Rice yield responses in Bangladesh to large-scale atmospheric oscillation using multifactorial model

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Abstract

This paper intends to explore rice yield fluctuations to large-scale atmospheric circulation indices (LACIs) in Bangladesh. The annual dataset of climate-derived yield index (CDYI), estimated using principal component analysis of Aus rice yield data of 23 districts, and five LACIs for the period 1980–2017 were used for this purpose. The key outcomes of the study were as follows: three sub-regions of Bangladesh, northern, northwestern, and northeastern, showed different kinds of CDYI anomalies. The CDYI time series in north and northeastern regions exhibited a substantial 6-year fluctuation, whereas a 2.75- to 3-year fluctuation predominated the northwestern region. Rice yield showed the highest sensitivity of LACIs in the northern region. Indian Ocean dipole (IOD) and East Central Tropical Pacific SST (Nino 3.4) in July and IOD index in March provide the best yield prediction signals for northern, northwestern, and northeastern regions. Wavelet coherence study demonstrated significant in-phase and out-phases coherences between vital climatic variables (KCVs) and CDYI anomalies at various time-frequencies in three sub-regions. The random forest (RF) model revealed the IOD as the crucial contributing factor of rice yield fluctuations in the country. The multifactorial model with different LACIs and year as predictors can predict rice yield, with the mean relative error (MRE) in the range of 4.82 to 5.78% only. The generated knowledge can be used to early assess rice yield and recommend policy directives to ensure food security.

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1 Introduction

Understanding the profound impacts of climate instability on agricultural systems is vital for developing appropriate adaptation strategies (Challinor et al. 2014; Deryng et al. 2014; Moore and Lobell 2014; Siebert and Ewert 2014; Ghose et al. 2021a; Hu et al. 2021). ENSO-driven climate anomaly can cause crop damage, food insecurity, malnutrition, and even famine and losses of life (Marlier et al. 2013; Iizumi et al. 2014; Salam et al. 2020a, b). Therefore, the teleconnection between large-scale atmospheric oscillations and crop yields has been widely studied at global and regional scales to provide the basis of crop yield forecasting (Falcon et al. 2004; Ray et al. 2012; Iizumi et al. 2014; Huang et al. 2017; Rahman and Islam 2019; Wahiduzzaman and Luo 2020).

Rice is the staple food grain and the most widely grown crop variety in many Asian countries, including Bangladesh. Many studies have examined the effects of ENSO on rice production in different Asian countries (e.g., (Zubair 2002; Selvaraju 2003; Falcon et al. 2004)). The studies showed an adverse effect of climate fluctuations on rice production. For example, Zubair (2002) found a detrimental effect of

El Nino on rainfall, crop growth and yields in one of the two main cropping seasons (Yala season), and a positive impact on another growing season (the maha season) in Sri Lanka. Naylor et al. (2007) showed rice and corn production in Indonesia is susceptible to climate variation linked to ENSO events. Roberts et al. (2009) found a significant effect of El Niño on irrigated and rain-fed rice production in the Philippines. Many recent studies also showed the adverse effects of El-Niño derived climate variation on agriculture of Malaysia, Thailand, and Cambodia (Al-Amin and Alam 2016; Vimean et al, 2017; Xu et al. 2020). Studies also showed El Niño effects on Bangladesh's agriculture through water shortage, soil depletion, and planting season disruption (Chowdhury 2003). Besides, drought, flood, soil salinity, and cyclone have been described as the ENSO-driven main climatic extremes unfavorably influencing agricultural crop production in Bangladesh (Harun-ur-Rashid and Islam 2007; Islam et al. 2017).

Approximately 80% of the total cultivated area in Bangladesh is transplanted with rice in various seasons, comprising more than 91% of the total crop production (BBS 2017). In Bangladesh, the Aus (Upland Rainfed) season starts in early March and ends in mid-August. The Aman (wet season) runs from May to late December, while the Boro (dry season-irrigated) runs from mid-November to late May. In the rice-growing seasons, the average yield of rain-fed Aus rice is 2.16 t/ha accounted for over 6.70% of the total rice production of Bangladesh (BBS 2018). However, the Bangladesh government wants to use the advantage of lower irrigation requirements of Aus rice cultivation to minimize water dependence and increase sustainability in agriculture (Uddin and Dhar 2018; Islam et al. 2021b). Therefore, the government has introduced an incentive program recently for small and marginal farmers to rejuvenate the Aus rice cultivation (Uddin and Dhar 2018). Given the significant impact of rice production on the agricultural system, livelihood, and food security, it is crucially essential to understand the critical agro-climate parameters and large-scale atmospheric circulation indices for Aus rice yield forecasting for different sub-regional ecotypes Bangladesh.

Long-term crop yield oscillation is mainly related to climatic influences and extreme weather events (Ghose et al. 2021b), while elevated temperatures can increase crop production. However, some studies have shown that crop yield drops significantly when daytime temperatures reach a specific crop-specific threshold (Islam et al., 2019). Each crop has optimal minimum and maximum temperature, precipitation, and relative humidity limits for its reproductive and vegetative growth stages. The crop yield changes dramatically when the temperature reaches the upper limit or falls below the lower threshold limit or humidity surpasses the upper threshold limit. Besides, extreme precipitation can make conditions for waterlogging and flooding, which also reduces crop production. Huang et al. (2017) assess the impact of precipitation on the rice yield where they found that rainfall adversely affected rice yield. Ara et al. (2016) reported that rice yield is negatively associated with heavy rain and extreme temperature in Bangladesh. Quan et al. (2013) explored the rice yield is responses by average temperature and annual rainfall in China. Revadekar and Preethi (2012) found that the Kharif rice yield is positively responded with the precipitation indices. Huang et al. (2018) found that rice yield is affected by precipitation indices in China. Tao et al. (2014) assessed the association between rice yield and maximum temperature, where they discovered that the relationship is significantly positive. Huang et al. (2021) investigated the correlation between several meteorological factors and large-scale atmospheric circulation index with maize yield and predicted the maize yield in north China.

ENSO effects on rainfall and temperature in Bangladesh have been reported in previous studies (Ahasan et al. 1970; Chowdhury 2003; Wahiduzzaman 2012). However, the impact of ENSO on weather and crop production has only received limited attention in the region. Chowdhury (2003) reported that the climate has a significant association with SOI extremes (despite a poor quantitative correspondence between the strength of ENSO and the rainfall anomaly), negative SOIs with dry and positive SOIs with wet conditions in Bangladesh. In a moderate SOI anomaly, the index-climate relationship, especially in Bangladesh, appeared to be contradictory during the mild El Nino years' wet season. In recent times, Wahiduzzaman and Luo (2020) suggested a strong relationship of ENSO with precipitation and temperature over the nation. Ghose et al. (2021a) recently revealed an increase in temperature by 1 °C and rainfall by 1% causes a decrease in Aman rice yields by 33.59% and 3.37%, respectively, in southwest and southeastern regions of Bangladesh. They also suggested that rice yield significantly affected by the Indian Ocean Dipole (IOD). However, the linkages vary for areas and seasons. However, no studies have been conducted to evaluate the effect of ENSO on crop yields in Bangladesh, except for the study of Ghose et al. (2021a; b).

