Hydrol. Earth Syst. Sci. Discuss., https://doi.org/10.5194/hess-2017-523
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Discussion started: 10 October 2017

Hydrology and Earth System Sciences
Open Access
Discussions

Modeling the Changes in Water Balance Components of Highly Irrigated Western Part of Bangladesh

A.T.M. Sakiur Rahman[1*], Md. Shakil Ahmed[2], Hasnat Mohammad Adnan[3], Mohammad Kamruzzaman[4], Md. Abdul Khalek[2], Quamrul Hasan Mazumder[3] and Chowdhury Sarwar Jahan[3]

Authors details:

[1]Graduate School of Science and Technology, Kumamoto University, 2-40-1 Kurokami, Kumamoto, Japan
[2]Department of Statistics, University of Rajshahi, Rajshahi 6205, Bangladesh
[3]Department of Geology and Mining, University of Rajshahi, Rajshahi 6205, Bangladesh
[4]Institute of Bangladesh Studies, University of Rajshahi, Rajshahi 6205, Bangladesh

*Corresponding author e-mail: shakigeo@gmail.com

Abstract. The objectives of the study are to explore the changes in water balance components (WBC) by co-utilizing discrete wavelet transformation (DWT) and different forms of Mann–Kendal (MK) test; and to develop wavelet autoregressive moving average (ARIMA) models for forecasting the WBC. Trend test results reveal that the most of the trends (about 73%) identified in potential evapotranspiration (P_{ET}) show decreasing tendency during the hydrological year 1981-82 to 2012-13 in the western part of Bangladesh, however most of the changes (about 82%) are insignificant at 5% significant level. Actual evapotranspiration (A_{ET}), annual deficit and annual surplus also show the almost similar tendency. Rainfall and temperature show increasing trends, but WBC show inverse of this tendency and suggesting that traditional concept of changes in P_{ET} associated with changes in temperature cannot explain the changes in WBC. Moreover, it is found that generally 8-years (D3) to 16-years (D4) periodic components are the effective components and are responsible for trends found in original data of WBC in western part of Bangladesh. Wavelet denoising of WBC time series has been done to improve the performance of models as actual data affected by noise and show unsatisfactory performances. The quality of denoised data has been ensured by relevant statistical analysis. Performance of wavelet ARIMA models have been assessed by Nash–Sutcliffe Efficiency (NSE) coefficient and coefficient of determination (R^2). The obtained results indicate that performances of wavelet ARIMA models of WBC are acceptable to very good and clearly demonstrate the advantages of denoising over actual data. The models validation results reveal that the forecasted values are very close to actual values with acceptable mean percentage error and residuals also follow normally distribution. Performances and validation results indicate that models can be used for short term forecasting of WBC. Further studies on different combinations of wavelet analysis would be facilitated to develop better models for WBC in context of climate change and findings of study can be used to improve water resources management in highly irrigated western part of Bangladesh.

1. Introduction

After introducing monthly water balance by Thronthwaite (1948), followed by Thornthwaite and Mather (1957), it has gone through modifications, development of new models and adaptation for different parts of the world (Xu and Singh, 1998). The water balance models can be implemented for reconstruction of catchment hydrology, climate change impact assessment, stream flow forecasting and sustainable water resources management (e.g. Alley, 1985; Arnall, 1992, Xu and Halldin, 1996; Molden and Sakthivadivel, 1999; Boughton, 2004; Anderson et al., 2006; Healy et al., 2007; Moriarty et al., 2007; Karimi et al., 2013; Thapa et al., 2016). Two important climatic variables like rainfall and P_{ET} that derives from the climatic variables are the main inputs in water balance modeling (Xu and Singh, 1998). A lot of research works for different parts of the world have been detected and quantified trends in historical hydro-climatic data such as rainfall, temperature, P_{ET} and stream flow (Araghi et al., 2014; Pathak et al., 2016), and attribute the changes to global climate change (Pathak et al., 2016).

The studies on spatio-temporal characteristics of rainfall and temperature have also attracted attention for Bangladesh. Studies (e.g. Shahid and Khairulmaini, 2009; McSweeney et al., 2010; Ahasan et al., 2010; Rahman and Lateh, 2016; Nury et al., 2016; Rahman et al., 2016; Syed and Al Amin, 2016) have found both positive and negative trends in annual and seasonal rainfall over the entire country. Moreover, Rahman and Begum (2013); Hossain et al. (2014) and Kamruzzaman et al. (2016a) studied the rainfall of Bhola, south-west coast and western part of Bangladesh respectively. Almost most of the studies found number of stations having increasing trends is higher than number of stations having decreasing trends in rainfall for different periods in Bangladesh. Endo et al. (2016) revealed that there is no clear trend in heavy rainfall index in Bangladesh during 1950-2008. Some recent studies (Rahman et al., 2015; Rahman et al., 2016) have also forecasted rainfall using ARIMA model. Rahman et al. (2015) showed a decrease in annual rainfall (average 153 mm/year) for the period of 2011-2020, whereas Rahman et al. 2016 showed an increase (+3.26 mm/year) in annual average rainfall for the entire country for the period of 2014-2020.

Moreover, some studies have been investigated the trends in temperature over Bangladesh; for example, Jones (1995) reported that there are no visible trends in annual maximum and minimum temperature during the period of 1949-1989 in Bangladesh. However, studies (Shahid, 2010; Nasher and Uddin, 2013; Rahman, 2015; Rahman et al., 2015; Syed and Al Amin, 2016; Kamruzzaman et al., 2016a) detected warming trends by MK test in Bangladesh and also studies (Keka, 2013; Basak et al., 2013; Bhowmik, 2013; Hasan and Rahman, 2015; Rahman and Lateh, 2016) detected raising trends by linear regression. Hasan et al. (2014) stated that though there are a lot of studies focusing on regional changes in reference evapotranspiration (ET_o) over the world; however there are no such studies for developing countries like Bangladesh. The study calculated decadal reference evapotranspiration for 28 meteorological stations over Bangladesh and found that ET_o has decreased during January to April, but slightly increases during July to December in recent decades. A recent study (Acharjee, 2017) found decreasing trends in crop evapotranspiration and irrigation requirement in four stations located in the northwest Bangladesh during the period of 1979-2013. Water balance study has not attracted much attention in Bangladesh too. Kirby et al. (2015) mentioned that there are two studies on water balance- an earlier study focused on rainfall and soil moisture by Khan and Islam (1966); and National Water Management Plan (WARPO, 2000), but these are not comprehensive study on water balance. However, to assess the impact of climate change on hydrologic cycle, it is utmost important to evaluate changes in P_{ET} and inter-annul variability (Ukkola and Prentice, 2013) since it is related to water demand, water resources planning, agricultural irrigation management and crop growth (Hatch et al., 1999; Sun et al., 2016). Kirby et al. (2015) studied the monthly water balance of the five hydrological regions in Bangladesh and their main results showed that fall of groundwater levels in pre-monsoon is largely related to the continuous withdrawal of groundwater for irrigation. So far, studies have been carried out on hydrological variables in Bangladesh have the following

Hydrol. Earth Syst. Sci. Discuss., https://doi.org/10.5194/hess-2017-523
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Discussion started: 10 October 2017

limitations: most of the studies were limited to detect trends or forecasting of rainfall and temperature and few studies on P_{ET} and water balance. There is no attempt to identify periodicity that has effects on trend in hydrological variables in Bangladesh. However, the analysis of periodicity using wavelet transformed details and approximation components of hydro-meteorological time series data can better reflect insight into trends and effects of time period on trend (e.g. Nalley et al., 2013; Araghi et al., 2014; Pathak et al., 2016). As a result wavelet transformation of hydro-meteorological time series are gaining popularity in recent years to detect periodicity (e.g. Partal and Küçük, 2006; Partal, 2009; Nalley et al., 2013; Araghi et al., 2014; Pathak et al., 2016) and increase the performance of models (Adamowski and Chan, 2011; Dong et al., 2015; Khalek and Ali, 2016) for forecasting.

