

Article

Interactive Contribution of Indian Summer Monsoon and Western North Pacific Monsoon to Water Level and Terrestrial Water Storage in the Mekong Basin

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Abstract: Water level (WL) and terrestrial water storage (TWS) are two important indicators for early alerts of hydrological extremes. Their variation is governed by precipitation under monsoon variability, in particular in the Mekong river basin, where it is affected by the interaction between the Indian summer monsoon (ISM) and western North Pacific monsoon (WNPM). This study aimed to quantify the contributions of two monsoons to the water levels of four hydrological stations (i.e., My Thuan, Can Tho, Chau Doc and Tan Chau) on the Mekong Delta and the terrestrial water storage of the entire Mekong River basin through relative importance analysis. Three methods—multivariate linear regression; Lindeman, Merenda and Gold (LMG); and the proportional marginal variance decomposition (PMVD) methods—were selected to quantitatively obtain the relative influence of two monsoons on water level and TWS. The results showed that, from 2010 to 2014, the proportions of the ISM impacts on the water level obtained with the three methods ranged from 55.48 to 81.35%, 50.69 to 57.55% and 55.41 to 93.64% via multivariate linear regression, LMG and PMVD, respectively. Further analysis showed that different choices of time spans could lead to different results, indicated that the corresponding proportion would be influenced by other factors, such as El Niño–Southern Oscillation (ENSO). The removal of ENSO further enlarged the relative importance of the ISM, and the mean values of the four stations were increased by 8.78%, 2.04% and 14.92%, respectively, via multivariate linear regression, LMG and PMVD. Meanwhile, based on the analysis of terrestrial water storage, it was found that the impact of the ISM on the whole Mekong River basin was dominant: the proportions of the impact of the ISM on terrestrial water storage increased to 68.79%, 54.60% and 79.43%, which rose by 11.24%, 2.96% and 19.77%, respectively, via linear regression, LMG and PMVD. The increases almost equaled the quantified proportion for the ENSO component. Overall, the novel technique of quantifying the contributions of monsoons to WL and TWS can be applied to the influence of other atmospheric factors or events on hydrological variables in different regions.

Keywords: monsoon; relative importance; Mekong basin; ENSO

1. Introduction

Monsoons are one of the most energetic components of the earth's climate system [1], affecting the livelihoods of more than 60% of the world population [2]. Recently, many research studies have revealed the relationship between the Asian summer monsoon and hydrological extreme events. For instance, the Asian monsoon is the key factor affecting the occurrence of drought and flood across different regions in India [3] and China [4] and the biogeochemical and hydrological processes in South Korea [5]. The Indian summer monsoon (ISM) and western North Pacific monsoon (WNPM) are the two main monsoon members in Asia that have significant influences on Southeast Asia. Two circulation indices, the ISM and WNPM [1], are normally selected to explain the regional hydrological and climatic conditions.

Various research studies have demonstrated that a significant interaction between the Asian monsoon and El Niño–Southern Oscillation (ENSO) exists [1,6,7]. For example, the East Asian summer monsoon is influenced by El Niño events, leading to more precipitation in the summer after El Niño for some regions [8]. Significant negative correlations have been found between the WNPM and ISM during the El Niño early onset years and during the El Niño decaying summer [9]. In fact, the respective relationships between ENSO and precipitation [10] and water levels [11] in the Mekong River basin have also been analyzed, and it was found that hydrological variables are significantly influenced by ENSO events. Applying the above findings, recent studies have been focused on water level reconstruction based on ENSO [12], drought indices and satellite gravimetry [13]. However, the quantification of the relative impacts of the above two monsoons on the water level and terrestrial water storage have never been reported.

As the largest river in Southeast Asia [14], the Mekong River basin (MRB), with a total basin covering an area of 795,000 km² across 25° of latitude [15], discharges freshwater southward from China, flowing through Myanmar, Laos, Thailand, Cambodia and Vietnam [16] to the South China Sea (SCS) [17] (Figure 1). The MRB is normally divided into two parts: the Upper Mekong basin in China (called the Lancang River) and the Lower Mekong basin beginning from the Chinese boundary and extending to the SCS. The terrain in the upper basin is steep and narrow but becomes relatively flat and open in the lower basin, especially from Cambodia to the SCS [17]. The climate of the MRB is significantly affected by the Asian–Pacific monsoon system [18], especially the downstream MRB. The MRB ranks tenth among the global megabasins on the basis of mean annual discharge at the estuary mouth [19], which is inhabited by around 65 million people [17]. Due to the Asian–Pacific monsoon system, the climate of the MRB presents obvious dry (from early May to October) and wet (from November to April) seasons [20], controlled by the cold air from the Eurasian continent and the summer monsoon by air from both the southwest and the southeast. Water discharge (WD) mainly comes from the rainfall in the rainy season in the downstream MRB [12].

WD monitoring is significantly important for managing water resources and obtaining alerts about hydrological extremes that can cause otherwise unforeseeable losses to the economy [21–23]. As a power function of the WD [24,25], the water level (WL) has an inseparable relationship with people's lives, production and even regional development. Given the high correlation with the precipitation, whether on land [26], lakes [27], or rivers [28,29], the WL and terrestrial water storage (TWS) are affected by precipitation and discharge through the monsoon, as this large-scale atmospheric circulation controls the spatiotemporal variability of precipitation [30].

As a key part of terrestrial water resources [31], the TWS, consisting of surface water storage (e.g., reservoirs and lakes), groundwater, soil moisture, snow and ice [32], can be inferred from Gravity Recovery and Climate Experiment (GRACE). This provides a synoptic view of its spatiotemporal variability [33], which can better reflect the change of terrestrial water quantity at a regional scale when compared to WL. It plays a major role in the exchange of water mass between the atmosphere and the ocean [34]. The TWS variability can be attributed to precipitation [35,36], evapotranspiration [35] and ice melting, to mention only a few factors [36]. Monsoons' effects on TWS have been investigated recently. He et al. [37] discovered that the shifting of TWS spatial distribution over East China is due to the varying strengths of local winds and Asian monsoons. On the other hand, the variability of TWS across China has long been attributed to the interaction of monsoons and a connection with El Niño–Southern Oscillation (ENSO); for instance, by Long et al. [38], Ni et al. [39], Tang et al. [40] and Zhang et al. [41]. Several research studies have quantitatively inferred that WL variations are linked to the TWS (e.g., [42–44]). For example, WLs have been reconstructed based on TWS and other indices in the Mekong and Yangtze river basins [13,45]. Though the relationship between WL and TWS has been scientifically investigated and the practical applications of the relationship have been explored, the direct comparison between the WL and TWS as affected by monsoons has

rarely been studied, let alone the quantification of the relative importance (or contribution) of the governing monsoons for the WL and TWS.

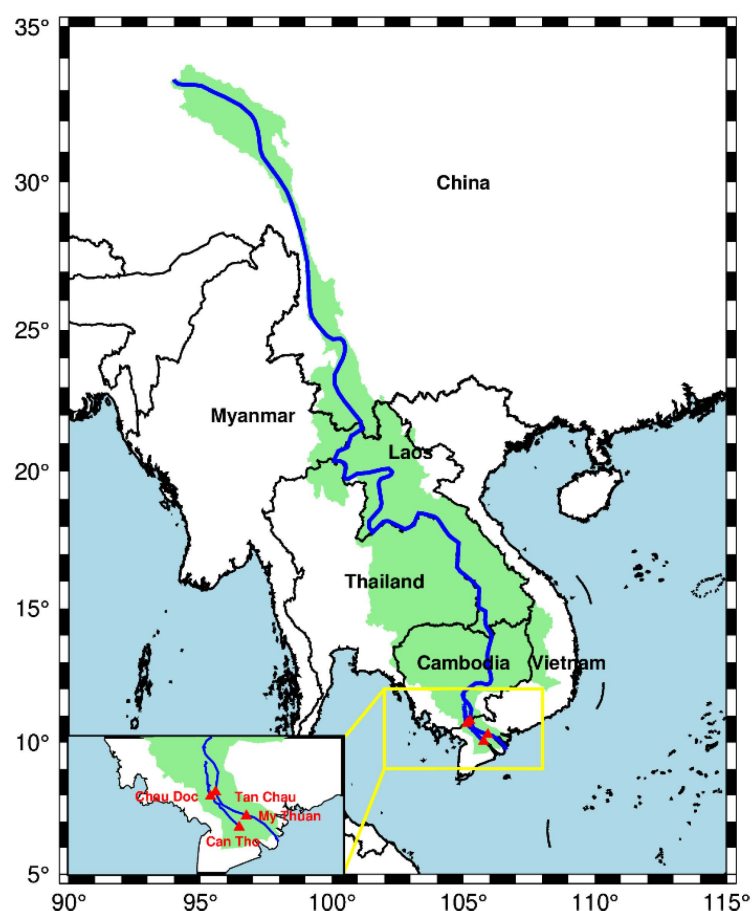


Figure 1. Map of Mekong basin with two pairs of selected hydrological stations (My Thuan and Can Tho, and Chau Doc and Tan Chau) located in the Mekong Delta.

This study aimed to quantify the influences of the ISM and WNPM on the WL of the Mekong Delta and the TWS in the MRB. Linear regression and relative importance (RI) analyses of long periods and continuous short periods were used to calculate their relative influence. The RI is a statistical tool for quantifying the relative contribution of each potential explanatory variable (i.e., regressor) comprising the value of R^2 [46–48]. After preprocessing, the relative importance of the ISM and WNPM indices for the WL and TWS was calculated with a multivariate linear model; the Lindeman, Merenda and Gold (LMG) model; and the proportional marginal variance decomposition (PMVD) model. Moreover, the relative importance of the data after removing the signal related to ENSO with wavelet transform coherence (WTC) was also analyzed. The results were compared to analyze the effect of ENSO on WL and TWS.

This article is structured as follows: The dataset is described in detail in Section 2, and the research methods and evaluation indicators are stated in Section 3, followed by the results of linear regression, LMG and PMVD in Section 4, with WTC used as well. The results are further analyzed also in Section 4 and the conclusion is given in Section 5.