Because of current anthropogenic climate change, it is essential to recognize effective adaptation alternatives for improving current food production and reducing crop systems' vulnerability to future climatic parameters (Islam et al., 2021a). There is also a need to understand the possible linkage of global and regional climate variabilities to crop yield to improve crop yield prediction capacity. However, a few studies have been focused on region-wise prediction for such specific rice type in Bangladesh. This study aims to assess how ENSO and related climate variability affect rice yield in different sub-regions of Bangladesh. The ultimate objectives of this work are (1) to evaluate the agro-climatic

regionalization of the Aus rice yield in Bangladesh using the principal component analysis of annual climate-derived yield index (CDYI) time-series estimated for 23 districts of Bangladesh for the period 1980–2017; (2) to investigate the inter-annual variability of CDYI of Aus rice in different climatic sub-regions using Pearson correlations, multiple regression, and wavelet coherence analysis; (4) to identify the critical large-scale atmospheric circulation indices (LACIs) affecting the fluctuation of Aus rice yield based on the CDYI-LACI association and random forest model; (5) to predict rice yield in three sub-regions of the country using the key LACIs as input in a multifactorial model. The novel aspect of this research is that the current study also contributes to generating scientific knowledge by investigating the response of rice yield to the large-scale atmospheric circulation indices and several meteorological factors. Understanding of Aus rice yield responses to climate oscillations would facilitate an early assessment of rice yield and recommend policy directives to ensure food security.

2 Data and methods

2.1 Study area

Bangladesh is the world's leading deltaic country, situated in the southeastern part of Asia, extending 20.30 to 26.45° N latitudes and 88.00 to 92.45° E longitudes (Fig. 1a). The total area of this deltaic country is 147,700 Km2. By and large, 80% land area of this country is the floodplain of three major trans-boundary rivers: the Brahmaputra, the Padma, and the Meghna and their tributaries. The elevation of the floodplain varies from 1 to 60 m (Islam et al. 2020). Hills and hillocks occupy only a small part of southeastern and northeastern regions. The biodiversity-rich Bay of Bengal surrounds the southern part of the country. The country is blessed with a monsoon climate. The monsoon rainfall is an inevitable element for the country's agricultural crop production. Bangladesh has three rice growing seasons: Aus, Aman, and Boro, based on climatic characteristics (Kamruzzaman et al. 2019). The present study is focused on the pre-Kharif Aus rice growing during April − July. Figure 1b shows the overview of Aus rice yield in the total study period. The country's average precipitation is about 2400 mm per year, mainly during June–September (monsoon season) (Jerin et al. 2021). On average sub-tropical monsoon climate dominates the country. However, the western and northwestern parts of this country often experience moderate to extreme droughts due to inter-annual rainfall variability.

The historical daily mean minimum temperature, maximum temperature, relative humidity, wind speed (at 2-m height), evapotranspiration, and net radiation for the whole country are 21.39 °C, 29.94 °C, 80%, 1.32 ms^{-1}, 3.72 mm day^{-1}, and 10.44 MJm^{-2} day^{-1}, respectively (Salam et al. 2020a). Bangladesh is sub-divided into seven
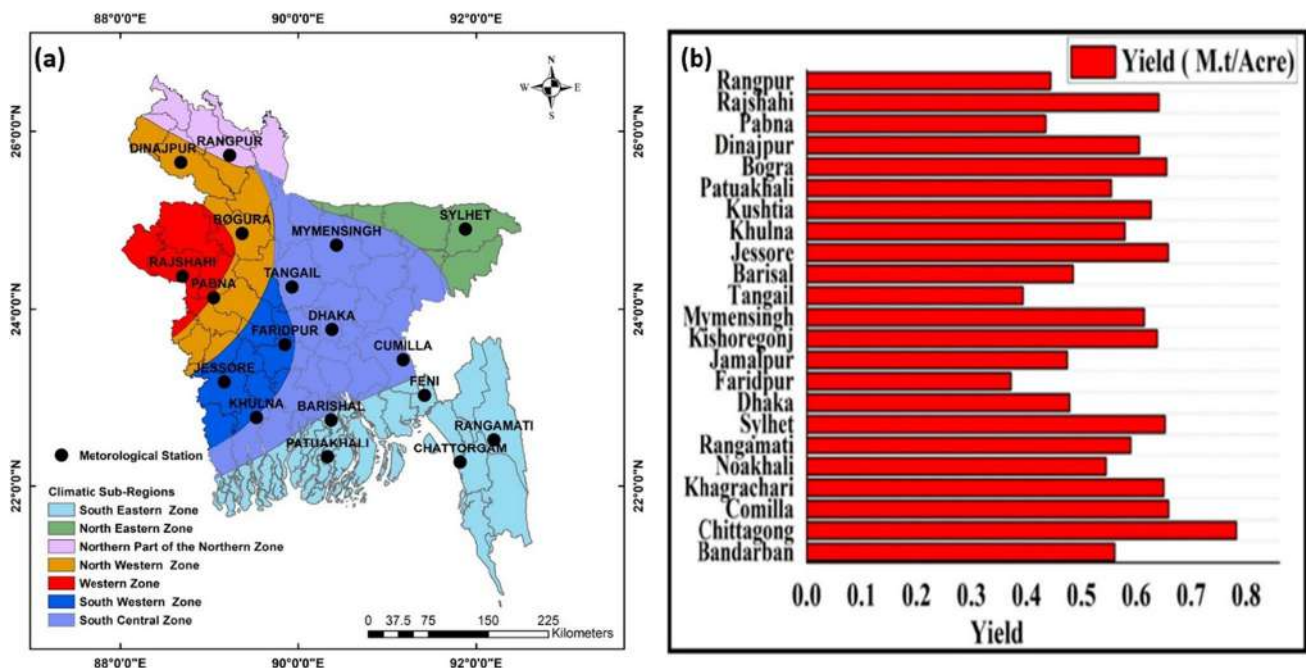

Fig. 1 (a) Location of meteorological stations and climatic sub-regions of Bangladesh; (b) Overview of Aus rice production in different districts of Bangladesh

climatic regions (Fig. 1), based on geography and climatology: (I) Southeastern; (II) Northeastern; (III) Northern part of the northern zone; (IV) Northwestern; (V) Western; (VI) Southwestern; and (VII) South-central. Three out of seven climatic regions, northern part of the northern zone, southwestern, and northeastern regions, were considered in the present study as Aus is widely cultivated in these regions.

2.2 Data sources

Daily precipitation, minimum, maximum, and average temperature data for 18 meteorological stations across the country were collected from the Bangladesh Meteorological Department (BMD) (http://bmd.gov.bd) for the period 1980–2017. Besides, monthly cloud cover and potential evapotranspiration data for 18 stations were acquired from the Bangladesh Agricultural Research Council (www://climate.barcapps.gov.bd). The percentage of missing data in the acquired datasets was less than 5%. The nearest stations' data were used to fill the missing data. The Staff of BMD checked all these data to ensure quality. We did not consider wind speed and sunshine period in this research work due to plenty of inconsistent temporal extent of time series data and issues of missing values. Considering missing values of daily climatic variables, we tested thoroughly employing a seasonally split missing value accusation system with na. sea split () (Mortiz et al. 2015) R function.

Some field observed data were used in this study: crop growth, rice development stages, and yields. Data of the crop growth and Aus rice development stages were acquired from Bangladesh Rice Research Institute (BRRI), and Aus rice yield data (yield/area, M.t/acre) of 23 districts were obtained from the statistical yearbook of Bangladesh Bureau of Statistics (BBS 2018) for the period 1980–2017. The selected 18 meteorological stations cover these 23 districts. Quality control was conducted on the yield time-series datasets in every single district, and a linear interpolation method was used for some missing yield datasets. Moreover, data of the five common atmospheric oscillation indices were also used, which are Indian Ocean Dipole (IOD), East Central Tropical Pacific SST (Nino 3.4), Southern Oscillation Index (SOI), Multivariate ENSO (El Niño-Southern Oscillation) index (MEI), and Central Tropical Pacific SST (Nino 4). These atmospheric indices' data were extracted from the National Oceanic and Atmospheric Association (NOAA) Climate Prediction Center (CPC) Website (http://www.cpc.ncep.noaa.gov/products/preci p/CWlin k/pna/nao.shtml) for the period 1980–2017. Though these indices are standardized, the large-scale oscillations in some atmospheric and oceanic factors happening in the period of El Nino and La Nina occurrences can affect the system of Earth's climate at the local to the global range. Each monthly LACI

series had accepted by employing a homogeneity test by using the ACMANT homogenization software improved by Domonkos (2011).

