**Analysing tropical spatio-temporal drought patterns and their linkage to large-scale climate variability for Peninsular Malaysia**

**Running head:** **tropical drought linked to large-scale climate variability (70 CHARACTERS)**

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# **Abstract**

Ocean-atmosphere modes of climate variability in the Pacific and Indian oceans, as well as monsoons, regulate the regional wet and dry episodes in tropical regions. However, how those modes of climate variability, and their interactions, lead to spatial differences in drought patterns over tropical Asia at seasonal- to interannual time scales remains unclear. This study aims to analyse the hydroclimate processes for both short- and long-term spatial drought patterns (3-, 6, 12- and 24-months) over Peninsular Malaysia using the Standardized Precipitation Index (SPI), Standardized Precipitation Evapotranspiration Index (SPEI), and Palmer Drought Severity Index (PDSI). Besides that, a generalised least squares regression is used to explore underlying circulation mechanisms of these spatio-temporal drought patterns. The tested drought indices indicate a tendency toward wetter conditions over Peninsular Malaysia. Based on principal component analysis, distinct spatio-temporal drought patterns are revealed, suggesting North-South (N-S) and East-West (E-W) gradients in drought distribution. The Pacific El Nino Southern Oscillation (ENSO), the South Western Indian Ocean (SWIO) variability, and the quasi-biennial oscillation (QBO) are significant contributors to the observed spatio-temporal variability in drought. Both ENSO and SWIO contribute to modulate the N-S gradient in drought conditions over Peninsular Malaysia, while the QBO contributes more to the E-W gradient. Through modulating regional moisture fluxes, the warm phases of ENSO and SWIO, and the western phases of QBO weaken the southwest monsoon and northeast monsoon, leading to precipitation deficits and droughts over Peninsular Malaysia. The E-W or N-S gradients in droughts are related to the middle mountains blocking SWM and NEM moisture fluxes toward Peninsular Malaysia. In addition, the ENSO and QBO variations are significantly leading to short-term droughts (less than a year), while SWIO is significantly associated with longer-duration droughts (two years or more). Overall, this work demonstrates how spatio-temporal drought patterns in tropical regions are related to monsoons and moisture transports affected by the oscillations over the Pacific and Indian oceans, which is important for national water risk management. (325 words)

**Keywords**: Peninsular Malaysia; Drought; El Nino Southern Oscillation; South Western Indian Ocean; Quasi-Biennial Oscillation; Atmospheric Circulation.

# **1. Introduction**

Drought is one of the most disruptive natural hazards, which has critical impacts on regional environments and socio-economic sectors (Sanusi, Jemain, Zin, & Zahari, 2015). Even though Peninsular Malaysia receives an average of 2430 mm of precipitation per year, the region is affected by frequent episodes of drought in response to changes in climate (Chinnasamy & Ganapathy, 2017). These droughts exacerbated desertification, increased occurrence of forest wildfires and reduced social stability over Peninsular Malaysia (Hui-Mean, Yusof, Yusop, & Suhaila, 2019; Yusof, Hui-Mean, Suhaila, & Yusof, 2013). While the social and ecological disturbances caused by short-term droughts (i.e. lasting less than a year) are generally manageable and recoverable, long-term droughts (i.e. lasting more than a year) can lead to irreversible hydrological and ecological changes (Munson, Bradford, & Hultine, 2020; Tallaksen & Van Lanen, 2004). Therefore, analysing droughts at different time scales, especially long-term droughts, provides insights into regional water management and mitigation measures (Sun, Zhu, Pan, Zhang, & Liu, 2018).

Droughts are quantified and investigated through hydroclimate observations, including precipitation (McKee, Doesken, & Kleist, 1993; Valipour, 2016), evapotranspiration (ET; Chen & Sun, 2015; Vicente-Serrano, Beguería, & López-Moreno, 2010), streamflow (Shukla & Wood, 2008; Wu, Miao, Tang, Duan, & He, 2018), groundwater (Li & Rodell, 2015; Thomas et al., 2017), and soil moisture (Martínez-Fernández, González-Zamora, Sánchez, Gumuzzio, & Herrero-Jiménez, 2016; Wang, Lettenmaier, & Sheffield, 2011). Based on proxies of such hydroclimate observations, different drought indices have been proposed and widely used (e.g., Fung, Huang, & Koo, 2020a; Tirivarombo, Osupile, & Eliasson, 2018; Xu, Ren, Ruan, Liu, & Yuan, 2012; Zhai et al., 2010), *e.g.*: i) the Palmer Drought Severity Index (PDSI; Palmer, 1965); ii) the Standardized Precipitation Index (SPI; McKee et al., 1993); iii) the Standardized Precipitation minus Evapotranspiration Index (SPEI; Vicente-Serrano et al., 2010),. The PDSI is developed based on the water balance, considering precipitation, temperature and soil moisture (Heim, 2002; Niemeyer, 2008), but does not emphasize different time scale for drought monitoring (Fung et al., 2020a). SPI and SPEI both allow for depiction of short-term and multi-year droughts, but do not account for soil moisture content, which plays an important role in drought formations (Yoon, Mo, & Wood, 2012). In addition, comparisons between the SPI, which only considers changes in precipitation, and SPEI, which includes evapotranspiration in its calculation, allow for including the effect of warming temperature in considering the shifts of drought conditions (e.g., Stagge, Kingston, Tallaksen, & Hannah, 2017; Tirivarombo et al., 2018; Vicente-Serrano et al., 2010). Considering their advantages and drawbacks, those drought indices are thus usually used together for drought monitoring.

