Influence of Natural Climate Variability on Extreme Wave Power over Indo-Pacific Ocean
Assessed using ERA5

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Version: 09-03-2021

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Abstract

In recent decades, wave power (WP) energy from the ocean is one of the cleanest renewable energy sources associated with oceanic warming. In Indo-Pacific Ocean, the WP is significantly influenced by natural climate variabilities, such as El Niño Southern Oscillation (ENSO), Indian Ocean Dipole (IOD) and Pacific Decadal Oscillation (PDO). In this study, the impact of major climate variability modes on seasonal extreme WP is examined over the period 1979–2019 using ERA5 reanalysis data and the non-stationary generalized extreme value analysis is applied to estimate the climatic extremes. Independent ENSO influence after removing the IOD trends (ENSO|IOD) on WP are evident over the eastern and central Pacific during December–February (DJF) and March–May (MAM), respectively, which subsequently shifts towards the western Pacific in June–August (JJA) and September–November (SON). The ENSO|PDO impact on WP exhibits similar yet weaker intensity year round compared to ENSO. Extreme WP responses due to the IOD|ENSO include widespread decreases over the tropical and eastern Indian Ocean (IO), with localized increases only over the South China and Philippine (SCP) seas and Bay of Bengal (BOB) during JJA, and the Arabian Sea during SON. Lastly, for the PDO|ENSO, the significant increases in WP are mostly confined to the Pacific, and most prominent in the North Pacific. Composite analysis of different phase combinations of PDO (IOD) with El Niño (La Niña) reveals stronger (weaker) influences year-round. The response patterns in significant wave height (SWH), peak wave period (PWP), sea surface temperatures (SST), and sea level pressure (SLP) helps to explain the seasonal variations in WP.

Keywords: Wave power energy, Climate Variability, Generalized extreme value(GEV)distribution, Indo-Pacific Ocean,
1. Introduction

The depletion of conventional energy resources and increasing global warming due to the consumption of fossil fuels have prompted interest in renewable energy resources in many countries (Cornett 2008). Among the various renewable energy resources such as wind, solar, hydro-power, etc., wave power is one of the most important and least studied renewable energy resources. Recent studies suggest that the spatial and temporal variations in wave power are induced by natural climate variabilities like El Niño–Southern Oscillation (ENSO), Pacific Decadal Oscillation (PDO), and Atlantic Multidecadal Oscillation (AMO) (Bromirski and Cayan 2015; Bromirski et al. 2013; Reguero et al. 2019; Yang and Oh 2020). Therefore, a better comprehension of the wave power and its relation with natural climate variability is essential for social and economic development.

WP, which measures the transport of energy that is transmitted by air-to-sea exchanges and used for wave motion (Donelan et al. 1997; Reguero et al. 2019), depends not only on wave height but also on wave period. Moreover, WP represents the accumulated wave energy over periods of time such as months, seasons, and years, unlike other wave climate parameters (e.g., SWH) that must be averaged (Reguero et al. 2019). Therefore, WP can represent the variations in the wave climate better than other wave parameters (e.g., wave height). Yet, to date, continuous efforts have been made to analyze the mean and extreme historical trends in wind and wave climate at the global (Aarnes et al. 2015; Caires et al. 2006; Fan et al. 2012; Gulev and Grigorieva 2004; Meucci et al. 2020; Reguero et al. 2012; Stopa et al. 2013; Young et al. 2011, 2012; Young and Ribal 2019) and regional scale (Allan and Komar 2006; Carter and Draper 1988; Gulev and Grigorieva 2006; Hemer et al. 2008, 2010; Menendez et al. 2008; Wang and Swail 2001, 2006; Wang et al. 2009, 2012; Young 1999; Young and Ribal 2019). In addition, other wave climate
indicators, such as wave period and/or direction, have also been investigated extensively to identify underlying properties in the changes to mean and extreme SWH (Chen et al. 2002; Semedo et al. 2011; Sterl and Caires 2005; Young 1999; Zhang et al. 2011; Zheng et al. 2016).

In context of WP, several studies have been carried out previously to analyze the monthly and annual variations in mean wave power at the global scale (Arinaga and Cheung 2012; Barstow et al. 2008; Cornett 2008; Gunn and Stock-Williams 2012; Hulls 1977; Mollison 1986; Mork et al. 2010). Further, the seasonal variations in mean wave power were examined by Mackay (2012). However, these analyses were conducted based on either satellite data or wave models such as Wave Watch-III (WW3) and ECMWF WAM for relatively short periods of 6 or 10 or 12 years. Long term seasonal and interannual variations in global mean wave power were investigated by Reguero et al (2015) using WW3 data for a 61–year period (1948–2008). In this regard, numerous regional studies have also been conducted. For example, the North Pacific (NP) (Bromirski et al. 2005, 2013; Yang and Oh 2020), North Atlantic (NA) (Bromirski and Kossin 2008; Bromirski and Cayan 2015; Santo et al. 2015), Black Sea (Aydogan et al. 2013), along the Australian coasts (Hemer et al. 2016, 2018), and shelf seas of India (Kumar and Anoop 2015; Sannasiraj and Sundar, 2016; Amrutha et al. 2019; Amrutha and Kumar 2020). However, seasonal/annual variations in extreme WP have not been assessed yet at the global and regional scale.

Although many studies have focused on seasonal/annual variations in mean WP as described above, the natural climate variabilities such as the El Niño–Southern Oscillation (ENSO), Indian Ocean Dipole (IOD), and Pacific Decadal Oscillation (PDO), etc. can exert a significant impact on wave climate through large-scale atmospheric circulation patterns with different seasonal and regional features (Hemer et al. 2010; Izaguirre et al. 2010, 2011; Kumar et al 2016, 2019;
Marshall et al. 2018; Menéndez et al. 2008; Patra et al. 2020; Wandres et al. 2018; Yang and Oh 2018). However, influences due to such large-scale natural climate variability modes on WP remains unclear, except for limited regional and global scale studies. For example, using the WW3 wave model for the period 1948-2008, the PDO influence on WP across the NP region was investigated by Bromirski et al. (2013) and NAO influence on WP across the NA region by Bromirski and Cayan (2015) during winter (November–March) and summer (May–September). Recently, Yang and Oh (2020) examined the effect of ENSO and PDO on WP during boreal summer (June-August, JJA) in the western NP. At the global scale, Reguero et al. (2015) analyzed the interrelation between the annual mean WP and fifteen climate variability modes which include ENSO, IOD, and PDO. Recently, the ENSO and Atlantic Multidecadal Oscillation (AMO) influence on annual mean WP have been reported by Reguero et al. (2019). Such studies were predominantly concerned with the seasonal/annual impact of natural climate variability on mean WP.

