Shifting hotspot of tropical cyclone clusters in a warming climate

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Abstract

Multiple tropical cyclones (TCs) could be present concurrently within one ocean basin, and these clusters can induce compound hazards within a short time window. Whilst the western North Pacific (WNP) has historically been home to most TC clusters, here we show that the North Atlantic (NA) has emerged as a TC cluster hotspot. Using observations and high-resolution climate model simulations, we develop a probabilistic model assuming that TCs are mutually independent and occur randomly. Against this baseline, we identify outliers as clusters with dynamic interactions between TCs. We find that recent global warming pattern induces a hotspot shift in TC cluster from the WNP to the NA by modulating TC frequency and synoptic-scale wave activity. Our probabilistic modeling indicates a tenfold increase in the likelihood of TC cluster frequency in the NA surpassing that in the WNP, from 1.4 ± 0.4% to 14.3 ± 1.2% over the past 46 years.

Main

On September 14, 2020, an extreme tropical cyclone (TC) cluster made headlines, with five TCs entrenched over the North Atlantic (NA). Hurricane Sally, one of the five, struck the contiguous U.S. with heavy rains across the Southeast (Fig. 1a and Supplementary Fig. 1)[1]. That year witnessed an unusually active Atlantic hurricane season, with nine storms forming in succession within 3 weeks (Fig. 1a). Such back-to-back TCs over the NA and their threat to the coastal U.S. have increased in recent decades[2-4], aligning with significant increasing trends in both TC frequency and TC cluster frequency (Fig. 1b). Here, we define TC clusters as two or more TCs present simultaneously within the same basin[5, 6]. Historically, only 40% of TCs appeared alone, with majority of TCs coming in clusters[6]. Beyond the combined impacts of individual TCs, TC clusters can lead to disproportionate damage along coastal regions because infrastructure, communities, and restoration resources cannot bounce back from the damage by the preceding TC within a short period of time[2, 7-9]. In addition, dispatching limited emergency supplies to affected areas is rather difficult when multiple TCs impact different regions concurrently. For example, Hurricanes Harvey, Irma and Maria hit U.S. sequentially within one month in 2017. The Federal Emergency Management Agency failed to provide adequate support to hurricane victims in Puerto Rico when Maria struck because most rescue resources were deployed for the responses to Hurricanes Harvey and Irma[10].

Although the extreme TC cluster in 2020 is relatively new to Atlantic coastlines, East and Southeast Asian coastal regions have long suffered from such temporally compound events. In late summer 2004, over the western North Pacific (WNP), nine disturbances intensified into TCs within 34 days[11, 12], five of which made landfall in East Asia (Fig. 1c). Although the WNP has long been home to most TCs globally, recent decades have witnessed decreasing TC activity in this basin (Fig. 1d). Meanwhile, the TC cluster frequency in the NA has reached or even surpassed that of the WNP nine times since 2005 (red dots in Fig. 1b). This indicates that the NA is emerging as a hotspot for TC clusters, although the underlying mechanisms for this phenomenon remain unclear.

The TC cluster frequency is not a linear function of TC frequency, as confirmed by the low Kendall rank correlation in Fig. 1d. Linking the contrasting trends in TC cluster frequency between the two basins to TC frequency trend is thus not straightforward. Previous studies have analyzed large-scale dynamic and thermodynamic conditions that are favorable for TC genesis to investigate TC cluster formation (e.g. ref.[4-6,13]). Also, recent studies have highlighted changes in TC climatology features, including frequency[14, 15], seasonality[16-18], and duration[19, 20] under anthropogenic warming. However, understanding how these TC climatology features besides the mechanisms at TC genesis influence TC cluster activity remains a challenge.

Two possible conditions for TC cluster formation exist. First, TC genesis may involve physical processes related to pre-existing TC(s), thus contributing to TC cluster formation[21, 22]. TC-induced Rossby wave dispersion[4, 5, 23, 24], synoptic-scale wave trains[12, 25, 26] and other equatorial waves[21, 27, 28] can lead to TC cluster formation, when subsequent TCs are pre-conditioned by synoptic-scale cyclonic disturbances (hereafter, “dynamically connected events”). Second, the TCs in an TC cluster may be independently generated and happen to coincide. Several studies, some mutually conflicting, have tried to delineate the two types of TC cluster formation based on linear wave theory[23, 24] or through case studies aided by numerical simulations[29, 30]. However, the relative importance of the two mechanisms for TC cluster formation remains unknown due to the lack of a robust theoretical framework and reliable diagnostic tools.

The present study develops a probabilistic model to establish a baseline of independent random TC occurrence and then identify dynamically connected TC clusters as outliers from the baseline. This novel method enables us to attribute TC cluster trends to recent La Niña-like global warming pattern.

TC cluster climatology explained by a probabilistic model

We develop a probabilistic framework for stochastic TC cluster simulations with TC parameters estimated from observations during 1979–2024 (Fig. 2; Methods). Probability density functions (PDFs) of TC genesis time are shown in Fig. 2a, b. The window of TC genesis over the NA is confined mainly to August–October, with a yearly peak in September, whereas the window is much wider for the WNP (Fig. 2a, b). Considering the relationship between TC occurrence time and lifespan, we then bin the genesis time into deciles and obtain the corresponding conditional PDF for TC lifespan for each decile of genesis time (Fig. 2c, d), which shows that NA TCs tend to last longer in the TC peak season, and thus TC clusters over the NA tend to concentrated due to the overlap of many long-lived TCs.