While drought indices are highly depending on precipitation amount, over Peninsular Malaysia, precipitation variability is primarily driven by monsoons (Fung et al., 2020a; Suhaila, Deni, Wan Zin, & Jemain, 2010), which show large variability from one year to another in response to changes in ocean-atmospheric modes of climate variability (Albani, Ibrahim, & Yong, 2018; Supari et al., 2018; Tangang et al., 2012). The hydroclimate variability over Malaysia has been found to be affected by sea surface temperature (SST) variability, especially over the Pacific Ocean (e.g., Daud, Akhir, & Muslim, 2019; Salimun, Tangang, Juneng, Behera, & Yu, 2014; Suhaila et al., 2010; Tangang & Juneng, 2004) and the Indian Ocean (e.g., Tan, Ibrahim, Cracknell, & Yusop, 2017; Tangang et al., 2012; Tangang et al., 2008). Furthermore, in both the Pacific and Indian oceans, SST variability has been linked to processes modulating the moisture distribution in the troposphere (Chakraborty, Behera, Mujumdar, Ohba, & Yamagata, 2006; Lee, Worden, Noone, Chae, & Frankenberg, 2015; Pillai & Mohankumar, 2010). However, very little is known about the role of the quasi-biennial oscillation (QBO) in triggering droughts in tropical regions, although the QBO was found to affect SST anomalies in the Pacific Ocean, and the Indian summer monsoon rainfall in tropical regions (Chattopadhyay & Bhatla, 2002). However, it remains unclear how those modes of climate variability in the Pacific and Indian Oceans, and their interactions, influence the mechanisms driving regional water balance, and what their roles are on temporal persistence (i.e. short and long-term drought) and spatial differences of droughts in Asian tropical regions.

Recent studies have reported that drought risks Malaysia may increase over Peninsular due to the progressively warming temperature over the next four decades (Fung et al., 2020a; Fung, Huang, & Koo, 2020b). Therefore, we examine spatio-temporal drought conditions in Peninsular Malaysia based on three drought indices at four different time scales (i.e., 3-, 6-, 12-, and 24-month). Moreover, we examine the relationships between drought conditions and large-scale climatic oscillations, including the QBO and SST variations in the Pacific and Indian oceans, and their relations with regional monsoons. This paper is organised as follows. In Section 2, the general hydrological characteristics of Peninsular Malaysia are summarized, and details on how droughts are quantified in the region are introduced. In Section 3, different methods for quantifying drought patterns and climate impacts are presented. In Section 4, the spatio-temporal drought conditions over Peninsular Malaysia are analysed, and how Peninsular Malaysia drought conditions interact with the regional circulations related to the Pacific and Indian oceans is investigated. In Section 5, we discuss the potential implications and possible future applications of our results in drought analysis in tropical regions.

# **2. Materials**

## **2.1. Study Area**

Peninsular Malaysia is characterized by humid and hot climate, with high mean annual rainfall (~2500 mm) and warm temperature (~26°C) throughout the year (Tan, Ibrahim, Duan, Cracknell, & Chaplot, 2015). Due to the weak temperature gradient in the tropic, the climate conditions are somewhat uniform for the whole region. However, Malaysian climate has strong seasonal variations in rainfall, in response to regional monsoon conditions (Fung et al., 2020a; Suhaila et al., 2010). The northeast monsoon (NEM) starts with a wet phase from December to mid-January, bringing heavy rainfall to Malaysia, and this season is then followed by a dry phase from late January to early March (Tan & Santo, 2018). The southwest monsoon (SWM; June to September) brings less rainfall, as compared to the NEM (Suhaila et al., 2010). In Peninsular Malaysia, the mountains in Main Range (i.e., Banjaran Titiwangsa) separate the West and East of the Peninsular (Suhaila et al., 2010), which affects the water distribution over the region. Based on geographical characteristics defined in Fung et al. (2020), we investigate the spatial hydroclimate conditions of four regions of Peninsular Malaysia (Figure 1): East, South, North, and Central.