“Extreme” events are significant departures from the normal climate state and often have widespread societal and ecological impacts. The changes in extreme and mean wave characteristics have been reported to be of different nature (Feng et al. 2012; Mori et al. 2010), and are observed to be linked with more frequent extreme events. So, it’s crucial to analyze the influence of natural climate variability on extreme parameters, which exert stronger impacts than mean. Further, the simple linear regression analysis is used for mean variables and cannot be applied to extreme variables because of their non-normality nature (Coles 2001), and recent studies have widely used the extreme value theory to investigate the impact of climate variability on extreme parameters such as SWH, wind, wave period, etc. (Izaguirre et al. 2010, 2011; Kharin and Zwiers 2005; Kumar et al. 2016, 2019; Menéndez et al. 2008; Min et al. 2013; Patra
et al. 2020; Zhang et al. 2010). But still, none of the previous studies assessed the impact of natural climate variability on extreme WP.

This study investigates the seasonal influence of dominant modes of natural climate variability, such as ENSO, IOD, and PDO on extreme WP in the Indo–Pacific Ocean using ERA5 reanalysis data for the 41 year period from 1979–2019. For this purpose, firstly, the four boreal seasons (i.e., December–February (DJF, winter), March–May (MAM, spring), June–August (JJA, summer), and September–November (SON, autumn)) are considered to understand the seasonal influence of natural climate variability on extreme WP and a non–stationary generalized extreme value GEV analysis (Kharin and Zwiers 2005; Zhang et al. 2010; Min et al. 2013) is applied to determine/capture the seasonal extremes. Regions with statistically significant responses at the 5% level are marked by hatching. In addition, the seasonal influence of natural climate variability on extreme SWH and Peak Wave Period (PWP) is also investigated to explore the associated underlying mechanisms in enhancing or reducing the WP in the Indo-Pacific Ocean as WP comprises information about SWH and PWP. The seasonal teleconnection patterns of WP and SWH are explained through/by SLP and SST.

As different modes of natural climate variability tend to interact with each other in specific seasons (Cai et al. 2011; Kumar et al. 2016, 2019). Therefore, independent analysis of seasonal mean and extreme WP, SWH, and PWP is carried out to assess the role of one variability mode in strengthening and weakening the other variability mode influence in different seasons. Additionally, the composite analysis of mean and extreme WP for the different phase combinations of natural climate variabilities (i.e. ENSO, IOD, and PDO) is also conducted to get further insight into the inter-relation between different variability modes. The novelty of the current study in comparison to previous relevant studies is detailed in Table 1.
The remainder of the paper is structured as follows. Data and methodology are detailed in section 2 and teleconnection patterns in section 3. Section 4 provides the detailed investigation of the influence of natural climate modes (in particular the ENSO, IOD, and PDO) and their impendent impact on seasonal mean and extreme WP, SWH, and PWP. Composite analysis for different phase combinations of ENSO with IOD and ENSO with PDO is presented in section 5. Section 6 provides a summary and conclusions.

2. Data and Methodology

2.1. Data

The latest reanalysis product from the European Centre for Medium-Range Weather Forecasting (ECMWF), referred to as the ERA5 reanalysis (Hersbach and Dee 2016), is used in the present study to analyze the mean and extreme WP for the 41-year period from 1979 to 2019 over the Indo–Pacific region for the four boreal seasons (i.e., December–February (DJF, winter), March–May (MAM, spring), June–August (JJA, summer), and September–November (SON, autumn).

The ERA5 reanalysis data have several advancements compared to its predecessor, ERA-Interim (Dee et al. 2011). In contrast to ERA-Interim, ERA5 has higher spatial and temporal resolution along with an improved representation of the tropospheric processes, including better representation of tropical cyclones, global balance of precipitation and evaporation cycle etc. In order to measure the WP, the seasonal mean and maxima of SWH (of combined wind waves and swell) and PWP are obtained from the six-hourly SWH and PWP data taken from ERA5. Similarly, the seasonal mean SLP and SST were also derived from 6-hourly SLP and SST data of ERA-5, respectively. In this study, the ERA5 reanalysis data for all the variables were downloaded from the ECMWF website (https://www.ecmwf.int/en/forecasts/datasets/reanalysis-
datasets/era5/) at a horizontal resolution of 0.5°×0.5° (i.e. SWH and PWP) or 0.25°×0.25° (i.e., SST and SLP).

2.2. Climate Indices

Indices used to represent climate variability associated with ENSO, IOD, and PDO over 1979–2019 were obtained from several online sources. Overall, ENSO is the dominant coupled ocean–atmosphere interaction occurring over the equatorial Pacific and significantly affects the interannual climate variability globally (Collins et al. 2010; Stevenson 2012). In order to examine the seasonal ENSO influence, the Niño-3.4 index (referred to as N34 herein) which represents the average SST anomalies over the equatorial eastern Pacific (5°N–5°S, 170°W – 120°W) was obtained from the National Oceanic and Atmospheric Administration/Climate Prediction Center [http://www.cpc.ncep.noaa.gov/data/indices/]. To quantify the IOD impact, the dipole mode index (DMI) was used (Saji et al., 1999; Webster et al., 1999), which is a measure of the difference between the area–averaged SST anomalies in the western tropical Indian Ocean (TIO) (50°–70°E, 10°S–10°N) and southeastern TIO (90°–110°E, 10°S–Equator). Monthly SST anomalies acquired from the extended Reconstructed Sea Surface Temperature (ERSST) dataset to calculate the seasonal DMI index. The PDO index, prescribed as the principal mode of NP monthly SST anomalies poleward of 20°N (Zhang et al., 1997), was obtained from the Joint Institute for the Study of the Atmosphere and Ocean (JISAO) at the University of Washington [http://research.jisao.washington.edu/pdo/].

Natural climate variability modes can interact with each other during different seasons (Cai et al., 2011). Consequently, the independent influence of each should be considered when assessing the impact of each mode. The seasonal correlation coefficients between the detrended N34 and DMI,
and N34 and PDO indices are shown in Table 2 for the period 1979–2019. A significant positive correlation (at the 1% level) between the N34 and PDO index is found during all seasons, with a range 0.397-0.545. For N34 and DMI indices, positive correlations only occur during JJA (i.e. 0.312, p-value<0.05) and SON (0.620, p-value<0.01). The significant correlation between ENSO and IOD in JJA and SON suggests that IOD can be largely determined by ENSO and seasonally modulated responses, yet some IOD events can occur independently of ENSO events (Cai et al. 2011; Kumar et al. 2019; Stucker et al. 2017). When analyzing the independent impact of each climate variability mode, the dependency of one climate variability index on the other is removed using linear regression analysis. For example, ENSO|IOD denotes the linearly independent residual ENSO index obtained after the removal of IOD from ENSO.