2.3 Climate-derived yield index

The climate-derived yield index (CDYI) is a common method for assessing climatic variables' impacts on crop yields (Zhao et al. 2015; Huang et al. 2020). The present study adopted this method for exploring the relationship between different climatic variables and Aus rice yield. The CDYI is expressed statistically as:

$$CIYi = 100 * \left(\frac{Y_{ai}}{Y_{mi}} - 1 \right) \tag{1}$$

where Y_{a_i} denotes accurate Aus rice yield, and Y_{m_i} denotes the 5-year moving average of field-induced Aus rice yield (Li et al. 2018). The CDYI can be expressed by the following equations also:

$$CIYI = a \times KCV + b \tag{2}$$

$$CIYI = a \times LACI + b \tag{3}$$

where a signifies the sensitivity of Aus yield variances to the selected key climatic variables (KCV). The effect of climatic variables on Aus rice yield can be estimated by multiplying a with the linear trend of climatic variables (Huang et al. 2019). Likewise, the effects of the LACI divergences on Aus rice yield can be assessed by multiplying it with LACI's linear trend. Adopting assumptions after Fang (2011), the present study considered three conditions, which are as follows: (i) during Aus rice-growing season, the trend of actual Aus rice yield must be equivalents to the management-induced Aus rice yield found from simulation curve; (ii) study area plays the main role for changing the factors of the management-induced Aus rice yield, and the variation of actual Aus rice yield varies with climatic variability of the respective area; and (iii) the impacts of the KCVs on the Aus rice growth must be analogous to the feature of Aus crop growth and the response of Aus crop to the KCV.

2.4 Key climatic variables limiting the CDYI of Aus rice

The field investigation explored the growing period of Aus rice and selected the KCVs, which affect the Aus rice yield. The variables that may affect the Aus rice yield, like field management and soil conditions, were omitted from the analysis. The present study determined the KCVs for seven climatic sub-regions of Bangladesh based on the Pearson correlation coefficient (PCC). The average precipitation (PRE), average temperature (TMP), potential

evapotranspiration (PET), average maximum temperature (TMX), average minimum temperature (TMN), and average cloud coverage (CLD) from April to July were estimated during the entire growth period of Aus rice. Finally, the relation between KCVs and the Aus rice CDYI were assessed.

2.5 Generating relationships between KCVs and Aus rice CDYI

The present study used multiple linear regression (MLR) to assess the functional relation between KCVs and Aus rice CDYI. The statistical equation of MLR is as follows:

$$Y = \beta_0 + \beta_1 x_1 + \beta_2 x_3 + \ldots\ldots.. + \beta_k x_k \qquad (4)$$

where Y is the CDYI of Aus rice, β_0 is the regression constant, β_k are the coefficients of partial regression, and x_k are the KCVs. This regression model is convenient to the scientific community by dint of its user-friendliness and easiness.

Weather and climate vary geographically and temporally, and therefore, the impacts of climatic variables on the crop yields in space and time. The correlation between KCVs and the CDYI of Aus rice in each station was used to demonstrate the comparable mean sub-zone status. However, this representation is not correct for all the sub-zones. Therefore, PCA was used for detecting the spatial variations of KCVs based on the likenesses and contrasts (Polong et al., 2019). In PCA, the non-correlated elements are excluded from the main rotating element to generate principal components (PC). The loadings of PCs indicate the correlation between the accompanying PC scores (PCS) and time-series data (Capra and Scicolone 2012). Based on the outcomes of the PCA analysis of Aus rice CDYI, the present study identified three climatic sub-regions of Aus-rice cultivation.

2.6 Evaluating spatiotemporal changes of Aus rice CDYI using multistatistical models

This study involves multiple models or models to evaluate spatiotemporal changes of Aus rice yields in Bangladesh. A multifactorial model is linked with the convergence of environmental and climatic phenomena (Ghose et al. 2021b). Such a model recognizes that depending on several factors, especially climatic and physical factors. For example, Pearson's correlation coefficient (PCC) was used for assessing the relationship between the time–frequency domain linkage between the Aus rice yield and the key LACI (Salam et al. 2020). The ensemble empirical mode decomposition (EEMD), proposed by Wu & Huang (2009), was used to decompose the non-linear and non-stationary time series signals into oscillatory modes, called intrinsic mode functions (IMFs) (Adarsh & Reddy, 2016; Alizadeh et al. 2019). The EEMD was used for detecting the variability of LACI and

decomposing the time series data. To explore the oscillation features of climatic factors, EEMD was used in this research work (Johny et al. 2019; Huang et al. 2020). EEMD can be employed to exceed the mode mixing point without showing an intermittent subjective check as in the EMD that is used due to time series decomposition in this research also, since it can divide ranges and necessities no previous criterion of subjective choice (Wu and Huang 2009). The EEMD estimates IMF using the following steps: (1) superimpose white noise with the finite amplitude on the original data; (2) estimation of signal variation to get IMF1 implementation of the EEMD; (3) superimpose a noise with a similar amplitude on the original data sequence which has been visible with IMF1; and (4) perform EEMD on the new sequence to obtain IMF2. The abovementioned phases are iterated until various IMFs and the trend objects are originated. The details of EEMD technique can be observed in the paper of Wu and Huang (2009).

The wavelet transform coherence (WTC) (Guo et al. 2018; Rahman and Islam 2019) was used to find the correlation between two time-series. The WTC measures the covariance magnitude between two time-series that fluctuates between 0 and 1 ($0 \leq R^2 \leq 1$), where 0 denotes no consistency and 1 means a flawless consistency (Iqbal et al. 2020). With the increase of the consistency, the symphony of time series variables also increases. The correlation is estimated using the following formula:

$$R^2(m,n) = \frac{\left| N\left(N^{-1} W_{xy}\right)(m,n) \right|^2}{N\left(N^{-1}\left|W_x(m,n)\right|^2\right) N\left(N^{-1}\left|W_y(m,n)\right|^2\right)} \qquad (5)$$

The present study utilized WTC for exploring the consistency or correlation between the CDYI of Aus rice and the KCVs.

2.7 Random forest model

Nowadays, various machine learning algorithms are commonly used in science, technology, engineering, and mathematics to solve complicated non-linear problems. Random forest (RF), proposed by Breiman (2001), is a supervised algorithm that uses two bagging and random tree algorithms. The RF has been widely employing in the literature for detecting features' importance (Salam and Islam 2020; Salam et al. 2020b, Rahman and Islam, 2019). This study utilized the RF model for exploring the importance of Aus rice CDYI against the LACI. An RF model with 100 trees, 1 execution slot, 7 seeds, and a maximum depth of 1 was used in this study. The scholars constantly use this model for

its robustness, reliable outcomes, flexibility, and scientific strength.