Therefore, the present study has conducted to detect trends and identify periodicities in all WBC such as potential evapotranspiration (P_{ET}), actual evapotranspiration (A_{ET}), annual deficit and surplus of water by co-utilizing DWT and different forms of Mann-Kendal (MK) test; and develop wavelet aided ARIMA models for forecasting the WBC after removing the noise from WBC time series data. These combinations are not well documented for all of these water balance component modeling. Hence, it is expected that the new combination will explore insight in to the water balance components.

2. Study Area, Data and Methods

2.1 Study area

Bangladesh enjoys a humid, warm and tropical climate. The geographic coordinates of the study area, western part of Bangladesh that covers about 60,165 km^2 or 41% of the country, extend between 21°36′-26°38′N latitude and 88°19′-91°01′E longitude. Annual rainfall and average temperature in the area vary from 1492 to 2766 mm with an average of 1925 mm and 24.18 to 26.17°C with an average of 25.44°C respectively (Kamruzzaman et al., 2016a). Bangladesh is the fourth biggest rice producing country in the world (Scott and Sharma, 2009) and the livelihoods of the major of the people (about 75%, Shahid and Behrawan, 2008; Kamruzzaman et al., 2016b) are related to agricultural practices. Crop calendar of Bangladesh is related to the climatic seasons. Rice which cultivates in three seasons namely *Aus*, *Aman* and *Boro* is the main crop that cultivates in 73.94% cultivable area in Bangladesh (Banglapedia, 2003). *Aus* and *Aman* are mainly rain-fed crops; however, *Boro* is almost groundwater-fed (Ravenscroft et al., 2005) and requires about 1m of water per square meter in Bangladesh (Harvey et al., 2006; Michael and Voss, 2009).

2.2 Data

National climate data base of Bangladesh prepared by Bangladesh Agricultural Research Council (BARC) has been used for the study. The data base is available for research and can be found in BARC website (http://climate.barcapps.gov.bd/). The data base has been prepared from the data recorded by Bangladesh Meteorological Division (BMD) and contains long-term monthly climate data such as rainfall (mm), minimum, maximum and average temperatures (°C), humidity (%), sunshine hours (hour), wind speed (km/h) and cloud cover (%). The locations of the meteorological stations in the study area are shown in Figure 1. The data has rearranged following the hydrological years, in Bangladesh, hydrological year starts in April and end in March.

2.3 Methods

Hydrol. Earth Syst. Sci. Discuss., https://doi.org/10.5194/hess-2017-523
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Discussion started: 10 October 2017

2.3.1 Calculation of P_{ET} and WBC

Potential evapotranspiration (P_{ET}) is the key parameter to estimate water balance components and there are several approaches to estimate it. The most common approaches are temperature based models (e.g. Thornthwaite and Mather, 1957; Hargreaves and Sammani, 1985; Hamon, 1963), water budget (e.g. Guitjens, 1982), mass-transfer (e.g. Harbeck, 1962), radiation-based (e.g. Priestley and Taylor, 1972). Moreover, there are also some methods which are the combinations of these two or more (Bakundukize et al., 2011). Bakundukize et al. (2011) found temperature model (Thornthwaite and Mather, 1957) over estimated P_{ET} and Hargreaves method also shows similar problems (Trajkovic and Kolakovic, 2009; Castaneda and Rao, 2005). Rahman (2016) have also found that PET value calculated from temperature model (Thornthwaite and Mather, 1957) is almost 20% higher than Penman-Monteith (Allen et al., 1998) for northwestern Bogra and Rajshahi district in Bangladesh. Moreover, P_{ET} estimated by less data demanding methods provide unstable results in context of climate change (Sperna Weiland et al., 2012) and it is particularly true for Asian monsoon climate (Fan and Thomas, 2012). To overcome the problems of over estimation or under estimation (Pereira and Pruitt, 2004; Trajkovic and Kolakovic, 2009), Bakundukize et al. (2011) calculated WBC using the concept of water balance in unsaturated zone (Thornthwaite and Mather, 1957) after estimating the P_{ET} from different methods (Thornthwaite and Mather, 1957; Hamon, 1963, Hargreaves and Sammani, 1985 modified Thornthwaite and Mather (Perreira and Pruitt, 2004). The study (Bakundukize et al., 2011) concluded that estimation of WBC using reference potential evapotranspiration (P_{ET}) of Penman-Monteith equation (Allen et al., 1998) can best represent the reality. In the present study, P_{ET} has been calculated by Penman-Monteith equation (Allen et al., 1998). Actual evapotranspiration (A_{ET}), Deficit and Surplus have been calculated using the concept of water balance in unsaturated zone (Thornthwaite and Mather, 1957) as these combination give the best estimation for the real world (Bakundukize et al., 2011). Field capacity of soil in the study area has been calculated using the soil texture map of Bangladesh prepared by Soil Resource Development Institute (SRDI, 1998) of Bangladesh and the description of soils of Bangladesh presented by Huq and Shoaib (2013). Water holding capacity of soil and rooting depth of the plants have been calculated from the Thornthwaite and Mather (1957) suggested values. The first step of the calculation is the subtraction of 5% rainfall from the monthly rainfall data as this amount of water has lost due to direct runoff (Wolock and McCabe, 1999). The reaming amount of rainfall has been applied to calculation. When rainfall is greater than P_{ET} the soil always remains full of water and a water surplus (S) occurs and when it is less than P_{ET} there is not enough water for the vegetation to use and moisture deficit (D) occurs. The amount of actual evapotranspiration (A_{ET}) depends on the amount of water available which in turn depends on the water holding capacity of the soil. A_{ET} is calculated as: (1) in wet months, when there is enough rain, i.e. $P > P_{ET}$, the A_{ET} is at its maximum value, which is equal to P_{ET}, (2) in dry months, when there is not enough rain, i.e., when $P < P_{ET}$, rain is no longer able to meet the evapotranspiration demand and A_{ET} is equal to the amount of extractable soil moisture.

