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Oceanic control of Northeast Pacific hurricane activity at interannual timescales

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Abstract
Sea surface temperature (SST) is not the only oceanic parameter that can play a key role in the interannual variability of Northeast Pacific hurricane activity. Using several observational data sets and the statistical technique of multiple linear regression analysis, we show that, along with SST, the thermocline depth (TD) plays an important role in hurricane activity at interannual timescales in this basin. Based on the parameter that dominates, the ocean basin can be divided into two sub-regions. In the Southern sub-region, which includes the hurricane main development area, interannual variability of the upper-ocean heat content (OHC) is primarily controlled by TD variations. Consequently, the interannual variability in the hurricane power dissipation index (PDI), which is a measure of the intensity of hurricane activity, is driven by that of the TD. On the other hand, in the Northern sub-region, SST exerts the major control over the OHC variability and, in turn, the PDI. Our study suggests that both SST and TD have a significant influence on the Northeast Pacific hurricane activity at interannual timescales and that their respective roles are more clearly delineated when sub-regions along an approximate north–south demarcation are considered rather than the basin as a whole.

Keywords: thermocline depth, sea surface temperature, upper-ocean heat content, Northeast Pacific hurricanes, interannual variability, ocean–atmosphere interactions, ocean dynamics

S Online supplementary data available from stacks.iop.org/ERL/8/044009/mmedia

1. Introduction

Though it is the second most significant basin in terms of active storm area, the Northeast Pacific has received relatively less attention for its hurricane activity since hurricanes in this region make landfall less frequently compared to storms in other basins [1–3]. However, the moisture associated with remnants of Northeast Pacific hurricanes has a profound impact on the rainfall in southwestern United States and Mexico [4]. With these regions projected to experience a prolonged drought-like condition in the future climate [5, 6], predicting Northeast Pacific hurricanes and their development could become more important.

Much of the work done in the past to understand the interannual variability of Northeast Pacific hurricane activity has revolved around the El Niño–Southern Oscillation (ENSO), a dominant mode of climate variability in this region [7]. Hurricanes were found to be more intense during El Niño years when compared to La Niña years [8]. Also, it was found that an increase in the storm lifetime and a westward shift in hurricane genesis locations and tracks occur during El Niño years, increasing the likelihood of

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landfall in Hawaii during the warm episodes [3, 9–13]. When the environmental factors that influence hurricane activity through ENSO were considered, it was seen that wind shear played a dominant role [14]. Based on the longitudinal distribution of causal factors, the Northeast Pacific hurricane basin was divided into two sub-regions, to the east and west of 120°W respectively [15]. Furthermore, while significant relationships were found between hurricane activity in the Western sub-region and some chosen environmental parameters, no significant relationship was found between any of those parameters and hurricane activity either in the eastern sub-region or when the basin was considered as a whole [15]. Notably, SST was the only oceanic parameter that was considered in these analyses.

The evolution of hurricanes depends critically on the heat supplied to them from the ocean surface. Under the blast of vertical mixing induced by hurricanes, the heat content in the upper ocean is converted to enthalpy flux at the air–sea interface that provides a heat source that influences hurricane intensification [16]. Consequently it is very important to understand the factors that govern the variability in the ocean heat content (OHC). The two factors that primarily determine OHC are the warmness of the upper ocean or sea surface temperature (SST) and the depth of the warm water or thermocline depth (TD) [17]. While a warm ocean surface promotes hurricane intensification by enhancing atmospheric instability, deep convection and the exchange of latent and sensible heat fluxes at the air–sea interface [18–20], a deep thermocline favors hurricane intensification by making it harder for hurricane-induced mixing to entrain colder, deeper water into the mixed layer and cool the SST [19–21]. The remarkable efficacy in retrieving OHC using SST and TD, obtained from satellite SST and altimetry data respectively, supports the role of SST and TD in modulating OHC [22].

Even though SST has been found to play an important role in hurricane activity in the Northeast Pacific [15], a simple cause-and-effect relationship may not exist between the two, making it important and necessary to investigate other environmental factors that may also modulate hurricane activity [23]. Since TD is the other significant factor besides SST that controls OHC, this study examines the role of TD in OHC variability in the Northeast Pacific hurricane basin at interannual timescales to determine the relative importance of TD in controlling hurricane activity. The letter is organized as follows. Data and methodology are described in section 2. The results are presented and explained in section 3 and finally in section 4, a brief discussion of the main conclusions and their implications are given.

