Spatiotemporal Profiling of Tropical Cyclones Genesis and Favorable Environmental Conditions in the Western Pacific Basin

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Abstract We analyze the spatiotemporal variations of tropical cyclone (TC) genesis and associated environmental conditions over the western North Pacific with a series of data science techniques, including Gaussian kernel estimator, wavelet, cross-wavelet coherence, and regression analyses. There are significant semiannual and annual variations of TC genesis over the northern South China Sea and oceanic areas east of the Philippines. Variations on the El Niño–Southern Oscillation timescale are prominent between 5°–10°N, 155°–160°E. With reconstructed TC series on those frequencies, we further quantify the influences of environmental variables on the primary TC signals over western North Pacific. Over northern South China Sea and oceanic areas east of the Philippines, 40% of the reconstructed TC variance can be explained by vertical shear of zonal wind, relative humidity, and absolute vorticity. The reconstructed TC series near (160°E, 7°N) has strong but varying in-phase relationships with El Niño–Southern Oscillation, which provides deeper insight into their nonstationary and nonlinear relations than their modest correlation.

Plain Language Summary Many previous studies about tropical cyclone formation mainly focused on basin-wide or global scale characteristics. This study provides a comprehensive analysis of the spatial and temporal distributions of tropical cyclones formation in the western North Pacific. We use observational and reanalysis data to investigate the spatial patterns of tropical cyclone formation in the western North Pacific. Over the South China Sea and oceanic areas east of the Philippines, tropical cyclone formation has strong half-yearly and yearly variations. Over the southeastern part of western North Pacific, tropical cyclone formation has strong 4- to 8-year variations, which are closely associated with El Niño–Southern Oscillation. We also explore the linear and nonlinear relationships between tropical cyclone formation and favorable formation variables spatially and temporally. The primary variability of tropical cyclone formation can be considerably explained by the change of wind with height, moisture, vorticity, and the El Niño–Southern Oscillation. In the southeastern part of western North Pacific, tropical cyclone formation reveals strong nonlinear and nonstationary relationships with the change of wind with height and vorticity.

1. Introduction

Tropical cyclones (TCs) often associate with extreme weather and can inflict enormous death and massive property damage (Peduzzi et al., 2012). Many researchers believe that based on current observational evidence, TCs are not becoming more frequent, but more intense worldwide (Elsner et al., 2008; Kang & Elsner, 2012; Knutson et al., 2010; Walsh et al., 2016). Among all basins, western North Pacific (WNP) is the most active region of TCs. In the past decades, multimtimescale variations of TC over WNP have been explored by many studies, ranging from intraseasonal (Chen et al., 2009; Huang et al., 2011; Zhao et al., 2015), interannual (Chan & Xu, 2009; Chia & Ropelewski, 2002; Ho et al., 2004) to decadal (Lin & Chan, 2015; Liu & Chan, 2008; Webster et al., 2005). Efforts have been made in the past decades to study changes of TC characteristics in WNP and investigate potential climate regulation on TC genesis. For example, Emanuel (2005) proposed an index, that is, Power Dissipation Index, incorporating TC frequency and intensity with a lifetime to characterize destructiveness of TC. Later, studies by Chan (2006) and Lin and Chan (2015) found that the observed Power Dissipation Index over WNP exhibits noteworthy interdecadal
variations: increasing between 1975 and 1997 and decreasing between 1960 and 1974 and 1998 and 2012. On the other hand, TC landfall in East Asia exhibits significant interannual variations in various parts of WNP, but no tendency of landfalling TC frequency over the entire WNP has been observed (Chan & Xu, 2009). Huang et al. (2011) found that seasonal modulation of intraseasonal oscillation in the tropics on TC genesis over WNP is strong in May–June, weaker in July–December. However, most of the current progress as exemplified above is done for the entire basin, variations within the basin deserve more investigation. In this study, we give comprehensive spatiotemporal profiling about the TC genesis within WNP and explore the relationships between the identified variations of TC genesis and environmental variables. Because in addition to TC activities on different timescales, another main pursuit in the research community is to investigate the impacts of environmental variables on TC, its genesis, and characteristics, with the ultimate goal of providing informative factors for prediction.