2.3.2 Trend Test

In the present study, the trends in WBC have been detected by non-parametric Mann–Kendall (Mann, 1945; Kendal, 1975) (MK) test as it shows the best performance to identify trends in hydrological variable in comparison to parametric test (Nalley et al., 2012). However, MK test cannot appropriately calculate the test statistic due to underestimate the variance (Hamed and Rao, 1998) if there is a significant serial correlation in

Hydrol. Earth Syst. Sci. Discuss., https://doi.org/10.5194/hess-2017-523
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Discussion started: 10 October 2017

Hydrology and Earth System Sciences
Open Access
Discussions

the time series data (Yue et al., 2002). The lag-1 auto-correlation has been checked before analyzing the time series data if there is a significant lag-1 auto-correlation at 5% level, the Modified MK (MMK) (Hamed and Rao, 1998) has been applied instead of MK test. The calculated '*Z*' values have been evaluated at 5% level of significance ($Z = 1.96$). Moreover, the sequential values of *u(t)* statistic of MK test derived from the progressive analysis of MK test (Sneyers, 1990), *u(t)* is similar to the *Z* statistic (Partal and Küçük, 2006), have been calculated in order to investigate the change point detection. The magnitude of trend has been calculated by Sen's slope estimator (Sen, 1968). There are many good explanations (notably Nalley et al., 2012) of the methods mentioned in this section and details regarding these, furthermore, can be referred to Mann (1945); Sen (1968); Kendall (1971); Hamed and Rao (1998); Sneyers (1990); Yue et al. (2002).

2.3.3 Wavelet Transform and Periodicity

The wavelet analysis has been used to identify periodicity in hydro-climatic time series data (e.g., Smith et al., 1998; Azad et al., 2015; Nalley et al., 2012; Araghi et al., 2014; Pathak et al., 2016) for different parts of the world. Wavelet transform (WT), a multi-resolution analytical approach, can be applied to analyze time series data as it offers flexible window function that can be changed over time (Nievergelt, 2001; Percival and Walden, 2000). It can be applied to detect the periodicity in hydro-climatic time series data (Smith et al., 1998; Pišoft et al., 2004; Sang, 2012; Torrence and Compo, 1998; Araghi et al., 2014; Pathak et al., 2016) and produces better performances in comparison to traditional approaches (Sang, 2013). There are two main kinds of wavelet transform and these are continuous wavelet transform (CWT) and discrete wavelet transform (DWT). The application CWT is complex as it produces a lot of coefficients (Torrence and Compo, 1998; Araghi et al., 2014), whereas DWT is simple and useful for hydro-climatic analysis (Partal and Küçük, 2006; Nalley et al., 2012). The wavelet coefficients following the DWT with dyadic format can be calculated as follows equation (1) (Mallat, 1989):

$$\psi_{m,n}\left(\frac{t-\tau}{s}\right) = s_0^{-m/2}\,\psi\left(\frac{n\,\tau_o\,s_0^m}{s_0^m}\right) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots . (1)$$

Where ψ is the mother wavelet; the integers *m* and *n* control wavelet dilation (scale) and translation (time) respectively; specified fixed dilation step (S_0) is greater than 1 and τ_o is location parameter. For the practical application, the values of parameters S_0 and τ_o are considered as 2 and 1 respectively (Partal and Küçük, 2006; Pathak 2016). After substituting these values in equation (1), the DWT for a time series *x(i)* becomes:

$$W_{m,n}\left(\frac{t-\tau}{s}\right) = 2^{m/2}\sum_{i=0}^{N-1} x_i\,\psi\,(2^{-m}\,i-n) \ldots\ldots\ldots\ldots\ldots\ldots . (2)$$

Where W indicates wavelet coefficient at scale $s_0 = 2^m$ and location $\tau_o = 2^m n$.

In the DWT, details (D) and approximations (A) can be emerged from the original time series after passing through low-pass and high-pass filters respectively. While approximations are the high scale and low frequency components, details are the low scale and high frequency components. Successive, iterations have been performed to decompose the time series into their several lower resolution components (Mallat, 1989; Misiti et al., 1997). In the present study, four levels (D1-D4) of decompositions have been performed following the dyadic scales (2^j, J=2, 4, 8 and 16) and referred as D1, D2, D3 and D4 which are corresponds to 2, 4, 8 and 16

Hydrol. Earth Syst. Sci. Discuss., https://doi.org/10.5194/hess-2017-523
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Discussion started: 10 October 2017

years periodicity. Daubechies wavelet has been used in the present study as it performs better in hydro-meteorological studies (Nalley et al., 2012, 2013; Venkata Ramana et al., 2013; Araghi et al., 2014). To confirm about the periodicity present in the time series, correlation coefficient (*Co*) between *u(t)* of original data, *u(t)* of decomposition time series and different models of decompositions (such as decomposition (D1+A……..D4+D3+A) has been calculated and the obtained results have been compared (Partal and Küçük, 2006; Partal, 2009).

2.3.4 ARIMA models

To identify complex pattern in data and to project the future scenario, autoregressive integrated moving average method (Box and Jenkins, 1976) has been used in hydrological science (e.g. Adamowski and Chan, 2011; Valipour et al., 2013; Nury et al., 2017; Khalek and Ali, 2016). The method includes three terms: (1) an autoregressive process (AR) represented by order-*p*, (2) non seasonal differences for non-stationary data termed as order-*d* and (3) moving average process (MA) represented by order-*q*. ARIMA model of order (p, d, q) can be written as:

$$\emptyset_p(L)\ (1-l)^d Y_t = \theta_0 + \theta_q(L)\ U_t \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots . (3)$$

Where, θ_0 and U_t are the intercept and white process with zero mean and constant variance respectively. $\emptyset_p(L)$ stands for AR term $(1 - \emptyset_1 L - \cdots - \emptyset_p\, L^p)$ and $\theta_q(L)$ represents MA term $(1 - \theta_1 L - \cdots;\ -\theta_p\, L^p)$.

2.3.5 Wavelet Denoising

Wavelet de-noising based on thresholds introduced by Donoho et al. (1995) has been applied to the hydro-meteorological analysis (Wang et al., 2005 and 2014; Chou, 2011). Three steps of denoising in the study are as follows:

1. Decomposing the time series data *x(t)* into *M* resolution level for obtaining the detail coefficients $(W_{j,k})$ and approximation coefficients using DWT.
2. The detail coefficients obtained from DWT (1 to *M* levels) have been treated with threshold (T_j)selection. There are soft threshold and hard threshold to deal with detail coefficients to get decomposed coefficient. In the study, soft threshold has been selected as it's performs better than hard (Wang et al., 2014; Chou, 2011):

   Soft threshold processing: $\acute{W}_{j,k} = \begin{cases} sgn(W_{j,k})\,,\ \left(\left|W_{j,k}\right| - T_j\right)\left|W_{j,k}\right| > T_j \\ \quad 0, \qquad \left|W_{j,k}\right| < T_j \end{cases}$
3. Details coefficients from 1 to *M* level and approximate coefficients at level *M* have been reconstructed to get denoised data.

It is also necessary to select the threshold value for denoising the data. There are many approaches such as universal threshold (UT), SURE or MINMAX and so on. Universal threshold (UT) proposed by (Donoho and Johnstone, 1994) and this method is satisfies the requirements in most application as the risk of thresholding is enough small (Luo and Zhang, 2012). In the study, UT has been used as it shows good performance in analyzing hydro-meteorological data (Wang et al., 2005; Chou, 2011).