## **2.2. Drought indices**

To quantify drought events, three drought indices are used: the SPI (McKee et al., 1993), SPEI (Vicente-Serrano et al., 2010), and PDSI (Palmer, 1965). The SPI is suitable for quantifying most types of drought events (Sun et al., 2018), but emphasizes on precipitation amount, unlike the SPEI, which emphasizes the impact of temperature as well (Vicente-Serrano et al., 2010). The SPI is calculated by standardizing precipitation following a Gamma distribution function. Similarly, the SPEI calculation standardizes the precipitation minus the potential evapotranspiration (PET), using a log-logistic distribution function. We use four time scales to capture both short-term (i.e. with a duration no more than a year) and long-term droughts (i.e., lasting more than a year) in the SPI and SPEI: 3-month, 6-month, 12-month and 24-month. In addition, we use the PDSI, which is a comprehensive index considering precipitation, temperature, and soil moisture content (Niemeyer, 2008). However, the conventional PDSI calculation by Palmer (1965), based on the empirical constants for the climatic characteristics of the middle parts of the United States (US), is not suitable for drought quantification in other areas (Wells, Goddard, & Hayes, 2004). Therefore, the self-calibrating PDSI (scPDSI; Wells et al., 2004) is used in this study. For the scPDSI, the empirical constants are adjusted with dynamically calculated values over the interested region. For simplicity, in following sections, we refer to the scPDSI as the PDSI. In addition, to further investigate droughts over Peninsular Malaysia, five drought levels of the three drought indices are defined (Table 1), and are ranging from no drought (D0) to extreme drought (D4), according to Sun et al. (2018).

Hydroclimatic variables used to calculate the three drought indices are extracted from the ERA5-Land monthly averaged dataset (<https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-era5-land-monthly-means?tab=form>), ranging from 1981 to 2019, at monthly time step (C3S, 2019). The ERA5-Land reanalysis dataset has enhanced the spatial resolution of 0.1×0.1°, as compared to the ERA5 dataset (0.25×0.25°). The ERA5-land reanalysis dataset is compared to the observed precipitation data from Kuala Krai station (northern part, 5.53°N, 102.20°E) and Senai station (southern part, 1.63°N, 103.57°E) to evaluate the suitability of the reanalysis data to the region. Generally, the ERA5-land dataset is suitable for the region, as the reanalysis data and observed precipitation match well, with correlations of 0.86 (Kuala Krai station) and 0.72 (Senai station), respectively (Figure A1).

**2.3. Climate Data**

To investigate the underlying climate drivers of drought conditions over Peninsular Malaysia, oceanic indices for the Pacific and Indian oceans have been used, together with an atmospheric oscillation index. The oceanic indices are derived from the extended reconstructed SST version 5 (ERSST.v5) of the National Climate Data Centre (<https://www.ncdc.noaa.gov/data-access/marineocean-data/extended-reconstructed-sea-surface-temperature-ersst-v5>) (Huang et al., 2017). The main advantage of ERSST.v5 is that this product is not affected by systematic cold SST bias induced by the use of satellite observations at the end of the twentieth century (Reynolds et al. 2002). The ENSO index is calculated based on empirical orthogonal function (EOF) of SST anomalies (SSTa) over the tropical Pacific Ocean (30°S-30°N; 110°E-95°W). This region has been deemed to be able to capture an optimal representations of the ENSO canonical pattern (Dieppois, Rouault, & New, 2015). The Dipole Mode Index (DMI) is commonly used for assessing the climate variability of the Indian Ocean (Biswas & Kundu, 2018; Harapan et al., 2020; Ibnu Khaldun, Wirasatriya, Dwi Suryo, & Kunarso, 2018). However, based on relative importance analysis, the SWIO is found to explain a larger part of SPI variance in Peninsular Malaysia than any other indices in the Indian Ocean (Figure A2). Therefore, to avoid redundancy and to overcome issues related to overfitting linear regression models, we only consider the SWIO in this study. As defined in Washington and Preston (2006), the SWIO index is the SSTa average over the south-west Indian Ocean (32°S-25°S, 35°E-90°E).

In tropical Asia regions, such as Malaysia and Singapore, the QBO has been demonstrated to be associated with several tropical surface climate variability, such as ENSO (Geller, Zhou, & Yuan, 2016; Liess & Geller, 2012) and Indian monsoon rainfall (Fasullo, 2004). As a stratosphere oscillation, the QBO refers to the downward propagating patterns of easterly and westerly zonal winds in the equatorial stratosphere with a period around 25-28 months (Marshall & Scaife, 2009). In this study, the QBO index is calculated from the zonal average of the 30mb zonal wind at the equator (Huang, Hu, Kinter, Wu, & Kumar, 2012), using the 0.25×0.25° ERA-5 reanalysis database (<https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-era5-single-levels-monthly-means?tab=form>), between 1981 and 2019 (C3S, 2017). To further investigate regional circulations associated with different climate indices, vertically integrated moisture flux divergence and water vapour flux data are extracted from the ERA5 dataset.