2. Data and methodology

Hurricane track data obtained from http://eaps4.mit.edu/faculty/Emanuel for the 27-year period '1984–2010' is used to find the hurricane track locations and maximum wind speed [24]. Since the 'Dvorak' technique that is used to track hurricanes began using night time hurricane data post 1983, historical record of hurricane intensities is more reliable beginning 1984 [23]. Monthly mean temperature data from three different sources, including the Geophysical Fluid Dynamics Laboratory's Ensemble Coupled Data Assimilation (ECDA v2.0) [25] obtained from www.gfdl.noaa.gov, European Center for Medium-Range Forecasting's Ocean Reanalysis System (ECMWF-ORAS4) [26] obtained from www.ecmwf.int, and National Center for Environmental Prediction's Global Ocean Data Assimilation System (NCEP-GODAS) [27] obtained from www.cpc.ncep.noaa.gov/products/GODAS/, are used to compute the hurricane-season mean SST, TD and OHC conditions for the 27-year period. Time-series of multivariate ENSO index (MEI) obtained from www.esrl.noaa.gov/psd/enso/mei [28] is used to identify El Niño and La Niña events.

The coefficient of variation is computed as the sample standard deviation divided by its mean. The TD is defined as the depth where the potential temperature decreases by 0.2 °C from its value at a reference depth of 10 m [29]. The OHC is calculated as the vertical average of temperature over the upper 100 m [30]. This is found to be a better metric of OHC for hurricane–ocean interaction than the traditional method of integrating the temperature from the surface to the depth of the 26 °C isotherm, especially for a region like the northeast tropical Pacific where the traditional method becomes degenerate due to the fact that SST in certain parts of the basin could be less than 26 °C [30]. The power dissipated by a hurricane is estimated as $\int_0^\tau V_{\max}^3$, where $V_{\max}$ is the maximum 10 m wind speed of the storm at each 6-hourly location and 'τ' is the number of 6-hourly locations in its lifetime. This value is then integrated over all the hurricanes in a given season to end up with the PDI for that year [24]. The SST, TD, OHC and MEI are averaged between June–December of each year to obtain the respective hurricane-season averages.

In this study, the statistical method of multiple linear regression is used to contrast the importance of different parameters, such as the competing roles of TD and SST in determining OHC and PDI variations. When performing multiple linear regression analysis, each time-series is first detrended to remove any long-term trend since we are only interested in the interannual variability. Next, we standardize them by taking the 'z-score' of the detrended time-series, which is obtained by subtracting the mean of the population from an individual value and then dividing the difference by the population standard deviation. This is done to estimate the relative significance of the regression coefficients obtained. The statistical significance of the regression coefficients is evaluated using the 'F-test' ('Wald' test). The F-value is given as $\frac{\mathrm{RSS2}-\mathrm{RSS1}/k1-k2}{\mathrm{RSS1}/n-k1}$, where 'RSS1' and 'RSS2' are the residual sum of squares and '$k1$' and '$k2$' are the number of parameters in the unrestricted and restricted models respectively and the total number of observations is 'n'. Throughout this study, the regression coefficients and variances that are reported to be statistically significant satisfy the criterion to reject the null-hypothesis at 95% level.

3. Results

Let us begin by considering the coefficient of variation, which is a normalized measure of the dispersion of a distribution, for