2. Datasets Description

2.1. Water Level Data

Daily WLs from 1 January 2008 to 31 December 2015 observed at four hydrological stations (i.e., My Thuan and Can Tho, approximately 80–110 km from the estuary mouth, and Chau Doc and Tan Chau, approximately 220 km from the estuary mouth) were obtained

from the Mekong River Commission (MRC; <http://www.mrcmekong.org>, accessed on 10 July 2020). Four station time series are displayed in Figure 2, with their basic information given in Table 1. In this study, the data time span for 2010–2014 was taken as an example for our initial investigation, and the rest were used for subsequent comparison and analysis.

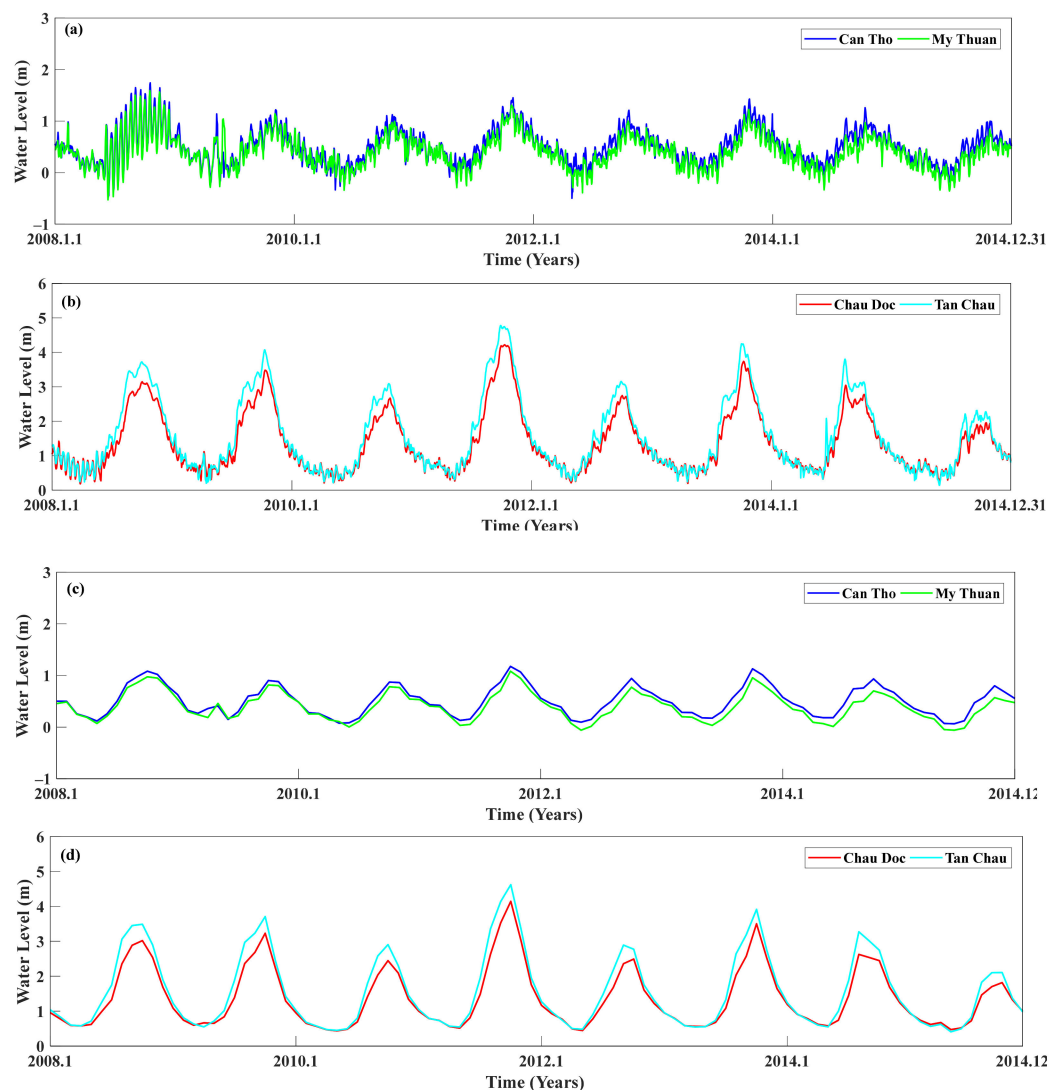


Figure 2. WLs of four selected stations in the Mekong River delta (MRD): (a,b) are the daily observed WLs and (c,d) are the WLs after monthly averaging.

Table 1. Maxima, minima, means and standard deviations of daily observed (and monthly averaged) WLs from four selected stations in the MRD.

Variable	Station	Max	Min	Mean	Standard Deviation
Daily observed water level(m)	My Thuan	1.594	−0.530	0.404	0.321
	Can Tho	1.742	−0.498	0.503	0.334
	Chau Doc	4.223	0.184	1.378	0.884
	Tan Chau	4.778	0.138	1.574	1.073
Monthly averaged water level (m)	My Thuan	1.081	−0.059	0.403	0.274
	Can Tho	1.175	0.065	0.504	0.289
	Chau Doc	4.142	0.435	1.375	0.866
	Tan Chau	4.620	0.408	1.569	1.053

The WL presented obvious annual periodic changes due to the seasonal precipitation and even monsoon activities [13]. Periodic changes were accompanied by small diurnal fluctuations, which are mainly caused by dominant semi-diurnal ocean tides in the southern SCS [49,50]. For Can Tho and My Thuan, which are closer to the coast, the backwater from the ocean intrudes into the estuary, which should dampen the amplitude of the WL [49]. As a result, the standard deviations of the WL at My Thuan and Can Tho were smaller than that at the upper pair of stations (i.e., Chau Doc and Tan Chau) (Table 1). To be consistent with the monthly monsoon index and basin-averaged TWS, monthly averaging was conducted to smooth the raw data [49] (Figure 2), and the statistics of the monthly averaged data are shown in Table 1 as well.

2.2. Indian Summer Monsoon (ISM) Index and Western North Pacific Monsoon (WNPM) Index

To numerically represent the intensity of the tropical westerly monsoon, the Indian summer monsoon (ISM) index and western North Pacific monsoon (WNPM) index [1] were used. The ISM index is defined by a difference of 850 hPa in the zonal winds between 5–15°N, 40–80°E and 20–30°N, 70–90°E, whereas the WNPM index is defined by a difference of 850 hPa in the westerlies between 5–15°N, 100–130°E and 20–30°N, 110–140°E [1], as shown in Figure 3. The 850 hPa zonal wind was used as an indicator because it better reflects the variations of the corresponding convective heating [51], from which the monsoon can be formed.

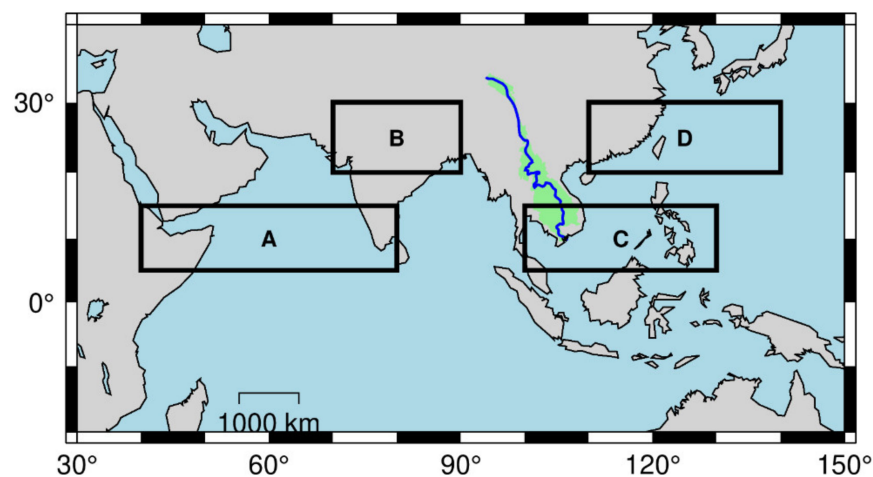


Figure 3. The definitions of the ISM index (a difference of 850 hPa in zonal winds between A and B, i.e., $U_A - U_B$) and WNPM index (a difference of 850 hPa in westerly winds between C and D, i.e., $U_C - U_D$).

The time series of the ISM index and WNPM index from 2003 to 2015 can be directly accessed at the website of the Asia-Pacific Data-Research Center (APDRC) (<http://apdrc.soest.hawaii.edu/projects/monsoon/realtime-monidx.html>, accessed on 10 July 2020), as displayed in Figure 4. Both indices display the obvious annual cycle and short-term fluctuations, similar to those for the WL.

2.3. Terrestrial Water Storage Data

The Gravity Recovery and Climate Experiment (GRACE) yields time-variable TWS data on a monthly scale [52]. The TWS data used here, with a theoretical spatial resolution of 3°, were computed from the CSR GRACE Level 2 Release 05 (RL05) GSM monthly gravity fields, accessible at the website of the Center of Space Research (CSR) managed by NASA (<http://www2.csr.utexas.edu/grace/RL05.html>, accessed on 10 July 2020). Two post-processing steps were applied to obtain TWS data from the GRACE gravity spherical harmonic coefficients. The GRACE C_{20} term was replaced by satellite laser ranging (SLR) and degree-one terms were restored to correct for geocenter motion [53,54], followed by a

de-stripping process and Gaussian filtering with a radius of 350 km [55,56]. The data time series of the Mekong River basin were then spatially averaged to obtain a single TWS time series for the entire Mekong basin for the period from 2003 to 2015, as given in Figure 5.