2.3. Methodology

2.3.1. Derivation of Wave Power (WP)

In essence, WP measures the transmission of energy by/through air-sea exchanges and used for wave motion (Donelan et al. 1997). For irregular waves, the total energy per unit area of water surface (in Joules/m²) is given as:

\[ E = \rho g \int_0^\infty S(f)df \]  

where \( g \) is the acceleration due to gravity, \( \rho \) is the sea water mass density (~1028 kg/m³), \( S(f) \) denotes the spectral density with respect to frequency \( f \), and the \( n^{th} \) order moment is expressed in terms of spectral density as:
The SWH ($H_s$) and energy period ($T_e$) are computed from the integral of the spectral density and expressed in term of moment as follows:

$$m_n = \int_0^\infty f^n S(f) df.$$  \hfill (2)

For each harmonic component of the wave spectrum, its energy travels at the group velocity defined by:

$$c_g(f, d) = \frac{1}{2} \sqrt{\frac{g}{k}} \frac{\tanh(kd)}{1 + \frac{2kd}{\sinh(2kd)}}.$$  \hfill (4)

where $d$ is the water depth, and $k$ is the wave number which is related to the frequency $f$ through the dispersion relation $(2\pi f)^2 = gk \tanh(kd)$. The total WP (also referred to as “wave energy flux”), in watts per meter (W/m) of wave crest width at any water depth $d$ is given as

$$WP = \rho g \int_0^\infty c_g(f, d) S(f) df.$$  \hfill (5)

On substituting equation (4) into equation (5) and using the dispersion relation:

$$WP = \frac{\rho g^2}{4\pi} \int_0^\infty f S(f) \left[ \left(1 + \frac{2k_f d}{\sinh(2k_f d)}\right) \tanh(k_f d) \right] df.$$  \hfill (6)

For large values of $k_f d$, the limits of $\sinh$ and $\tanh$ approaches to $\infty$ and 1, respectively. Thus, equation (6) reduces to:
Substituting equations (2) and (3) into equation (7), WP is expressed as:

\[ WP = \frac{\rho g^2}{4\pi} \int_0^\infty S(f) df. \]  

(7)

The energy period is estimated from the spectral shape and other parameters. When PWP \((T_p)\) is known, the energy period is estimated by using the following relation (Cornett, 2008):

\[ T_e = \alpha T_p, \]

(9)

where \(\alpha\) depends on the shape of the wave spectrum and \(\alpha\) increases towards unity with decreasing spectral width. Hagerman (2001) assumed \(T_e = T_p\) in the assessment of the wave energy resources over southern New England. In this study, the same assumption is adopted. On substituting \(T_e = T_p\) into equation (8), WP is expressed as:

\[ WP = \frac{\rho g^2}{4\pi} \left( \frac{T_p H^2}{16} \right). \]

(10)

2.3.2. Generalized Extreme Value (GEV) Distribution

Climate extremes are significant departures from the normal climate state and often have widespread societal and ecological impacts. Thus, the correct representation of extreme events is essential to understand their impacts. Extreme value theory provides the statistical description of extremes in stationary and non-stationary processes. However, in the context of environmental
variables (e.g., SWH, temperature, precipitation), a non-stationary variable is used (Coles and Casson 1999; Gellens 2002; Nogaj et al. 2007; Kharin and Zwiers 2000, 2005), whereby extreme events are defined by three extreme value distributions, i.e., Gumbel distribution, Fréchet distribution, or Weibull distribution, arising from the limiting theorem of Fisher and Tippett (1928). The three distributions can be combined into a single form, the non-stationary GEV distribution, and its cumulative distribution function is given as:

\[
F(x, \mu_t, \sigma_t, \xi_t) = \begin{cases} 
\exp[-\exp(-\frac{x-\mu_t}{\sigma_t})], & \xi_t = 0 \\
\exp[-(1+\xi_t \frac{x-\mu_t}{\sigma_t})^{-\frac{1}{\xi_t}}], & \xi_t \neq 0, 1 + \xi_t \frac{x-\mu_t}{\sigma_t} > 0 
\end{cases},
\]

(11)

where \(-\infty < \mu_t < \infty, \sigma_t > 0, and -\infty < \xi_t < \infty\) represent the location, scale, and shape parameters, respectively. For the non-stationary GEV distribution, the climate variability \(v_t\) (here, IOD, ENSO, and PDO indices, which are detrended and normalized) that varies with time \((t)\) is used as a covariate of the GEV parameters. The location parameter \((\mu_t)\) as a function of climate variability is written as:

\[
\mu_t = \mu_0 + \mu_1 (v_t - v_0),
\]

(12)

where \(\mu_0\) represents the location parameter at time \(t_0\), and \(\mu_1\) denotes the regression coefficient representing the relationship between the climate variable and location parameter. Additionally, the scale and shape parameters can also be expressed as a function of climate variability as follows:

\[
\ln \sigma_t = \ln \sigma_0 + \sigma_1 (v_t - v_0) \quad \text{and} \quad \xi_t = \xi_0 + \xi_1 (v_t - v_0),
\]

(13)
where \( \sigma_0 \) and \( \xi_0 \) are the scale and shape parameter values at time \( t_0 \), respectively, and \( \sigma_1 \) and \( \xi_1 \) are the corresponding regression coefficients. In order to examine the statistical significance of climate variability on extremes, the log–likelihood ratio test is used. The log–likelihood test compares the non–stationary GEV model with the stationary GEV model and assesses the GEV parameters (Kharin and Zwiers 2005; Zhang et al. 2010).

