formation rate distribution (formation events per 10^4 km² per year) for 1971–2014 (left), 2015 (center), and the difference (right). Color scales are the same for the three panels, with red corresponding to the peak 1971–2014 mean rate of 0.66 per 10^4 km² per year.

Fig 6.

Top: Mean annual formation rate distribution (formation events per 10^4 km^2 per year) for simulated TCs with category-1+ LMI for 1971–2014 conditions (left), 2015 SST conditions (center), and the difference (right). Color scales are identical for the three panels, with red corresponding to the peak 1971–2014 mean rate of $0.42 \text{ per } 10^4 \text{ km}^2 \text{ per year}$. Also shown as heavy black curves in the left and center panels are the mean TCs tracks that make category-1+ landfall. Bottom: As in the top, but for category-5 and red corresponding to the peak 1971–2014 category-5 LMI mean formation rate of $0.017 \text{ per } 10^4 \text{ km}^2 \text{ per year}$.

Fig 7.

Top: TC counts 1971–2014 binned by Saffir-Simpson category of LMI in warm (red) and cold (blue) years. Bottom: Warm to cold year rate ratio in the same LMI bins. Black indicates the actual counts and gray is the inner 90% percent from a permutation test. Black outside gray indicates that warm years have significantly higher rates than cold years.

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Fig 8.
As in Fig 6, but for the period 1990–2014.

Fig 9.

Left: Hawaii and the eight gates surrounding it across which TC crossings are counted. Also shown are the historical TC tracks of Fig 1d. Right: Mean annual gate crossing rates in Saffir-Simpson category thresholds (category-0+, category-1+, etc). Blue represents 1971–2014 and red 2015 conditions. The symbol is the best-estimate value, while the vertical ranges indicate the 5%–95% confidence on the means from the bootstrap analysis.