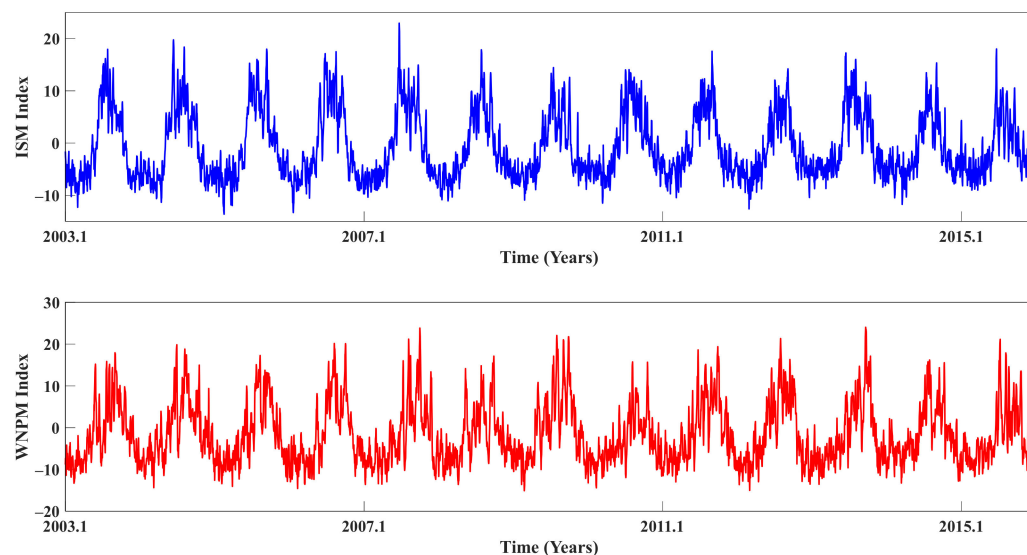


Figure 4. Indian summer monsoon (ISM) index and western North Pacific monsoon (WNPM) index from 2003 to 2015. A positive ISM index means that the monsoon activity in region A is stronger than that in region B (Figure 3), and the negative value indicates the opposite. A positive WNPM index means that the monsoon activity in region C is stronger than that in region D (Figure 3), and the negative value indicates the opposite.

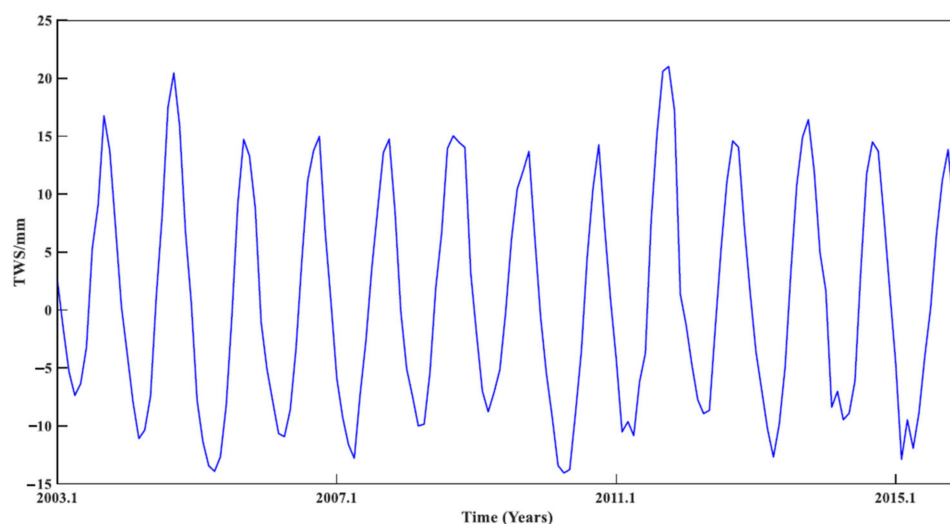


Figure 5. TWS time series for the entire Mekong basin for the period from 2003 to 2015.

2.4. Multivariate ENSO Index (MEI)

As a wind field and sea surface temperature oscillation occurs in the equatorial eastern Pacific region, ENSO can be detected from the anomalies of sea-level pressure difference and sea surface temperature (SST) [57]. In this study, the multivariate ENSO index (MEI) was considered as a more integrated index than other ENSO indices for the quantification of the strength and variability of ENSO [58] because the MEI is calculated based on the sea surface pressure, the zonal and meridional components of the surface wind, the SST and the total cloudiness fraction of the sky over the tropical Pacific [30]. The MEI dataset was downloaded on 10 July 2020 at <http://www.esrl.noaa.gov/psd/enso/mei.ext/table.ext.html>.

3. Method and Evaluation Metrics

3.1. Research Flow

The flow of this study included the following aspects: pretreatment (including time lag analysis); calculation of the relative contributions of the ISM and WNPM via linear regression, LMG and PMVD; and removal of the ENSO effect from the monsoon index through WTC (Figure 6).

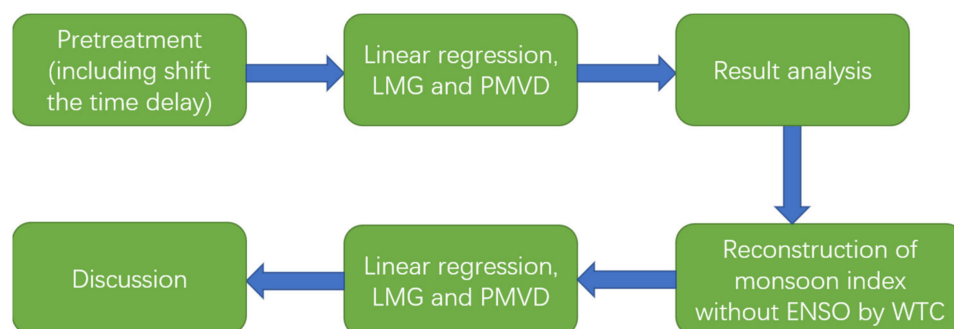


Figure 6. The research flowchart of this study.

3.2. Time Lag Analysis

Considering that only the quantitative relationship between the monsoon index and water level was explored, a time lag between them must exist (Figure 7). This is because time is required for the monsoonal wind to generate the process that, through precipitation (recharge)–storage–discharge, ultimately affects the water level at the estuary. Cross-correlation was employed to align the time series [59], defined as

$$c_k = \sum_i u_i v_{k+i-1} \quad (1)$$

where u and v are time series of length N , i means the i -th sample of the time series and k means the k -th number of the cross-correlation. The cross-correlation is maximized when the time series u and v are aligned well with a time lag between them. For instance, in this study, u is the monsoon index and v is the WL or TWS, and c_k is maximized when the monsoon index and WL or TWS are aligned well with a time lag between them.

The degree of the maximum value of c_k , denoted as $imax(c)$, is the parameter used to calculate time lag, τ , as follows:

$$\tau = -\Delta t(imax(c) - N) \quad (2)$$

where τ stands for the time lag and Δt is the sampling interval of the time series. The lag is positive when time series v occur later than that of time series u . The time lag between the monsoon index and the daily WL observed at station (monthly basin-averaged TWS), with the Δt in terms of the day (respectively, month), was calculated (Table 2).

Table 2. The time lag between the monsoon index and WL (or basin-averaged TWS).

Variable	Station	Time Lag with ISM (days)	Time Lag with WNPM (days)
WL	My Thuan	98	89
	Can Tho	85	88
	Chau Doc	68	44
	Tan Chau	60	39
TWS	—	Time Lag with ISM (months)	Time Lag with WNPM (months)
		2	1

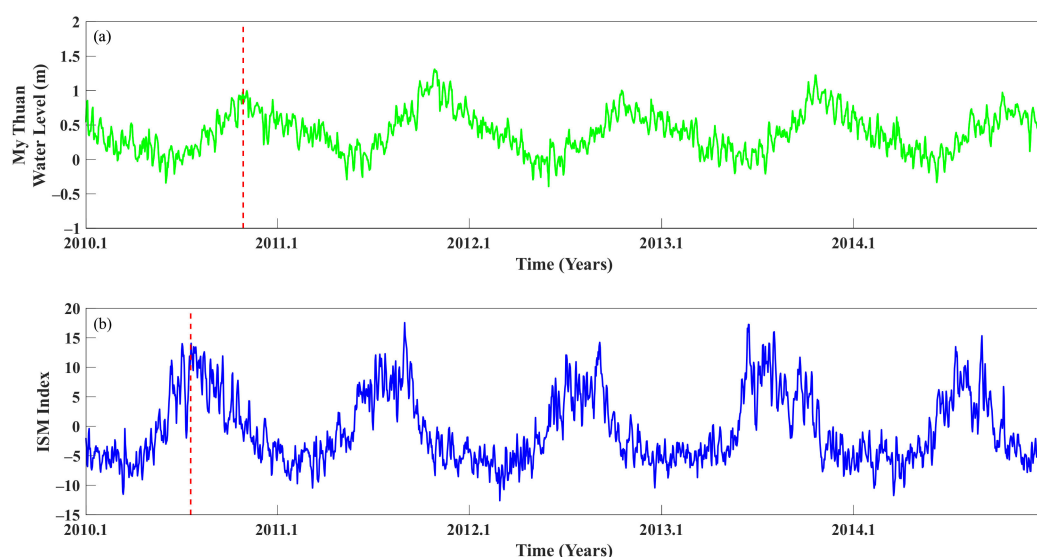


Figure 7. Time lag between (a) WL at My Thuan and (b) Indian summer monsoon index.

The time lags of the WNPM for four selected stations were all shorter than those of the ISM except the one at Can Tho. This indicates that the influence of the WNPM arrives earlier than that of the ISM. This might be attributable to the defined zone of the WNPM being 1500 km closer to the location of the MRB, as shown in Figure 3.

Differently from the daily WL fluctuation resulting purely from the land surface hydrology, the long-period ocean tides, such as semi-annual and annual tidal constituents, play an important role in providing a backwater effect on the WL at the river mouth, such that the effect of the monsoon is not reflected instantly. Consequently, the time series for the station pair closer to the ocean (i.e., My Thuan and Can Tho) presented a longer time lag (i.e., ~3 months) than that of the upper station pair (i.e., Chau Doc and Tan Chau). Compared to the difference between the time lags of the two station pairs, that of the two monsoon indices was relatively small at the same station. For instance, 9 day and 3 day time lags were present at My Thuan and Can Tho, and 16 day and 21 day time lags were present at Chau Doc and Tan Chau.