# **3. Methods**

**3.1. Trend detection**

Using multiple drought indices, we first identify potential temporal trends using a non-parametric Mann-Kendall test (Kendall, 1975; Mann, 1945). However, as it is recognised that the MK trend test can be unreliable if serial-correlations are ignored (Hamed, 2008; Khaliq, Ouarda, & Gachon, 2009), we use a modified MK test, accounting for serial-correlation (Hamed & Ramachandra Rao, 1998). In addition, trend slopes are estimated through Thiel-Sen’s slope, which provides a better estimate in the presence of outliers (Sen, 1968).

**3.2. Identifying spatio-temporal drought patterns**

To explore the spatio-temporal drought patterns over Peninsular Malaysia, principal component analysis (PCA) is used (e.g., Awange et al., 2014; Rieser, Kuhn, Pail, Anjasmara, & Awange, 2010). Spatio-temporal gridded datasets (*X*), describing three drought indices, are decomposed into EOF modes and principal components (PCs), representing the spatial and temporal variations, respectively. It can be written as:

 $X=SP^{T}$ (1)

where the columns of *S* and *P* represent the spatial EOF modes and corresponding temporal PCs, respectively. $P^{T}$ is the transposition of matrix *P*. The first three largest EOFs/PCs are usually selected, as they can grasp the main characteristics of original signals and reduce the complexity of original dataset (Awange et al., 2011). To avoid losing some underlying information (Jolliffe, 1989), in this study, detrend and rotation procedures are not applied to PCA procedures.

**3.3. Generalised least square (GLS) regressions**

The ENSO, SWIO and QBO indices are then used to develop empirical models for drought indices, based on the generalised least square (GLS) regression, for drought indices. These models account for serial correlations, and can be expressed as follows:

$DI=β\_{0}+β\_{ENSO}ENSO+β\_{SWIO}SWIO+β\_{QBO}QBO$ (2)

where *DI* represent the drought indices, and $β\_{ENSO}$, $β\_{SWIO}$, and $β\_{QBO}$ are the regression coefficients for their corresponding climate modes of variability. Such GLS regression has also been used to investigate the impacts of climate indices on the regional atmospheric circulations. The statistical significance of the GLS regression coefficients is tested based on asymptotically normal tests.

**3.4. Wavelet transform coherence (WTC)**

To investigate climate impacts on droughts at multiple time scales, the wavelet transform coherence (WTC) is used (e.g., He et al., 2020; Torrence & Webster, 1999). Wavelet coherence evaluates the level of linear correlation between two time series *Y* and *Z* at time *n* and on a variability scale *s*. The WTC is then calculated as:

 $R\_{n}^{2}\left(Y,Z\right)=\frac{\left|M\left(s^{-1}W\_{n}^{YZ}\left(s\right)\right)\right|^{2}}{M\left(s^{-1}\left|W\_{n}^{Y}\left(s\right)\right|^{2}\right)∙M\left(s^{-1}\left|W\_{n}^{Z}\left(s\right)\right|^{2}\right)}$ (3)

where *M* is a smoothing operator. $W\_{n}^{Y}\left(s\right)$ and $W\_{n}^{Z}\left(s\right)$ are the continuous wavelet transform (CWT) of two time series *Y* and *Z* of length N (n=1, 2, …, N), respectively. $W\_{n}^{YZ}\left(s\right)$ is the cross-wavelet spectrum, defined as:

$$W\_{n}^{YZ}\left(s\right)=W\_{n}^{Y}\left(s\right)W\_{n}^{Z}\left(s\right)^{\*}$$

where $\*$ represents the complex conjugate. The significance level of WTC is calculated against red-noises, using 1000 Monte Carlo simulations.

# **4. Results and discussion**

# **4.****1. Trend patterns over Peninsular Malaysia**

Between 1981 and 2019, both the SPI and SPEI show a tendency toward wetter conditions over most regions of Peninsular Malaysia and at each time scale (Figure 2a-h). Drier conditions, however, emerge locally in the northernmost regions of peninsular (Figure 2a-h). PDSI also shows a significant trend toward wetter conditions over most Peninsular Malaysia (Figure 2i). Over northeastern regions, which coincide with the mountain regions (Figure 1), the PDSI shows a tendency toward drier conditions (Figure 2i). Despite a significant increase in precipitation over those mountain regions, as indicated by the SPI and SPEI (Figure 2a-d), these regions are becoming drier according to the PDSI (Figure 2i). Such discrepancy between the SPI/SPEI and the PDSI could indicate that precipitation water could not entirely be stored in the sub-surface (i.e. soil moisture) in the mountain regions, which may have exceed their water holding capacity after a prolonged period of excess precipitation. Even though the whole Peninsular Malaysia receives more precipitation, some local regions can thus still suffer from droughts due to regional geomorphological and hydrological characteristics.