3. SST and SLP mean Teleconnection

The patterns of seasonal mean SST and SLP regressed onto ENSO|IOD, IOD|ENSO, ENSO|PDO, and PDO|ENSO over the period 1979–2019 are shown in Fig.1 and regions with statistically significant responses at the 5% level are indicated by hatching. Significant canonical responses in SST to ENSO|IOD are evident over the eastern PO (warmer conditions during El Niño) and western PO (colder conditions) throughout the year. In the IO, the strongest signals in SST are found over the majority of the NIO and TIO in DJF and MAM, NIO in JJA, and NIO and western TIO in SON (Fig. 1a). Further, the ENSO|IOD influence on SLP shows high and low pressure anomalies in eastern and western regions of the southern Indo–Pacific Ocean, respectively, during DJF. This anomalous pressure pattern generates strong winds over the southern Indo-Pacific Ocean, leading to an enhancement in both SWH and PWP in DJF (Fig. 1b). Similarly, the Southern Oscillation pattern of the coupled high and low pressure anomalies is also seen in DJF over the western and eastern PO, respectively. This too presumably leads to both strong winds and enhances the wave parameters (i.e., SWH and PWP) over the eastern PO (Fig. 1b). With the progression of the seasons from DJF through to SON, the high and low pressure anomalies shift from the western PO and eastern PO to central-western PO and eastern PO, respectively, during JJA and SON.
Additionally, high pressure anomalies are observed over the eastern parts of the SO, NIO, and TIO, with low pressure anomalies over the central parts of the SO during MAM, JJA, and SON. Such strong responses associated with SLP changes will also lead to strong responses in the winds and wave parameters (Fig. 1b).

Significant impacts of IOD|ENSO on SST is predominantly confined to the western IO and AS in DJF, which extend into parts of the tropical Pacific in MAM. During JJA and SON, the IOD|ENSO is associated with positive SST anomalies over the western-to-central IO in JJA and SON (Fig. 1a). The corresponding responses in SLP during DJF show high pressure anomalies over most of the tropical and mid-latitude region of the Indo–Pacific Ocean, and low pressure anomalies over the AS and high-latitude region of the Indo–Pacific Ocean. In MAM, the IOD|ENSO influence is most significant over the mid-to-high latitudes in both hemispheres. In JJA, high SLP anomalies expand over the mid-latitudes of Indo-Pacific Ocean, from the eastern IO to central PO, and low pressure anomalies strengthen and expand over the western IO. In SON, high SLP anomalies are evident over the eastern IO and tropical PO, and develop over the eastern southern PO, whereas the low pressure anomalies over the western IO are similar to JJA. Such high and low SLP anomalies, with progressing seasonal patterns, will consequently produce strong winds and consequently enhance the wave parameters in the respective regions (Fig. 1b).

The ENSO|PDO impact closely resembles that of ENSO|IOD whereby warmer SSTs are evident over the eastern PO and colder SST over the western PO year around (c.f. first and third rows in Fig 1a). In the IO, significant positive signals in SST due to ENSO|PDO are again evident over large parts of the NIO and TIO in most seasons, being weakest in JJA (Fig. 1a). Further, the ENSO|PDO influence on SLP is also consistent with that of ENSO|IOD whereby the significant signals being associated with the widespread high and low pressure anomalies over the western
and eastern Indo-Pacific Ocean, respectively (c.f. first and third rows in Fig. 1b). However, high pressure anomalies are subdued in the western IO during SON for ENSO|\textit{PDO} compared to that associated with ENSO|\textit{IOD}. Thus, the above changes of both ENSO|\textit{IOD} and ENSO|\textit{PDO} are likely to generate the similar variations in the generated winds and wave fields in the respective regions, except for the western IO.

The independent PDO influence (i.e., PDO|\textit{ENSO}) on SST is observed to induce consistent year-round pattern with long-term SST increases (warm SST) over the eastern PO (extending towards the west along the equator) and decreases (cold SST) over the western NP and southwest tropical PO (Fig. 1a). This represents the typical pattern associated with a positive PDO. In the IO, the strong PDO|\textit{ENSO} influences on SST occur over the AS in MAM, NIO and SCP seas in JJA, and BOB and SCP seas in SON (Fig. 1a). The corresponding responses in SLP exhibit an anomalous low pressure over the north and tropical Pacific and an anomalous high pressure over the eastern TIO in DJF (Fig. 1b). In addition, anomalous high and low pressure centers are evident over the south Pacific in DJF. In MAM, positive responses in SLP to the PDO|\textit{ENSO} are observed over the large section of the tropical and mid-latitude region of the Indo-Pacific Ocean, with counter responses (low-pressure anomalies) over high latitudes of the Indo-Pacific Ocean. In JJA, the PDO|\textit{ENSO} influence on SLP is most significant over the western Pacific Ocean (PO) (high-pressure anomalies) and eastern NP and Southern Ocean (SO) (low-pressure anomalies). These anomalies propagate into the western NP (high-pressure anomalies) and central NP (low-pressure anomalies) in SON. In SON, high and low pressure anomalies are evident over the SO.
4. Influence of Indo-Pacific Climate Variability

4.1. ENSO Influence

Spatial patterns of the seasonal mean and extreme WP (WPavg and WPmax), SWH (Havg and Hmax), and PWP (Pavg and Pmax) responses to independent ENSO|IOD influence (i.e. the independent ENSO influence obtained after the removal of IOD signals) over the period 1979–2019 in the Indo–Pacific Ocean are shown in Fig. 2. In addition, the original seasonal ENSO influence (i.e., no removal of covarying IOD signals) on the mean and extreme WP, SWH, and PWP is also provided in Supplementary Fig. 1 to assess the role of IOD in strengthening and weakening the ENSO impact. Overall, mean responses in WPavg, Havg, and Pavg were acquired by using linear regression whereas extreme responses in WPmax, Hmax, and Pmax were based on the non-stationary GEV analysis. Regions with statistically significant responses at the 5% level are indicated by hatching.

Widespread positive responses in WPmax to ENSO|IOD are evident over the eastern Pacific and southern part of the IO (an extension from south of Australia) in DJF (Fig. 2a). As the seasons progress from DJF through to SON, large seasonal variations in WP are observed in both the IO and PO. In the PO, positive amplitudes of the WPmax occur more over the central Pacific in MAM, which shift further towards the western Pacific in JJA and SON (Fig. 2a). The strong increases in extreme WP in the western NP and BOB during JJA, and in the western NP during SON, presumably arises from the enhanced tropical cyclone activities during that time of year (Shanas and Kumar 2014; Yang and Oh 2020, 2018; Zhan et al. 2011). However, WPmax exhibit larger seasonality in the IO compared to the PO. For example, the WP increases over the western TIO in MAM, over the western TIO, BOB, SCP seas in JJA, and over the eastern TIO
during SON in response to ENSO|IOD (Fig. 2a). The regression patterns of ENSO|IOD on mean WP are similar to the extreme. Consistently, the ENSO|IOD influence on Havg and Hmax over the Indo-Pacific Ocean (Fig. 2b) shows similar seasonal and regional variations as WPavg and WPmax, due to SWH being a dominating factor in determining the WP (Bromirski et al. 2005, 2013; Reguero et al. 2019; Yang and Oh 2020). Lastly, the impact of ENSO|IOD on Pavg and Pmax is found to be largest over the eastern PO in DJF and over the western PO in JJA and SON (Fig 2c). Such regions exhibit a significant relationship, whereby changes to tropical SST anomalies due to the warm ENSO phase resulted in variations in anomalous long PWP. In the IO however, significant increases in Pavg and Pmax are observed over large parts of the IO year-round due to ENSO|IOD, but more so in DJF and MAM (Fig. 2c).