3.3. RI Calculated from Linear Regression Coefficients

A multivariate linear model is commonly used to quantify the relationships among different variables. For a dependent variable y and multiple independent variables $x_1, x_2, x_3 \dots$, the basic linear model is

$$y = b_0 + b_1x_1 + b_2x_2 + \dots + b_nx_n + \varepsilon \quad (3)$$

where b_0 is the constant offset, $b_1, b_2, b_3 \dots$ are the coefficients for each independent variable and ε is the random error with a mathematical expectation that equals zero. According to Equation (3), the quantitative relationship between the WLs at stations and the two monsoon (ISM and WNPM) indices can be formulated as follows:

$$WL = b_0 + b_1 \cdot ISM + b_2 \cdot WNPM \quad (4)$$

Therefore, the relative importance (or contribution) of each monsoon index can be calculated as

$$C_{ISM} = \frac{b_1}{b_1 + b_2} \times 100\%, C_{WNPM} = \frac{b_2}{b_1 + b_2} \times 100\% \quad (5)$$

3.4. Evaluation Indices

The Pearson correlation coefficient (PCC) was selected to evaluate the performance of the WL modeled from the linear regression against the observed one. Its definition is shown in Equation (6), where X_{obs} and X_{mon} represent the WL/TWS from observation and from the linear regression based on monsoon indices, respectively. $\bar{X}_{obs}$ refers to the mean of X_{obs} , so too does $\bar{X}_{mon}$.

$$PCC = \frac{\sum_{i=1}^N (X_{obs}^i - \bar{X}_{obs})(X_{mon}^i - \bar{X}_{mon})}{\sqrt{\sum_{i=1}^N (X_{obs}^i - \bar{X}_{obs})^2} \sqrt{\sum_{i=1}^N (X_{mon}^i - \bar{X}_{mon})^2}} \quad (6)$$

Additionally, two other metrics were also selected: the normalized root mean squared error (NRMSE) and the Nash–Sutcliffe efficiency model (NSE). The NRMSE, as an indicator to reflect the accuracy in normalized form, is defined as follows:

$$NRMSE = \frac{\sqrt{\frac{\sum_{i=1}^N (X_{mon}^i - X_{obs}^i)^2}{N}}}{\max(X_{obs}) - \min(X_{obs})} \quad (7)$$

The NSE, which was first introduced by Nash and Sutcliffe in 1970 [60], is a widely used coefficient for the evaluation of hydrological models against observed data, with a range from $-\infty$ to 1. The numerical value of the NSE reflects the best performance of the model when it approaches 1. It can be calculated as Equation (8) shows.

$$NSE = 1 - \frac{\sum_{i=1}^N (X_{mon}^i - X_{obs}^i)^2}{\sum_{i=1}^N (X_{obs}^i - \bar{X}_{obs})^2} \quad (8)$$

3.5. RI from Linear Regression Using LMG and PMVD Methods

Since the RI refers to the quantification of an individual regressor's contribution to a multivariate linear model [61], assigning shares of “relative importance” to each one of a set of regressors is one of the keys to linear regression [62]. Choosing from among many methods for determining the RI, the Lindeman, Merenda and Gold (LMG) [63] and proportional marginal variance decomposition (PMVD) [64] methods were used here to decompose R^2 into the contributions of each regressor. R^2 refers to the coefficient of determination, which is defined as follows:

$$R^2(M) = \frac{\sum_{t=1}^n (\hat{y}_t - \bar{y})^2}{\sum_{t=1}^n (y_t - \bar{y})^2} \quad (9)$$

where y_t is the observed value at time t , and $\hat{y}_t$ is the linear estimate of y_t . $\bar{y}$ is the average of the dependent variable y and $M = \{x_1, x_2, \dots, x_N\}$ is the set of N possible regressors contributing to the overall description of the dependent variable. In this study, y stands for WL/TWS and M consists of the ISM index and WNPM index; that is $M = \{x_1, x_2, \dots, x_N\} = \{\text{ISM index, WNPM index}\}$. In Section 4.4, MEI is added into M as a possible factor as well. The LMG and PMVD methods eliminate the dependence of the contribution of regressors (x_i) by replacing orders of regressions and averaging marginal contributions of replaced regressors. Suppose T represents the input of a set of regressors into the model, and $r = (r_1, r_2, \dots, r_N)$ represents different orders of $x_1, x_2, \dots, x_N$ in the model. The set of regressors before x_i in order r is denoted as T_i^r . Consequently, the marginal contribution M_i of the regressor x_i in the order r , denoted as $seqR^2(x_i|T_i^r)$, can be written as

$$M_i = seqR^2(x_i|T_i^r) = R^2(\{x_i\} \cup T_i^r) - R^2(T_i^r) \quad (10)$$

With the LMG method, all M_i s are simply averaged in the order r , which is calculated as

$$\begin{aligned} LMG(x_i) &= \frac{1}{N!} \sum_{\text{repermutation}} seqR^2(x_i | T_i^r) \\ &= \frac{1}{N!} \sum_{T_i^r \in M\{x_i\}} n(T_i^r)! (N - n(T_i^r) - 1)! seqR^2(x_i | T_i^r) \end{aligned} \quad (11)$$

where $n(T_i^r)$ is the number of regressors in T_i^r .

However, with the LMG method, when one regressor x_i is related to other regressors, a biased marginal contribution is obtained, even if the regression coefficient of x_i and the dependent variable y is zero. Therefore, the PMVD method, which is a weighted analogue of the LMG method using data-dependent weights, has been proposed to solve this problem [64]. The data-dependent weights, $\omega(r)$, are derived from a set of axioms and used to weight the permutation in the PMVD method, which is defined as

$$\begin{aligned} PMVD(x_i) &= \frac{1}{N!} \sum_{\text{repermutation}} \omega(r) seqR^2(x_i | T_i^r) \\ &= \frac{1}{N!} \sum_{T_i^r \in M\{x_i\}} n(T_i^r)! (N - n(T_i^r) - 1)! \omega(r) seqR^2(x_i | T_i^r) \end{aligned} \quad (12)$$

3.6. Wavelet Transform Coherence

Wavelet transform coherence (WTC), first put forward by Torrence and Webster (1999) [65], has been widely used in time series analysis [66,67]. The continuous wavelet transform (CWT) is one class of wavelet transforms. The CWT of the time series of the WNPM index, for example, with length n and uniform time step ΔT , can be defined as $C_i^{WNPM}(j)$, which is a convolution of the WNPM index with the scaled and normalized wavelet [67]:

$$C_i^{WNPM}(j) = \sqrt{\frac{\Delta T}{j}} \sum_{k=1}^n WNPM_k \cdot \varphi_0 \left[(k-i) \frac{\Delta T}{j} \right] \quad (13)$$

where i represents the time index and j is the wavelet scale. The φ_0 is a particular wavelet basis, called the Morlet wavelet, defined as:

$$\varphi_0(\eta) = \pi^{-\frac{1}{4}} e^{-\frac{\eta^2}{2} + i\omega_0\eta} \quad (14)$$

where ω_0 is the dimensionless frequency and η is the dimensionless time. Aiming at striking a good balance between frequency and time, the ω_0 was chosen to be 6 [68].

According to [27], the cross-wavelet spectrum of two time series, for example, WNPM and MEI, can be defined as $C_i^{WNPM,MEI}(j)$:

$$C_i^{WNPM,MEI}(j) = C_i^{WNPM}(j) C_i^{MEI}(j)^* \quad (15)$$

Here, $*$ represents the complex conjugate. Then, according to [31], the WTC of these two time series, $R_i^2(WNPM, MEI)$, can be calculated as:

$$R_i^2(WNPM, MEI) = \frac{|S^o(j^{-1} C_i^{WNPM,MEI}(j))|^2}{S^o(j^{-1} |C_i^{WNPM}(j)|^2) \cdot S^o(j^{-1} |C_i^{MEI}(j)|^2)} \quad (16)$$

Here, S^o is a smoothing operator. The significance level of the WTC can be calculated using the Monte Carlo method. The phase difference is:

$$\psi_i(s) = \arg \left(S^o \left(j^{-1} C_i^{WNPM,MEI}(j) \right) \right) \quad (17)$$

4. Results and Discussion

4.1. RI Analysis from Linear Regression, LMG and PMVD

The results obtained from the multivariate linear model are shown in Table 3. Although the defined boundary of the WNPM index was closer to the MRD (Figure 3), the contribution of the ISM to the water level was larger than that of WNPM at the estuary. Combined with the geographical locations of the hydrological stations (Figure 1), it can be seen that the contributions of the two monsoons to the WL varied considerably. This was particularly apparent for the pair consisting of My Thuan and Can Tho, where the contribution ratio of the ISM and WNPM was four to one (i.e., 4:1). From east to west, the relative contribution of the ISM decreased from 81% to 55%, while that of the WNPM increased. This implies that the WL at stations closer to the open ocean (i.e., Can Tho and My Thuan) was subject to a stronger influence from the ISM. The contribution ratio of the ISM index for the TWS was similar to the results for the WL for Chau Doc and Tan Chau, the reason being that a basin-averaged TWS was employed. For the influence on both the WL and on the TWS, the contribution of the ISM was larger than that of WNPM (Table 3), implying that the ISM plays a stronger role.

Table 3. The RI of the ISM and WNPM indexes generated from the multivariate linear models.

Variable	Station	b_0	b_1	b_2	C_{ISM}	C_{WNPM}	PCC	NRMSE	NSE
WL	My Thuan	0.4340	0.0384	0.0088	81.35%	18.65%	0.9121	0.0977	0.8318
	Can Tho	0.5564	0.0370	0.0148	71.45%	28.55%	0.9259	0.1001	0.8573
	Chau Doc	1.5659	0.0860	0.0652	56.88%	43.12%	0.9100	0.1000	0.8281
	Tan Chau	1.8021	0.1045	0.0839	55.48%	44.52%	0.9306	0.0944	0.8660
Basin-averaged TWS	—	2.9387	1.0426	0.7689	57.55%	42.45%	0.9482	0.0905	0.8990

In terms of evaluation metrics (i.e., PCC, NRMSE and NSE), it can be seen from Table 4 that the ISM and WNPM were, to a large extent, able to explain the fluctuation of the WL and basin-averaged TWS via the multivariate linear model in Equation (3). Therefore, the analyses of the relative contributions of the ISM and WNPM seem to have been appropriate. Among these analyses, the data fitting based on the basin-averaged TWS appears to have been the best (the PCC was 0.9482, the NRMSE was 0.0905 and the NSE was 0.8990). However, the WL obtained by the linear model was not in fact completely consistent with the actual measurement results (Figure 8), most obviously at the peak and the trough. For instance, the peak of observed TWS during 2011–2012 was lower than that of the model based on monsoon indices, as was that of the WL. This could be attributed to the influence of a medium La Niña event in 2010–2012, which might have increased the water in the MRB [8,10], leading to the higher values for the WL and TWS. Therefore, the model with only two monsoon indices could not precisely reconstruct the specific changes in the WL and TWS.