**4.2. Spatio-temporal modes of variability for drought over Peninsular Malaysia**

To further explore the spatio-temporal variability in drought over Peninsular Malaysia, the first three EOFs of the SPI (i.e., SPI-EOF1, SPI-EOF2, and SPI-EOF3) are extracted for different time scales (Figure 3).

Representing around 60% of the total variance of SPI, EOF1 is the main modes of spatio-temporal drought variability, indicating the averaged spatial variations of SPI over Peninsular Malaysia (Figure 3a-d). Spatially, SPI-EOF1 shows homogeneous dry or wet conditions, but slightly stronger in the South (Figure 3a-d). Due to the weak temperature gradient in the tropic, the climate conditions over Peninsular Malaysia are somewhat uniform for the whole region. For temporal variations of SPI-PC1 are strongly correlated to the average SPI variations over Peninsular Malaysia, with correlation values reaching 0.97, at p-value < 0.05, for all time scales (Figure 4).

SPI-EOF2 and -EOF3 express much lower fraction of spatio-temporal variance for drought in Peninsular Malaysia (~14% and 7%, respectively; Figure 3e-l). However, these two EOFs allow for examining background spatio-temporal variations, which could not be detected using the regionally averaged SPI over the region, as it is not significantly correlated to the SPI-PC2 and -PC3 (Figure 4). SPI-EOF2 shows a North-South (N-S) gradient, with alternating wet (dry) conditions over the northern regions, but opposite conditions over the southernmost regions (Figure 3e-h). SPI-EOF3 refers to alternating dry (wet) conditions over the western regions of Peninsular Malaysia, while wet (dry) conditions occur in the eastern regions (hereafter called East-West [E-W] gradient; Figure 3i-l). Combining the SPI-EOF2 and -EOF3, four different regions with consistent spatio-temporal variations can thus be identified (Figure A3): East, North, South, and Central part of Peninsular Malaysia. Note that similar modes of spatio-temporal drought variability are found using the SPEI over Peninsular Malaysia (Figure A4). For PDSI, although three EOFs only explain around 50% of total variances, its EOF2 (EOF3) still roughly indicates spatial differences between South (West) and North (East) (Figure A5).

**4.3. Temporal changes in drought spatial extensions over Peninsular Malaysia**

**4.3.1. PDSI vs. SPI/SPEI variations**

The PDSI is a comprehensive drought index integrating precipitation, temperature, and soil water holding capacity, but this index does not allow for investigating drought at different time scales, and this could explain some discrepancies with SPI and SPEI in trend and EOF analysis (cf. Sections 4.1-2). In this section, to further examine the similarities and differences between PDSI and SPI/SPEI at temporal scale, PDSI, SPI, and SPEI variations at different time scales, are thus regionally averaged over the whole Peninsular Malaysia.

The temporal variability of PDSI matches well with those of SPI and SPEI, especially at 6-month time scale (Figure 5; Table 2). This suggests that the PDSI is better capturing the droughts at around 6-month time scale. In the following sections, the 6-month SPI and SPEI (i.e. SPI-6 and SPEI-6) have thus been used for further comparison with PDSI.

**4.3.2. Spatial extension of drought in Peninsular Malaysia**

Our previous trend analysis indicates that most regions of Peninsular Malaysia are becoming wetter between 1981 and 2019. We here examine the drought spatial extensions further by looking at the percentages of area impacted by droughts, based on SPI-6, SPEI-6, and PDSI (Figure 6). SPI-6, SPEI-6, and PDSI show very similar pattern, suggesting that between 1981 and 2019, Peninsular Malaysia experienced several severe droughts (Figure 6): 1981-1983, 1986, 1992, 1997-1998, 2003-2005, and 2015-2016. These drought events correspond with the El Nino events (Figure A6). Among these droughts, the 1982-1983 drought is the most severe in terms of the spatial extension and duration (Figure 6). In 1982-1983, almost the whole Peninsular Malaysia experienced a certain degree of droughts (i.e., from mild drought to extreme drought), and around 60% of the region suffered from extreme drought (Figure 6). The 1982-1983 drought corresponds to the 1982-1983 El Nino event, one of the strongest El Nino events of the 20th century (Figure A6). This suggests that drought severity might increase with the strength of El Nino events. In addition, we note that, between 1981 and 2019, drought is becoming less severe and less widespread over Peninsular Malaysia (Figure 6), which is consistent with wetter conditions, as indicated by trend analysis (Figure 2).