Many previous studies have investigated how environmental variables, including vertical wind shear, relative humidity (RH), relative vorticity, sea surface temperature (SST), and Coriolis parameter, contribute to TC genesis (Fink & Speth, 1998; Gray, 1975; Gray & Brody, 1967; Wang & Moon, 2017) and how TC genesis frequency changes in face of climate change (Elsner et al., 2008; Kang & Elsner, 2012; Knutson et al., 2010; Walsh et al., 2016). Among those studies, one common approach is to adopt some genesis indices. Gray (1975) first proposed a useful and concise measure—the seasonal genesis parameter (SGP) calculated by some environmental variables—to investigate TC genesis. Many other genesis indices, such as genesis potential (GP) index (Emanuel & Nolan, 2004), GP index (GPI; Emanuel, 2010), genesis frequency index (McGauley & Nolan, 2011), cyclone genesis index (Bruyère et al., 2012), and intraseasonal GPI (ISGPI; Wang & Moon, 2017), have been defined after Gray’s work and show improved skill in replicating the observed genesis variations. However, genesis indices may have undesirable performance in some specific basins, for example, GPI in western part of North Atlantic and ISGPI in eastern part of North Atlantic (Moon et al., 2018), and they sometimes are arbitrarily constructed: For example, ISGPI have different definitions for the North Hemisphere by Wang and Moon (2017; ISGPI = −0.366 × ω800 + 0.188 × Vz500 + 0.682 × f950 (NS)) and South Hemisphere as in Moon et al. (2018; ISGPI = −0.51 × ω500 − 0.21 × Vz500 + 0.20 × f950 (S)). Although these genesis indices can be calculated to vary spatially within the basin, there are still regions where existing indices are not able to capture the variability of TC signals (see Figure 13 in Bruyère et al., 2012). Genesis indices can to some extent empirically quantify the relative contributions of environmental variables to TC genesis over a basin (Camargo et al., 2007; Moon et al., 2018), within-basin variations of their contributions over space and time are still missing in the literature. We suspect that not all environmental variables have homogeneous contributions to TC genesis within a basin, especially a big one like WNP. That postulation motives this study to probe spatial variations of the importance/contribution of different key environmental variables for TC genesis in WNP.

This study is primarily guided by the following questions:

1. What is the complete spatiotemporal profile, that is, spatially varying time-frequency configuration, of TC genesis within WNP?
2. What are the associated environmental conditions and climate teleconnection for the patterns identified in the profile?
3. How do their contributions to the TC variability vary across the basin?

The paper is organized as follows: Section 2 describes the data science methods used for the analysis. Section 3 provides a detailed discussion of our results. A summary is provided at the end.

2. Methodology

We define the study area as WNP, bounded by 0–35°N, 100–188°E. The TC origins are recorded in the best track data provided by the Japan Meteorological Agency (JMA) from 1979–2017 (the robustness test of the results using different best track data sets [JMA, China’s Meteorological Administration, and Joint Typhoon Warning Center] can be found in the supporting information, SI). We use the first record of a given storm (tropical depression) as TC origin. Based on previous studies (Gray, 1975; Wang & Moon, 2017; Wei et al., 2018), we select three key environmental variables (see SI section S3.2 for additional variables considered) to address the research Questions 2 and 3: vertical shear of zonal wind (Vz), RH, and absolute vorticity (Vor), which are retrieved from ERA5 reanalysis data (Hersbach & Dee, 2016) from 1979–2017 with a 1° × 1°
spatial (the data were coarsened to 1° × 1° from a high resolution of 0.28125°) and 6-hourly temporal resolution. Comparison of results between ERA5 and ERA-interim is included in section S1 in the SI. Monthly Oceanic Niño Index (Null, 2016) is provided by the National Oceanic and Atmospheric Administration Climate Prediction Center. $V_{zs}$ is calculated as the difference of the zonal winds between 200 and 850 mb; $RH (V_{or})$ is taken at 600 mb (850 mb), following previous studies (e.g., Camargo et al., 2007; Emanuel, 2010).