Table 4. Results of relative importance analysis for the two monsoons with regard to the WL and TWS.

Variable	Station	Total Response Variance	Proportion of Variance	Contributions of the ISM		Contributions of the WNPM	
				LMG	PMVD	LMG	PMVD
WL	My Thuan	0.007492	83.18%	57.55%	93.64%	42.45%	6.36%
	Can Tho	0.086046	85.73%	57.33%	82.84%	42.67%	17.16%
	Chau Doc	0.812452	82.81%	50.94%	56.87%	49.06%	43.13%
	Tan Chau	1.175889	86.60%	50.69%	55.41%	49.31%	44.59%
TWS	—	101.5007	89.90%	51.64%	59.66%	48.36%	40.34%

The RI of the ISM and WNPM resulting from the LMG and PMVD methods was also calculated (Table 4). Compared to the multivariate linear regression result (Table 4), the proportions of RI for the ISM and WNPM resulting from the LMG and PMVD methods for the TWS were almost the same. For the WL, the total response variances at My Thuan and Can Tho were much smaller compared to those at Chau Doc and Tan Chau. This was due to the difference in amplitudes. The proportion of variance explained by the model,

expressed as R^2 , was relatively similar. Although the difference between the LMG and PMVD methods lies in the data-dependent weights of the PMVD, the results generated from both methods were very different from each other, especially for the WL at My Thuan and Can Tho.

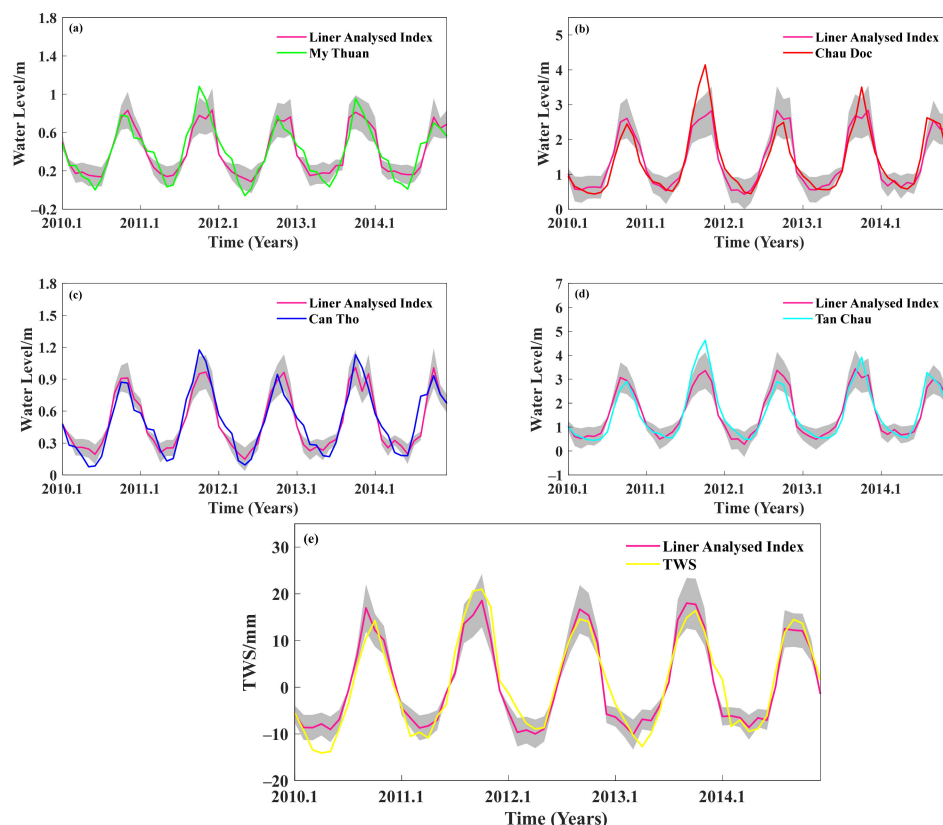


Figure 8. WL and linear regression fitting for the period from 2010 to 2014 at (a) My Thuan, (b) Chau Doc, (c) Can Tho and (d) Tan Chau, along with (e) the TWS and its linear regression fitting for the period from 2010 to 2014.

With respect to the results from Table 4, the resulting proportions of RI for My Thuan and Can Tho yielded high consistency with each other when using the LMG method, and the RI of the ISM accounted for more than 57%. However, the RI of the ISM was about equal to that of the WNPM at Chau Doc and Tan Chau. For the results generated from the PMVD, the proportions of RI of the ISM at the four stations for the WL were higher than those of the LMG, especially at My Thuan (36.09% higher) and Can Tho (25.51% higher).

4.2. Comparison among Three Methods

Comparing Table 3 with Table 4, it can be seen that similarities and differences existed among the results generated from different RI methods. Taking the results for the WL as an example, the ISM accounted for a larger relative contribution to WL than the WNPM for all four stations. The ISM relative contribution to the WL at My Thuan and Can Tho was higher than at the other two stations. However, there were significant differences in the specific values: the results generated with multivariate linear regression were closer to those of the PMVD, especially in the pair consisting of Chau Doc and Tan Chau. The proportions of RI of the ISM at My Thuan and Can Tho obtained from multivariate linear regression were lower than those obtained with the PMVD method. For the LMG method, all the results were in favor of an equilibrium between the ISM and WNPM, and the proportions of the ISM at all stations were all lower than with the previous two methods.

In essence, it is the characteristics of the methods themselves that leads to different results. The three methods are fundamentally linear regression, which aims to measure the

influence of each explanatory variable on a dependent variable. The first method, multivariate linear regression, is an ideal model based on the hypothesis that all explanatory variables are unrelated to each other. When considering the correlation between variables, the order in which variables participate should not be ignored during the model interpretation process. As stated in Section 3.4, the LMG method is simply the average of the marginal contributions of all permutations. Based on the LMG method, the PMVD method assigns different weights in different orders to ensure that variables with coefficients of zero do not participate in the relative importance calculation process. Consequently, as shown in Figure 9, the results of the LMG method tended to show more balance between the ISM and WNPM, whereas the PMVD method, on the other hand, highlighted the part with greater influence, reminding us of the factors dominantly related to the dependent variable. In addition, the resulting proportions of RI of the ISM and WNPM for the dependent variables obtained from the PMVD method and linear regression were relatively close, indicating that a direct relation between the ISM and WNPM did not exist.

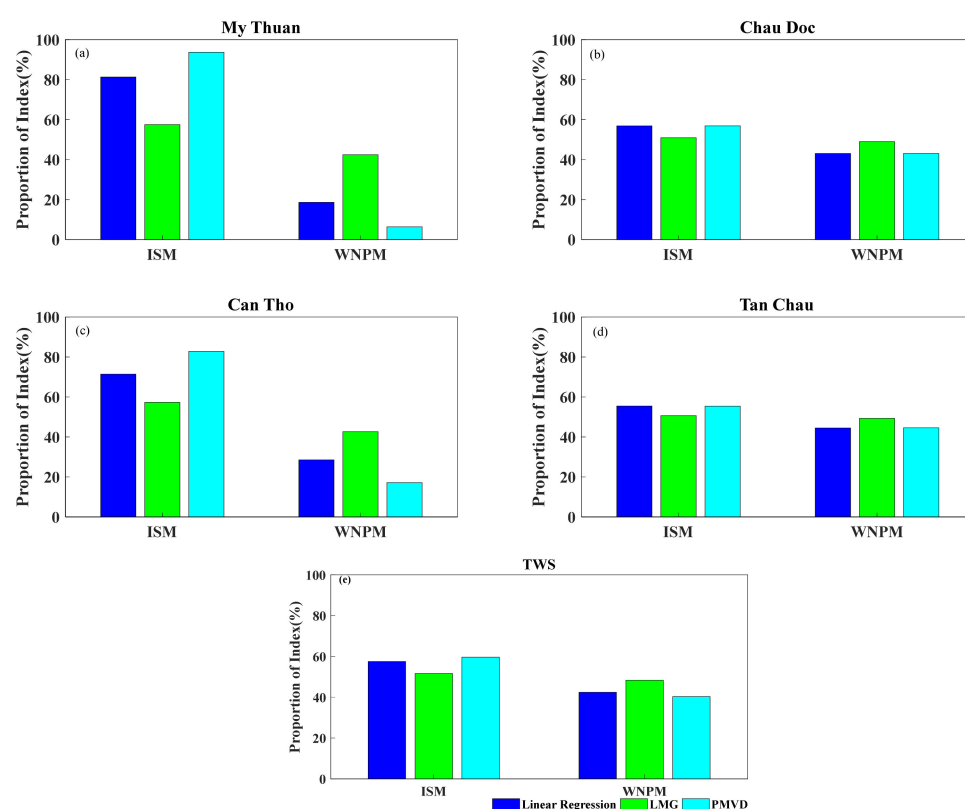


Figure 9. The comparisons of different resulting proportions of RI for the ISM and WNPM in the period from 2010 to 2014 obtained by three methods (multivariate linear regression, LMG and PMVD) for the WL at (a) My Thuan, (b) Chau Doc, (c) Can Tho and (d) Tan Chau, along with (e) those for the TWS.

4.3. Influence of Different Data Time-Span Selections

The above results were based on five years of data from 2010 to 2014. To examine whether a change in the selected data time-span would produce different results, data spanning from 2008 to 2012 were employed.