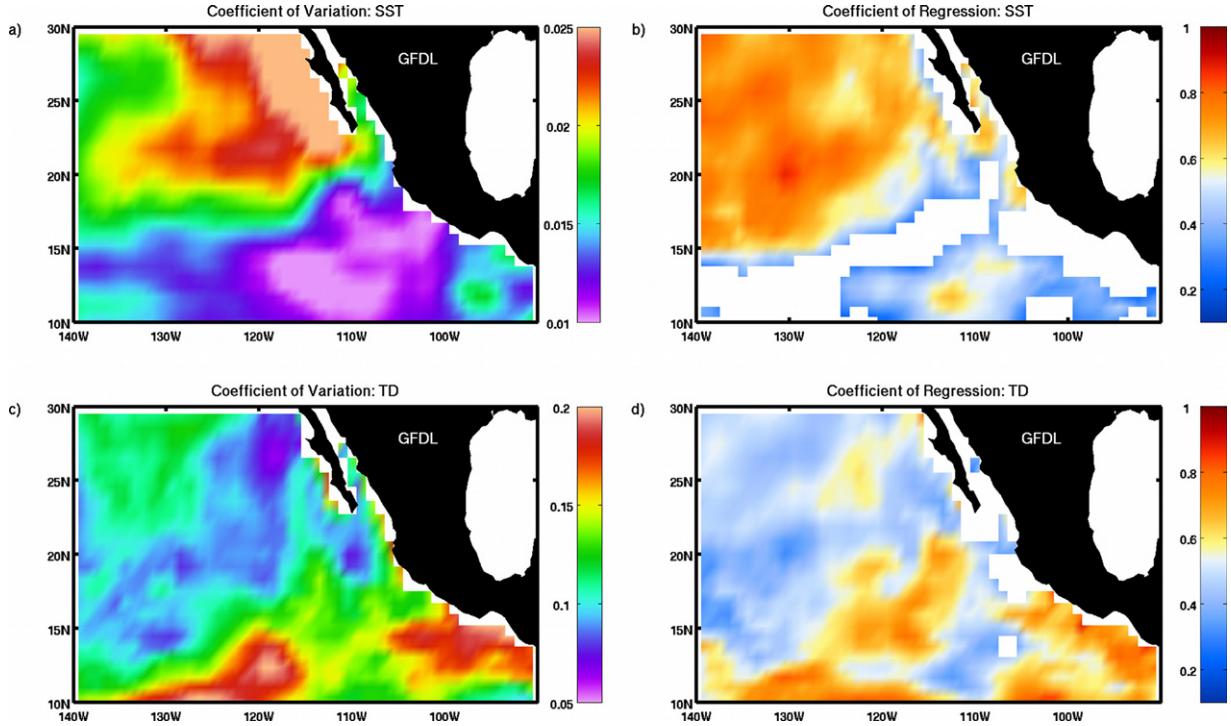

Figure 1. Left: coefficients of variation for (a) SST and (c) TD. Right: coefficients of regression for (b) SST and (d) TD and for the equation: OHC $= x\mathrm{SST} + y\mathrm{TD} + z$. The unshaded regions indicate areas where the regression coefficients are statistically insignificant. (The above figures are based on the analysis of GFDL ocean assimilation data. Figures based on a similar analysis of ECMWF and NCEP assimilation products are shown in the supplementary material, available at stacks.iop.org/ERL/8/044009/mmedia.)

hurricane-season mean SST and TD at interannual timescales. The coefficient of variation for SST (figure 1(a)) shows that the region where most of the variability in SST occurs is in the northern part of the basin. Peak variability occurs along the Baja California coast and decreases in magnitude as it extends westwards and southwards into the open basin. The eastern end of the southern boundary of this region begins a few degrees to the south of the tip of Baja California, at about 105°W and 20°N. From here it extends southwestwards until 125°W and 15°N and then continues westwards until the western boundary at 140°W. On the other hand, the coefficient of variation for TD (figure 1(c)) indicates that the region where most variability in TD occurs is in the southern part of the basin. Maximum TD variability occurs approximately in a band between 10 and 15°N starting from the Central American coast extending westwards until about 122°W, except between 112 and 102°W where the variability is reduced. Beyond 122°W high TD variability occurs only near the southern boundary of the basin. Some TD variability also occurs near the northwestern part of the basin, albeit of a lower magnitude. Thus, there is a demarcation of interannual variability in hurricane-season mean SST and TD that roughly divides the Northeast Pacific hurricane basin into two sub-regions, with SST variability dominating the northern part while TD variability is confined to the southern part.

Since SST and TD are the two major parameters that primarily control the OHC, is the spatial structure of the interannual variability in SST and TD reflected in their relative significance in determining the interannual variability in OHC? To answer this, we perform a multiple linear regression analysis using hurricane-season mean SST and TD as predictor variables and hurricane-season mean OHC as the response variable. Figures 1(b) and (d) show that the spatial structures of regression coefficients obtained for SST and TD are broadly consistent with those of their own variability (figures 1(a) and (c)). To the north of 18°N, variability in SST primarily controls the variability in OHC in most of the basin. Between 14 and 18°N, SST exerts the major control to the west of the line connecting 115°W, 18°N and 125°W, 14°N. In the remaining part of the basin, TD drives the variability in OHC with SST playing almost no role, except for a small region centered at about 110°W and 12°N. Thus, based on the parameter that controls the interannual variability of OHC, the Northeast Pacific hurricane basin can be divided into two sub-regions: (1) Northern sub-region—where SST plays the dominant role and (2) Southern sub-region—where TD plays the major role.