### 2.1. Space-Time Poisson Process and Gaussian Kernel Smoothing

Severe weather event can be modelled as a space-time Poisson process, as exemplified by Lu et al. (2015) who studied tornado genesis with a simpliﬁed model that only focused on the average variations over the entire study region but missed the spatial variations within the area. This paper is an extension from Lu et al.’s approach with a complete spatial time-frequency screening of TC genesis over the entire WNP basin.

In our study area, we have 3,204 (≈ 36 * 89) grids. Daily ($t$) TC genesis ($Y_{t,k}$) at each of these grids ($k$) can be assumed to follow an independent Poisson process. $Y_{t,k}$ is simply the counts of TC genesis at grid $k$ on day $t$ ($t$ is from 1 January 1979 to 31 December 2017). However, considering the potential spatial dependency of TC genesis, instead of modeling it as a simple space-time Poisson process, we adopt another data science technique, wavelet analysis (section 2.3), to investigate its full spatial time-frequency profiles. Before wavelet analysis, considering the effect of sampling variance at each grid, we ﬁrst employ Gaussian kernel smoothing (GKS) at each grid to obtain a spatially averaged rate of TC genesis ($\hat{Y}_{t,k}$).

The GKS estimator is denoted as below

$$K_L(d,h) = \frac{1}{\sqrt{2 \pi h}} e^{-d^2/(2h^2)},$$

(1)

where $h$ is the scaling factor, here taken to be 500 km (the sensitive test for different $h$ values is provided in the SI section S2); $d_k (\leq 500 \text{ km})$ is the distance measured along the surface of the earth from any TC genesis location to the center $L$. We apply the GKS to each 1° × 1° grid with centers $L = (0°, 100°E), (0°, 101°E), \ldots, (188°E)$, $L = (1°, 100°E), (1°, 101°E), \ldots$, $L = (35°N, 100°E), (35°N, 101°E), \ldots, (35°N, 188°E)$.

The spatially averaged rate of genesis ($\hat{Y}_{t,k}$) at grid $L$ on day $t$ is then calculated by

$$\hat{Y}_{t,k} = \frac{1}{N_L} \sum_{i=1}^{N_L} K_L(d_i, h) \times Z_{i,t},$$

(2)

where $Z_{i,t}^t$ is the number of TC genesis at location $i = 1, 2, \ldots, N_t$, in this study $Z_{i,t}^t = 1$; $N_t$ is the total number of TC occurred within 500 km on day $t$.

The same spatial smoothing is applied to $V_{zs}, RH$, and $V_{or}$. Since the environmental variables are gridded data (1° × 1°), we deﬁne $h$ in equation (1) to be half of the longest distance between any pair of adjacent corners along a side of a 9° × 9° grid box with grid $L$ in the center, such that $h \approx 500 \text{ km}$ too. At each grid $L$, we thus obtain one time series of spatially averaged TC genesis rate ($\hat{Y}_{t,k}$) and three time series of spatially comparable environmental variables ($\hat{V}_{\beta,L,t}, \hat{R}H_{L,t}, \hat{V}_{or,L,t}$; Lu et al., 2015).

### 2.2. Normalization

We normalize the spatially averaged time series of TC by their corresponding annual totals over the entire study region, to remove possible trend due to varying observational capability over the data period:

$$Y_{t,d}^*= \frac{\hat{Y}_{t,d}}{\sum_{L \in (36.89)} \sum_{t \in (1, 14)} \hat{Y}_{t,d}},$$

(3)

where $j = 1979, 1980, \ldots, 2017$ and $d = 1, 2, \ldots, n'$ ($n' = 366$ when year $j$ is a leap year, otherwise $n' = 365$).
This process is to ensure that the spatial time-frequency profile at each grid \( L \) will not be masked by the possible trend signal due to observational capability. Note that although the interannual variation over the entire basin might also be removed by the normalization process, the within-basin interannual variation smoothed at each grid is preserved for the wavelet analysis below (additional justification for normalization process is provided in section 3.1).