According to this framework, we can estimate TC cluster frequency and their total occurrence days (denoted as 'duration') under the assumption that TCs independently and randomly occur (boxplots in Figs. 2e-h). The probabilistic model simulates the observed relationship between TC frequency and TC cluster activity quite well, with most observations (blue dots) falling within the boxplots. Both the TC cluster frequency and duration increase with TC frequency.

We further couple the probabilistic model with seven high-resolution climate models capable of resolving TC activity[31, 32] (CMIP6-HighResMIP; Methods; Extended Data Figs. 1 and 2). Simulated TC cluster features from these full-physics high-resolution climate models align well with the estimation in the probabilistic modeling. Compared to linear regression results (red lines), the probabilistic simulations (boxplots) better capture the increasing tendency from zero at a relatively low TC frequency and the saturation behavior of TC cluster frequency at higher TC frequency. This saturation is intrinsic to the TC cluster definition, as a high TC frequency leads to persistent overlap among multiple TCs, causing a level off or even a decline in TC cluster frequency (Extended Data Fig. 2a). Thus, TC cluster duration may serve as a better indicator of potential TC cluster hazards under high TC frequency conditions.

To further validate the model across other basins, we perform probabilistic simulations in all six major TC genesis basins based on observations and the multi-model ensemble (MME) of the seven high-resolution climate models from CMIP6-HighResMIP (Extended Data Figs. 3 and 4). The TC cluster frequency and duration are well distributed in the boxplots generated by Monte Carlo simulations across the six basins. This result indicates that the effect of TC climatology in frequency, lifespan, and genesis time predominantly govern TC cluster climatology, and the probabilistic model can be used to decompose the relative contributions of each individual parameter to TC cluster changes.

Changing TC cluster activity and its drivers

The probabilistic framework enables us to vary one parameter while keeping the others fixed to disentangle the individual contributions of changes in TC climatology features to changes in TC cluster activity (Methods). The quantitative contributions of each parameter in both observations and model projections are presented in Fig. 3a-h and Extended Data Tables 1 and 2. During the recent 46 years, there has been an increase in TC cluster frequency by 2.3 events and an increase in duration by 7.8 days over the NA. Conversely, the frequency of TC clusters has decreased by 1.3 events, and the duration has decreased by 11.6 days over the WNP. The contrasting changes in TC cluster activity between the NA and the WNP are projected to continue through mid-21st century in the MME and individual model projections (Supplementary Table 1)[6]. These changes are well captured by the probabilistic modeling, except for a marked underestimation of the projected decrease in TC cluster frequency over the WNP (Fig. 3f), which explains only 54.7% of the TC cluster changes.

The bias of the probabilistic model arises from both model uncertainty and systematic error, with the latter due to assuming TCs in clusters are generated independently. Intense TCs can induce alternating cyclonic and anti-cyclonic disturbances, as observed in 2004 over the WNP (Fig. 1b), leading to subsequent TCs in the wake of pre-existing TCs[12]. Such dynamic processes, involving enhanced synoptic wave trains, are favorable for TC cluster formation[5, 22, 24, 33], contributing to the systematic underestimation of TC cluster frequency in the probabilistic model (Fig. 3i-j). In contrast to TC cluster frequency, the bias distribution of TC cluster duration does not show a robust positive shift from zero in the mean value (Fig. 3k-l), likely due to damping effects by the randomized TC lifespan. Especially, the bias distribution for TC cluster frequency over the WNP (Fig. 3j) exhibits statistically significant differences between the future (2020–2049) and historical (1981–2010) periods, as shown by Kolmogorov-Smirnov (K-S) test ($p<<0.01$), which mainly stems from a shift in the model's mean bias. This significant shift can partially explain the probabilistic model's failure to simulate the projected decrease in TC cluster frequency over the WNP (Fig. 3f). The underlying physical processes of this discrepancy are investigated in the following section.

An increase in TC frequency can directly enhance TC cluster activity, as shown in Fig. 2e-f. TC seasonality and lifespan influence TC cluster activity by modulating the genesis time interval and the likelihood of overlap between TCs, respectively. In general, TC frequency change is the primary contributor to TC cluster change, explaining 46.0% to 128.4% of TC cluster changes (Fig. 3a-h; Extended Data Table 1 and 2). Changes in TC lifespan and seasonality play a secondary role in regulating TC cluster activity over time. Observed changes in TC lifespan and seasonality lead to 8.5% reduction in TC cluster frequency and 17.5% reduction in TC cluster duration over the NA. These results may be due to the recent increase in short-lived TCs over the NA[19]. The probabilistic model explains a larger portion of the changes in TC cluster activities when focusing on relatively long-lived TCs (lasting ≥ 2 days; Extended Data Fig. 5).

Note that the relationship between TC lifespan and genesis time may introduce additional complexity. However, our decomposition results show that the contributions of collaborate changes in TC lifespan and seasonality can be linearly reconstructed based on each parameter's individual contribution (the last three columns in Extended Data Table 1 and 2), thereby enhancing our confidence in the results within the probabilistic framework.

Identification of dynamically connected TC clusters

In the Northern Hemisphere, TCs typically move northwestward due to climatological steering flow and the Beta effect[34]. If a TC is pre-conditioned by a Rossby wave train or other synoptic-scale disturbance linked to a pre-existing TC, the genesis location of this new TC will most likely be in the southeastern quadrant relative to the pre-existing one because of the wave energy dispersion under easterly vertical wind shear[4, 5, 24]. We evaluate the likelihood of a new

TC formation southeast of the pre-existing TC against the random probabilistic framework to identify dynamically connected TC clusters.