To further delineate the difference between the two sub-regions, the hurricane-season mean SST, TD and OHC are averaged over each sub-region and multiple regression analysis with SST and TD as predictor variables and OHC as the response variable for the respective sub-region is performed. The coefficients of regression for the Southern sub-region (table 1(a)) indicate that the variability in OHC is predominantly controlled by that in TD and to a lesser extent by that in SST. Also, the regression relationship reveals that the linear combination of SST and TD explains as much as 83%–92% of the total interannual variability in OHC.

Table 1. Regression coefficients and R-squared values using GFDL, ECMWF and NCEP reanalysis data for the (a) Southern sub-region and (b) Northern sub-region of the Northeast Pacific and (c) Atlantic and for the regression equation: OHC $= x$SST $+$ yTD $+ z$. Here OHC, SST and TD are averaged over the hurricane season and each region. The values indicated in bold are statistically significant at 95%.

(a) Southern sub-region	GFDL	ECMWF	NCEP
x	**0.30**	**0.27**	**0.40**
y	**0.70**	**0.75**	**0.65**
R-squared	**0.88**	**0.92**	**0.83**
(b) Northern sub-region	GFDL	ECMWF	NCEP
x	**0.61**	**0.71**	**0.60**
y	**0.44**	**0.44**	**0.43**
R-squared	**0.69**	**0.74**	**0.64**
(c) Atlantic	GFDL	ECMWF	NCEP
x	**0.92**	**1.12**	**1.06**
y	**0.32**	**0.63**	**0.51**
R-squared	**0.86**	**0.82**	**0.83**

On the other hand, in the Northern sub-region, interannual variations in SST dominate those in OHC while TD plays a relatively minor role (table 1(b)). The linear combination of SST and TD explains between 64% and 74% of the total OHC variability in this sub-region. This characteristic feature of the Northeast Pacific hurricane basin to exhibit distinct modes of OHC variability in two sub-regions controlled by SST versus TD makes it very different from the Atlantic hurricane basin across the isthmus. Figures 2(a) and (b) show the regression coefficients for SST and TD obtained by performing multiple linear regression analysis using hurricane-season mean SST and TD as predictor variables and hurricane-season mean OHC as the response variable for the Atlantic. From the two figures it is clear that while SST dominates the regression relationship in the majority of the basin, TD plays a secondary role. The dominance of SST over TD is further revealed when we consider the regression relationship between the basin averages (table 1(c)). The linear combination of SST and TD explains about 82%–86% of the total interannual variability in OHC with SST being the chief contributor.

Having established the relative control of SST and TD on the interannual variability of OHC, we next explore their potential role in the Northeast Pacific hurricane activity. The hurricane locations in this basin are approximately divided into two sample sets, based on the sub-regions defined above (figure 3(a)). Interestingly, an overwhelming majority of hurricane genesis locations are in the Southern sub-region. This is consistent with previous studies that suggest that majority of the Northeast Pacific hurricanes form between 10 and 15°N and between the Mexican coast and Clipperton Island [3, 15]. The time-series of PDI for the two sub-regions (figure 3(b)) show comparable magnitude and interannual variability. To understand the relative significance of SST and TD for the interannual variability of the PDI in the Southern and Northern sub-regions, we perform multiple linear regression analysis with hurricane-season mean SST and TD averaged over each sub-region as predictor variables