# **4.4. Underlying climate mechanisms driving drought conditions**

**4.4.1. Regional drought variations and large-scale climate variability**

To explore the underlying climate drivers of drought conditions over Peninsular Malaysia, Figure 7 displays the regression maps between ENSO, SWIO, QBO, and SPI.

ENSO and SWIO show significant negative relationships with SPI variations over most Peninsular Malaysia, while QBO shows positive relationships (Figure 7). This suggests that the warm phases of ENSO (i.e. El Nino) and SWIO favour droughts over the whole region, while the positive QBO (i.e. more stratospheric easterly winds) alleviates drought conditions. Moreover, eastern region is generally much drier than other parts of Peninsular Malaysia during El Nino year, indicating the spatial differences in ENSO impacts (Figure 7a-d). Similarly, the impacts of SWIO on droughts over Peninsular Malaysia are stronger in the southern region than in the northern region (Figure 7e-h). The QBO impacts are generally much stronger in the eastern peninsular compared to the western part (Figure 7i-l). We also note that the strength of the impacts of climate drivers on droughts varies among different time scales (Figure 7). ENSO impacts on droughts are stronger at 6- and 12-month time scales (Figure 7a-d). SWIO contributions to droughts are more pronounced on longer time scales (e.g., 24-month; Figure 8e-h), while QBO impacts are stronger at 12-month time scale (Figure 7i-l). In summary, spatially, the N-S and E-W gradients showed in SPI-EOFs may be attributed to the spatial differences in impacts of ENSO, SWIO, and QBO on droughts. In addition, ENSO and QBO may affect more for droughts lasting a year or less, while SWIO has a stronger impact on longer-term or multi-year drought conditions (i.e., 2 years or more).

To examine the contribution of warming temperature to droughts, we examine the same regression maps, but using the SPEI (Figure 8). As for the SPI, ENSO, and SWIO have significant negative impacts on the SPEI over the most peninsular Malaysia, while QBO has positive effects (Figure 8). However, compared to the SPI, the impacts of ENSO, SWIO and QBO on SPEI strengthen. Such strengthening in the impacts of ENSO, SWIO, and QBO on droughts over Peninsular Malaysia suggests a significant role of such modes of climate variability on temperature and evapotranspiration, enhancing their impacts on droughts. The same regressions, but using the PDSI, show similar impact strengthening patterns (Figure 9), confirming the impacts of rising temperature and evapotranspiration on droughts over Peninsular Malaysia.

**4.4.2. Time-scale dependence of links between drought spatio-temporal variations and large-scale climate variability**

Section 4.4.1 suggests spatial differences in the impacts of large-scale climate variability on droughts, and its persistence (i.e., short-term and long-term drought). We here examine how the relationship between climate indices and drought spatio-temporal variations (EOF1 to 3) evolve over time, and at different time scales, using WTC (Figure 10).

The WTC analysis between ENSO and SPI6-PC1 (i.e. homogeneous, but stronger in South, dry or wet conditions) reveals a strong relationship, specifically centered on 4-year time scale (Figure 10a). We also note that the time lag (i.e., phase lag) for the relationship between ENSO and SPI6-PC1 is changing over time, from 0.5 year during 1981-1990 to 0 year during 1991-2019 on 4-year time scale (Figure 10a). Similarly, the relationship between SPI6-PC1 and SWIO is only significant, and particularly pronounced, on 4-8 year time scales, with a time lag around 1-2 years (Figure 10b). The QBO impacts on SPI6-PC1 are much weaker, but centered on high-frequency time scales (≤2 years; Figure 10c). ENSO shows a strong relationship with SPI6-PC2, which represents a N-S gradient in drought conditions (Figure 10d). Such relationship is mainly on 2-4 year time scale, with a time lag around 0.5-1 year (Figure 10d).

The timing of ENSO impacts on SPI6-PC1 (~4 years) and -PC2 (2-4 years) is however different, suggesting the interannual changes in the relationship between ENSO and drought spatio-temporal variability over Peninsular Malaysia (Figure 8a, d). Moreover, the impacts of SWIO on SPI6-PC2 (i.e., N-S gradient in drought conditions) are significant on 4-year time scale between 2000 and 2010, but much weaker than that on SPI6-PC1 (Figure 8e). For SPI6-PC3 (i.e. the E-W gradient in drought conditions), the impacts of ENSO and SWIO are generally much weaker than on SPI6-PC1 and -PC2 (Figure 8g-h). However, QBO shows significant impacts on SPI6-PC3 at 2-year time scale, much stronger than that on SPI6-PC1 and-PC2 (Figure 8c, f, i).

Altogether, the results indicate that both ENSO and SWIO contribute to more or less pronounced the N-S gradient in drought conditions over Peninsular Malaysia. Likewise, the QBO has a stronger impact on the E-W gradients in drought conditions over Peninsular Malaysia.