We begin by comparing the spatial distribution of newly formed TCs relative to pre-existing TCs in the outlier group and the normal group (Methods). Outliers are defined as TC clusters with yearly frequency or duration (e.g., blue dots in Fig. 2e) that is above the 95th percentile of the Monte Carlo simulations (e.g., boxplots in Fig. 2e), while events positioned at the median value of the Monte Carlo simulations are categorized as the normal group. In both groups, the largest proportion of TCs is located in the southeastern quadrant of the pre-existing TCs because of the general west-poleward propagation of TCs (Fig. 4a-d). Notably, however, a higher concentration of TCs is observed within this quadrant in the outlier groups in both the NA and WNP, with ratios increasing by 10.53% and 5.12%, respectively. These results suggest that the increased TC ratio in the wake of pre-existing TCs (that is, the southeastern quadrant) is likely associated with active dynamic connections between TCs. The enhanced activity of synoptic-scale wave trains may lead to an underestimation by the probabilistic model. Similar conclusions are drawn from observational data, except for results categorized by TC cluster duration over the WNP (Supplementary Fig. 2).

To validate robustness of the contribution from dynamic connections, we gradually increase the threshold used to define outliers from the 0th to the 95th percentile (Methods), and investigated the changes in TC ratio in the southeastern quadrant (Fig. 4e, f). The ratios remain nearly unchanged at lower percentile thresholds and rapidly increase once the threshold reaches the 70th percentile. Ratios calculated based on data below the 50th percentile are significantly different from those in the second half, indicating a robust signal of dynamic connections. Previous attempts to detect dynamically connected events by comparing differences between TC clusters conditions with a climatological base state[12, 33] and single TC conditions[5, 24] suffer from an inaccurate baseline, while numerical case studies[29, 30] are limited by insufficient sample sizes. Our study sidesteps these issues, presenting a more accurate baseline from the probabilistic model with adequate samples based on the MME with seven full-physics climate model simulations. Systematic deviations from this baseline arise from neglecting dynamically connected events. This approach novelly identifies the role of dynamic connections in TC clusters and their underlying physical drivers as demonstrated below.

Shifting hotspot driven by the surface warming pattern

Local and remote SST forcings modulate synoptic-scale wave variability through large-scale circulations[12, 35, 36](Methods). We investigate the SST patterns that favor dynamic connections between TCs (Fig. 5a-d; Methods). The enhanced dynamic connections between TCs over the WNP and NA are associated with El Niño and La Niña conditions, as evidenced by both climate model simulations and observations (Fig. 5a-d). Observational composites of synoptic-scale wave intensity for the corresponding groups of years (categorized into outlier years and normal years) support the linkage between dynamically connected TC clusters and enhanced synoptic disturbance activity (Fig. 5e, f; Supplementary Fig. 3 for validation in another reanalysis). Synoptic-scale wave activities strengthened over the broad subtropical NA, while synoptic-scale wave intensity anomalies are characterized by a northwest-southeast oriented band in the WNP. In these regions with large zonal wind shear, synoptic-scale wave trains can develop by converting barotropic energy from the mean flow[13]. Similar patterns are observed when composites are grouped based on TC cluster duration (Supplementary Fig. 4).

La Niña events can increase TC frequency in the NA by reducing the vertical wind shear[37, 38], whereas they primarily redistribute TC genesis locations in the WNP with a slight decrease in TC frequency[39, 40]. In addition to direct TC frequency changes, we show that the contrasting effects of ENSO on TC cluster frequency and duration over the two basins can be further reinforced by changes in dynamically connected events, especially for the WNP. The lower Kendall rank correlation between TC frequency and TC cluster frequency over the WNP, compared to the NA, also confirms the weaker influence of TC climatology features on TC cluster formation in this basin (Fig. 1c, d).

Recent decades have witnessed a cooling trend over the tropical Pacific, known as La Niña–like warming[41]. While it is known that interannual ENSO causes seesaw changes in TC cluster activity between the two basins, the impacts of La Niña–like global warming pattern on TC cluster activity need to be further qualified. We take daily outputs of the highresSST-present and highresSST-future simulations from MRI-AGCM3-2-H, whose results show good agreement with the MME in projected changes in TC clusters over the NA and WP (Supplementary Table 1). As the forced warming pattern between the two periods (1981–2010 and 2020–2049) after tropical mean warming rate subtracted is similar to the observed cooling in tropical Pacific (Extended Data Fig. 6), the differences in synoptic-scale wave intensity are taken as the responses to the recent La Niña–like global warming pattern (Fig. 5g, h). The synoptic-scale wave intensity is projected to increase across the NA (Fig. 5g), indicative of enhanced dynamic connections. Meanwhile, there is a significant decrease in synoptic-scale wave intensity over the mean flow confluence regions in the WNP (Fig. 5h), indicating that the La Niña–like global warming pattern will lead to suppression of the dynamically connected TC clusters over the WNP by reducing barotropic energy conversion. In addition, the widespread increase and decrease synoptic-scale wave intensity over the two basins agree well with TC track density changes (Fig. 5g, h), implying contrasting trends in TC frequency by changes in pre-TC synoptic-scale disturbances, which typically refer to as "TC Seeds"[35, 42-44]. Observational evidence confirms that the increase in TC frequency over the NA and decrease over WNP are associated with tropical Pacific cooling and warming elsewhere, including the positive Atlantic Multidecadal Oscillation (AMO)-like anomalies (Extended Data Fig. 7)[45-48]. These results, together with findings in Fig. 5e-h, suggest that long-term La Niña–like global warming pattern (Extended Data Fig. 6) contributes to contrasting changes in TC clusters over the NA and WNP in both observations and model projections through modulating TC frequency and synoptic-scale wave intensity.