2.3.6 Assessment of Model Performance

There are several indicators to assess the performance of models. Among these Nash–Sutcliffe Efficiency (NSE) (Nash and Sutcliffe, 1970) coefficient which is a normalized goodness-of-fit statistics is the most powerful and popular method for measuring the performance of hydrological models (McCuen et al., 2006; Moussa, 2010; Ritter and Muñoz-Carpena, 2013). To evaluate and make comparison between ARIMA and wavelet aided ARIMA model, NSE has been used in the study. NSE can be calculated as (Nash and Sutcliffe, 1970):

$$NSE = 1 - \frac{\sum_i^N (O_i - P_i)^2}{\sum_i^N (O_i - \bar{O})^2} = 1 - \left(\frac{RMSE}{SD}\right)^2 \dots\dots\dots\dots\dots\dots\dots.(4)$$

Where, N, O_i and P_i are the sample size, number of observation and P_i model estimates respectively and $\bar{O}$ and SD are the mean and standard deviation of the observed values. Performance of a model can be evaluated based on NSE value as: very good (NSE ≥ 0.90); good (NSE = 0.80-0.90); acceptable (NSE ≥ 0.65); and unsatisfactory (NSE<0.65) (Ritter and Muñoz-Carpena, 2013). E_{RMS} is the root mean square error that can be calculated as:

$$E_{RMS} = \sqrt{\frac{\sum_i^N (O_i - P_i)^2}{N}} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots (5)$$

The coefficient of determination (R^2) is another goodness of fit test to measures the performance of the model. The perfect fit of the model draws a line between the actual values and fitted values with R^2 value is 1. If y_i is the observations data and $\bar{y}_i$ is the mean value taken over N, N is the number of data point used and $\hat{y}_i$ is the model forecasted values of y_i. The R^2 can be given as (Sreekanth et al., 2009):

$$R^2 = 1 - \frac{\sum_{i=1}^N (y_i - \hat{y}_i)^2}{\sum_{i=1}^N (y_i)^2 - \frac{\sum_{i=1}^N (\hat{y}_i)^2}{N}} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots (6)$$

Moreover mean percentage error (E_{MP}) and mean error (E_M) have also been calculated and evaluated for validation of model. E_{MP} reveals the percentage of bias (larger or smaller) of forecasted data over the actual counterparts (Khalek and Ali, 2016). E_{MP} and E_M can be calculated as follows:

$$E_{MP} = \left(\frac{1}{n}\sum_{t=1}^{n} \frac{Y_t(actual) - Y_t(forecasted)}{Y_t\ (actual)}\right) \times 100\% \ \dots\dots\dots (7)$$

$$E_M = \frac{1}{n}\sum_{t=1}^{n} [Y_t(actual) - Y_t(forecasted)]^2 \ \dots\dots\dots\dots\dots\dots\dots (8)$$

2.3.7 Programming and Mapping

In the present study, the open sources programming platform “R” (R 3.4.0) (R Core Development Team, 2016) has been used for relevant analysis. ‘R’ code for MK test, MMK test and Sen’s Slope can be found in electronically supplementary material (ESM). Moreover, mapping has been done in ArcGIS version 10.2. The spatial distribution maps have been prepared using geostatistical analyst tool integrated into ArcMap following the inverse distance weighting (IDW) technique and details about the method can be found in Burrough and McDonnell (1998).

3. Results of Analysis

3.1 Exploratory Statistics of WBC

Mean annual P_{ET} for hydrological year during the period of 1981-82 to 2012-2013 in the study area varies from 1228 to 1460 mm (Figure 2) with an average of 1338 mm. The higher P_{ET} values are found in the central part of the area where the annual rainfall is lower, but temperature is higher (Kamruzzaman et al., 2016). The standard deviations of P_{ET} vary from 205 mm (in Jessore station) to 41 mm (in Bhola station). The A_{ET} value (annual average 925 mm) is almost 31% less than the P_{ET} value as during the dry months (Dec-May), soil moisture condition reaches in critical stage and A_{ET} value is much lower than P_{ET}. Annual surplus of water varies from 515 to 1277 mm with an average for the area is 838 mm. According to Wolock and McCabe (1999), 50% of surplus water can be considered as runoff for the major parts of the world. The higher surplus amount of water has been found in the northern part of the area and along the coastal area. The annual deficit of water that mainly occurs during dry season form Dec to May vary from 329 to 556 mm with an average of 416 mm (Figure 2). The highest annual deficit of water found in Rajshahi which is located in northwest central part of the area where the depth of groundwater below the ground surface increases rapidly (Shamsudduha et al., 2009; Rahman et al., 2016).

3.2 Trend and Periodicity in WBC

3.2.1 P_{ET}

The MK test or MMK test based on the lag-1 auto-correlation has been applied to detect the trend in P_{ET}. Table-1 shows the *Z* statistic of MK or MMK test of original time series data of P_{ET} along with the values of the decomposition time series (D1-D4), approximation (A) and their different combinations (D1+A…..D3+D4+A). The estimated *Z* statistic of original data ranges from -2.07 (Satkhira station) to 2.37 (Bhola station). These two stations out of total eleven stations show significant trends in P_{ET}. The plot of sequential values of *u(t)* statistic of SMK test of these two stations are shown in Figure 3 where the dashed lines corresponds to 5% significance level (±1.96). The decreasing mode of P_{ET} in Satkhira station started during 1985-86 hydrological year and significant decreasing tendency started during 1993-94 hydrological year; and trend becomes reverse after 2007-08. However, the significant increasing trend in P_{ET} of Bhola station has been started very recently after some fluctuation.

Most of the trends (73%) in the study are negative and statistically insignificant at 95% confidence level or 5% significance level. Moreover, *Z* values of approximation (A) time series obtained by DWT indicate decreasing trends in P_{ET} for all stations and the calculated '*Z*' value is about -1.80 after rounding the figure for all stations. The individual time series values are different, but the similarity in the patterns in approximation (A) time series data of P_{ET} (Electronic Supplementary Material (ESM) Fig. S1) are the main reason for almost same values of '*Z*' statistic. The magnitude of changes ranges from -10.89 mm/year in Satkhira station to 1.67 mm/year in Bhola station (Figure 4). A recent study has also found negative trend in ET_o in four stations located in northwest Bangladesh (Acharjee et al., 2017). However, annual rainfall and temperature of the most of the stations in the western part of Bangladesh show increasing trends (e.g. Shahid and Khairulmaini, 2009; Kamruzzaman et al., 2016a). Though annual rainfall and temperature of Satkhira station show positive trends