Comparing independent ENSO influences (ENSO|IOD) to the original ENSO signals (c.f. Fig. 2 and Supplementary Fig. 1), it is found that WPavg is enhanced more over the eastern TIO in JJA and SON, and over the central NP in SON for the independent ENSO influence. This indicates that the IOD acts to reduce the ENSO impact in these regions during JJA and SON. In addition, enhancement in the independent ENSO influence is also exhibited in the mean and extreme SWH responses when the covarying IOD signal is removed during JJA and SON (c.f. Fig. 2b and Supplementary Fig. 1b). However, positive responses in mean and extreme PWP associated with ENSO in the IO are significantly reduced during SON when the covarying IOD signal is removed (c.f. Fig 2c and Supplementary Fig. 1c). In DJF and MAM, the ENSO|IOD impact on mean and extreme WP, SWH, and PWP exhibits similar regional variations as observed for the complete ENSO signals as the IOD is not active during these seasons.

4.2. IOD Influence
Seasonal spatial regression patterns of mean and extreme WP, SWH, and PWP against the independent IOD influence (denoted as IOD|ENSO) after removing the ENSO signal over 1979–2019 in the Indo-Pacific Ocean are presented in Fig. 3. Further, the original seasonal IOD influence (here using the DMI) on the mean and extreme WP, SWH, and PWP that include variability due to ENSO is also provided in Supplementary Fig. 2.

Statistically significant IOD|ENSO influences on WPavg and Havg are limited in the Indo–Pacific Ocean and are generally less intense than ENSO influences (c.f. Fig. 2 and Fig. 3). During DJF and MAM, the positive responses of extreme WP and SWH to IOD|ENSO are evident over the SO, and the responses extend into the IO for PWP (Fig. 3). Significantly decreased signals are also found over the AS and central-to-western IO during MAM. However, the IOD is not active during this half of the year; therefore, such signals may be related to other variability intrinsic to the IO, such as the Indian Ocean Basin Mode (IOBM), which are shown to prolong ENSO effects (Yuan et al. 2008). During JJA and SON, decreases in WP and SWH are evident over the majority of the eastern IO, with increases only in extremes in the BOB in JJA (related to increased cyclonic activity), and over the AS and southwestern IO in SON (Fig. 3a-b). The opposite occurs for mean and extreme PWP, where weak decreases are found over the entire IO in JJA, but large increases are found over the eastern IO alongside decreases over the western IO in SON. The IOD|ENSO influence on extreme WP and SWH is evident over the eastern PO in DJF, over the central north Pacific in MAM, over the western PO in JJA and SON (Fig. 3a,-b). The mean responses to IOD|ENSO are also observed to follow similar patterns as the extreme, except for the western PO and BOB in JJA. The western PO and BOB are subject to high WP due to intensified tropical cyclone activity during JJA (Shanas and Kumar 2014; Yang and Oh 2020,
2018); however, negative amplitudes in these regions suggest that El Niño hampers such activity and resulting in smaller WP.

Overall, an increase in SWH and decrease in PWP over regions such as the BOB and the northwestern Australian coast in DJF are associated with the seasonal increase in small fetch winds (Remya et al. 2020). In addition, significant impact of the IOD|ENSO on SWH is constrained to the eastern IO and BOB in JJA, with decreases in mean PWP. This indicates that whilst swells dominate the IO, wind seas (directly generated and strongly coupled to local winds) are also of importance in JJA during positive IOD events (Remya et al., 2020). In SON, the strongest IOD|ENSO responses in PWP are evident over the entire IO, except the far western IO. However, in the PO, positive responses of PWP to IOD|ENSO occur over the eastern PO except in SON, where decreases in PWP occur over the majority of the PO (Fig. 3c).

Lastly, comparing independent IOD influences (IOD|ENSO) to the original IOD signals (c.f. Fig. 3 and Supplementary Fig. 2), the independent IOD impacts on WP, SWH, and PWP are similar to the complete IOD signal, yet slightly reduced over the entire Indo–Pacific Ocean in DJF and MAM, and over the IO during SON. This emphasizes the significant influence of the IO climate variability over the Indo–Pacific Ocean in DJF and MAM, and over the IO in SON even in the absence of ENSO. In the PO, decreases in WPavg and Havg over the western NP in JJA and SON occur, indicating that ENSO plays a vital role in enhancing the IOD influences in this region (c.f. Fig. 3a-b and Supplementary Fig. 2a-b). Similarly, the negative responses of Pavg to IOD|ENSO are evident over the western NP in JJA and SON, yet they are positive when the covarying ENSO influence is included. This suggests that the PWP signals in the western NP are significantly subdued when the IOD and ENSO are in phase (c.f. Fig. 3c and Supplementary Fig. 2c).
4.3. PDO Influence

Seasonal regression patterns of WPavg and WPmax, Havg and Hmax, and Pavg and Pmax against the ENSO|PDO (i.e., ENSO independent of the PDO variability) and PDO|ENSO (i.e., PDO independent of the covarying ENSO signals) over 1979–2019 in the Indo-Pacific Ocean are displayed in Figs. 4 and 5, respectively. In addition, the original ENSO and PDO influence on the mean and extreme WP, SWH, and PWP are also provided in supplementary Fig. 1 and Fig. 3, respectively.

Overall, the ENSO|PDO influence on mean WP exhibits similar regional and seasonal variations as in the original ENSO but with a slight reduction in the amplitude throughout the year, apart from the PO in MAM, indicating the dominant impact of ENSO even in the absence of PDO (c.f. Fig. 4a and Supplementary Fig. 1a). In MAM, a decrease in WPavg is evident over the central Pacific. This reveals that PDO enhances the WP over the central Pacific in MAM (c.f. Fig. 4a and Supplementary Fig. 1a). The impact of the ENSO|PDO on WPmax is similar to WPavg yet with stronger amplitudes. The regression patterns of mean and extreme SWH associated with the ENSO|PDO are also consistent with the regression patterns of mean and extreme WP throughout the year (Fig. 4b). Further, the Pavg and Pmax response patterns to ENSO|PDO are similar to those of the original ENSO year-round except in MAM. In MAM, a reduction in response patterns of Pavg and Pmax to ENSO|PDO over the central NP (Fig. 4c) is associated with the SST changes driven by the PDO (Fig. 1a).