Above analysis shows that changes in synoptic-scale wave intensity driven by the recent La Niña–like global warming pattern can further increase (decrease) dynamically connected TC cluster activity over the NA (WNP), leading to a systematic bias in the probabilistic model (Fig. 3i-k). The significant decrease in model bias in projected TC cluster frequency in the WNP is closely related to the suppression of dynamically connected events under forced La Niña–like warming conditions (Fig. 3j). We highlight that the changes in synoptic-scale wave intensity driven by surface warming patterns, which regulate the dynamic connections between TCs, are a non-negligible factor for TC cluster changes.

Discussion

We have developed a probabilistic model to investigate changes in TC cluster activity over the NA and WNP, and disentangle the individual contributions of changes in TC climatology features to TC cluster changes. This model is used as a baseline for random occurring independent TCs, against which we identify outliers as dynamically connected TC clusters. This approach sidesteps the uncertainties arising from limited sample sizes and establishes a more accurate baseline to identify dynamically connected TC clusters. We reveal that the NA has recently emerged as a TC cluster hotspot due primarily to the increased TC frequency and dynamically connected TC clusters driven by the recent La Niña–like global warming pattern. Whether this warming pattern is internally generated or externally forced remains an open question and warrants further investigations. Nonetheless, we find that the contrasting trends in TC cluster frequency between the NA and WNP remain robust even when the study period is extended to 1961 (Supplementary Fig. 5), implying the presence of a long-term change signal that goes beyond the impacts of inter-decadal variability. We perform a suite of high-resolution climate model experiments with different global warming patterns to test the hypothesis (Methods). When forced with the observed La Niña–like global warming pattern over 1960–2014, the hotspot for TC clusters shifts from the WNP to the NA basin (Extended Data Fig.8). When forced with the projected El Niño–like warming, the TC cluster activities are suppressed in both basins, with a larger decrease occurring over the WNP. Future studies can further quantify the basin-dependent contributions of inter-decadal variability and long-term warming trends to the shifting TC cluster hotspot observed in recent decades.

Estimated based on TC climatology feature changes, the possibility for TC cluster frequency over the NA to exceed that of the WNP has sharply increased, by as much as tenfold from 1.4 ± 0.4% to 14.3 ± 1.2% over the past 46 years (Methods). With the ongoing Pacific decadal cooling, this likelihood will further increase when changes in dynamically connected TC clusters are considered, highlighting a rapidly growing TC cluster threat to coastal NA. The probabilistic model well represents TC cluster climatology when extended to other TC basins, suggesting that the model is a useful framework to study the underlying dynamics and physical drivers of TC cluster activity on a global scale.

Investigating systematic biases in probabilistic modeling based on seven full-physics high-resolution climate models, we robustly identify the role of enhanced synoptic-scale wave intensity in dynamically connected TC clusters. However, quantifying this contribution from dynamically connected events remains a challenge and should be further pursued. Regardless, our research highlights the importance of TC clusters for hazard assessment, which often assumes independent TC events. Future research could explore more sophisticated modeling to explicitly capture dynamic interactions within TC clusters and investigate the landfall phase of TC clusters to support hazard assessment frameworks toward better representation of such temporally compound events.

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Author Contributions Statement

W.Z. supervised the study. Z.-H.F. and D.X. initiated the idea and designed the research in discussion with S.-P.X., W.Z., and N.L.. Z.-H.F. performed the probabilistic modeling, conducted the analysis, and produced the figures. J.Z. and J.C.L.C. helped improve the probabilistic model. S.-P.X. and J.Z. suggested further validation in a high-resolution climate model. J.Z. performed the HIRAM experiments. X.W. processed the synoptic-scale wave intensity data. Z.-H.F. and D.X. wrote the initial manuscript. All authors contributed to interpreting the results and improving the manuscript.

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Competing Interests Statement

The authors declare no competing interests.

Figure Legends

Fig. 1 | Extreme TC cluster seasons and observed changes in TC frequency and TC cluster frequency. a, c, TC activity from August 31 to September 23, 2020, in the NA (**a**) and from August 4 to September 7, 2004, in the WNP (**c**). The histogram shows the daily TC counts within the period, and the map shows colored tracks for each TC. Hurricane Paulette (red line in **a**) regenerated into a TC after its extratropical transition, so we connected the two tracks with a dotted line. **b, d,** Time series of TC frequency (blue lines) and TC cluster frequency (orange lines) during 1979–2024 over the NA (**b**) and WNP (**d**). Kendall rank correlations (Tau) between TC frequency and TC cluster frequency are shown at the upper left. The linear trends of TC frequency (T1) and TC cluster frequency (T2) are plotted as dotted lines, with the associated 10-year trend values presented in the upper panel. Asterisks denote significance at the 95% confidence level based on the 1000-sample bootstrapping. Bold dots in **b** indicate that the frequency over the NA reaches or exceeds that over the WNP, occurring in five years for TC frequency and ten years for TC cluster frequency during 1979–2024.

Fig. 2 | Probabilistic modeling of TC clusters. a, b, Histogram and PDF of TC genesis time in the NA (**a**) and WNP (**b**) derived from the 6-hourly best track dataset during 1979–2024. **c, d,** Joint distribution of TC genesis time and lifespan in the NA (**c**) and WNP (**d**). The average values of TC lifespan in every 10th percentile of TC genesis time are plotted as blue lines, and the shaded area indicates the range of the first quartile to the third quartile of the data. **e, f,** Relationship between yearly TC frequency and yearly TC cluster frequency in the NA (**e**) and WNP (**f**) in observations (blue dots) and 1000 Monte Carlo simulations (boxplots) during 1979–2024. **g, h,** Same as in **e, f** but for TC cluster duration. Linear regressions between TC frequency and TC cluster frequency/duration in observations are shown as red lines, with 95%

confidence intervals shaded based on the two tailed Student's t-test. The function, R-squared (R^2), and p-value ($p<<0.01$) of the models are presented at the upper left. In each boxplot, the box spans from the first quartile to the third quartile of the data, with a line marking the median. The whiskers extend from the box by 1.2× the interquartile range.