(Kamruzzaman et al., 2016a), P_{ET} shows significant downward trend. The trends in P_{ET}, therefore, cannot explain by trends obtained in rainfall and temperature time series, though the temperature is the primary driver of changes in P_{ET} (IPCC, 2007). Increasing trends in temperature found in Yunnan Province of South China; but P_{ET} shows decreasing trend (Fan and Thomas, 2012). McVicar et al. (2012) have also found decreasing trends in P_{ET} in the different parts of the world. The MK or MMK test has also been applied to the decomposition time series and model time series generates from the combination of approximation and decomposition time series data (Table 1 represent results of four stations based on alphabetic order and the full Table can be found in ESM Table S1). To find out the dominant periodicity affecting the trends in P_{ET}, two steps of analysis have been done. First, we have compared the Z statistic of original data and estimated from different models (decomposition time series, D+A and D+A+A component combinations) and found out the nearest Z statistic of the model and original data. We have also estimated the correlation coefficient (Co) of $u(t)$ statistic of SMK between the original and model time series data. For example, the Z statistic of sub series D4 of Barisal is 0.76 which is the nearest to Z statistic (0.72) of original data among the different models (Table 1). Moreover, Z statistic of D3+D4+A combination is 0.56 which is the second nearest value to original time series with high correlation coefficient (Co = 0.85) between the $u(t)$ time series of original data and D3+D4+A combination time series. Again D4 is present, hence D4 (16-years) is the dominant periodic components on the trend in original data. However, D3 have also effect on the trend in the data. Therefore, D4 (16-years) is the basic periodic component, but 8-years (D3) periodicity has also effect on the trend. An additional example, original time series Z (2.47) statistic of Bhola station is closest to Z (2.36) statistic of D2+D4+A combination, however when we look separately we found that no individual component is responsible for trend in data as D2 (Z = 0.61 with Co = 0.21), D4 (1.20 with Co = 0.81), D2+ A (Z = 0.48) and D4+A (0.90). It is also notable that trend in original time series is statistically significant, trend in D2+D4+A combination is significant among different model of DWT data and Z statistic is also closest to the original. Moreover, Z statistic values of D4 components are higher than D2 components and Co values of SMK are also higher. It is, therefore, clear that D4 is main periodic components responsible for trend in data, however D2 has also effect on the trend as after adding this trend become significant similar to the original time series. Almost half of the stations show the harmoniousness between the Z statistic of D3+D4+A combination and original data. When we have done research separately in subseries D3 and D4, it is found that the higher relationship exists between D4 and original data based on correlation coefficient of SMK. Again, three stations (Dinajpur, Ishurdi and Jessore) show the similarity of estimated Z statistic of original data and D1+D4+A combination with higher Co values of $u(t)$ statistic of SMK between D4 subseries and original data except Ishurdi. However, only the two stations (Bhola and Satkhira) show significant trends in original data and the closest Z statistic between original data and model data is found in D2+D4+A combination model for both the cases. Again, D4 (16-years periodicity) is the dominant periodic component based Co for both stations. Therefore, 16-years periodicity is main periodic components over the study area. Moreover, D3 (8-years) periodicity have also some effect on the trends and present almost in some stations (Table 1 and also see ESM Table S1). Partal and Küçük (2006) found 16-years periodicity is dominant in annual rainfall in Marmara region in Turkey. Araghi et al. (2016) found that 8 to 16 years periodicity is responsible for trends in annual temperature in Iran.

3.2.2 A_{ET}

All of the stations except Bogra station show decreasing trends in A_{ET} and the calculated Z statistic rages from -2.90 in Bogra station to 0.31 in Ishurdi station. Similar to the trends in P_{ET}, trends in A_{ET} are also insignificant at 5% significance level except Ishurdi station which shows significant (5%) decreasing trend in A_{ET}. The magnitudes of the trends of original data vary from -5 mm/year in Faridpur station to 0.75 mm/year in Bogra station. Distribution of the magnitude of trend is shown in Figure 4b. The periodicity in A_{ET} is slightly different from P_{ET} (see ESM Table S2). Almost half of the (five) stations show that D2 (4-year) is the dominant periodic component and D4 (16-years) has also effects on trend as Z statistic of D2+D4+A is the nearest to original series for Khulna and Ishurdi stations. Moreover, D4 is dominant periodicity for Rangpur and Rajshahi stations. In addition, D1 is the dominant periodicity in Barisal, Bhola and Bogra stations. A_{ET} depends on climatic factors such as P_{ET} and rainfall as well as on soil moisture conditions. The variations in periodicity of A_{ET} from P_{ET}, hence, are mainly related to soil moisture conditions of the area.

3.2.3 Surplus

Almost 82% stations show insignificant decreasing trends in annual surplus of water. The magnitude of trends of original data ranges from -11.63 mm/year to 6.71 mm/year (Figure 4c). There is a similarity in periodicity characteristics of P_{ET} and surplus (See EMS Table S3). D4 (16-years) is the main periodic component presents in seven stations and most of the cases D2 is also present (D2+D4+A) except Rajshahi. D3 (8-years) is mainly responsible for trend in surplus in three stations. Surplus mainly occurs during the rainy season (Jun-Oct) in the study area when soil moisture almost full and A_{ET} is equal to P_{ET}. Surplus mainly depends on rainfall. Therefore, it also provides idea about the periodicity in rainfall.

3.2.4 Deficit

Approximately 73% stations show increasing trends in annual deficit of water. The increasing trends are significant in two stations at 95% confidence level (see ESM Table S4). However, Satkhira station shows significant decreasing trend (Z = -2.08) in deficit. The magnitude of trends of original data rages from -8.1 to 7.7 mm/year (Figure 4b). The periodicity analysis reveals that D4 (16-years) periodicity is the main responsible factor for trends in deficit and the Z statistic of D2+D4+A combination is close to the Z statistic of original time series data (ESM Table S4). D3 (8-years periodicity) is also responsible for two stations.

3.3 Model Selection and Forecasting Ability

Firstly, ARIMA model has been selected for forecasting the WBC time series. Four steps have been taken during the time series modeling: (1) stationarity of the data checked by Augmented Dickey–Fuller (ADF) test, (2) auto-correlation function (ACF) for selecting the order of MA process (see ESM Fig. S2-S5), (3) partial auto-correlation (PACF) for order of AR process (see ESM Fig. S2-S5) and (4) finally, selecting the appropriate model based on several trials, model estimation criteria of Akaike information criterion (AIC) and Bayesian information criterion (BIC). During the trails for selecting the model, besides the manual models selection based on ACF, PACF, AIC and BIC, auto ARIMA function of 'forecast' package (Hyndman et al., 2017) of R (R 3.4.0 language developed by R Development Core Team, 2016) has been used to get reasonable information about the nature of the data for modeling. The best model has been selected based on lower values of AIC, BIC,