**4.4.3. Mechanisms driving climate-drought teleconnections in Peninsular Malaysia**

Here, we examine the regional circulation associated with ENSO, SWIO, and QBO to identify the mechanisms of large-scale processes leading to the spatio-temporal variability in droughts over Peninsular Malaysia. Figure 11 shows the regressed surface atmospheric moisture flux associated with ENSO, SWIO, and QBO, and their relations to the SWM in boreal summer (JJA) and the NEM in boreal winter (DJF).

During JJA, the SWM wind brings heavy moisture to the western coast of the Indochinese Peninsula and the western part of Peninsular Malaysia, while other parts of the peninsular have relatively low precipitation (Figure 11a). In boreal summer, ENSO has significant positive impacts on moisture flux divergence over Peninsular Malaysia (Figure 11b), indicating that El Nino events favour the export of continental moisture toward the ocean, reducing precipitable water over land. Warmer SWIO seems to promote northeasterly/easterly moisture flux, weakening the SWM wind, and favouring precipitation deficits over the western part of Peninsular Malaysia (Figure 11c). Over Peninsular Malaysia, the positive QBO promotes westerly moisture flux, as well as moisture convergence over land, favouring more precipitation (Figure 11d).

In boreal winter (DJF), the NEM wind brings precipitation to the eastern part of Peninsular Malaysia (Figure 11e). During that season, the warm phases of ENSO and SWIO significantly weaken the NEM winds, favouring droughts as a response of precipitation deficits over the peninsula (Figure 11f-g). QBO impacts are statistically non-significant in DJF (Figure 11h).

In summary, ENSO, SWIO, and QBO are related to the SWM and NEM winds, and contribute to precipitation deficits and droughts over the peninsula. Their impacts on droughts largely contribute to the differences between northern and southern regions, as well as eastern and western regions. These spatial differences may, however, partly be attributed to the geographic characteristics, as the Main Range Mountains separate the western and eastern parts of the peninsular (Suhaila et al., 2010), and mountains in the northeastern region (Figure 1) also separate the northern and southern part. The SWM in JJA brings moistures to western coast of peninsular, and the mountains prevent moisture from entering the eastern part. QBO brings more precipitation by enhancing SWM, which combined with orographic effects, explains why QBO is associated with the E-W gradient in drought conditions over Peninsular Malaysia. Similarly, during DJF, ENSO and SWIO weaken the NEM, which interact with mountains in the northeastern region (Figure 1), and lead to N-S gradient in precipitation deficits.

# **5. Conclusions**

Using three drought indices from 1981 to 2019, we analyse the spatio-temporal drought patterns over Peninsular Malaysia at four time scales (i.e., 3-, 6-, 12-, and 24-month). Over the past decades, there is generally a significant tendency toward wetter conditions over the region, based on all drought indices (i.e. the SPI, SPEI, and PDSI). Moreover, based on the analysis of interannual changes in the drought severity and drought spatial extensions, results indicate that, from 1981 to 2019, droughts are less severe and less widespread over Peninsular Malaysia. Based on the PCA results, the first EOF shows consistent pattern with trend patterns. Moreover, the second mode of drought spatio-temporal variability reveals the N-S gradient of drought conditions over Peninsular Malaysia, while the third mode indicates the E-W differences in droughts.

To characterise how large-scale ocean-atmosphere oscillations are related to drought conditions, the GLS models have been used to establish the relationships between drought indices and three climate indices: ENSO, SWIO, and QBO. All three indices are found to be linked to drought conditions, via modulations of the SWM and NEM winds. Droughts are more likely to occur over the peninsula during the El Nino events, the warm phases of SWIO and the westerly phase of QBO. Moreover, those modes of large-scale climate variability show stronger impacts on droughts using the SPEI and PDSI, rather than the SPI. It indicates that those climate oscillations may affect the local temperature and evapotranspiration, exacerbating drought patterns over Peninsular Malaysia.

Additionally, the response of drought patterns to ENSO and SWIO largely contributes to differences between the North and South, while the impacts of QBO may contribute more to the E-W differences. These spatial differences may, however, be related to interactions between the large-scale atmospheric circulations and the orographic factors over the region. For instance, moisture fluxes associated with the SWM in JJA, and the NEM in DJF, are prevented from spreading throughout the peninsular by the mountains. In addition, ENSO and QBO show stronger impacts on droughts lasting a year or less, while SWIO is associated with multi-year droughts (i.e. ≥2 years).