Fig. 3 | Quantifying contributions of TC climatology changes to TC cluster changes in probabilistic modeling. a, b, Observed TC cluster frequency change (yellow histogram) and the changes simulated by probabilistic modeling (boxplots) between 1979–2001 and 2002–2024 (the latter minus the former) in the NA (**a**) and WNP (**b**). Contributions from changes in TC climatology ('All') and individual parameters are simulated by varying the given parameter(s) while keeping the other(s) fixed (Methods). The boxplots show the averages of every 1000 Monte Carlo simulations (in total, 100 averages). The box spans from the first quartile to the third quartile of the data, with a line marking the median. The whiskers represent the range from the 5th to the 95th percentile of the data. Asterisks indicate that the mean value is significantly different from zero at the 95% confidence level based on the 1000-sample bootstrapping. **c, d,** Same as in **a, b** but for TC cluster duration with periods between 1979–2001 and 2002–2024. **e-f,** Same as in **a-d** but for the MME of seven high-resolution climate models from CMIP6-HighResMIP with periods between 1981–2010 and 2020–2049. **i, j,** Deviations of average TC cluster frequency in probabilistic modeling from model outputs scaled by the standard deviation of residuals in corresponding linear regression models in the NA (**i**) and WNP (**j**) based on the MME. **k, l,** Same as in **i, j** but for TC cluster duration. The blue and red vertical dotted lines in **i-l** denote the mean bias of the probabilistic model during 1981–2010 and 2020–2049, respectively. The p-value of the K-S test used to test the statistical difference between the bias distributions during the two periods is shown at the upper left of **i-l**.

Fig. 4 | Identification of dynamically connected TC clusters. a, b, Relative locations between pre-existing TCs (red star) and subsequent TCs (orange dots) at the cyclogenesis time of the subsequent TCs in the outlier group (left) and normal group (right) categorized by TC cluster frequency in the NA (**a**) and WNP (**b**) based on the MME of the highresSST-present simulation in seven high-resolution climate models from CMIP6-HighResMIP during 1950–

2014. **c, d,** Same as in **a,b** but categorized by TC cluster duration. Percentages of subsequent TCs in each quadrant are indicated in the four corners. Considering wave energy dispersion for limited distance, our analysis focuses on a region extending 35° north and south in latitude and 50° east and west in longitude from each pre-existing TC. **e, f,** Percentages of subsequent TCs located in the southeastern quadrant with different percentile thresholds to define the outlier group in the NA (**e**) and WNP (**f**), categorized by TC cluster frequency (red lines) and TC cluster duration (blue lines) (Methods). The average ratios between the two regimes, separated by a threshold of 50%, are plotted as dotted lines. The mean ratios between the two stages are statistically different with p-values less than 0.01 based on the 1000-sample bootstrapping.

Fig. 5 | Patterns of SST and synoptic-scale wave activity that are favorable for dynamically connected TC clusters. a, b, Composite differences in SST (K) between TC cluster outlier group and normal group during 1950–2014 based on the MME of the highresSST-present simulations from CMIP6-HighResMIP. To isolate the dynamically connected TC clusters from randomly generated events, the normal and outlier groups are categorized by the 15th and 95th percentile of TC cluster frequency based on the probabilistic modeling in the NA (**a**) and WNP (**b**) (Methods). **c, d,** Same as in **a, b** but for observations with two groups divided by 50th percentile of TC cluster frequency during 1979–2024, to ensure a sufficient and comparable sample size for the two groups. **e, f,** Same as in **c, d** but for differences in synoptic-scale wave intensity (10^{-6} s^{-1}) over the NA (**e**) and WNP (**f**). **g, h,** Impacts of long-term La Niña–like warming in the tropical Pacific on synoptic-scale wave activity (shading) and TC track density (contour) in the MRI-AGCM3-2-H experiments in the NA (**g**; [0.5, 1] red contours) and WNP (**h**; [-1.5, -0.5] blue contours). As the SST trend in the experiments between the periods 1981–2010 and 2020–2049 shows a cooling in the tropical Pacific (Extended Data Fig. 7), the differences in synoptic-scale wave intensity and TC track density are considered to be forced by La Niña–like global warming pattern. Averages of changes are shown for TC peak seasons in each basin (i.e., JAS for the NA and JASO for the WNP). In all panels, the dots indicate statistically significant differences at a 95% confidence interval based on the 1000-sample bootstrapping and false discovery rate test.

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Methods

<u>Probabilistic TC cluster model</u>

To statistically analyze the climatology of TC clusters, we design a probabilistic TC cluster model based on a probabilistic TC occurrence model developed from refs [2, 3]. Within this modeling framework, we do not account for the dynamic connections between TCs in a TC cluster, i.e., the occurrence of each TC is assumed to be independent of the occurrence of the others. Thus, the probabilistic model can serve as a TC cluster baseline contributed by randomly occurring independent TCs. The deviations from this baseline can be used to identify the dynamically connected TC clusters.

The model consists of three parameters, namely the annual basin-wide TC genesis frequency n, the date of TC genesis T, and the TC lifespan D. Here the genesis frequency n is a deterministic value either obtained from historical observations and simulations or prescribed as a given value, while the genesis date T and the duration D of each of the n TCs are considered to be random variables. The genesis date and duration of TCs are shown to be correlated (Fig. 2c, d). However, limited historical observations and climate simulations prevent a robust estimation of the joint probability distribution of the two variables. Instead, we first obtain the kernel density estimations (KDE) of TC genesis time T. Then we bin every 10th percentile of T and obtain the conditional PDF of TC lifespan D for each bin of T using the KDE. The estimation is performed for historical observations in each basin, and for two periods (1950–2014 and 2015–2050) for each climate model simulation.