3 Results

3.1 Calculation of Aus rice CDYI for Bangladesh

Crop yield data is often not an accurate estimate of a region's yield as it is affected by various management factors. Filters are generally used to remove the inherent problem in yield data and estimate the regional field average (Zhao et al. 2017). Therefore, filters were used to estimate the CDYI of Aus rice of every district. Different filters, including exponent, power, HP, logarithmic, and quadratic, were fitted to CDYI to estimate the average regional CDYI. The estimated regional average CDYI using different filters were correlated with the meteorological disaster indicators. The meteorological disasters considered in this study include drought, flood, cold wave, and waterlogging indicators. Three indicators related to each disaster were considered, as described in Table 1. The first indicator of each catastrophe is the total crop planting area's ratio to the disaster-affected area. The second indicator is the crop planting area's ratio of the disaster suffered area. The third indicator is the intensity of the disaster or the second to the first indicator ratio. Three indicators of four disasters produced a total of 12 indicators.

The correlation of CDYI generated by different fitting models with the disaster indicators is given in Table 2. The table shows that CDYI has a notable negative association ($r < -0.4$) with the first two drought indicators, DD1 and DD2 (described in Table 1). These are analogous with the past studies on Aus rice's response to climate change in different sub-regions. Ghose et al. (2021a) found a stronger association of yield with precipitation than the other climatic factors. The average areal CDYI obtained using a high pass (HP) filter showed higher negative associations with DD1 and DD2 than other fitted models. Therefore, an HP filter was used to extract the average CDYI of each of the 23 districts.

3.2 Regional temporal variability of CDYI using PCA

PCA of Aus rice CDYI series of 23 districts was used to estimate the variance contributions and eigenvalues. Figure 2a shows the variance contributions of different PCs. The results showed that the first three PCs were adequate to

Table 1 Definition of meteorological disaster indicators

Types of agro-meteorological disasters	Disasters indicators	Definition	Units
Drought disaster (DD)	DD1	Ratio of the DD-affected area to crop planting area	%
	DD2	Ratio of the DD-suffered area to crop planting area	%
	DD3	DD intensity (DD2/DD1)	%
Flood disaster (FD)	FD1	Ratio of the FD-affected area to crop planting area	%
	FD2	Ratio of the FD-suffered area to crop planting area	%
	FD3	FD intensity (FD2/FD1)	%
Cold wave disaster (CD)	CD1	Ratio of the CD-affected area to crop planting area	%
	CD2	Ratio of the CD-suffered area to crop planting area	%
	CD3	CD intensity (CD2/CD1)	%
Waterlogging disaster (WD)	WD1	Ratio of the WD-affected area to crop planting area	%
	WD2	Ratio of the WD-suffered area to crop planting area	%
	WD3	CD intensity (WD2/WD1)	%

Table 2 Correlation of regional average CDYI generated using different fitting models and disaster indicators

	DD1	FD1	CD1	WD1	DD2	FD2	CD2	WD2	DD3	FD3	CD3	WD3
5-year moving average	**−0.43**	0.005	0.20	0.003	**−0.41**	0.15	0.23	−0.23	0.008	0.05	0.13	0.10
Linear regression	**−0.40**	0.02	0.17	0.02	**−0.4**	0.23	0.15	0.28	0.18	−0.19	−0.09	0.21
Exponent curve	**−0.42**	0.12	0.15	−0.06	**−0.48**	0.004	0.006	0.14	0.19	0.14	0.18	0.03
Power curve	**−0.40**	0.08	0.16	0.18	**−0.44**	0.09	0.08	0.09	0.20	0.005	0.03	−0.08
HP filter	**−0.52**	−0.09	0.20	0.023	**−0.49**	0.07	−0.09	0.07	−0.19	−0.19	0.02	0.09
Logarithmic curve	**−0.45**	0.08	0.18	0.08	**−0.40**	0.05	0.04	−0.01	0.17	0.05	0.09	0.11
Quadratic curve	**−0.41**	0.23	0.11	0.06	**−0.44**	0.18	−0.08	0.08	0.15	−0.03	−0.19	−0.10

Bold faces indicate a significance level ($p<0.05$)

(b)	PC1	PC2	PC3
Rangpur	**0.91**	-0.59	0.09
Dinajpur	0.31	**0.81**	0.03
Bogura	0.03	**0.87**	0.37
Pabna	0.17	**0.91**	-0.04
Kushtia	0.31	**0.83**	0.2
Rajshahi	0.38	-0.58	0.22
Jashosre	0.18	0.01	-0.07
Khulna	-0.12	0.16	-0.02
Faridpur	-0.06	0.42	0.4
Jamalpur	-0.42	0.19	-0.05
Mymensingh	-0.28	0.28	-0.01
Tangail	0.23	-0.58	-0.37
Kishoregonj	0.26	0.15	0.31
Barisal	0.06	-0.19	-0.21
Dhaka	0.13	-0.15	-0.01
Comilla	0.34	-0.73	-0.3
Sylhet	-0.33	0.41	**0.89**
Khagrachari	0.05	-0.26	0.17
Noakhali	-0.36	0.11	0.16
Patuakhali	0.15	-0.08	0.06
Rangamati	0.25	-0.49	-0.23
Bandarban	0.17	0.04	-0.15
Chattogram	-0.05	0.06	0.3

Fig. 2 (a) Results of PCA of the annual CDYI time series in 23 districts. *a*: eigenvalues and explained variances by different principal components (PCs); (b) loading patterns of three first PCs of CDYI series in each district; (c) climatic regionalization based on PCA loadings

elaborate on the interannual variations of CDYI for the study period of 1980–2017. Therefore, the top-loading (> 0.8) of each PC was employed (Fig. 2b) for climatic regionalization analysis. The three temporal forms with different CDYI of Aus rice alterations were grouped based on PCA as follows: PC1 represents the northern part of Bangladesh, denoted as region I, PC2 characterizes the southwestern part (region II),

and PC3 represents the northeastern part (region III). The strong synchronicity between corresponding regional mean CDYI and PCS is presented in Fig. 3. The higher climate-driven yield losses were observed before 1995 for all the regions and also after 2005 in region I.

EEMD revealed several periodic CDYI oscillation in each sub-region (Fig. 4). However, there was a noticeable regional