### 2.3. Spatiotemporal Profiling and Primary Signal Reconstruction

We adopt wavelet analysis to decompose the normalized TC rate \( (Y^*_{L,d}) \), hereafter as \( Y^*_{L,L} \), into a time-frequency space (Torrence & Compo, 1998), to obtain a complete temporal profile of TC variability centered at each grid. We use the Morlet wavelet, consisting of a plane wave modulated by a Gaussian:

\[
\psi(\eta) = \pi^{-1/4} \omega^{|\eta|} e^{-\omega^2/4},
\]

where \( \omega \) is the nondimensional frequency, here taken to be 6 to meet the admissibility condition for wavelets (Farge, 1992); \( \eta \) is a nondimensional “time” parameter.

Given the lag-1 autocorrelation of each normalized TC time series \( (Y^*_{L,L}) \), we compute the 95% confidence level of the local wavelet power spectrum with a red noise process. At each grid center \( L \), we obtain one global wavelet spectrum as exemplified by the right columns in Figures 1e–1h. Based on global wavelet red noise significant test at each grid center, Figures 1a–1d show that the global spectrum power is substantial on semiannual (4–6 months), annual (8–12 months) timescales in northern South China Sea (NSCS) and oceanic areas east of the Philippines (OAEP) and very significant on El Niño–Southern Oscillation (ENSO; 4–8 years) timescale in the southeastern part of WNP (\(-160^\circ\)E and 7°N, hereafter as SEWNP). More discussion is provided in section 3. To extract these primary signals, at each center \( L \), we reconstruct the TC time series \( Y^*_{L,L} \) on the semiannual, annual and ENSO frequency bands. The original and reconstructed TC time series are compared in Figure S7. The reconstructed TC time series are denoted as \( \text{Re} Y^*_{L,L} \). Technical details regarding the reconstruction process can be traced in (Torrence & Compo, 1998).

### 2.4. OLS and WTC

To explore the relationships between TC variations and environmental variables, linear regression is used:

\[
Y^*_L = \beta_{L,1} V_{DL} + \beta_{L,2} RHI_L + \beta_{L,3} \text{Vor}_L + \epsilon_L,
\]

where \( V_{DL} \), \( RHI_L \), and \( \text{Vor}_L \) are standardized and the coefficients \( [\beta_{L,1}, \beta_{L,2}, \beta_{L,3}] \) can be used to infer the importance/contribution of the corresponding environmental variables. Box-Cox power transformation is applied to \( Y^*_L \) due to their substantially positive skewness. Leave-one-year-out cross validation is employed for assessing the goodness of fit. Adjusted R-squared is used to quantify the performance of fitting (39 models for each grid center \( L \), shown in Figure 2a) and skill of prediction (39 left-out years in the 39 models fitting for each grid center \( L \), shown in Figure 2e). Normality of the residual term \( \epsilon_L \) is also verified. Statistical significance of the 39 fitted models and 39 sets of coefficients are validated by the \( F \) test and \( t \) test.