Based on the above results, despite that Peninsular Malaysia recorded a tendency toward wetter conditions, we show that, from one year to another, some regions may still suffer from droughts due to the interactions between large-scale atmospheric circulations and orographic factors. Local stakeholders may need to pay more attention to such regional droughts in the future. In particular, warming ocean temperature, especially in the Indian and Pacific oceans, might contribute to increase drought risks over Peninsular Malaysia (Cai et al., 2014; Chu et al., 2018). The expected future risks in droughts could thus put more pressure on the local Malaysian Government for water supply and food security. Overall, the empirical relationships between drought conditions over Peninsular Malaysia and the atmosphere-ocean oscillations linked with monsoon circulations can be valuable to develop seasonal to multi-year empirical forecast for water resources management in tropical Asia.

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**Tables**

**Table 1.** Different drought levels based on the drought indices (Sun et al., 2018).

**Table 2.** The correlations between SPI/SPEI and PDSI from 3- to 24-month time scales. \* indicates the correlation is statistically significant at p-value < 0.05.

**Figures**

**Figure 1.** Elevation (m a.s.l; green to brown colour shades) over Peninsular Malaysia. The whole Peninsular Malaysia is divided into four regions: East, South, North, and Central.

**Figure 2.** The trend pattern (per year) over Peninsular Malaysia based on SPI (a-d), SPEI (e-h) at 3-month, 6-month, 12-month and 24-month time scale, and PDSI (i). The black dots indicate significant values at 0.1 significance level according to the modified MK-test. Red to blue colour shades indicate different level of dryness and wetness, respectively.

**Figure 3.** The EOF1 (a-d), EOF2 (e-h), and EOF3 (i-l) of SPI at 1-month, 6-month, 12-month, and 24-month time scale. The percentage indicates the fraction of variance of EOFs. Red to blue colour shades indicate different level of dryness and wetness, respectively.

**Figure 4.** The SPI PCs and SPI at 3-, 6-, 12-, and 24-month time scale.

**Figure 5.** The averaged PDSI against SPI and SPEI at 3-month, 6-month, 12-month, and 24-month time scales.

**Figure 6.** The percentage of area impacted by drought over Peninsular Malaysia. Drought are here estimated using SPI-6 (a), SPEI-6 (b), and PDSI (c), and at different levels of drought severity from no drought (D0, blue) to extreme drought (D5, dark red; cf. Table 1).

**Figure 7.** The maps of regression coefficients of ENSO (a-d), SWIO (e-h) and QBO (i-l) for SPI at 3-month, 6-month, 12-month, and 24-month time scale. The black dots indicate statistically significant values at 0.1 significance level according to the asymptotically normal tests. Red to blue colour shades indicate negative and positive impacts of climate indices on SPI, respectively.

**Figure 8.** The maps of regression coefficients of ENSO (a-d), SWIO (e-h), and QBO (i-l) for SPEI at 3-month, 6-month, 12-month and 24-month time scale. The black dots indicate statistically significant values at 0.1 significance level according to the asymptotically normal tests. Red to blue colour shades indicate negative and positive impacts of climate indices on SPEI, respectively.

**Figure 9.** The maps of regression coefficients of ENSO, SWIO and QBO for PDSI. The black dots indicate statistically significant values at 0.1 significance level according to the asymptotically normal tests. Red to blue colour shades indicate negative and positive impacts of climate indices on PDSI, respectively.

**Figure** **10.** The WTC analysis of the SPI-6 PCs and the ENSO, SWIO and QBO at different time scales. The thick black contour represents the 5% significance level against the red noise. The thin black line is the boundary of the cone of influence (COI), i.e., the edge effects caused by zero-padding effect. The phase lag is denoted by the arrow directions (right (left) is 0 (180) degree phase lag; up (down) is 270 (90) degree phase lag).

**Figure 11.** The surface climatological moisture flux with precipitation distribution (a), and moisture flux (divergence) regressed by ENSO, SWIO, and QBO during JJA (b-d). The (e-h) are similar as the (a-d) but for DJF. For (a) and (e), the magenta arrows and shaded area are climatological moisture flux and precipitation. For other figures, the arrows and shaded areas represent the regressed wind and regressed coefficients of moisture flux divergence. The magenta and black arrows in (b-d) and (f-h) are significant and non-significant results at p-value < 0.1, respectively. For shaded area, only significant results with the significance level of p-value < 0.1 are provided.

**Appendix**

**Figure A1.** The scatterplot and correlations between ERA5 and observed precipitation.

**Figure A2.** The relative importance analysis for the Indian variability indices to the SPI over Peninsular Malaysia.

**Figure A3.** The scatterplot between EOF2 and EOF3 of SPI-3.

**Figure A4.** The EOF1 (a-d), EOF2 (e-h), and EOF3 (i-l) of SPEI at 1-month, 6-month, 12-month and 24-month time scale.

**Figure A5.** The EOF1 (a), EOF2 (b), and EOF3 (c) of PDSI.

**Fi****gure A6.** The SST anomaly shows the warm and cold phase of the ENSO during 1900 and 2019.