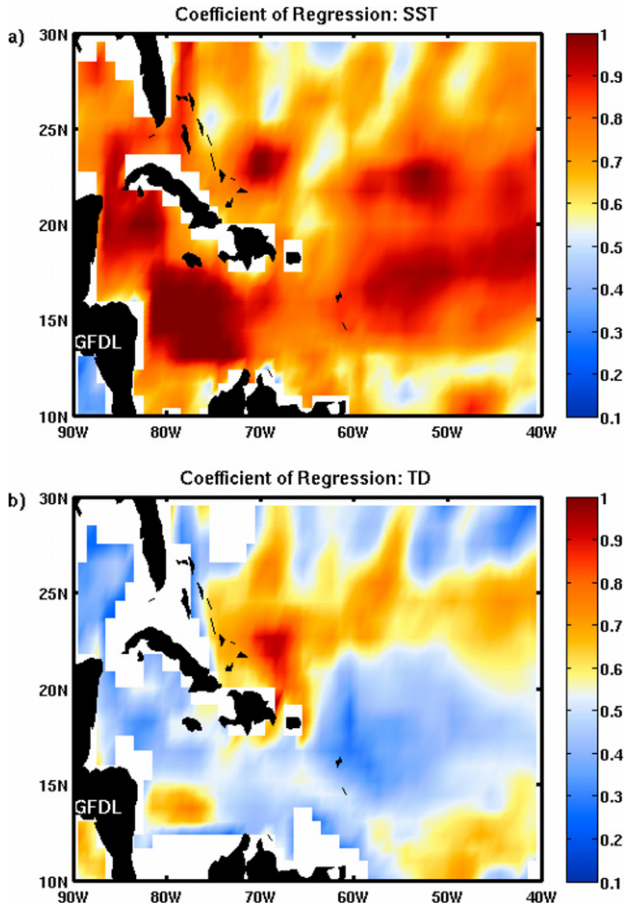

Figure 2. Coefficients of regression for (a) SST and (b) TD and for the equation: OHC $= x$SST $+$ yTD $+ z$. The unshaded regions indicate areas where the regression coefficients are statistically insignificant (figures are based on the GFDL ocean assimilation data).

and the PDI for the corresponding sub-region as the response variable respectively. Table 2(a) shows that for the Southern sub-region, TD almost exclusively controls the regression relationship with the coefficients of SST being statistically insignificant and that 30%–48% of the interannual variability in PDI is explained by variations in TD. On the other hand, table 2(b) reveals that for the Northern sub-region, SST solely dominates the regression relationship with TD regression coefficients being statistically insignificant. Also, interannual variations in SST explain about 27%–30% of the interannual variability in PDI for this sub-region. Thus, our division of the Northeast Pacific hurricane basin into sub-regions based on the parameter that controls OHC variability is meaningful for understanding the variability in hurricane activity.

4. Discussion

Previous study [15] suggests that the Northeast Pacific hurricane activity may be better understood by dividing the ocean basin into eastern and western sub-regions along 120°W with an important contrast of hurricane activity showing some and no dependence on environmental factors in the western and eastern sub-regions respectively. Although

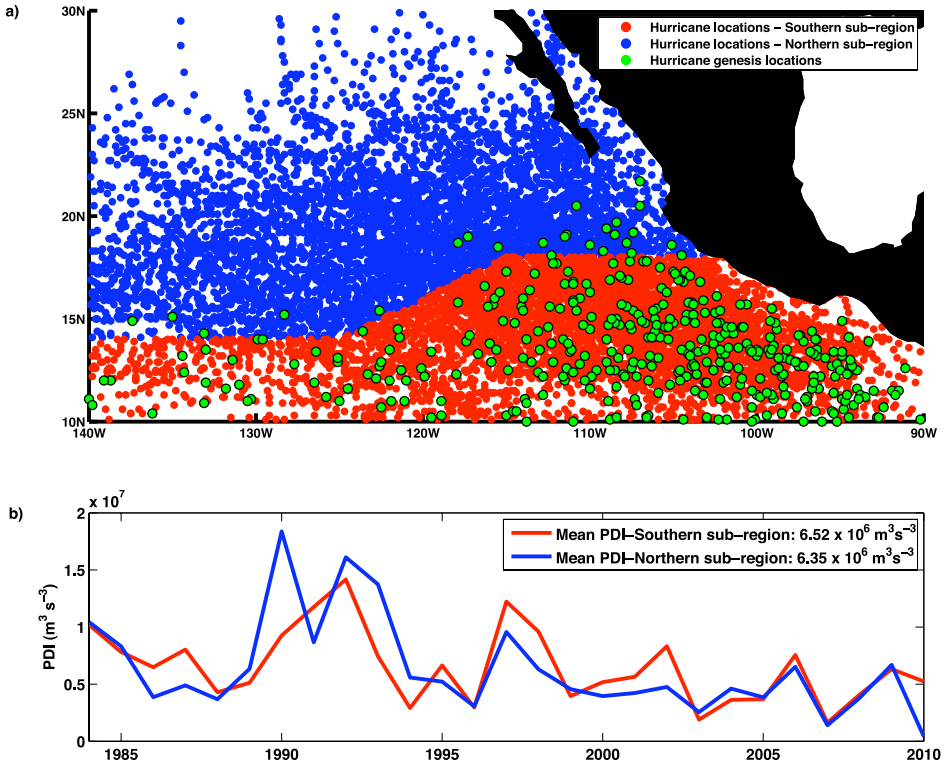

Figure 3. (a) Hurricane locations from the Southern sub-region (in red) and from the Northern sub-region (in blue) with hurricane genesis locations on top (in green). (b) The time-series of PDI for the Southern sub-region (in red) and the Northern sub-region (in blue) with the long-term mean PDI values for the respective sub-regions shown in the legend.