Fig. 3 Annual time series of PCs and regional average CDYI in three sub-regions during the observation period (1980 − 2017)
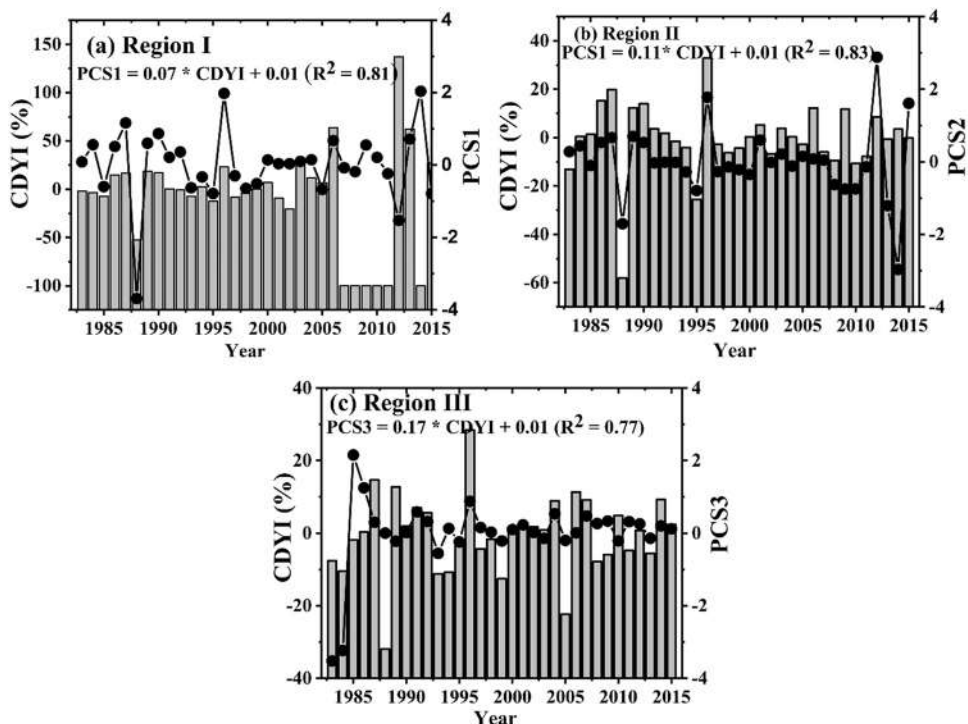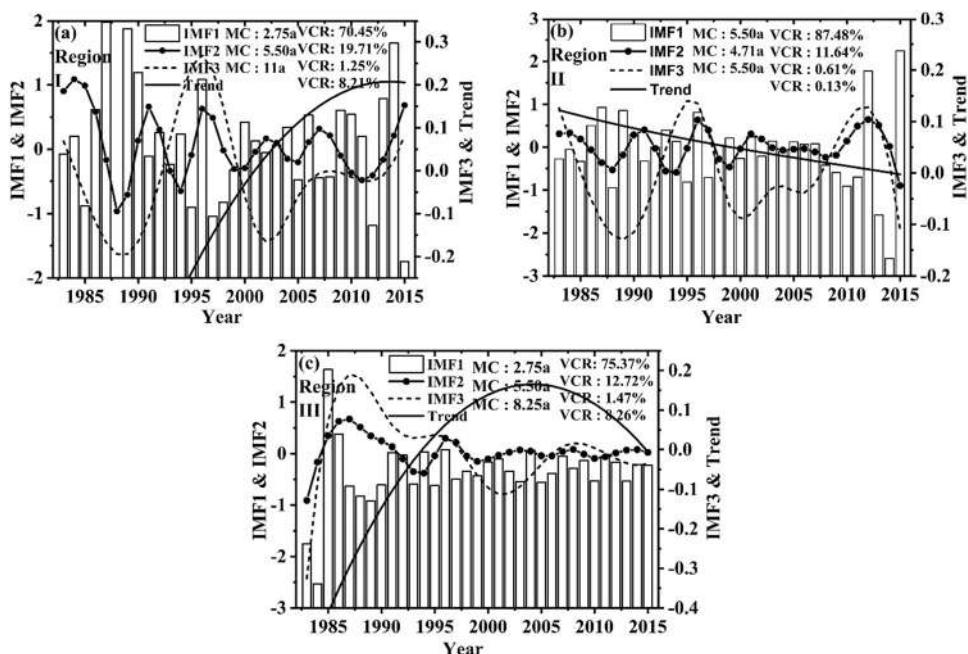

Fig. 4 Major cycles (MC) in regional CDYI and their contributions to CDYI variance

variability in the prominent CDYI oscillation modes. The CDYI series exhibited a more noteworthy quasi 6-year fluctuation for northern and northeastern regions, with the IMF2 reaching maximum values ranging from 12.72 to 19.71% (Fig. 4a, c). On the other hand, the IMF1 of CDYI time series was 87.48%, demonstrating a quasi 2.75- to 3-year fluctuation in CDYI time series in the northwestern region (Fig. 4b). Besides, notable short-term fluctuations were observed in the northern and northeastern regions and medium-range fluctuations in the northwestern region.

3.3 Connection of CDYI with KCVs and LACIs

Figure 5 shows the correlations of Aus rice yield with different KCVs in three sub-regions of the study area. The results showed large variability in the influence of different

(a)	TMX	TMP	TMN	PET	PRE	CLD
March	0.1	0.05	-0.07	0.04	0.01	0.1
April	0.44	0.19	0.01	0.13	-0.69	-0.68
May	0.05	-0.45	-0.33	0.02	0.08	-0.42
June	0.17	0.37	0.13	0.12	-0.12	-0.05
July	0.02	0.01	0.03	0.01	0.12	0.1
(b)	TMX	TMP	TMN	PET	PRE	CLD
March	0.1	-0.09	-0.16	0.09	-0.11	-0.03
April	-0.21	-0.31	-0.16	0.13	0.41	-0.07
May	0.21	0.13	-0.09	0.31	-0.12	-0.1
June	-0.01	-0.03	-0.12	-0.13	-0.03	-0.11
July	-0.21	-0.43	-0.31	-0.16	0.25	0.3
(c)	TMX	TMP	TMN	PET	PRE	CLD
March	-0.1	0.12	0.27	-0.47	-0.01	0.21
April	-0.1	-0.09	-0.11	-0.18	0.1	0.11
May	0.23	0.23	-0.47	0.33	-0.42	-0.21
June	0.1	-0.11	-0.32	-0.15	0.11	0.11
July	0.13	0.13	-0.19	0.11	-0.21	0.09

Fig. 5 Correlations between Aus rice yield and climate variables in regions ((a) region I, (b) region II, (c) region III; the number within a solid line frame indicates; the bold fonts denote the key climate variables (KCVs) affecting yield, estimated using multiple stepwise regression analysis)

| (a)	IOD	NINA4	MEI	NINA3.4	SOI
March	0.23	0.03	0.2	0.11	0.14
April	-0.42	0.05	0.18	0.05	0.25
May	0.13	0.38	0.01	0.09	0.22
June	0.35	0.19	0.16	0.31	0.19
July	0.21	0.11	0.22	0.13	0.1
(b)					
March	0.2	0.28	0.14	0.14	0.23
April	0.11	0.14	0.31	0.22	0.1
May	0.33	0.16	0.24	0.18	-0.39
June	0.14	0.19	0.14	0.19	0.11
July	0.19	0.2	0.11	-0.4	0.15
(c)					
March	-0.41	0.21	0.11	0.24	0.28
April	0.1	0.18	0.14	0.17	0.24
May	0.25	0.33	0.22	0.36	0.29
June	0.33	0.24	0.24	0.21	0.24
July	0.25	0.14	0.14	0.26	0.34

Fig. 6 Correlation between CDYI and LACIs in different sub-regions ((a) region I, (b) region II, (c) region III; the solid line frame denotes the key LACIs screened by the multiple stepwise regression analysis)

KCVs in different sub-regions. CDYI showed the strongest association of -0.69 with Apr_PRE in the northern region (region I), the largest correlation (-0.43) with Jul_TMP in the northwestern region (region II), and the highest correlation (-0.47) with May_TMN in the northeastern (region III) (Fig. 5a, 5b, 5c). The CDYI correlations were significant seven indices in the northern region at $p < 0.01$. Among them, positive association with Apr_ TMX and Jun_ TMP, and negative association with Apr_ PRE, CLD May_ TMP, TMN, CLD (Fig. 5a). In region II, CDYI showed a positive association with Apr_ PRE and May_ PET and a negative association with Apr_ TMP, Jul_ TMP, and TMN at $p < 0.01$ (Fig. 5b). In region III, only May_ PET showed a significant positive association with CDYI, while Mar_ PET, May_ TMN, PRE, and Jun_TMN showed a significant negative association at $p < 0.01$ (Fig. 5c). The results indicated higher sensitivity of Aus rice yield to different climate variables in the northern region.

The stepwise multiple regression model relating CDYI with KCVs also revealed Apr_ PRE for region I, Jul_ TMP for region II, and May_ TMN for region III as the most influencing variable define CDYI fluctuation. These three KCVs showed significant influence on Aus yield at $p < 0.05$, indicating substantial sensitivity of Aus rice yield to different climatic variables.