For the RI of the ISM and WNPM for the WL, the ISM was obviously still dominant in the long term, but interannual fluctuations might exist (Table 5). Although the basic characteristics for the period from 2008 to 2012 were consistent with that for the period from 2010 to 2014, the proportions of RI of the ISM obtained with the three methods for the period from 2008 to 2012 were consistently larger than those for the period from 2010 to 2014. This was particularly apparent at Chau Doc and Tan Chau, where the contribution of

the ISM to the WL increased by ~5% using the LMG method, while with multivariate linear regression (PMVD) it increased by ~15% (30%). Moreover, no significant changes were found in the RI results for My Thuan and Can Tho, especially when using the LMG method.

Table 5. Results of different intervals. The percentage in brackets indicates the change of the value compared with that for the period from 2010 to 2014. The change of the WNPM is opposite that of the ISM.

Time Interval	Monsoon	Variable	Station	Liner Regression	LMG	PMVD
2010.1–2014.12	ISM	WL	My Thuan	81.35%	57.55%	93.64%
			Can Tho	71.45%	57.33%	82.84%
			Chau Doc	56.88%	50.94%	56.87%
			Tan Chau	55.48%	50.69%	55.41%
	WNPM	WL	My Thuan	18.65%	42.45%	6.36%
			Can Tho	28.55%	42.67%	17.16%
			Chau Doc	43.12%	49.06%	43.13%
			Tan Chau	44.52%	49.31%	44.59%
2008.1–2012.12	ISM	WL	My Thuan	88.06% (+6.71%)	60.30% (+2.75%)	97.83% (+4.19%)
			Can Tho	82.09% (+10.64)	58.83% (+1.50%)	94.57% (+11.73%)
			Chau Doc	72.76% (+15.88%)	55.89% (+4.95%)	87.46% (+30.59%)
			Tan Chau	72.58% (+17.1%)	55.54% (+4.85%)	84.39% (+28.98%)
	WNPM	WL	My Thuan	11.94%	39.70%	2.17%
			Can Tho	17.91%	41.47%	5.43%
			Chau Doc	27.24%	44.11%	15.24%
			Tan Chau	27.42%	44.46%	15.61%
	TWS	—		34.00% (−23.55%)	43.69% (−7.95%)	17.42% (−42.24%)
				66.00%	56.31%	82.58%

However, the resulting proportions of RI of the ISM and WNPM for the TWS were quite different. During 2008–2012, the RI of the WNPM increased by 23.55%, 7.95% and 42.24%, as obtained via multivariate linear regression, LMG and PMVD, respectively, occupying the dominant position of influence on the TWS. Combined with the comprehensive performance results shown in Table 6, it can be seen that the change in the monsoons' influence on the TWS was significantly larger than that on the WL.

To further explore the short-term proportions of RI of the ISM and WNPM for the WL and TWS, six (respectively, eleven) three-year time-spans for the period from 2008 to 2015 (respectively, 2003 to 2015) were selected with a rolling data window. We found that the results were not the same as the results shown in Table 5 (Figure 10). For the proportions of RI of the ISM and WNPM for the WL at the four stations in the estuary, those at My Thuan and Can Tho showed a consistent change pattern in the ISM contribution, in which they all decreased first, then increased, and then decreased again; this was also found at Chau Doc and Tan Chau. However, the times of the turning points were not exactly the same. This shows that the monsoons' interactions varied with time. For example, the minimum RI of the ISM for the WL at My Thuan was in the period from 2009 to 2011, while that at Can Tho was in the period from 2010 to 2012. The results for My Thuan in the period from 2013 to 2015 were almost the same as for 2012–2014, whereas Can Tho showed a significant downward trend. As My Thuan and Can Tho are located in two main tributaries downstream of the Mekong Delta (Figure 1), we speculate that the length of the tributaries and the distance of the hydrologic stations from the estuary mouth might have led to the difference in the observed WL which was revealed in our results. The influence of the ISM on the TWS also fluctuated up and down, similar to the results for the WL. The results obtained with the LMG method were the most stable due to the simple averaging of the marginal contribution of each regressor. We speculate that ENSO might play a substantial role in the short-term variability in the strength of monsoons. This is further explored in a later section.

Table 6. Comparison of results before and after ENSO removal. The percentage in brackets indicates the change of the value compared with that before the ENSO signal was removed, which can be regarded as the influence proportion of ENSO. The change of the WNPM is opposite to that of the ISM.

Time Interval	Monsoon	Variable	Station	Liner Regression	LMG	PMVD
2010.1–2014.12 (with ENSO)	ISM	WL	My Thuan	81.35%	57.55%	93.64%
			Can Tho	71.45%	57.33%	82.84%
			Chau Doc	56.88%	50.94%	56.87%
			Tan Chau	55.48%	50.69%	55.41%
	TWS	—	57.55%	51.64%	59.66%	
	WNPM	WL	My Thuan	18.65%	42.45%	6.36%
			Can Tho	28.55%	42.67%	17.16%
			Chau Doc	43.12%	49.06%	43.13%
Tan Chau			44.52%	49.31%	44.59%	
TWS	—	42.45%	48.36%	40.34%		
2010.1–2014.12 (without ENSO)	ISM	WL	My Thuan	80.69% (−0.66%)	57.06% (−0.49%)	93.18% (−0.46%)
			Can Tho	76.74% (+5.29%)	56.96% (−0.37%)	89.61% (+6.77%)
			Chau Doc	73.90% (+17.02%)	56.08% (+5.14%)	86.44% (+29.57%)
			Tan Chau	68.94% (+13.46%)	54.56% (+3.87%)	79.20% (+23.79%)
	TWS	—	68.79% (+11.24%)	54.60% (+2.96%)	79.43% (+19.77%)	
	WNPM	WL	My Thuan	19.31%	42.94%	6.82%
			Can Tho	23.26%	43.04%	10.39%
			Chau Doc	26.10%	43.92%	13.56%
Tan Chau			31.36%	45.44%	20.80%	
TWS	—	31.21%	45.40%	20.57%		
2008.1–2012.12 (with ENSO)	ISM	TWS	—	34.00%	43.69%	17.42%
	WNPM			66.00%	56.31%	82.58%
2008.1–2012.12 (without ENSO)	ISM			71.81% (+37.81%)	55.63% (+11.94%)	84.19% (+66.77%)
	WNPM			28.19%	44.37%	15.81%

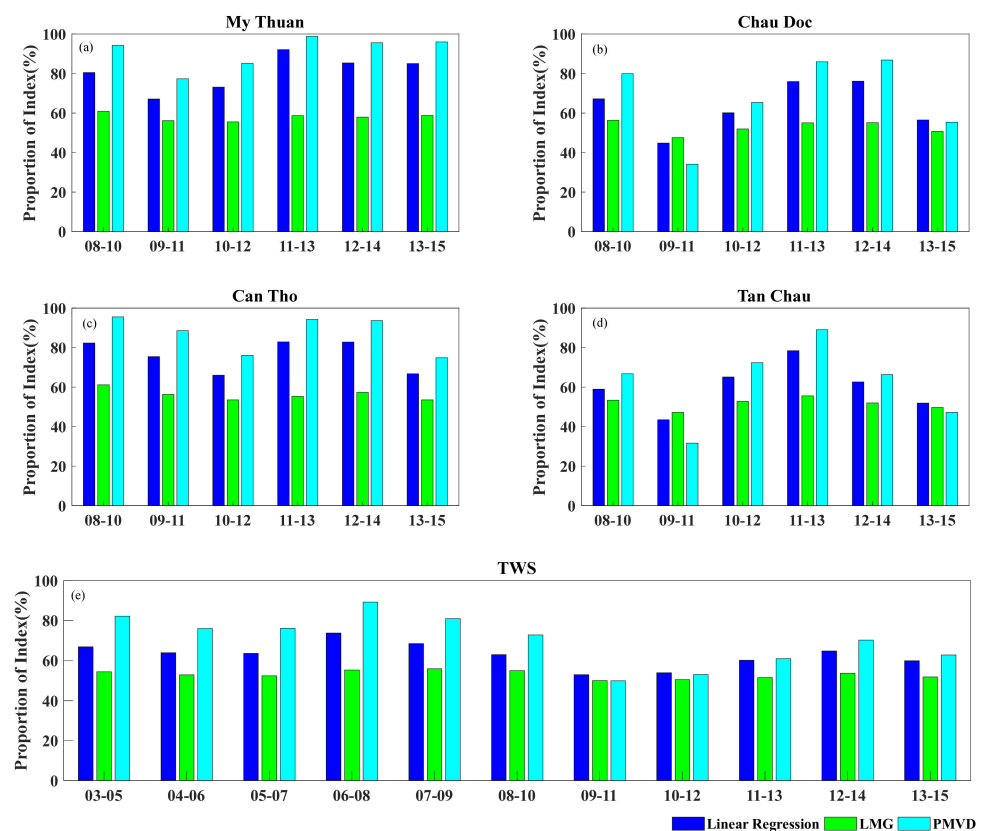


Figure 10. The temporal changes of the ISM's effects on the WL for six three-year time-spans for the period from 2008 to 2015 at: (a) My Thuan, (b) Chau Doc, (c) Can Tho and (d) Tan Chau, along with (e) that for the TWS for eleven three-year time-spans for the period from 2003 to 2015.

4.4. Influence of ENSO

Figure 10 indicated that the RI of the ISM for the WL had a change cycle, but the reasons for the periodicity were not clear, nor were those for the significant change in the monsoons' influence on the TWS during the periods from 2008 to 2012 and 2010 to 2014 (Table 5). To explore the reasons behind the changes of influence, the MEI index was further incorporated into the linear regression analysis. After introducing the MEI index, the influence proportions for the changes in the WL and TWS were calculated using the same methods (Figures 11 and 12).