For the independent PDO influence (i.e. PDO|ENSO), significant increases in mean and extreme WP and SWH are mostly confined to the PO and most prominent in the NP (Fig. 5a-b). Over the IO, positive PDO|ENSO responses in WP and SWH are most prevalent during JJA. However,
strong counter responses (i.e. significant decreases in WPavg and Havg) are evident over the same regions during SON (Fig. 5a-b). Overall, the extreme responses to PDO|ENSO for WP and SWH are consistent with those of the mean responses. The strongest impact of independent PDO (i.e. PDO|ENSO) on Pavg and Pmax is observed over the central NP in DJF and SON, and over the eastern and southern PO in MAM and JJA (Fig. 5c). This suggests that enhanced PWP in these regions are related to the SST changes associated with positive PDO phase (Fig. 1a). In DJF and MAM, PWP decreases and SWH increases in the western NP are related to the seasonal increase in wind seas. In the IO, positive responses to PDO|ENSO in Pavg and Pmax are evident over the mid-latitudes of the SIO in DJF, and over the western IO in MAM. In JJA, an increase in Pavg and Pmax values occurs over the entire IO apart from a small part of the western SIO. Conversely, counter responses in Pavg and Pmax (i.e. decreases over the IO) are found in SON.

Lastly, comparing the seasonal PDO influence independent of ENSO (i.e., PDO|ENSO) to the original PDO signals (c.f. Fig. 5 and Supplementary Fig. 3), it is evident that excluding the co-occurring ENSO signals from PDO reduces the response amplitudes over the eastern PO and mid-latitudes of the SIO in DJF, western TIO, and SIO in MAM, western PO in JJA, and western PO and SIO in SON. This reveals that ENSO plays a significant role in enhancing PDO influences in these regions during these seasons. However, enhanced WP also occurs over the western PO in MAM and the eastern Pacific in JJA (c.f. Fig. 5 and Supplementary Fig. 3).

5. Composite Analysis

5.1. Composite Analysis of ENSO and IOD

As various natural climate variabilities modes interact with one another in a particular season. So, the independent influence of ENSO, IOD, and PDO is analyzed above (in section 4). To get
further insight into the interrelation between the various modes of natural climate variability, the
composite analysis of the mean and extreme WP for different ENSO and IOD, and ENSO and
PDO phase combinations is conducted for the 41 year period over the Indo – Pacific Ocean. In
this section composite analysis is conducted between ENSO and IOD. For this, El Niño
(ENSO+), La Niña (ENSO−), and positive and negative IOD (pIOD and nIOD, respectively)
years are chosen from the detrended and normalized time series of the original indices for those
values where ENSO and IOD indices exceeded a threshold value of ±0.5 (list of the years is
provided in Table. 3). This gives a total of 9, 3, 5, and 9 sample years in JJA and 11, 3, 4, and 12
sample years in SON for the combination of El Niño/pIOD, La Niña/pIOD, El Niño/nIOD, and
La Niña/nIOD, respectively. The composite patterns of (left panel) mean and (right panel)
extreme WP anomalies in (a) JJA and (b) SON for various ENSO and IOD combinations are
shown in Fig. 6.

The WPavg and WPmax increases during the El Niño/pIOD years and decreases during La
Niña/nIOD years over the western PO, BOB, western TIO, and western SIO in JJA and over the
western PO in SON (Fig. 6a and b). The combination of an El Niño event with a pIOD (or nIOD)
leads to increase in mean and extreme WP over the western NP and counter response is evident
for the combination of La Niña with pIOD (or nIOD) in JJA and SON, reveals the strengthening
of ENSO in enhancing/reducing WP in western NP (Fig. 6a and b). During out – phase
combinations (i.e. El Niño/nIOD and La Niña/pIOD), an increase in mean and extreme WP is
observed over the south-east Indo – Pacific Ocean during La Niña/pIOD and decrease during El
Niño/nIOD in JJA and SON.

5.2. Composite Analysis of ENSO and PDO
The composite patterns of (left panel) mean and (right panel) extreme WP anomalies in (a) DJF, (b) MAM, (c) JJA, and (d) SON for various ENSO and PDO combinations are displayed in Fig. 7. For composite analysis, El Niño (ENSO+), La Niña (ENSO−), and positive and negative PDO (pPDO and nPDO, respectively) years are chosen from the detrended and normalized time series of the original indices for those values where ENSO and PDO indices exceeded a threshold value of ±0.5 (list of the years is provided in Table. 4). This yields a total of 8, 5, 2, and 8 sample years in DJF, 13, 5, 3, and 11 sample years in MAM, 7, 3, 6, and 8 sample years in JJA, and 12, 5, 2, and 12 sample years in SON for the combination of El Niño/pPDO, La Niña/pPDO, El Niño/nPDO, and La Niña/nPDO, respectively.

For El Niño/pPDO events, WPavg increases over the eastern PO in DJF, the central NP in MAM, NPO, SIO, BOB, and western TIO in JJA, and western PO in SON and decreases over the NIO, TIO, SCP seas, and western NP in DJF, western NP and eastern SPO in MAM and JJA, and in the eastern PO, NIO, and TIO and its counter responses are observed during La Niña/nPDO (Fig. 7, left panel). In SIPO and PO apart from the coastal regions of the western NP, an El Niño (La Niña) event with a pPDO leads to a significant increase (decrease) in WPavg in DJF (Fig. 7a, left panel). The increase in WPavg is seen over the larger parts of the NIO and TIO in MAM during in-phase combinations (i.e., El Niño/pPDO or La Niña/nPDO) (Fig. 7b, left panel). In western NP, WPavg increases for the combination of El Niño with a pPDO (or nPDO) and decreases for the combination of La Niña with a pPDO (or nPDO) in JJA and SON. This reveals that ENSO is responsible for enhancing/subsiding the WP over the western NP in JJA and SON. Further, a La Niña event associated with pPDO, enhances the WPavg over the IO while, the counter responses are evident for the combination of a La Niña with nPDO in JJA. The combination of an El Niño (or a La Niña) with pPDO, decreases the mean WP over the
larger parts of the IO, while increases for the combination of an El Niño (or a La Niña) with nPDO in SON. When ENSO and PDO are in out phase combinations (i.e. El Niño/nPDO and La Niña/pPDO), the patterns are noisy and even change the sign in DJF, depicts a decrease in WP over the larger parts of the Indo-Pacific Ocean in MAM, and an increase in WPavg over the BOB and western TIO and decrease in WPavg over the eastern PO in JJA. In SON, an enhance in WPavg is observed over the larger parts of the IO, western PO and mid-latitudes of the SPO during El Niño/nPDO events and decreases during La Niña/pPDO (Fig. 7d). The impact of the ENSO and PDO combinations on extreme WP extreme appears over the same region as in the mean WP year around (Fig. 7, right panel).