The correlation coefficients between Aus rice CDYI and LACI for the Aus rice-growing season (March to July) were also estimated (Fig. 6). The most remarkable CDYI-LACI

relationship was noticed for region I (northern region), where its highest negative value was -0.42 and the positive value was more than 0.3. The maximum positive and negative correlations were 0.33 and -0.40 for regions II and 0.36 and -0.41 for region III, respectively. All the negative association of CDYI with LACIs was significant at $p < 0.01$, indicating the potential of CDYIs in Aus rice yield prediction in the study area. The stepwise multiple regression of CDYI with LACIs identified IOD in April (Apr_IOD), NINA3.4 in July (Jul _NINA3.4), and IOD in March (Mar_ IOD) as the most influencing LACI of Aus rice yield fluctuation in regions I, II, and III, respectively (Fig. 6).

A 10-year moving correlation between CDYI and LACI (Fig. 7) revealed noticeable temporal variations in CDYI_ LACI relationship. A decrease followed by an increase and then again decreased CDYI_LACI relationship was observed in all three sub-regions. The highest negative correlations between CDYI and IOD_ Apr were found during 1992–2004 in region I (Fig. 7a). A significant positive correlation between CDYI and LACI was observed during 1988 − 1992, 2004 − 2007, and 2012 − 2016 in region II (Fig. 7b), and 1988 − 1993, 2002 − 2006, and 2013 − 2016 in region III (Fig. 7c).

The relationship between KCVs and LACIs for 0 to 4 months lags for the study period 1980–2017 is shown in Fig. 8. Many of the KCVs were found significantly correlated to different LACIs with different lag months. The

Fig. 7 The 10-year moving Pearson correlation series in each sub-region (histograms represent the correlation time series and red dashed lines represent its smooth curve)
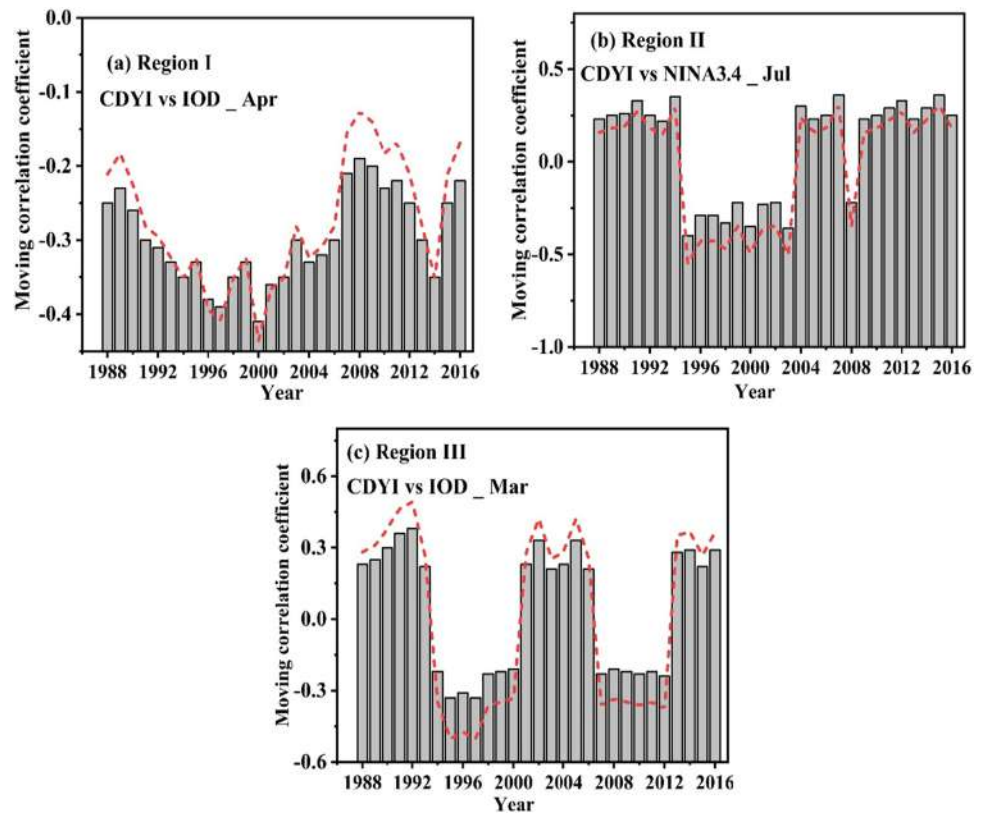
KCV showed a positive relationship with IOD and MEI with lag periods of 0 to 3 months, indicating early forecasting of KCVs, and thus, Aus yield using IOD and MEI. Besides, NINO3.4 and NINO4 showed a significant positive association with May_TMN with a lag of 3 months.

Interestingly, MEI showed a significant negative impact with a lag period of 3_month, and SOI showed no significant influence on Aus yield. Furthermore, except the 3-month lag

MEI, there was no discrepant impact of LACI on Aus rice yield. The maximum correlation values of 0.37, 0.38, and 0.39 for MEI, NINO3.4, and IOD, respectively, explaining a potential influence of those LACI on Aus rice yield. However, the dominance of KCVs on LACI varies significantly with time.

3.4 Impacts of KCVs on rice yield fluctuation

Figure 9 shows the wavelet transform coherence between KCVs and PCs in three sub-regions of Bangladesh. The arrows unto the right side indicate a positive association (in_phase) between the KCVs and PCs and vice versa. Figure 9a exhibits arrows on the left side, stating a negative (out _phase) relationship between PC1 and PET_Apr during 1985–1990 and 1995–2003 in region I. Figure 9b shows no significant relationship between PC2 and TMP_Jul in region II (Fig. 9b). In region III, a strong significant positive relationship was noticed between PC3 and TMN_May in 2 to 4 years (Fig. 9c). The red circle in Fig. 9 indicates a correlation value of 0.80, representing a significant relationship.

The RF was used to explore the relative importance of contributing factors. This technique confirmed the significance of the contributing factors of Aus rice yield in Bangladesh. The results presented in Table 3 revealed IOD and NINO3.4 as the principal contributing LACIs. The most