For each year, with a fixed number of TCs, we apply the KDE of T and the conditional KDE of D to perform 1000 Monte Carlo simulations of the genesis date and duration of TCs in that year. In each Monte Carlo simulation, when two or more TCs co-exist simultaneously, we count it as one TC cluster event (frequency) and document the duration of the co-existence as the duration of the TC cluster (days). The simulated TC cluster frequency and duration of the 1000 Monte Carlo members are used to represent the climatology of the TC cluster.

Decomposing the contribution to TC cluster changes from TC climatology features

The abovementioned probabilistic model enables the flexibility to investigate the influence of the change in each individual feature of TC climatology on changes in the frequency and duration of TC cluster activity. We perform the sensitivity tests to decompose the impact from genesis frequency n ('Fre.'), date of TC genesis T ('Time'), and TC lifespan D ('Life.') individually, as well as the joint impact from the changes in T and D together ('L+T') on TC cluster changes. To study the individual influences in MME, we change one parameter at a time from its historical probability distribution during 1981–2010 to its future probability distribution during 2020–2049 estimated from climate model outputs, while keeping the other parameters the same as their historical values. We also investigate the individual influence of the changes in observations between 1979–2001 and 2002–2024. We repeat these sensitivity experiments 100 times (that is, 100000 simulations in total) for every parameter to obtain statistically robust results. The differences between the estimated probability distributions of the simulated TC cluster frequency or duration and the historical probability distributions are used to represent the influence of the selected parameter(s). To estimate the change in the possibility of NA TC cluster frequency exceeding that of the WNP in observations, we compare the simulated TC cluster frequency over the NA and WNP in the two periods (1979–2001 and 2002–2024) by the probabilistic model. The possibility is calculated as the percentage of instances where the TC cluster frequency over the NA surpasses that of the WNP.

Observational data

TC best-track data are obtained from the International Best Track Archive for Climate Stewardship[49] (IBTrACS), which is compiled by six Regional Specialized Meteorological Centers and four Tropical Cyclone Warning Centers affiliated with the World Meteorological Organization. We use 6-hourly TC records for the period of 1979–2024 in the NA and WNP, as data quality before 1979 is poor due to the absence of routinely used geostationary satellites for monitoring. Thus, pre-1979 records should be interpreted with caution due to observational limitations. Nevertheless, extending the TC dataset to the 1950s will not alter the contrasting TC cluster trends between the NA and WNP (Supplementary Fig. 5). TC records from 1979 to 2022 are also analyzed for the other four basins, the East Pacific (EP), North Indian (NI), South Indian (SI), and South Pacific (SP). Since our focus is on TC genesis and its persistence in a basin rather than its intensity — a parameter that suffers from significant uncertainty[50] — our probabilistic model results are not sensitive to the dataset selection. We considered only TCs that reached at least tropical storm intensity ($\geq$ 35 kt) during their lifetime. However, our conclusions remain unchanged when tropical depressions, extratropical cyclones, and subtropical storms are included (Supplementary Fig. 6).

Monthly SST data are obtained from the Extended Reconstructed Sea Surface Temperature version 5 (ERSST.v5) [51] during 1950–2024. To calculate synoptic-scale wave intensity, we use 6-hourly zonal and meridional wind data at 850 hPa during 1979–2024, based on the fifth-generation atmospheric reanalysis from the European Centre for Medium-Range Weather Forecasts (ERA5) [52]. We also analyze the results using daily reanalysis data from the

National Centers for Environmental Prediction–Department of Energy (NCEP/DOE Reanalysis II) during 1979–2020. Consistent with the findings from ERA5, the synoptic-scale wave intensity patterns exhibit a northwest-southeast oriented enhanced band over the WNP and a uniformly enhanced band over the NA in the NCEP/DOE dataset (Supplementary Fig. 3). We exclude the linear trends of the data to eliminate the possible influence of global warming when investigating the favorable SST pattern for dynamically connected TC clusters.

High-resolution climate simulations

The CMIP6-HighResMIP initiative employs a multi-model framework to evaluate the regional impacts of climate change on TC activity[53]. In this study, we analyze Tier 1 and Tier 3 simulations from seven high-resolution climate models: CNRM-CM6-1-HR[54]; EC-Earth3P-HR[55]; HadGEM3-GC31-HM[56]; MRI-AGCM3-2-S[57]; MRI-AGCM3-2-H[57]; NICAM16-8S[58]; and NICAM16-7S[58] (detailed in Supplementary Table 2). Limited in simulating observed warming pattern, coupled models are not included, which generally have poor performance in simulating the TC climatology and observed interannual variability of TC activity[59, 60]. Tier 1 comprises atmosphere-only simulations forced by observed daily SST and sea ice concentration from HadISST2 spanning 1950–2014 (referred to as ‘highresSST-present’). Tier 3 extends Tier 1 simulations through 2049 or 2050, with an option to continue to 2100 under scenario SSP585 (referred to as ‘highresSST-future’). For Tier 3, SST forcing incorporates the local warming rates derived from an ensemble mean of CMIP5 RCP8.5 simulations and includes interannual variability from observational data. Model resolutions are set at 50 km or finer to capture key statistics of TC climate and variability, such as genesis frequency, spatial distribution, and intensity[32]. Original TC tracks are identified by the TRACK algorithm in Ref. [61], which detects TCs by tracking vorticity features on a common T63 spectral grid and accounting for warm-core criteria and storm lifespan. We focus on the first ensemble member from each model and compare the differences between 1981–2010 and 2020–2049 based on the MME results.