Wavelet Coherence Analysis (WTC) is an effective technique to investigate the covarying relationships in time-frequency space between two time series (Grinsted et al., 2004; Torrence & Webster, 1999). Like a traditional correlation coefficient, the wavelet coherence is defined as the square of the cross spectrum normalized by the product of individual power spectrum (equation (6); Grinsted et al., 2004).

\[
WC(s) = \frac{|W_{XY}(s)|^2}{W_X(s)W_Y(s)}, \tag{6}
\]

\[
\theta = \text{arg} (WCS) \quad \text{with} \quad WCS = \frac{W_{XY}(s)}{\sqrt{W_X(s)W_Y(s)}}, \tag{7}
\]

where \( W_{XY}(s) \) is the cross spectrum between two time series \( X \) and \( Y \); \( W_X(s) \) and \( W_Y(s) \) are the individual spectra; \( \theta \) is the phase angle.
Figure 1. Spatial distributions of significant TC variations on (a) semiannual, (b) annual, and (c) ENSO timescales using wavelet analysis described in section 2.1. Wavelet analysis gives significant signals on each time scale for each grid (i.e., one time-frequency configuration centered at each grid, e.g., panels e–h), only regions with statistically significant wavelet power (95% confidence level) are plotted with their time-averaged global power on the three timescales in (a)–(c). (d) Four subregions are highlighted given their outstanding strength of signals: NSCS, OAEP1, OAEP2, and SEWNP. Normalized TC series are averaged over the four subregions, then we apply wavelet analysis again on the four time series to obtain time-frequency profiles for (e) NSCS, (f) OAEP1, (g) OAEP2, and (h) SEWNP. The color bar shows the unitless spectra power; the right columns are the global wavelet spectra averaged over 39 years. TC = tropical cyclone; ENSO = El Niño–Southern Oscillation; NSCS = northern South China Sea; OAEP = oceanic areas east of the Philippines; SEWNP = southeastern part of western North Pacific.
In this study, we apply WTC to the reconstructed TC \((Y_{RE}; t)\) and each of the environmental variables \((V_{zsL}, t, RH_{L}, t, Vor_{L}, t)\) to examine their phase relationships on the complete temporal profiles.

### 3. Results

#### 3.1. TC Genesis Spatiotemporal Variations

TC genesis over NSCS and OAEP exhibits prominent semiannual and annual cycles (Figures 1a and 1b). This result agrees with several previous studies (Cinco et al., 2016; Wang et al., 2007; Yuan et al., 2009), which have suggested that TC frequencies over the two regions are higher than other areas in WNP. Our results further quantify and explain such localized high frequencies over NSCS and OAEP in the context of their stronger semiannual and annual variations. The area between 10°N and 20°N exhibits stronger semiannual and annual variability because environmental conditions in this area are more often in favor of TC genesis. In the subtropical regions, vertical shear of zonal wind is usually stronger (Gray & Brody, 1967; Yuan et al., 2007) and SST is relatively lower (Gray, 1979). Near the equator

![Figure 2. Results of linear regression between reconstructed tropical cyclone and selected environmental variables. (a) Adjusted R-squared for 39 models fitting. Coefficients of (b) \(V_{zs}\), (c) \(RH\), and (d) \(Vor\) are averaged among the 39 models. (e) Adjusted R-squared on test set, that is, the left-out year for prediction. Only statistically significant coefficients and adjusted R-squared are plotted (95% significance level).](image-url)
(usually <5°), the Coriolis force is too small to maintain the cyclonic circulation (Wang et al., 2007). On the ENSO timescale (4–8 years), TC variation is remarkable in SEWNP (Figure 1c). Some previous studies have recognized that there is a southeast-northwest oscillation of TC genesis location between SEWNP and central WNP and have attributed such pattern to (a) the east-west Walker Circulation variation and (b) the eastward extension-westward retraction of the monsoon trough (Chen et al., 1998; Du et al., 2011; Wang & Chan, 2002). Noteworthily, the interannual variability of the intertropical convergence zone (ITCZ) may also contribute to the southeast-northwest oscillation of TC genesis. Tropical disturbances produced by ITCZ breakdown can develop into tropical depressions (Wang & Magnusdottir, 2006). Cao et al. (2012) also found that TC genesis tends to be in the center of the ITCZ region. During active TC seasons in WNP, the ITCZ extends eastward to SEWNP and only reaches central WNP (135°E) in suppressive TC seasons (Ding & Reiter, 1983). Based on our analysis and aforementioned discussions by others, we hypothesize that during El Niño years, abnormally warm SST over the eastern Pacific Ocean weakens, and may even reverse, the Walker Circulation. As a result, the westerly winds will bring warmer and higher than average RH air toward SEWNP (Chan, 1985). Furthermore, with an enhanced monsoon trough, the low-level (850 hPa) vorticity will be greater. The resulting environment becomes more favorable for TC genesis in SEWNP (Chen et al., 1998). In sections 3.2 and 3.3, we will further discuss the quantitative relationships between the TC variations and selected environmental variables.