Fig. 8 Correlations between KCVs and LACIs in different sub-regions ((a) region I, (b) region II, (c) region III; the number within a solid line frame indicates significant correlation at $p < 0.01$)
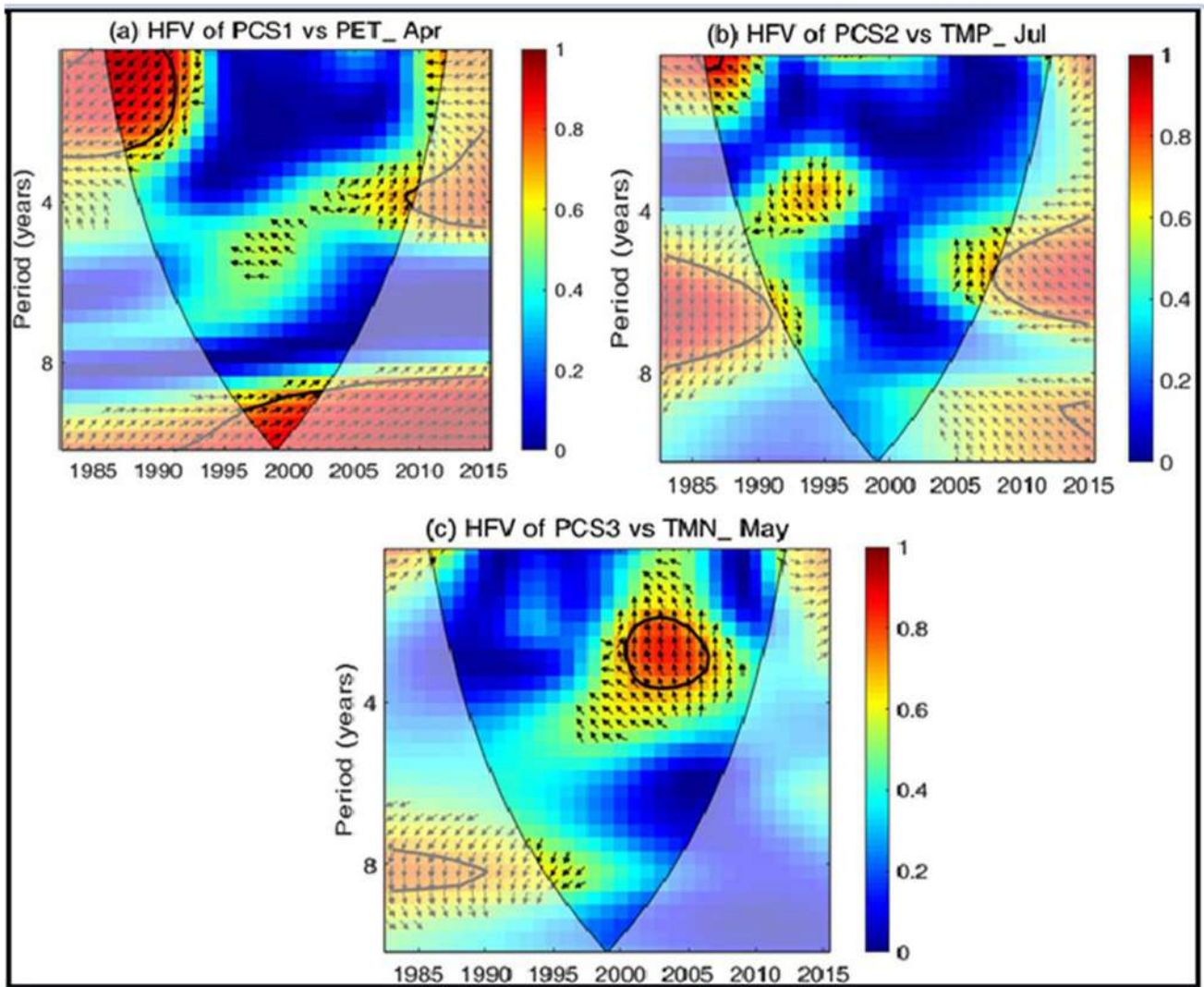
Fig. 9 Wavelet coherence and phase difference between PCs and KCVs in different sub-regions ((a) region I, (b) region II, (c) region III). The thick black contour designates the 95% confidence level against red noise)

Table 3 The outcomes of significance analysis of LACI in different regions in Bangladesh using random forest (RF) model. Values in the table indicate importance degree of different LACIs

Sub-region	IOD	NINO 3.4	SOI	MEI	NINO 4
Region I	89.00	88.14	63.17	62.65	62.13
Region II	21.17	21.01	18.28	18.05	17.10
Region III	20.23	19.11	19.03	17.70	17.25

influencing factors for all three regions were IOD (89.00, 21.17, and 20.23 for regions I, II, and III respectively). The NINO3.4 was the second largest contributing factor of Aus rice variability followed by SOI, MEI, and NINO4. The stronger influence of all LACIs was in region I (89.00,

88.14, 63.17, 62.65, and 62.13 for IOD, NINO3.4, SOI, MEI, and NINO4 respectively) compared to the other two regions.

3.5 Yield prediction for Aus rice using LACI

The multiple linear regression models were developed to predict Aus rice yield. Two types of models were developed in this study, multifactor and single-factor model. In the multifactor model, the most influencing LACIs of a sub-region and year were used as input. For example, IOD_Apr and year were used for multifactor development model in region I. For the single-factor model, the only year was used as input. The multifactor and single-factor models developed for different sub-regions using simple multiple regression analysis are presented in Table 4. The model performance

Table 4 Linear relationship between Aus rice yield with LACI and year in different sub-regions of Bangladesh

Sub-region	Model type	Yield prediction models	R^2	p
Region I	Multifactorial	Yield = 69.1 * Year − 511 * IOD_Apr − 13,344.2	0.63	0.001
	Single-factor	Yield = 65.5 * Year − 122,366.3	0.49	< 0.001
Region II	Multifactorial	Yield = 75.9 * Year − 212 * NINA3.4_Jul − 668,378.1	0.58	< 0.001
	Single-factor	Yield = 72.3 * Year − 108,710.2	0.44	< 0.001
Region III	Multifactorial	Yield = 37.5 * Year − 432 * IOD_Mar − 322,363.5	0.60	< 0.001
	Single-factor	Yield = 71.9 * Year − 116,409.3	0.51	< 0.001

was evaluated using coefficient of determination (R^2). The R^2 values for multifactor models were highest for region I (0.63), followed by region III (0.60), and region I (0.58). The performance of single-factor model was a less than the multifactor models. The R^2 for single-factor models for the three sub-regions were in the range of 0.44 to 0.49. The best performance of single-factor model was in region I, like the multifactor model.

The performance of the models in replicating observed yield in different sub-regions was also evaluated through visual inspection of observed and simulated yield time series (Fig. 10). The figure shows a good analogy between simulated and observed yield series in different sub-regions. The maximum relative error in predicted yield was higher before 1998. The prediction precision of the multifactorial model in region III was best, with the mean relative error (MRE) of only 4.82%, followed by region II with MRE of 5.51%. The prediction error was relatively higher in region I than in the other two regions.

4 Discussions

The present study evaluated the influence of KCVs and LACIs on Aus rice yield in various sub-regions in the country for 1980–2017. Three climatic regions, north, northwest, and northeast, were identified based on different Aus yield response to climate variability. This outcome is analogous to Ghose et al. (2021a). They explored six climatic regions, including north, northwest, west, southwest, south-central, southeast, based on the susceptibility of rain-fed rice yield to climate variability for the whole of Bangladesh (Ghose et al. 2021a and b). The present study revealed Aus rice yield in the northern part of Bangladesh is more susceptible to climatic anomalies. Climate variables oscillated in the range of 2.75 to 3 years as identified in the northwestern sub-region, while quasi of 6-year fluctuation was noticed in the northern and northeastern regions. These findings are similar to the findings of Ghose et al. (2021a). The precipitation showed a negative correlation with yield in the northern part. The wavelet coherence analysis outcomes ensured this

Fig. 10 Simulation results for Aus rice yield using multifactorial model
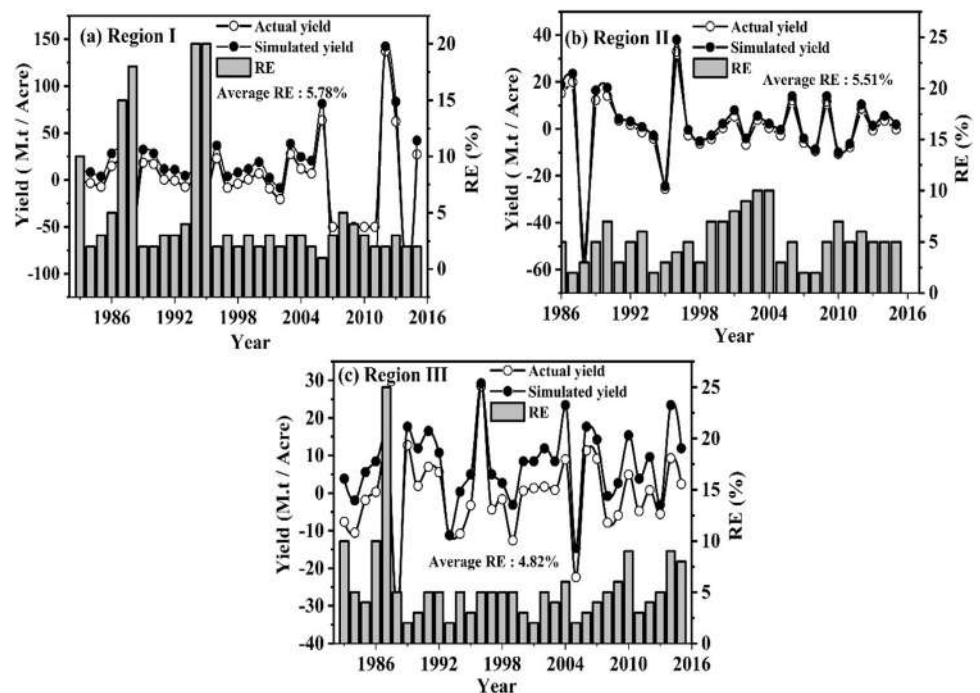
association (Fig.). Sarker et al. (2012) showed a significant relationship between Aus rice yield and precipitation, consistent with this study. The outcome of this result is also in line with Huang et al. (2018). However, this study's findings are inconsistent with Amin et al. (2015), where an insignificant association between Aus rice yield and rainfall has been shown. During the primary stage of Aus growing period, it needs supplementary irrigation (BRRI, 1991). About 10–25% of the annual precipitation occurs during the pre-monsoon hot season (March–May). This pre-monsoon mean rainfall varies from 200 mm northwest to 800 mm in the north and the northeast (Cottam 1997). The extreme droughts in the northern part of Bangladesh, where yearly mean rainfall is relatively more minor, often bring water scarcity and long-term environmental calamities (Sheffield et al. 2009).