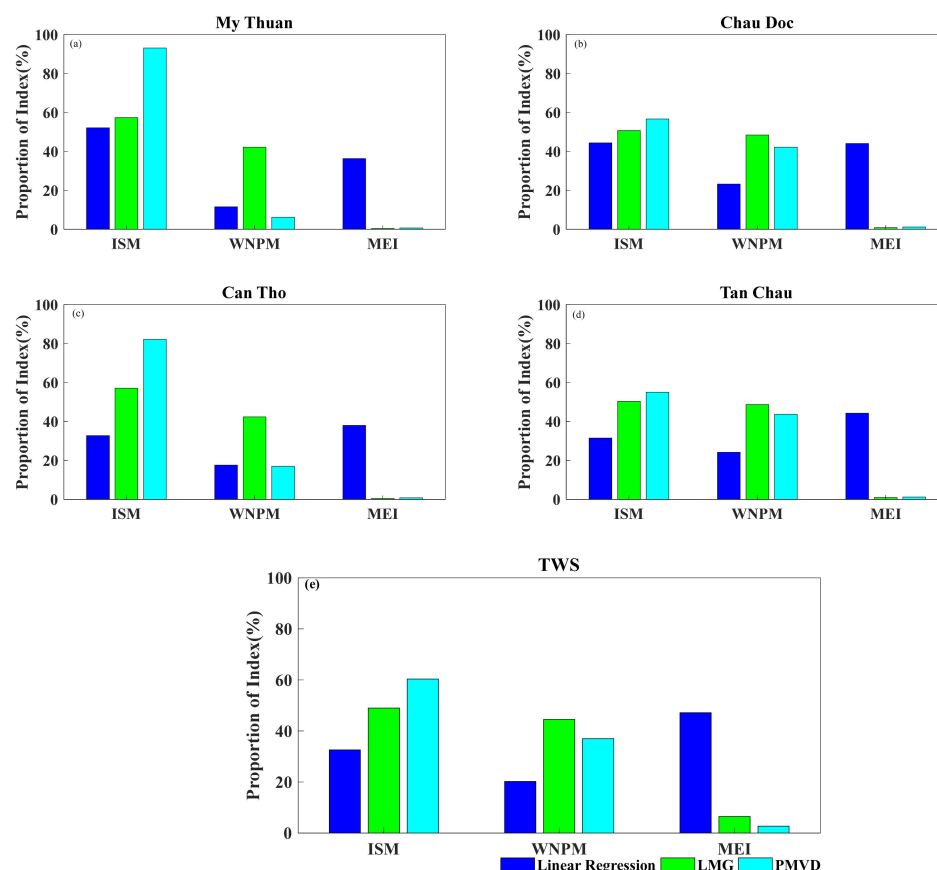


Figure 11. The resulting proportions of RI for the ISM, WNPM and MEI in the period from 2010 to 2014 for the WL at (a) My Thuan, (b) Chau Doc, (c) Can Tho and (d) Tan Chau, along with (e) those for the TWS.

As shown in Figure 11, the incorporation of the MEI indices into the RI analysis via linear regression resulted in an enlarged RI for the MEI index when compared to that obtained via the LMG and PMVD methods. In terms of the regularity of changes, the results generated from the LMG and PMVD method were similar to those from before. In the results generated from the LMG and PMVD methods, the MEI accounted for a negligible contribution. The reasons for the differences in the methods were described in Section 4.3. The results show that the ENSO effect, represented by the MEI, did play a role in the change in the WL and TWS, although it was relatively weak.

To quantify the influence of the ISM and WNPM on the WL of the Mekong River estuary separately from the influence of ENSO, it was necessary to eliminate the signal of the MEI index in the monsoon index. This was achieved via WTC, as mentioned in Section 3.4. The difference between the results before and after removing ENSO's influence can be seen as the quantified influence of the ENSO. Taking the WNPM as an example, based on WTC, it is not difficult to see that there was a significant relationship (higher than 0.7) between the WNPM and MEI for the period between 1.8 and 5 years, with a time lag

of about 1.5 months, as shown in Figure 13, and the coherence in the period from about 2 years to 3.5 years was the highest, higher than 0.8. It is clear that the WNPM was greatly influenced by the MEI for the period between 1.8 and 5 years, especially at around 2 years and 3.5 years. As a result, the signals for this part were removed.

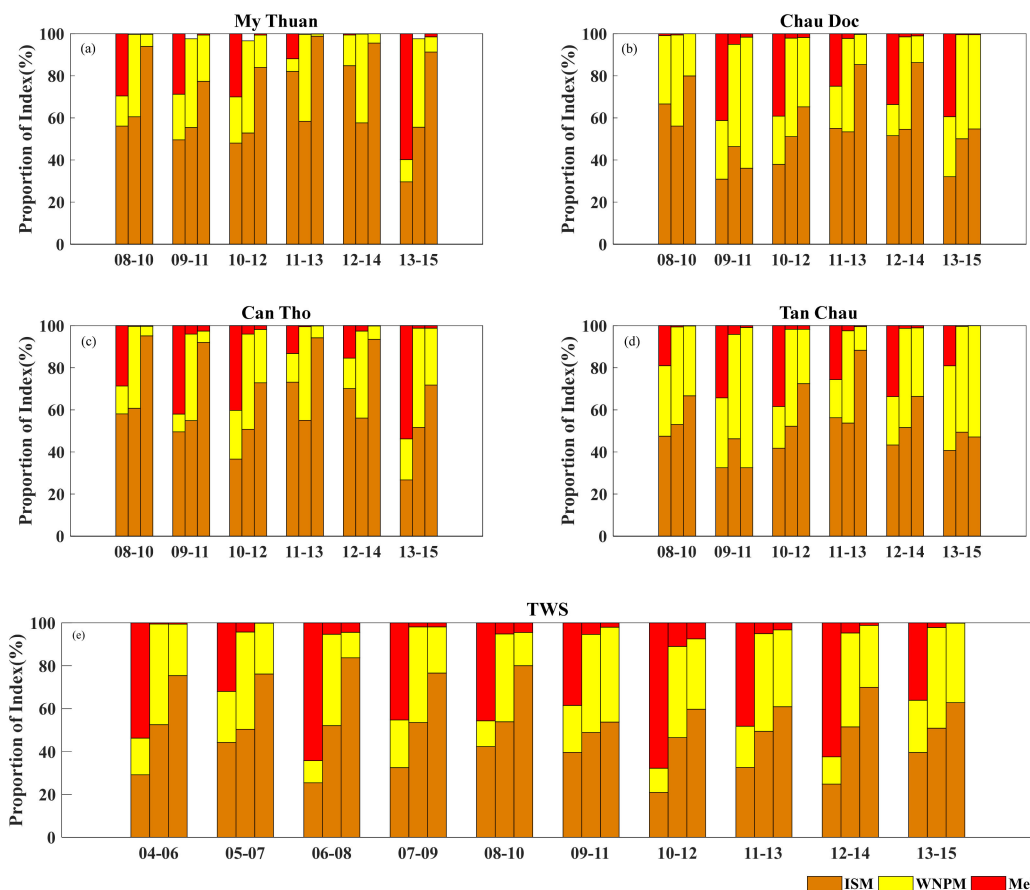


Figure 12. The temporal changes in the resulting proportions of RI for the ISM, WNPM and MEI for the WL for six three-year time-spans from 2008 to 2015 at (a) My Thuan, (b) Chau Doc, (c) Can Tho and (d) Tan Chau, along with (e) those for the TWS for ten three-year time-spans from 2004 to 2015. Each group of histograms was the result of three methods: linear regression, LMG and PMVD (from left to right).

After removing the signals at the period between 2 and 5 years, the WNPM and MEI no longer showed any obvious coherence in the short-wave signal (Figure 13). Thus, it was considered that the influence of ENSO had been removed from the time series of the monsoon index. The same processing was applied to the ISM time series in order to obtain the time series without ENSO's influence. The ISM and WNPM indices after the removal of the MEI were utilized to recalculate the proportions of RI of the ISM and WNPM for the WL at the four stations for the period from 2010 to 2014, as shown in Table 6.

Comparing the results after removing ENSO with the original results (Table 6), the following changes could be found: For the proportions of RI of the ISM and WNPM for the WL, the linear regression results enlarged the RI of the ISM at all stations except My Thuan, while the RI resulting from the LMG method was slightly smaller at My Thuan and Can Tho and larger at Chau Doc and Tan Chau. The changes in results for the PMVD method were similar to those at My Thuan and Can Tho, but much larger at Chau Doc and Tan Chau. In addition, the RI of the ISM was higher and the difference between the maximum and minimum was narrower. Compared with those obtained before removing the influence of ENSO, the mean values (ranges) increased (decreased) by 8.78% (14.12%), 2.04% (4.36%) and 14.92% (24.25%), as obtained via multivariate linear regression, LMG

and PMVD, respectively. As a result, ENSO can be considered as a potential factor that interferes with results. The influence of the ISM on the water level was more obvious and stable for the monsoon indices after removing the MEI. The influence of the ISM on the TWS increased to 68.79%, 54.60% and 79.43%, as obtained via multivariate linear regression, LMG, and PMVD, respectively. The ISM remained dominant in terms of RI. From 2008 to 2012, after removing the influence of ENSO, the ISM surpassed the WNPM again, rising from 37.81%, 11.94% and 66.77% to 71.81%, 55.63% and 84.19%, as obtained via multivariate linear regression, LMG and PMVD, respectively.

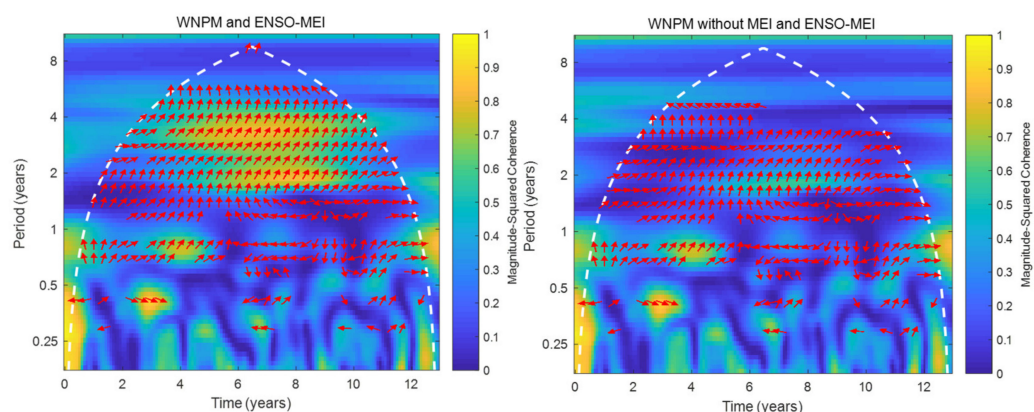


Figure 13. The coherence between the WNPM and MEI, and the coherence between the MEI and WNPM after the removal of the MEI. The red arrow represents the 5% significance level of high coherence areas, and the phase lag is denoted by the directions (right (left) indicates a phase lag of 0 (180) degrees; up (down) indicates a phase lag of 270 (90) degree).