6. Summary and Conclusions

This study investigates the impact of natural climate variability modes such as ENSO, IOD, and PDO on seasonal extreme WP in the Indo-Pacific Ocean using ERA5 reanalysis data over the period 1979–2019. A non-stationary GEV distribution is applied on the seasonal extremes to determine the regions with significant impact, where the natural climate variability modes are taken as the covariates. In addition, the response patterns of SWH, PWP, SST, and SLP to climate variability modes are also evaluate to understand the underlying physical mechanism involved in increasing (or decreasing) the WP. Overall, the strongest ENSO|IOD influence on extreme WP is evident over the eastern Pacific and southern part of the IO (an extension from south of Australia) in DJF, the central Pacific and western TIO in MAM, the western Pacific, western TIO, BOB, SCP seas in JJA, and the western Pacific and eastern TIO in SON. The positive responses of extreme WP to IOD|ENSO are observed over the eastern PO and SO in DJF, the central north Pacific and SO in MAM, the western PO and BOB in JJA, and the southwestern IO in SON whereas, significantly decreased signals are found over the AS and central-to-western
IO during MAM and the western PO in SON. The ENSO|\text{PDO} influence on extreme WP exhibits similar regional and seasonal variations as in the original ENSO but with a slight reduction in the amplitude throughout the year apart from the PO in MAM. For the PDO|\text{ENSO} influence, significant increases in extreme WP are mostly confined to the PO and most prominent in the NP. Over the IO, positive PDO|\text{ENSO} responses in WP are most prevalent during JJA and over the SIO and eastern IO.

The independent seasonal influence of each climate mode on mean and extreme WP, SWH, and PWP was compared with the original to assess the role of one variability mode in strengthening or weakening the influence of another variability mode. The ENSO influence on extreme WP, independent of IOD, exhibits enhanced WP\text{max} over the eastern TIO in JJA and over the eastern TIO and central NP in SON compared to the original ENSO signals. This implies that the IOD reduces the ENSO signals in these regions during that time of year. The independent IOD impact on WP shows a decrease in WP\text{max} over the western NP in JJA and more so in SON. This suggests that ENSO plays an important role in enhancing the IOD influence in this region during JJA and SON. The independent ENSO influence on WP\text{max}, obtained after the removal of PDO, reveals that the PDO has little to no influence over ENSO signals in the Indo–Pacific Ocean except in MAM. In MAM, the PDO has a strong impact over the influence of ENSO in the PO. Lastly, the independent PDO impact, after removing the ENSO signals, is related to a decrease in WP\text{max} over the eastern PO in DJF, and western NP in JJA and SON. This demonstrates that ENSO is responsible for increasing the WP in these regions during that time of the year. In MAM, ENSO reduces the PDO signals over the PO. In addition, seasonal SLP teleconnection patterns regressed against ENSO|\text{IOD}, IOD|\text{ENSO}, ENSO|\text{IOD}, and PDO|\text{ENSO}, exhibit a high and low pressure anomaly that in turn generates strong winds (Kumar et al 2016, 2019; Patra et al. 2020;
Remya et al., 2020; Yang and Oh 2018) and consequently enhances the wave parameters (i.e. \( H_s \) and \( T_p \)) in the respective localized regions. Overall, the mean WP patterns were highly correlated with the extreme WP patterns year-round. Maximum WP increases were often found during seasons when there are increases in tropical cyclone activity and strong winds, such as NIO during JJA.

Composite analysis of mean and extreme WP for the different phase combinations of natural climate variabilities (i.e. ENSO with IOD and ENSO with PDO) strengthen the conclusions drawn from the independent influence patterns (i.e. ENSO, IOD, and PDO separately), which shows that the IOD (or PDO) plays an important role in enhancing or reducing the intensity of ENSO-related responses, or vice versa, depending on the season. During JJA, the IOD enhances (reduces) the ENSO impact on WP when both are in-phase (out-phase) combinations. In SON, (i.e., when ENSOs generally develop and IODs reaches in its mature phase), ENSO is able to enhance the IOD influence on WP\(_{avg}\) and WP\(_{max}\) significantly. While, PDO (i.e. pPDO or nPDO events) enhances (reduces) the ENSO influence on WP during El Niño (La Niña) year-round.

Acknowledgements

All the data (SWH, PWP, SST, and SLP) used in this manuscript is obtained from ERA5 reanalysis from the ECMWF website (https://www.ecmwf.int/en/forecasts/datasets/reanalysis-datasets/era5). We would like to acknowledge the working groups for the development of the ERA5 reanalysis datasets. In addition, the current research is supported by Ministry of Earth Sciences (MoES), Government of India and Department of Applied Sciences, National Institute of Technology Delhi.
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Table 1. A list of previous studies on natural climate variability influence on WP in comparison with the current study

| Reference                | Data (Period)                  | (Season)Variables               | Climate Variability | Analysis Domain | Analysis Method                      |
|--------------------------|--------------------------------|----------------------------------|---------------------|-----------------|---------------------------------------|
| Bromirski et al. (2013)  | WW3 wave model (1948-2008)     | (winter and summer) 90^{th} percentile | PDO, ENSO, PNA      | North Pacific   | Linear trend and EOF                   |
|                          |                                | SWH, PWP, WP                     |                      |                 |                                        |
| Bromirski and Cayan (2015)| WW3 wave model (1948-2008)     | (winter and summer) 90^{th} percentile | NAO, PNA, PDO, ENSO | North Atlantic | Linear trend and EOF                   |
|                          |                                | SWH, PWP, WP                     |                      |                 |                                        |
| Reguero et al. (2015)    | WW3 wave model (1948-2008)     | (Annual) mean SWH, MWP, WP       | AO, AMO, EA, NAO, SOI, TNA, PNA, WP, EP-NP, SAM, SCA, DMI | Global          | Correlation analysis                   |
| Reguero et al. (2019).   | WW3 wave model (1948-2008), satellite altimetry (1992–2008) | (Annual) mean SWH, MWP, WP       | ENSO and AMO        | Global          | Linear trend                           |
| Yang & Oh (2020)         | WW3 wave model (1979-2009)     | (summer) 99^{th} percentile SWH, PWP, WP | ENSO, PDO           | western NP      | Regression analysis, Composite analysis (ENSO and PDO) |
| Recent study             | ERA5 (1979-2019)               | (seasonal) mean and extreme SWH, PWP, WP | ENSO, IOD, PDO      | Indo-Pacific    | Non-stationary GEV, Composite analysis (ENSO with IOD and PDO) |
Table 2: Correlation coefficients between the seasonal N34 with DMI and PDO indices for the period 1979–2019. All indices are linearly detrended. Statistically significant correlations at the 5% and 1% significance levels are marked with * and **, respectively.