Figures 1e–1h illustrate the TC wavelet power spectrum in NSCS, OAEP1 (125°–135°E, 10°–20°N), OAEP2 (138°–145°E, 10°–20°N), and SEWNP, respectively. Interestingly, in the NSCS, significant annual variations are piecewise (1981–1987, 1994–2004, and 2009–2011), that is, active for several years with an intermission. Liu and Chan (2013) have identified one inactive period (1998–2011) of WNP TC activity and related the inactive period to a downward trend of TC genesis frequency in the main development region, which is partly consistent with our result (2004–2009 in NSCS). One interesting difference is that Liu and Chan’s study has suggested a significant decreasing trend in SEWNP during 2005–2011, which is not found in our result. Two kinds of Pacific Ocean warming are found to have substantial impacts on TC frequency over NSCS: (1) the El Niño Modoki with central Pacific warming has positive modulation on TC frequency; while (2) the TC frequency is suppressed when the canonical El Niño with eastern Pacific warming occurs (Chen, 2011). Based on observations and simulations, the frequency of El Niño Modoki occurrence shows an increasing tendency (Chen & Tam, 2010), suggesting more TCs in NSCS, which may greatly influence southeastern China and surrounded islands. Besides, the influences of different phases of the Indian Ocean SST on TC genesis in the NSCS are also claimed by Wang et al. (2013). They find that the warm (cold) phase of the Indian Ocean SST is unfavorable (favorable) for TC genesis. The changing oceanic boundary conditions in the Pacific and Indian Oceans on the annual-to-interannual timescale might together lead to the varying strength of the TC annual cycle in NSCS found in this study. On the other hand, the annual variations in OAEP1 and OAEP2 are consistently significant through our analysis period, with some notable intensification around 1999 and 2011 in OAEP1, and around 2011 in OAEP2. Both 1999 and 2011 are strong La Niña years, which may explain the intensification of TC variations in the entire OAEP. In the SEWNP, variations on the ENSO timescale are substantial overall except a break between 1990 and 1995. It also indicates that the ENSO-timescale variations might get intensified after 2014. However, the data period limits our confidence in this postulation, and further analysis should be conducted once future data become available. But using future projection simulations from CMIP5 global climate models, Zhang, Karnauskas, et al., 2017 found that TC genesis frequency over SEWNP exhibits a robust increasing trend. In general, there is no obvious trend of TC frequency on different timescales in the four regions over the past four decades, which is consistent with the study by Wu and Zhao (2012) in the WNP based on JMA data set. Based on our complete profiling of the TC genesis within the basin, we suspect that anomalous circulation in the tropics induced by the interactions of different heating sources (central Pacific, eastern Pacific, Indian Ocean, etc.) plays a key role in TC variations at different subregions of WNP. Such response has also been identified by our previous study in constructing a global time-lagged dipole network quantifying anomalous synoptic-scale circulation responses to slowly changing oceanic boundary conditions (Lu et al., 2016). The atmospheric responses to tropical oceanic heating were found informative for predicting extreme events in the tropics and extratropics (Lu et al., 2016). Additionally, some previous studies (Zhang et al., 2016; Zhang, Wang, et al., 2017) have suggested that the extratropics significantly impact the frequency of TCs in the Atlantic via Rossby wave breaking by changing...
atmospheric condition affecting TC formation and intensification such as tropospheric moisture and vertical wind shear. The extratropical processes may also be a key factor regulating TC genesis variations over WNP, which needs to be confirmed in the future study.