The above results show that the influence of ENSO on the basin-averaged TWS was higher than that on the WL at the estuary. The result is consistent with findings of He et al., (2020) [37]. He et al., (2020) [37] discovered that the ENSO indirectly affected the TWS through the Asian monsoon (including the ISM and WNPM), based on WTC analysis. In addition, the ISM was weakened during ENSO, which was consistent with results from [69–72]: as El Niño develops in the northern spring, an eastward shift of the Walker circulation over the center of the Pacific occurs, causing the growth of subsidence over South Asia. This suppresses convection over South Asia, leading to a weaker summer monsoon. Though the coherence between ENSO and the WNPM over a long period (e.g., the period between 1.8 and 5 years in Figure 13) has not been previously analyzed, the WNPM has been confirmed to be strengthened during ENSO due to the Pacific negative SST anomalies [73–75].

Figure 14 shows the influence of ENSO on the TWS and WL via the rolling data windows. For the WL, the change of results between linear regression and PMVD is more obvious. For the TWS, the RI of the ISM for the TWS increased significantly in the periods from 2008 to 2010 and 2009 to 2011 after the removal of ENSO, whether obtained by linear regression or PMVD. This also coincided with the time of ENSO activity, which happened from 2009 to 2010 [76].

4.5. Future Research and Applications

In this study, after quantifying the contributions of two monsoon indices (i.e., the ISM index and WNPM index) using three RI methods, the ENSO effect was further discussed by introducing the MEI index into the analysis. However, other potential influencing factors (e.g., ocean tides on WL [49,50,77], precipitation and evapotranspiration on TWS) and the restriction of the number of valid factors on RI analysis remain unexplored. Furthermore, we mainly studied the interannual variance (i.e., 3-year and 5-year cycles) of monsoons with regard to the WL and TWS. Nonetheless, for relatively short-term anomalies, such

as the performance in drought or flood years in the MRB [4,78], further studies could be conducted in the future.

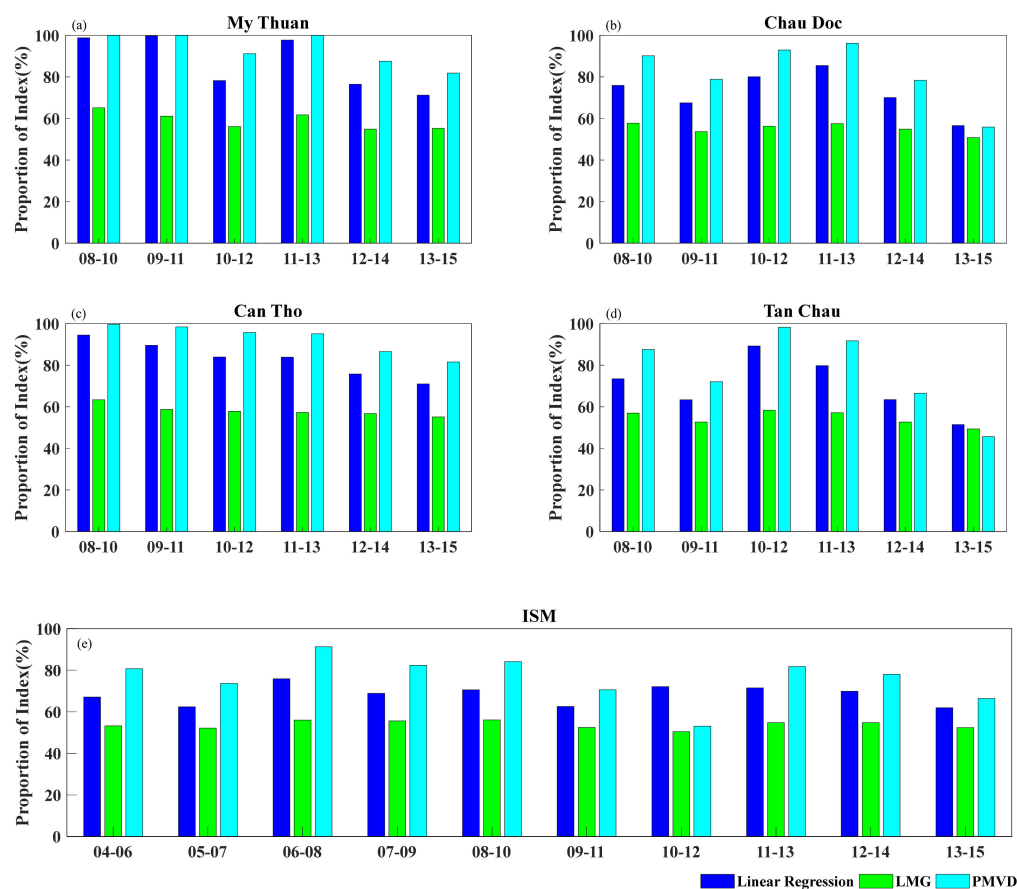


Figure 14. The temporal changes of the ISM's effects after ENSO factor removal on the WL for six three-year time-spans from 2008 to 2015 at (a) My Thuan, (b) Chau Doc, (c) Can Tho and (d) Tan Chau, along with (e) those on the TWS for ten three-year time-spans from 2004 to 2015. The changes in the WNPM's effects were the opposite.

In addition, other hydrological variables, such as the water discharge [79–81], regional precipitation [79–81] and evapotranspiration [81,82], could be incorporated into the RI analysis in the form of explanatory or response variables. When combined with the terrestrial water storage [49,83], these hydrological variables should form a terrestrial water balance that allows a more comprehensive analysis. Other regional monsoon or global climate indices can also serve as explanatory variables in this regard. The above proposed elements allow us to extend our methodology and apply it to other large basins with similar geographic configurations and hydroclimatic characteristics as those of the MRB.

5. Conclusions

Aiming at exploring the influences of two monsoons (the Indian summer monsoon (ISM) and western North Pacific monsoon (WNPM)) on the water level (WL) of the Mekong River delta (MRD) and on the terrestrial water storage (TWS) of the entire Mekong River basin (MRB), multivariate linear regression and the Lindeman, Merenda and Gold (LMG) and proportional marginal variance decomposition (PMVD) methods were selected to quantify the relative importance (RI) (or contributions) of the two monsoons. The results showed that the ISM accounts for the majority of the RI for the WL, as well as that for the TWS in the MRD.

Comparing stations closer to (e.g., My Thuan) and farther away from (e.g., Chau Doc) the ocean, the resulting proportions of RI of the ISM for the WL at My Thuan (Chau

Doc) station were 81.35% (56.88%), 57.55% (50.94%) and 93.64% (56.84%), as obtained via multivariate linear regression, LMG and PMVD, respectively. This indicates that the WL at stations closer to the ocean is subject more to the influence of the ISM, rendering different results from the three methods. Moreover, the proportions of RI of the ISM for the TWS were 57.55%, 51.64% and 57.99%, as obtained via multivariate linear regression, LMG and PMVD, respectively.

In addition, the same method led to different results using data from different data time-spans, indicating that the RI of the two monsoons' influences on the WL and TWS varied with time. Considering that climate factors might have caused the fluctuation in the monsoons' contributions to the WL and TWS, the El Niño–Southern Oscillation (ENSO) index (i.e., the multivariate ENSO index (MEI)) was incorporated into the linear regression analysis. It was found via wavelet transform coherence (WTC) analysis that the MEI presented high correlations with the ISM and WNPM in the periods between 2 and 5 years, highlighting the need for the removal of the ENSO signal from the monsoon indices. Using the ENSO-eliminated data to recalculate the influence of the monsoons on the WL and TWS, the proportions of RI of the ISM for the WL at the four stations were higher while the ranges of change were narrower. The same applied to the TWS. These results indicated that ENSO signals presented a substantial effect on the monsoons. The quantified contributions of influence on the WL for the mean values of four stations (TWS) were 8.78% (11.24%), 2.04% (2.96%) and 14.92% (19.77%), as obtained via multivariate linear regression, LMG and PMVD respectively.

A comparison between the relative importance methods indicated that the linear regression enlarged the existence of the ENSO MEI index compared to the LMG and PMVD methods. This was because linear regression tends to search for the best-fitting result, leading to the enlargement of some variables along with a large deviation in the results. Furthermore, the more balanced results derived from the LMG method demonstrated its comprehensiveness in reflecting the proportions of factors, while the PMVD method focused more on the dominant factor related to the dependent variables. Further improvement could also be possible by including long-period ocean tides (i.e., semiannual and annual tidal constituents) in the analysis. All in all, this study managed to quantify the contributions of two monsoons (the ISM and WNPM) to two hydrological variables (the WL and TWS) in the MRB, which can be generalized to interpret the interactive relations between monsoons and other variables for regions with similar geographic configurations.

Author Contributions: Conceptualization, H.S.F.; methodology, H.S.F. and T.S.; software, T.S.; validation, Z.M., H.S.F. and T.S.; formal analysis, T.S. and H.S.F.; investigation, T.S. and H.S.F.; resources, H.S.F.; data curation, Z.M.; writing—original draft preparation, T.S.; writing—review and editing, T.S., H.S.F. and Z.M.; visualization, T.S.; supervision, H.S.F. and Z.M.; project administration, H.S.F.; funding acquisition, H.S.F. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement: The download links for the water level, monsoon indices, terrestrial water storage and multivariate ENSO Index data are respectively provided in Sections 2.1–2.4 within the text.

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Conflicts of Interest: The authors declare no conflict of interest.

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