Hydrol. Earth Syst. Sci. Discuss., https://doi.org/10.5194/hess-2017-523
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Discussion started: 10 October 2017

and higher value of R^2. The Q-Q plot has been prepared to check the normality of residual. The performance of ARIMA (model parameters can be found in ESM Table S5) model has been evaluated by NSE and R^2 (Table 2). The estimated values of NSE of ARIMA model of PET time series vary from -0.60 for Bhola station to 0.81 for Jessore station (Table 2). ARIMA models for almost all stations show unsatisfactory performance as the average NSE value of eleven stations is 0.38 and R^2 values range from 0.10 to 0.81 with an average of 0.38. Moreover, NSE value of Bhola station indicates that ARIMA model is not suitable for forecasting the P_{ET}. ARIMA model has also been applied to A_{ET}, surplus and deficit. After carefully checking the ACF and PACF (see ESM Figure S2–S5), it is found that there is no significant spikes in ACF and PACF. Moreover, results obtained from auto ARIMA functions also show similar results. Therefore, ARIMA model is not satisfactory for forecasting the variability or changing pattern in A_{ET}. For other two WBC such as, the performance of ARIMA model is almost similar except few cases. As the hydro-meteorological data are affected by noise from different hydro-physical processes (Wang et al., 2014) as a result ARIMA models show the unsatisfactory performances. To improve the model performance, it is necessary to remove the noise from the data. DWT denoising has been applied to the WBC data in the present study and the qualities of the denoised data have been checked before further processing. The important criterions to select a method for denoising the time series using wavelet transformation are the mean of the original series and wavelet denoised series should be close; however standard deviation of denoised series should be less than the original series (Wang et al., 2014). Figure 5(a) displays mean of the actual time series of P_{ET} and mean of wavelet denoised time series of P_{ET}. It is seen that there are no visible differences between the mean of original series and DWT wavelet denoised series. However, the standard deviation of P_{ET} of denoised series is lower than original series (Figure 5b). A_{ET}, surplus and deficit time series also show the similar results (see ESM Figure S4–S5). Moreover, lag-1 auto-correlation of denoised time series must be higher than the original time series (Wang et al., 2014) for hydro-meteorological data. For this consideration, wavelet denoised series also shows that lag-1 absolute value of auto-correlation is higher than that of original series value (see ESM Figure S2 (b), S3 (b), S4 (b) and S5 (b)).

The performances of ARIMA models of wavelet denoised WBC time series data are given in Table 2. After denoising the data, the model performance, in generally, is satisfactory for all WBC time series data (Table 2). The average NSE value of wavelet ARIMA model for P_{ET} time series of eleven stations located in the western part of Bangladesh is 0.76 with an average of R^2 is 0.67. Both of these performance indicators reveal that wavelet ARIMA models perform better than ARIMA model of actual data (Table 2). Moreover, the average NSE value of wavelet ARIMA models of A_{ET} time series of these stations is 0.92 that indicates the performance of the model is very good and the average R^2 value is 0.89 that indicates the model can explain almost 89% variance of the data (Table 2). Results obtained from wavelet ARIMA models of annual surplus and annual deficit also indicate very good performances of the models (Table 2). The average NSE value of eleven stations of wavelet ARIMA models for annual surplus is about 0.92 with average R^2 value is 0.90 that also indicates very good performance of the models. Wavelet ARIMA models for annual deficit (average NSE=0.88) show good performance. The comparative study of wavelet ARIMA models of WBC reveals that model performances are very good or good for A_{ET}, annual surplus and deficit; however performance is acceptable for P_{ET}. This deviation may arises from the variability of the P_{ET} is higher than others WBC or may related to the variability of climatic variables.

Hydrol. Earth Syst. Sci. Discuss., https://doi.org/10.5194/hess-2017-523
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Discussion started: 10 October 2017

Moreover, validations of the models have been done to explore the forecasting ability of the fitted models. The mean percentage error (E_{MP}) of the forecasted values for the four year period from 2008-09 to 2012-13 has been calculated to know the percentage bias of the forecasted data (Table 3). The average E_{MP} of eleven stations of wavelet ARIMA model for P_{ET} is -0.6 (with ranges from 0.75 to -3.34) that indicates the forecasted values for the hydrologic year 2009-10 to 2012-13 are slightly lower than the actual values. The typical plots of the actual time series data versus fitted model data, normal Q-Q plot of residuals of the models; and actual and observed values of WBC (plots for all stations can be found in ESM Fig. S6–S9) are shown in Figure 6. The plot of actual versus forecasted values (Figure 6) indicate that generally the actual verses forecasted values are very close for the hydrologic years 2009-10 and 2010-11, however the differences are generally increases after these periods for all WBC (also see ESM Figure S5). Moreover, the actual versus model calculated fitted values are very close to each other's and the normal Q-Q plots reveals that residuals of the models are near normal. The E_{MP} values for wavelet denoised ARIMA models for A_{ET} range from -0.7 to 0.2 with an average of -0.09 that also indicates forecasted values are slightly lower than actual A_{ET} values. The E_{MP} values for annual surplus (average = -0.75) and annual deficit (average = -0.12) are almost similar to the A_{ET} and P_{ET}. It is also notable that the average E_{MP} values for all WBC are negative which indicate that the forecasted values of WBC are slightly lower than the actual values for most of stations.

4. Summary and Conclusions

The study explores the changes in WBC using wavelet aided various forms of MK test and develop wavelet aided ARIMA models for forecasting the WBC. The results obtained from trends analysis indicate that decreasing trends are dominant in all WBC in the western part of Bangladesh during the period of 1982-83 to 2012-13. However, most of the trends are insignificant at 95% confidence level. One positive and one negative significant trend in P_{ET} have been found in Satkhira and Bhola stations respectively. The study analyzed different combinations of D and A (i.e. D+A and D+A+A) components of DWT with *Co* of *u(t)* statistic of SMK test that provides details information about the dominant periodicity that clearly affects the trend in original data and the time period which has also effect on trend in data (see section trend and periodicity or for example of Bhola station). These findings of the study reveal that to get details about the time period responsible for trends in data; it is necessary to analyze different combinations of D+A and D+A+A components rather than only details component (D) or approximation of wavelet transform data. Moreover, study explored that changes in temperature or rainfall or both of these are not only associated with changes in P_{ET}. Before concluding the attribute of changes in P_{ET}, it is necessary to do details analysis of all the climatic variables and climate controlling phenomena like El Niño Southern Oscillations (ENSO). In the western part of Bangladesh, D3 (8-years) and D4 (16-years) components have dominant effects on trends in original WBC time series data. D2 (4-years) periodicity are also present in some cases especially for A_{ET}. As surplus occurs during the rainy season and most of the rainfall occurs during this season; it may point out that rainfall pattern may have similar periodicity (D3 to D4).

Modeling of the study reveals that WBC are affected by noises from different hydro-physical interactions as a results classic ARIMA models show unsatisfactory performance for most of the cases (for example P_{ET}) or unable to model the variability and changes in A_{ET}, surplus and deficit. The study showed that ARIMA model can be used to model the WBC time series after the denoising the WBC time series using DWT with universal threshold. The quality of wavelet denoised time series data has been evaluated and found satisfactory results for WBC denoising. The performances of the models evaluated statistically (average NSE values with R^2 of eleven stations located in western part of Bangladesh are 0.76 with R^2 is 0.67 for P_{ET}; 0.92 with R^2 is 0.89 for A_{ET}; 0.92 with R^2 is 0.90 for annual surplus; and 0.88 with R^2 is 0.88 respectively) show that performances of the wavelet ARIMA models are acceptable to very good for the short term forecasting of WBC as the validation for the period of 2009-10 to 2012-13 shows acceptable E_{MP} values, however the gap between the actual data and forecasted data increases with increasing time period. The obtained results are encouraging for further studies to find out a realistic model for real world application under the changing climate. The results of the study can be incorporated to water resources management plans for highly irrigated western part of Bangladesh where groundwater resources at critical stage. Further studies, therefore, denoising of hydrological time series data using different wavelet such as haar, coiflet and determination of thresholds using MINMAX, SURE or entropy based adaptive denoising approaches; comparisons of different combinations, would be helpful for developing the better models for hydro-climatic time series in context of climate change and would be beneficial for managing water resources in sustainable manner.