Mean temperature and minimum temperature were found as the critical climatic factor in the northwestern and northeastern regions. These two climatic factors showed negative impacts on Aus rice yield. Sarker et al. (2017) stated that maximum temperature positively influences whether the minimum temperature negatively affects the rice yield, which is relatively consistent with the results found in this study. Due to the ENSO connected indices, seasonal drought occurs during the El Nino stage (Chen et al. 2018). In the current study, indices like IOD, NINA4, NINA3.4, MEI, and SOI showed a significant relationship with rice yield in different sub-regions. The most influencing indices were IOD_Apr, NINA3.4_Jul, and IOD_Mar for northern, northwestern, and northeastern regions. This result is similar to Chen et al. (2020), where they found that NINO1 + 2, PDO, NAO, and SOI strongly influence winter wheat yield in Henan province, North China. Huang et al. (2021) used different LACIs, including NINO3, PDO, TSA, NINO4, and NP as the influencing factors of summer maize yield in Henan province in North China which is also in good agreement with the present study. Ahmad et al. (2019) also identified the CDYI and LACI relationship. A good association between KCVs and LACI in different sub-regions in Bangladesh, found in this current study, indicates ENSO-climate associations in Bangladesh. Aus rice yield is most influenced by 0 to 3 month lagged IOD followed by NINO3.4 and SOI. The previous studies showed less dominance of NINO4 and NINO3.4 on rice yield (Li et al., 2015; Lizumi et al., 2014; Ray et al., 2012), which is in line with the present study. Limsakul (2019) also showed a less negative relationship between rice yield and MEI in Thailand.

In Bangladesh, the northern part often experiences Rabi droughts, preliminarily connected to MEI and El-Nino (Zhao et al. 2016; Zhang et al. 2014). They emphasize the demand for adaptation and maintenance of drought during the Rabi (winter) season, particularly in March. A significant Aus rice yield deficit, specifically before 1995 in the northern and northwestern zone, while after 2005 in the north of region may be linked to droughts in the area in 1991, 1992, 1994, 1995, 1997, 1998, 2000, 2003, 2005, 2007, 2009, and 2010 (Afrin et al. 2018; Islam et al. 2014; 2017; Shahid and Behrawan 2008). El-Nino occurrences are linked to rice yield's heavy retrenchment during 1994/1995 and 2015/2016, as Rahman et al. (2017) reported.

The mean relative error (MRE) in yield prediction based on the multifactorial model with LACI and year as input was between 4.82 and 5.78% for different sub-regions of Bangladesh. The yield prediction technique with LACI and year as inputs showed powerful aptness, stronger exactness, and more accessible actions. Overall, the yield prediction error was high in the northern region. This region has experienced prolonged drought, water scarcity, groundwater depletion, and extensive cultivation management (Afrin et al. 2018; Rokonuzzaman et al. 2018). Thus, fluctuations of Aus rice yield in the northern region were comparatively more comprehensive and more difficult to predict. There is the precedent that such climate occurrences like drought, flood, and cyclone are the consequences of global warming, bringing catastrophic outcomes to rice yield's retrenchment (Zinat et al. 2020). This study concentrated on association with the CDYI of Aus rice anomalies to the LACIs and KCVs in Bangladesh. Climate change response to Aus rice yield in Bangladesh of the last three decades has also been differentiated in this study. The outcomes provide an unprecedented basis for sustainable Aus rice production in Bangladesh to cope with the forthcoming climate change. The connection between KCVs of Aus rice and CDYI depends on the use of data, i.e., the observed Aus rice yields. In this way, if the observed yields were accurate and representative or not, it would affect the evaluation precision of CDYI. However, maximum observed rice yields were found on manual datasets. Some observation mistakes may present that were not trimmed in this research study and may have outperformed the associations between them.

Furthermore, the potential anomalies in the several Aus rice growing-stages in response to regional climatic features and kind of crop management have not been considered, making these correlations questionable. However, these shortcomings demonstrate a profound insight into the correlations among Aus rice CDYI and LACIs and KCVs at the region period in Bangladesh. This study signifies that climate anomalies influence several climatic regions in several ways. The outcomes are cautionary performing policies for coping at the country level, which would not be fruitful. It provides evidence that coping guidelines should be established for the climatic region and regional specific basis, which further gives surety the necessity for a region-specific research work crop production and climate anomalies. Thus, this will assist in launching micro-level or local adaptation policy to decline the Aus rice yield, ensure food guaranty,

and lessen poverty to earn sustainable development goals in the aspect of climate variation.

5 Conclusion

The linkage of Aus rice yield in Bangladesh with large-scale atmospheric oscillation indices is explored in this study. The primary outcomes of this research study are as follows: the temporal modes of rice CDYI time series of 23 districts of Bangladesh for the period $1980-2017$ identified three analogous sub-regions: north, northwest, and northeast. IOD_Apr, NINA 3.4_July, and IOD_March were recognized as the vital LACIs significantly influencing CDYI in north, northwest, and northeast sub-regions, respectively. The higher IOD_Apr causes a more significant rice yield reduction in the northern region. The PET_Apr revealed a substantial negative (anti_phase) coherence with yield fluctuations at $0-3$- and $9-10$-year frequency in the north. The RF model revealed IOD as the most influencing LACI in describing Aus rice yield fluctuation in the study area. The yield prediction using LACIs and the year as predictors revealed their potential to predict Aus rice yield in Bangladesh. The new knowledge generation and the novel rice yield prediction pathway shown in this study would certainly help in mitigating crop loss due to climate variability and climate-resilient sustainable agricultural development in Bangladesh. The novelty of this research is that this study explored the prediction on a regional basis for the Aus rice yield and also investigated the relationship between Aus rice yield and different type of meteorological factors. However, future research should highlight working the performance of anthropological effects on regional climate change. Further studies should explore the extreme climate occurrence mechanisms, promote early warning, and take sufficient adaptation and mitigation guides for a better policy response to future agricultural crop water management and food security in Bangladesh.

Data availability Data are available upon request on the corresponding author.

Code availability Not applicable.

Declarations

Ethical approval Not applicable.

Consent to participate Not applicable.

Consent to publish Not applicable.

Conflict of interest The authors declare no competing interests.

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