Since HighResMIP simulations do not provide the SST variable online, we use variable surface air temperature (SAT) as a substitute[6] to show long-term changes in SST patterns. To ensure data reliability, we assess the Niño3.4 index derived from both observed SST and SAT in the highresSST-present simulation spanning 1979–2014 (Supplementary Fig. 7). The high correlation coefficient between the indices suggests that the SAT serves as a reliable proxy for SST.

The SST patterns in Fig. 5a, b are composited on a year-to-year timescale without any trend information, and therefore the intensified synoptic-scale wave in the dynamic connections cannot be directly attributed to the decadal SST warming pattern in the tropical Pacific (Extended Data Fig. 6). To confirm the effects of surface warming patterns on dynamically connected events, we use daily outputs from the MRI-AGCM3-2-H model to calculate the changes in synoptic-scale wave intensity. This model has good agreement with the MME in projected changes in the NA and WNP (Supplementary Table 1). In highresSST-future simulations, the model is forced by patterned warming from an ensemble mean of CMIP5 to 2050 plus observed interannual variability. The differences between the periods 1981–2010 and 2020–2049 are a La Niña–like warming pattern after tropical mean warming rate subtracted shown in Extended Data Fig. 6a, b. Therefore, the changes in synoptic-scale wave intensity between the two chosen periods can be considered as the responses to La Niña–like global warming patterns.

Constraint detection for simulated TC tracks

In this study, we define TC track density at a grid point with a 1° resolution as the number of TCs passing through a 15° longitude × 15° latitude area centered at that grid point. We select a 15°×15° box to capture synoptic waves (such as equatorial Rossby waves, mixed Rossby–gravity waves, and easterly waves) that could trigger TC genesis[62].

The simulated global distribution of TC track density without constraints is shown in Supplementary Fig. 8a, which shows large overestimations, particularly in the WNP, NI, and Southern Hemisphere. These overestimations stem from uniform detection parameters and wind speed thresholds, leading to excessive TC frequency in very-high-resolution climate models[6]. To mitigate the bias and ensure equitable representation of each model in the MME, we implement additional constraints based on the TRACK algorithm, detailed in Supplementary Table 2. Due to the different parameterization schemes used in simulating the planetary boundary layer, some high-resolution models tend to reach very strong wind speed artificially (such as NICAM16-8S and NICAM16-7S)[63]. We increase the wind speed thresholds in these models since our focus is TC frequency rather than intensity. Furthermore, we use a relatively weak constraint on lifespan to retain short-lived TCs, which might become more prevalent in the future[19]. Besides the traditional wind speed and duration criteria, we further filter out storms generated in the region where climatological SST is lower than 26°C, which are often misinterpreted as TCs in the TRACK algorithm[64].

The bias of TC track density is largely reduced after the constraint detection methods are implemented, although an overabundance of TCs persists in the NI, likely due to the misidentification of monsoonal low-pressure systems[65, 66] (Supplementary Fig. 8b, c). TC frequency across six basins agrees better with the observations, particularly for the WNP. Additionally, the standard deviations of TC frequency in the MME are reduced to levels comparable to the observations, indicative of the improvement of the constrained results (Supplementary Table 3).

Outlier analysis

The observed and simulated TC cluster frequencies and durations (blue dots in Fig. 2e-h) that exceed the 95th percentile of the respective Monte Carlo simulations (boxplots) are defined as outliers. To maintain an adequate sample size, events falling within the 5th to 95th percentiles of the simulations are included in the normal group for comparison with the outlier group, as depicted in Supplementary Fig. 2. In the Monte Carlo simulations based on climate model outputs, events positioned at the median value of the boxplots are considered as the normal group for comparison (Fig. 4a-d), ensuring a comparable sample size with outlier groups.

We investigate the relative locations between pre-existing TCs and subsequent TCs within TC clusters and quantify the TC ratio in each quadrant. The wave energy dispersion in synoptic trains cannot extend beyond 5000 km due to its decaying feature and basin size[67], and thus we only utilize the results within a 35-degree latitudinal and 50-degree longitudinal distance. The different ratios between the abovementioned outlier and normal groups are attributed not to the co-occurrence of independent stochastic arrivals but to dynamic connections between TCs, as evidenced by enhanced synoptic wave intensity (Fig. 5e, f). Furthermore, we modify the threshold for defining outliers, incrementally increasing from the 0th to the 95th percentile (in

5-percentile intervals) of the Monte Carlo simulations, and calculate the corresponding ratio of subsequent TCs located in the southeastern quadrant to confirm the role of dynamic interactions in increasing TC cluster activity. The sample sizes of the outlier group at each percentile threshold in the climate simulations are sufficiently large to yield robust conclusions (Supplementary Fig. 9). The conclusions remain unchanged when no constraints on distance are applied (Supplementary Fig. 10).

To determine the underlying mechanisms for dynamically connected TC clusters, we composite the differences in SST and synoptic-scale wave intensity according to the deviations of the probabilistic model as follows. In the highresSST-present simulations (1950–2014), we classify the two groups as above the 95th percentile and below 15th percentile. In observations, we divide the years into two groups based on whether the TC cluster frequency reaches the 50th percentile of the probabilistic simulations, to ensure a sufficient and comparable sample size for the two groups, and the results remain consistent when using TC cluster duration for classification (Supplementary Fig. 4). We compute the differences in SST and synoptic-scale wave intensity during the TC season from July to October (JASO) for the WNP[68] and from August to October (ASO) for the NA[69].