References

Acharjee, T. K., Halsema, G., Ludwig, F. and Hellegers, P. Declining trends of water requirements of dry season Boro rice in the north-west Bangladesh. Agricultural Water Management, 180, 148–159, 2017.

Adamowski, J. and Chan, H. F. A wavelet neural network conjunction model for groundwater level forecasting. Journal of Hydrology, 407(1), 28–40, 2011.

Ahasan, M. N., Chowdhary, M. A. M. and Quadir, D. A. Variability and trends of summer monsoon rainfall over Bangladesh, Journal Hydrometeorology, 7(1), 1–17, 2010.

Allen, R. G., Pereira, L. S., Raes, D. and Smith, M. Crop evapotranspiration: guidelines for computing crop water requirements. FAO Irrigation and Drainage Paper, No. 56, Rome, Italy, p.328, 1998.

Alley, W. M. Water balance models in one-month-ahead stream flow forecasting, Water Resources Research, 21(4), 597–606, 1985.

Anderson, R., Hansen, J., Kukuk, K. and Powell, B. Development of watershed-based water balance tool for water supply alternative evaluations. Proceeding of the Water Environment Federation, (WEF06), 2006.

Araghi, A., Baygi, M. M., Adamowski, J., Malard, J., Nalley, D. and Hasheminia, S. M. Using wavelet transforms to estimate surface temperature trends and dominant periodicities in Iran based on gridded reanalysis data, Atmospheric Research, http://dx.doi.org/10.1016/j.atmosres.2014.11.016, 2014.

Arnall, N. W. Factors controlling the effects of climate change on river flow regimes in a humid temperate environment, Journal Hydrogeology, 132, 321–342, 1992.

Azad, S., Debnath, S. and Rajeevan, M. Analysing predictability in Indian monsoon rainfall: a data analytic approach. Environmental Processes, 2(4), 717–727, 2015.

Bakundukize, C., Camp, M. V. and Walraevens, K. Estimation of groundwater recharge in Bugesera region (Burundi) using soil moisture budget approach, Geologica Belgica, 14/1–2, 85–102, 2011.

Banglapedia. National Encyclopedia of Bangladesh. Asiatic Society of Bangladesh, Dhaka, 2003.

Basak, J. K., Titumir, R. A. M. and Dey, N. C. Climate Change in Bangladesh: A Historical Analysis of Temperature and Rainfall Data. Journal of Environment, 02(02), 41–46, 2013.

Hydrol. Earth Syst. Sci. Discuss., https://doi.org/10.5194/hess-2017-523
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Discussion started: 10 October 2017

Bhowmik, A. K. Temporal Patterns of the Two-Dimensional Spatial Trends in Summer Temperature and Monsoon Precipitation of Bangladesh. ISRN Atmospheric Sciences Volume, Article ID 148538, 16 pages, http://dx.doi.org/10.1155/2013/148538, 2013.

Boughton, W. Catchment water balance modelling in Australia 1960–2004. Agricultural Water Management, 71, 91–116, 2004.

Burrough, P. A. and McDonnell, R. A. Principles of geographical information systems. Oxford University Press, Oxford, 1998.

Box, G. E. P. and Jenkins, G. M. Time Series Analysis: Forecasting and Control (Revised edition), San Francisco: Holden Day, 1976.

Castaneda, L. and Rao, P. Comparison of methods for estimating reference evapotranspiration in southern California. Journal of Environmental Hydrology, 13(14), 1–10, 2005.

Chou, C. A threshold based wavelet denoising method for hydrological data modelling, Water Resources Management, 25, 1809–1830, doi:10.1007/s11269-011-9776-3, 2011.

Dong, L., Shimada, J., Kagabu, M. and Fu, C. Teleconnection and climatic oscillation in aquifer water level in Kumamoto plain, Japan. Hydrological Processes, 29, 1687–1703, doi:10.1002/hyp.10291, 2015.

Donoho, D. L. and Johnstone I. M. Ideal Denoising in an Orthonormal Basis Chosen from a Library of Bases. Comptes Rendus De L Academie Des Sciences Serie I-Mathematique, 319(12), 1317–1322, ISSN 0764-4442, 1994.

Donoho, D. L. De-noising by soft-thresholding. IEEE transactions on information theory, 41(3), 613–627, ISSN 00189448, 1995.

Endo, N., Matsumoto, J., Hayashi, T., Terao, T., Murata, F., Kiguchi, M., Yamane,Y. and Alam, M. S. Trends in Precipitation Characteristics in Bangladesh from 1950 to 2008. SOLA, 11, 113–117, doi:10.2151/sola.2015-027, 2015.

Fan, Z. and Thomas, A. Spatiotemporal variability of reference evapotranspiration and its contributing climatic factors in Yunnan Province, SW China, 1961–2004, Climatic Change, doi:10.1007/s10584-012-0479-4, 2012.

Guitjens, J. C. Models of Alfalfa Yield and Evapotranspiration. Journal of the Irrigation and Drainage Division, Proceedings of the American Society of Civil Engineers, 108(IR3), 212–222, 1982.

Hamed, K. H. and Rao, A.R. A modified Mann–Kendall trend test for autocorrelated data, Journal Hydrology, 204, 182–196, 1998.

Hamon, W. R. Computation of direct runoff amounts from storm rainfall, International Association of Scientific Hydrology Publication, 63, 52–62, 1963.

Harbeck, G. E. Jr., A practical field technique for measuring reservoir evaporation utilizing mass transfer theory. United States Geological Survey Professional Paper, 272(E), 101–105, 1962.

Hargreaves, G. L. and Samani, Z. A. Estimating potential evapotranspiration, Journal of Irrigation and Drainage Engineering, 108(3), 225–230, 1982.

Harvey, C. F., Ashfaque, K. N., Yu, W., Badruzzaman, A. B. M., Ali, M. A., Oates, P. M., Michael, H. A., Neumann, R. B., Beckie, R., Islam, S. and Ahmed, M. F. Groundwater dynamics and arsenic contamination in Bangladesh, Chemical Geology, 228, 112–136, 2006.

Hasan A. B. M. S. and Rahman, M. Z. Change in Temperature over Bangladesh Associated with Degrees of Global Warming. Asian Journal of Applied Science and Engineering, vol. 2, No 2, ISSN 2305-915X, 2013.

Hasan, M. A., Islam, A. K. M. S. and Bokhtiar, S. M. Changes of reference evapotranspiration ETo in recent decades over Bangladesh. 2nd International Conference on Advances in Civil Engineering, 26–28 Dec, 2014 CUET, Chittagong, Bangladesh, 2014.