### 3.2. FAVORABLE TC GENESIS CONDITIONS

Ordinary Least Square Model (OLS) exhibits some skill in reproducing environmental variables impacts on reconstructed TC signals over NSCS and OAEP (adjusted R-squared up to 0.40; Figure 2a). Coefficients of the selected predictors vary within the basin (Figures 2b–2d). The coefficient of $V_{zs}$ ($\beta_1$) peaks in NSCS and OAEP. In agreement with section 3.1, zonal vertical wind shear is usually smaller in these two regions, which is favorable for TC genesis and development. The variability of $V_{zs}$ in the two regions is large enough, however, to impact the frequency of TC genesis. Moisture is generally transported towards the Indonesian region via easterly trade winds. RH variability (Figure 2c) reveals significant relationships with TC variations over those oceanic areas [8–18°N, 130–155°E]. $Vor$ variability (Figure 2d) is more informative over SEWNP where TC genesis shows large ENSO-timescale variations (Figure 1c). This further quantifies our previous discussion in section 3.1 that the low-level vorticity, often associated with the monsoon trough, might play a key role in TC formation in SEWNP.

Although $V_{zs}$, RH, and $Vor$ are all vital factors for TC genesis, their contributions have large spatial variations within WNP. The spatial distributions of coefficients suggest that $V_{zs}$ and RH variability better explain TC genesis variations in NSCS and OAEP. In SEWNP, TC variations are mostly influenced by variability in $V_{zs}$ and $Vor$. Since the variables are standardized before fitting, we can imply their order of importance from the magnitudes of their coefficients. Based on the differences in their coefficients, $V_{zs}$ is on average nearly two times as important as RH and $Vor$.

### 3.3. PHASE RELATIONSHIPS BETWEEN RECONSTRUCTED TC GENESIS AND ENVIRONMENTAL VARIABLES

We have found that TC genesis has strong ENSO variability signals in SEWNP in section 3.1, but OLS is not able to capture the identified TC variations in section 3.2 (Figures 2a and 2e). We suspect that relationships between TC genesis and those selected environmental variables might vary over time in SEWNP, which would explain the poor skill of OLS in SEWNP. This question led to our further analysis using WTC (Figure 3). We first focus on the strength of the coherence (heatmap without the arrows). Over the entire data period, the reconstructed TC and environmental variables except RH show significant coherence on the 4- to 8-year frequency band (ENSO timescale), with low coherence elsewhere. Although the TC wavelet power spectrum (Figure 1h) shows minimal power for the interval from 1989 to 1996, the high coherence persists between reconstructed TC and environmental variables ($V_{zs}$ [Figure 3a] and $Vor$ [Figure 3c]), suggesting that their coherence on the ENSO timescale is independent of the strength of TC activities (Torrence & Webster, 1999). The wavelet coherence between reconstructed TC and two environmental variables ($V_{zs}$ and $Vor$) is greater than 0.6 for most of the time within the 4- to 8-year frequency band; and it even exceeds 0.8 when TC variation exhibits intensification from 1979 to 1985 (Figures 1h, 3a, and 3c), 1996 to 2006 (Figures 1h and 3c), and 2013 to 2017 (Figures 1h, 3a, and 3c). Especially for $Vor$, from 1989 to 2005 there is an extended period of peak coherence from 4-8 years, which indicates a shorter response time of TC to $Vor$. In addition to the strength of coherence between the analyzed variables, the arrows in Figure 3 illustrate the phase difference at each time-period combination. On the ENSO (4–8 years) band, the reconstructed TC and $V_{zs}$ or $Vor$ are consistently in phase (0–90°). It is noteworthy that their phase difference (Figures 3a and 3c) decreases from about 60° to 0° (completely in phase) after 1993, which suggests that the in-phase relationships between reconstructed TC and these two variables became stronger. It implies that $V_{zs}$ and $Vor$ whose variations are substantially regulating the TC genesis in SEWNP are local responses to ENSO signals during strong ENSO years. Such regulation is becoming even more prominent and immediate (decreasing phase difference) after 1993, manifested by enhanced TC variations.