Table 2. Regression coefficients and *R*-squared values using GFDL, ECMWF and NCEP reanalysis data for the (a) Southern and (b) Northern sub-regions and for the regression equation: $\mathrm{PDI} = x\mathrm{SST} + y\mathrm{TD} + z$. Here SST and TD are averaged over the hurricane season and each region and PDI is evaluated over the sub-region. The values indicated in bold are statistically significant at 95%.

(a) Southern sub-region	GFDL	ECMWF	NCEP
x	−0.11	−0.32	0.15
y	**0.62**	**0.87**	**0.55**
R-squared	**0.30**	**0.48**	**0.39**
(b) Northern sub-region	GFDL	ECMWF	NCEP
x	**0.51**	**0.52**	**0.55**
y	0.06	0.02	−0.09
R-squared	**0.28**	**0.27**	**0.30**

this regionalization enhances our understanding of the factors that control the Northeast Pacific hurricane activity, we find that processes that control hurricane activity are more complex than can be described by a simple east–west partitioning along 120°W. More specifically, our study shows that TD, a parameter that was not included in previous analyses, plays a pivotal role in the interannual variability of OHC and hurricane activity in the southern part of the Northeast Pacific basin, which includes the hurricane main development area. On the other hand SST drives the interannual variations in the upper-ocean thermal field and hurricane activity mainly in the northern part of the basin.

The eastern tropical Pacific Ocean that forms the eastern end of the equatorial Pacific current system dynamically interacts with the downward branch of the Walker circulation and plays an important role in ENSO, the most significant climate phenomenon at interannual timescales [31]. Since the ENSO signal manifests itself so prominently in the eastern tropical Pacific, it likely has an important influence on the interannual variability of SST and TD in this region. To estimate the influence of ENSO on the factors controlling the Northeast Pacific hurricane activity, the hurricane-season mean MEI index was regressed onto the hurricane-season mean SST from the Northern sub-region and the hurricane-season mean TD from the Southern sub-region (table 3). While ENSO explains 38%–45% of the SST variability in the Northern sub-region, the range of TD variability explained in the Southern sub-region is relatively large at 22%–60%. Hence, despite part of the SST variability in the Northern sub-region and TD variability in the Southern sub-region being attributable to ENSO, a substantial amount of variability remains unexplained. A better understanding of factors governing SST and TD variability at interannual timescales may improve seasonal forecasting of Northeast Pacific hurricane activity.

Despite the broad consistency of various relationships obtained, there are some differences among the three reanalysis products used in this study when it comes to the exact magnitude. More specifically, while the magnitudes of

Table 3. *R*-squared values using GFDL, ECMWF and NCEP reanalysis data for (1) the Southern sub-region and the regression equation: TD = xMEI + y, and for (2) the Northern sub-region and the regression equation: SST = xMEI + y. Here SST, TD and MEI are averaged over the hurricane season and SST and TD are additionally averaged over each sub-region. The values indicated in bold are statistically significant at 95%.

R-squared	GFDL	ECMWF	NCEP
Southern sub-region	**0.54**	**0.60**	**0.22**
Northern sub-region	**0.38**	**0.45**	**0.41**

interannual variability in PDI explained by SST (27%–30%) and the interannual variability in SST attributable to ENSO (38%–45%) in the Northern sub-region converge reasonably well, there is a relatively larger discrepancy when it comes to the magnitudes of interannual variability in PDI explained by TD (30%–48%) and the interannual variability in TD attributable to ENSO (22%–54%) in the Southern sub-region. This probably indicates differences in TD simulation in the Southern sub-region among the different data products. The spatial structure of TD in the Southern sub-region of northeastern tropical Pacific results from complex ocean dynamics operating in this region. To the west of 110°W, the spatial structure of TD is dominated by the thermocline ridge–trough system caused by the north equatorial current and the north equatorial counter current. On the other hand, to the east of 115°W, the TD spatial structure is determined by the wind stress curl on the ocean surface created by the strong Tehuantepec, Papagayo and Panama jets blowing through gaps in the Central American Cordillera [32]. These gaps in the mountains or passes are 100 km or less in width [33], making an accurate representation of TD in models difficult unless the coupled models or assimilated winds have the resolution needed to resolve these fine orographic features and the associated jets. Thus, there is a need to use high-resolution models to better simulate TD conditions in the northeastern tropical Pacific, with the potential to improve seasonal hurricane forecasting in this region.

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