|       | N34–DMI | N34–PDO |
|-------|---------|---------|
| DJF   | 0.071   | 0.397** |
| MAM   | -0.125  | 0.458** |
| JJA   | 0.312*  | 0.437** |
| SOA   | 0.620** | 0.545** |

Table 3: List of years when a combination of El Niño or La Niña and/or positive or negative IOD events greater than plus or minus one-half standard deviation occurred during the period 1979–2019 for (a) JJA, and (b) SON.

| (a) JJA | ENSO(+) or El Niño | ENSO(−) or La Niña |
|---------|-------------------|-------------------|
| DMI(+) or pIOD | 1982, 1983, 1991, 1993, 1994, 1997, 2012, 2015, 2019 | 1999, 2007, 2008 |
| DMI(−) or nIOD | 1990, 1992, 2002, 2004, 2009 | 1981, 1984, 1989, 1995, 1996, 1998, 2010, 2013, 2016 |

| (b) SON | ENSO(+) or El Niño | ENSO(−) or La Niña |
|---------|-------------------|-------------------|
| DMI(+) or pIOD | 1982, 1986, 1987, 1991, 1994, 1997, 2002, 2006, 2015, 2018, 2019 | 1983, 1985, 2011 |
| DMI(−) or nIOD | 1979, 2003, 2009, 2014 | 1981, 1984, 1988, 1989, 1995, 1996, 1998, 1999, 2001, 2005, 2010, 2016 |
Table 4: List of years when a combination of El Niño or La Niña and/or positive or negative PDO events greater than plus or minus one-half standard deviation occurred during the period 1979–2019 for (a) DJF, (b) MAM, (c) JJA, and (d) SON.

| (a) DJF | ENSO(+) or El Niño | ENSO(–) or La Niña |
|---------|-------------------|-------------------|
| PDO(+) or pPDO | 1986, 1987, 1997, 2002, 2009, 2014, 2015, 2018 | 1983, 1984, 1985, 2005, 2017 |
| PDO(-) or nPDO | 1990, 1994 | 1988, 1998, 1999, 2007, 2008, 2010, 2011, 2012 |

| (b) MAM | ENSO(+) or El Niño | ENSO(–) or La Niña |
|---------|-------------------|-------------------|
| PDO(+) or pPDO | 1983, 1987, 1992, 1993, 1994, 1995, 1997, 1998, 2005, 2015, 2016, 2017, 2019 | 1981, 1984, 1986, 1988, 1996 |
| PDO(-) or nPDO | 1982, 1991, 2002 | 1985, 1989, 1999, 2000, 2001, 2007, 2008, 2009, 2011, 2012, 2013 |

| (c) JJA | ENSO(+) or El Niño | ENSO(–) or La Niña |
|---------|-------------------|-------------------|
| PDO(+) or pPDO | 1983, 1987, 1992, 1993, 1997, 2015, 2019 | 1995, 2007, 2016 |
| PDO(-) or nPDO | 1982, 1991, 1994, 2002, 2009, 2012 | 1984, 1998, 1999, 2000, 2008, 2010, 2013 |

| (d) SON | ENSO(+) or El Niño | ENSO(–) or La Niña |
|---------|-------------------|-------------------|
| PDO(+) or pPDO | 1979, 1986, 1987, 1991, 1997, 2002, 2003, 2009, 2014, 2015, 2018, 2019 | 1983, 1984, 1995, 2016, 2017 |
| PDO(-) or nPDO | 1994, 2006 | 1985, 1988, 1989, 1998, 1999, 2000, 2001, 2005, 2007, 2008, 2010, 2011 |
Figure 1. Seasonal regression patterns of mean (a) SST (in K) and (b) SLP (in Pa) onto ENSO|IOD, IOD|ENSO, ENSO|PDO, and PDO|ENSO in the Indo–Pacific Ocean over the period 1979–2019. Hatching represents the statistically significant regions at the 5% level.
Figure 2. The seasonal ENSO influence independent of IOD (denoted as ENSO|_{IOD}), obtained after the removal of IOD signals, on the mean and extreme WP (i.e., WP_{avg} and WP_{max}), SWH (H_{avg} and H_{max}) and PWP (P_{avg} and P_{max}) in the Indo–Pacific Ocean over the period 1979–2019. Hatching represents statistically significant regions at the 5% level. The unit of WP, SWH and PWP are given as kilowatts per meter (kW/m), meter (m) and seconds (s).
Figure 3. As in Fig. 2, but for the seasonal IOD influence independent of ENSO (denoted as IOD|ENSO), obtained after the removal of ENSO signals.
Figure 4. As in Fig. 2, but for the seasonal ENSO influence independent of PDO (denoted as ENSO|\text{PDO}), obtained after the removal of PDO signals.
Figure 5. As in Fig. 2, but for the seasonal PDO influence independent of ENSO (denoted as PDO|\textsubscript{ENSO}), obtained after the removal of ENSO signals.
Fig. 6. Composite patterns of mean WP (left panels) and extreme WP anomalies (right panels) during (a) JJA and (b) SON for the four different combinations of ENSO and IOD: El Niño/pIOD, La Niña/pIOD, El Niño/nIOD, and La Niña/nIOD over the 41 year period from 1979–2019 (see list of years in Table 3).
Fig. 7. Composite patterns of mean WP (left panel) and extreme WP anomalies (right panel) during (a) DJF, (b) MAM, (c) JJA, and (d) SON for the four different combinations of ENSO and PDO: El Niño/pPDO, La Niña/pPDO, El Niño/nPDO, and La Niña/nPDO over the 41 year period from 1979–2019 (see list of years in Table 4).