In summary, except RH, $V_{zs}$, and $Vor$ exhibit high coherence and in-phase relationships with reconstructed TC on the ENSO timescale over the entire period. This is consistent with the OLS results in section 3.2 but further reveals that even their coherence and in-phase relationship vary over time. In addition to the prominent ENSO timescale, all three variables show significant coherence in a piecewise fashion across the 5- to 20-month frequency band. The environmental variables have strong semiannual and annual variations.
wavelet analysis results not shown). Figure 1h shows that the reconstructed TC will contain substantial signals on semiannual and annual time scales, although they are piecewise over the data period. That might explain the inconsistent phase relationships between reconstructed TC and environmental variables on the 5- to 20-month frequency band. Since local environmental variables are manifestations of the climate variabilities, we suspect that the varying phase relation and coherence leads to a weak correlation between reconstructed TC and ENSO signal.

To verify that, we first correlate the original and reconstructed TC with Oceanic Niño Index (ONI), respectively. The results confirm that their Pearson correlation coefficients are indeed quite weak ($r_1 = 0.09$, $r_2 = 0.11$). Then we apply WTC to the reconstructed TC and ONI (Figure 3d). There is a significant wavelet coherence (overall >0.7) between the reconstructed TC and ONI, suggesting that TC variations and ENSO might have strong nonlinear and nonstationary relationships in SEWNP. In particular, from 1979 to 1993, there is a persistent 90°, that is, 1–years, phase difference, between ONI and the reconstructed TC, with ONI leading TC. After 1994, the phase difference decreases from 90° to almost completely in-phase (~0°). Such enhancement of in-phase relationships is consistent with (thus can be explained by) the intensification of TC variations after 1993.

4. Summary

This study provides a holistic analysis of the spatiotemporal variations of TC genesis and its favorable environmental conditions in WNP. TC genesis exhibits strong semiannual and annual cycles in NSCS and OAEP, with strong ENSO-timescale variations in SEWNP. Such within-basin TC variations in WNP may be affected by anomalous circulation in the tropics and/or the results of the interactions of different heating sources.
After reconstructing the TC series over those significant frequencies, the influences of environmental variables on the identified TC variations are further revealed and quantified using OLS and WTC. OLS has good skill in reproducing the environmental variables impacts on reconstructed TC signals over NSCS and OAEP, where TC has strong semiannual and annual variations. The coefficients of the selected predictors exhibit large spatial variations, implying that not all environmental variables are equally important in explaining the TC variations at different subregions of WNP. Specifically, (1) RH is climatologically sufficient in the deep tropics, thus its variability regulated by Walker Circulation is more informative in the mid WNP; (2) low-level vorticity is a key predictor for ENSO-timescale variation in SEWNP, where vorticity is enhanced during El Niño years; (3) V250 has larger contributions than RH and Vor in reproducing TC signals over the entire WNP, especially in NSCS and OAEP, where V250 is usually smaller than other regions in WNP; and (4) in SEWNP, the nonstationary and nonlinear covarying relationships between TC and the selected environmental variables are unveiled by WTC. Reconstructed TC and V250 or Vor show high but varying coherence and in-phase relationships on the ENSO timescale over the entire period, consistent with a weak linear correlation between original/reconstructed TC and ENSO signal in SEWNP. Our presented study provides a comprehensive profile of spatiotemporal variations of TC genesis within WNP basin and reveals both linear and nonlinear/nonstationary relationships between prominent TC variations and environmental variables.

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Erratum
In the originally published version of this article, co-first authorship between Mengqian Lu and Rui Xiong should have been noted. This error has since been corrected, and the present version may be considered the version of record.