<u>Synoptic-scale wave activity</u>

The lower-tropospheric synoptic-scale wave train favors dynamically connected TCs[12, 24]. To quantify the synoptic-scale wave activity, we apply a Butterworth bandpass filter to daily zonal and meridional wind data at 850-hPa, with half power at 3 and 7 days (denoted as u^s and v^s, respectively). The standard deviation of the synoptic-scale relative vorticity (ζ^s) is subsequently utilized as a metric for the intensity of the wave train. The synoptic-scale relative vorticity in the spherical coordinate system can be calculated as follows[25, 70]:

$$\zeta^s = \frac{\partial v^s}{\partial x} - \frac{\partial u^s}{\partial y} + \frac{u^s}{a}\tan\varphi \qquad (1)$$

where ζ^s indicates the synoptic-scale relative vorticity (in s^{-1}), a is the radius of the Earth (in meters), and φ is the latitude (in radians).

To assess the intensity of the synoptic-scale wave train for a specific month, we compute the standard deviation of the synoptic-scale relative vorticity in that month in a given grid. This approach allows a detailed analysis of wave train intensity month by month.

HIRAM experiments

To confirm the effects of long-term warming patterns on TC clusters, we conducted numerical experiments using the high-resolution atmospheric general circulation model (HIRAM-C180) developed by the Geophysical Fluid Dynamics Laboratory (detailed in ref. [71]). The model features a horizontal resolution of approximately 50 km with 32 vertical levels, making it comparable to the high-resolution climate models used in this study.

We design three experiments, a control (CTRL) run and two future climate (GWLA and GWEL) runs, to elucidate the influence of different warming patterns. The CTRL run is forced by the observed monthly mean SST. The GWLA run is driven by a La Niña–like global warming pattern, represented by the SST in the CTRL run plus the observed SST trend over 1960–2014. In the GWEL run, the model is forced by the SST from the CTRL run combined with an El Niño–like global warming pattern, derived from the MME of 12 CMIP5 models for the 2006–2099 period under the RCP8.5 scenario (similar to CMIP6-HighResMIP and refs. [72,73]). A widely used TC detection algorithm (www.gfdl.noaa.gov/tstorms/) for global climate models is used to detect TCs in the simulations. The model simulations were conducted from January 1990 to December 2009 for each run. In our analysis, differences in TC cluster activity between the GWLA (GWEL) and CTRL runs, evaluated through 55-year resampling repeated 1000 times, are taken as the response to the La Niña–like (El Niño–like) global warming pattern (Extended Data Fig. 8).

It is important to note that inter-decadal variability in SST may influence the results. To minimize this impact, we selected the period 1960–2014, during which the positive and negative phases of the AMO and Interdecadal Pacific Oscillation (IPO) are largely offset[73]. Nevertheless, we found that the La Niña–like global warming pattern persists regardless of the chosen periods (Supplementary Fig. 11), consistent with ref. [41].

Statistical significance test

In our study, all significance tests are conducted at the 95% confidence level. Kendall rank correlation is used to evaluate the correspondence of TC cluster frequency and TC frequency, which measures the similarity of the ordering of the two series when ranked by each of the quantities[74]. Before coupling the probabilistic model with observations and model simulations, we evaluate the independence of TC frequency, duration, and genesis time distributions using the Chi-squared test. We use the deviations of the probabilistic model from model outputs scaled by the standard deviations of residuals in the linear regression model in TC cluster frequency/duration to represent normalized bias distribution. This approach enables inter-basin comparisons of bias distributions in the probabilistic modeling. To determine the changes in bias distribution between the two periods in the probabilistic model, we conduct a K-S test. A 1000-sample bootstrapping approach is applied to evaluate the linear trends in both TC frequency and TC cluster frequency, as well as the differences in TC ratio, SST, and synoptic wave intensity between two given periods[75]. The false discovery rate test is also used to assess the significance of grid points in the spatial pattern[76, 77]. The uncertainty of the linear regression model is represented by the standard deviation.

Data Availability

The data that support the findings of this study are all openly available online. The best-track TC data with 6 h temporal resolution are available at https://www.ncei.noaa.gov/products/international-best-track-archive. The CMIP6-HighResMIP data are openly available at https://data.ceda.ac.uk/badc/cmip6/data/CMIP6/HighResMIP. The daily wind fields at pressure levels from MRI-AGCM3-2-H in CMIP6-HighResMIP can be downloaded at https://aims2.llnl.gov/search/cmip6/. The tropical storm tracks calculated by the TRACK algorithm can be downloaded at https://catalogue.ceda.ac.uk/uuid/0b42715a7a804290afa9b7e31f5d7753. Hourly reanalysis data on pressure levels from the ERA5 at https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-era5-single-levels?tab=overview, and from the NCEP/DOE Reanalysis II at https://psl.noaa.gov/data/gridded/data.ncep.reanalysis2.html. ERSST.v5 data from NOAA are available at https://psl.noaa.gov/data/gridded/data.noaa.ersst.v5.html. All the map figures (Fig. 5 and Extended Data Figs. 6, 7 and Supplementary Figs. 3, 4, 8, and 11) were generated using Python Cartopy v.0.22.0 (https://doi.org/10.5281/zenodo.1182735) (ref. [78]). The data necessary to reproduce the main results are provided at https://doi.org/10.5281/zenodo.15383539 (ref. [79]).

Code Availability

Analysis and figure generation were performed using Python (version 3.9.7). The code and scripts used to calculate the tropical cyclone clusters, perform the probabilistic modeling, and generate the figures in the main text are available at Code Ocean (https://doi.org/10.24433/CO.0176970.v2) (ref. [80]).

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