Hatch, U., Jagtap, S., Jones, J. and Lamb, M. Potential effects of climate change on agricultural water use in the southeast U.S., Journal of American Water Resources Association, 35(6), 1551–1561, 1999.

Healy, R. W., Winter, T. C., LaBaugh, J. W. and Franke, O. L. Water Budgets: Foundations for Effective Water Resources and Environmental Management. United States Geological Survey, Reston, Virginia, 2007.

Hossain, M. S., Roy, K and Datta, D. P. Spatial and Temporal Variability of Rainfall over the South-Western Coast of Bangladesh, Climate, 2, 28–46, doi:10.3390/cli2020028, 2014.

Huq, S. M. I. and Shoaib, J. U. The Soils of Bangladesh, 1–172, ISBN 978-94-007-1128-0, doi:10.1007/978-94-007-1128-0, 2013.

Hyndman, R., Mitchell O'Hara-Wild, M., Bergmeir, C., Razbash, S. and Wang, E. R. Language Forecast Package Development team, 113p. 2017.

IPCC (Inter-governmental Panel on Climate Change). In: Solomon, S. et al. (eds.) Technical summary of climate change 2007: the physical science basis. Contribution of working group I to the fourth assessment report of the intergovernmental panel on climate change. Cambridge University Press, Cambridge, 2007

Jones, P. D. Maximum and minimum temperature trends in Ireland, Italy, Thailand, Turkey and Bangladesh. Atmospheric Research, 37, 67–78, 1995.

Kamruzzaman, M., Rahman, A. T. M. S., Kabir, M. E., Jahan, C. S., Mazumder, Q. H. and Rahman, M. S. Spatio-temporal Analysis of Climatic Variables in the Western Part of Bangladesh, Environment, Development and Sustainability, 18(6), doi:10.1007/s10668-016-9872-x, Published online: 22 October 2016, 2016a.

Kamruzzaman, M., Kabir, M. E., Rahman, A. T. M. S., Mazumder, Q. H., Rahman, M. S. and Jahan, C. S. Modeling of Agricultural Drought Risk Pattern using Markov Chain and GIS in the Western Part of Bangladesh, Environment, Development and Sustainability, 18(6), doi 10.1007/s10668-016-9898-0, 2016b.

Karimi, P., Bastiaanssen, W. G. M. and Molden, D. Water Accounting plus (WA+)- a water accounting procedure for complex river basins based on satellite measurements, Hydrology and Earth System Sciences, 17, 2459–2472, 2013.

Keka, I. A., Matin, I. and Banu, D. A. Recent Climatic Trends in Bangladesh, DIU Journal of Science and Technology, 8(2), 43–49, http://hdl.handle.net/20.500.11948/922, 2013.

Kendall, M. G. Rank Correlation Methods, Griffin, London, 1975.

Khalek, M. A. and Ali, M. A. Comparative Study of Wavelet-SARIMA and Wavelet-NNAR Models for Groundwater Level in Rajshahi District. IOSR Journal of Environmental Science, Toxicology and Food Technology (IOSR-JESTFT), e-ISSN: 2319-2402, p-ISSN: 2319-2399. vol. 10, Issue 7, Ver. I, 01–15, 2016.

Khan, F. K. and Islam, M. A. Water balance of East Pakistan, Oriental Geographer, 10, 1–9, 1966.

Kirby, M., Ahmad, M. D., Mainuddin, M., Palash, W., Qadir, M. E., Shah-Newaz, S. M. and Hossain, M. N. The impact of irrigation development on regional groundwater resources in Bangladesh. Agricultural Water Management, 159, 264–276, doi:10.1016/j.agwat.2015.05.026, 2015.

Luo, G. and Zhang, D. Wavelet Denoising, Advances in Wavelet Theory and Their Applications in Engineering, Physics and Technology, Dr. Dumitru Baleanu (Ed.), ISBN: 978-953-51-0494-0, InTech, Available from:

http://www.intechopen.com/books/advances-in-wavelet-theory-and-their-applicationsin-engineering-physics-and-technology/wavelet-denoising, 2012.

Mallat, S. G. A theory for multi-resolution signal decomposition: the wavelet representation, IEEE Transactions on Pattern Analysis and Machine Intelligence, 11(7), 674–693, 1989.

Mann, H. B. Nonparametric tests against trend, Econometrica, 13, 245–259, 1945.

McCuen, R. H., Knight, Z. and Cutter, A. G. Evaluation of the Nash–Sutcliffe Efficiency Index. Journal of Hydrological Engineering, 11, 597–602, 2006.

McSweeney, C., New, M. and Lizcano, G. UNDP climate change country profiles: Bangladesh, 2010. Available: http://country-profiles.geog.ox.ac.uk/. Accessed 10 May 2013.

McVicar, T. R., Roderick, M. L., Donohue, R. J., Li, L. T., Van Niel, T. G., Thomas, A., Grieser, J., Jhajharia, D., Himri, Y., Mahowald, N. M., Mescherskaya, A. V., Kruger, A. C., Rehman, S. and Dinpashoh, Y. Global review and synthesis of trends in observed terrestrial near-surface wind speeds: Implications for evaporation, Journal Hydrology, 416–417, 182–205, doi:10.1016/j.jhydrol.2011.10.024, 2012.

Michael, H. A. and Voss, C. I. Controls on groundwater flow in the Bengal Basin of India and Bangladesh: regional modeling analysis, Hydrogeology Journal, 17, 1561–577, 2009.

Misiti, M., Misiti, Y., Oppenheim, G. and Poggi, J. Wavelet Toolbox User's Guide. The Math Works, Inc. 1997.

Mohan, S. and Arumugam, N. Forecasting weekly reference crop evapotranspiration series. Hydrological Sciences Journal, 40, 689–702, doi:10.1080/02626669509491459, 1995.

Molden, D. and Sakthivadivel, R. Water accounting to assess use and productivity of water. International Journal of Water Resources Development, 15(1–2), 55–71, http://dx.doi.org/10.1080/07900629948934, 1999.

Moriarty, P., Batchelor, C., Abd-Alhadi, F., Laban, P. and Fahmy, H. The Empowers Approach to Water Governance Guidelines, Methods and Tools. Jordan: Inter-Islamic Network on Water Resources Development and Management (INWRDAM), 2007, 2007.

Moussa, R. When monstrosity can be beautiful while normality can be ugly: assessing the performance of event–based flood models. Journal of Hydrological Science, 55(6), 1074–1084, 2010.

Nalley, D., Adamowski, J. and Khalil, B. Using discrete wavelet transforms to analyze trends in streamflow and precipitation in Quebec and Ontario (1954–2008). Journal of Hydrology, 475, 204–228, 2012.

Nalley, D., Adamowski, J., Khalil, B. and Ozga-Zielinski, B. Trend detection in surface air temperature in Ontario and Quebec, Canada during 1967–2006 using the discrete wavelet transform. Atmospheric Research, 132–133, 375–398, 2013.

Nash, J. E. and Sutcliffe, J. V. River flow forecasting through conceptual models, part I: a discussion of principles. Journal of Hydrology, 10, 282–290. http://dx.doi.org/ 10.1016/0022-1694(70)90255-6, 1970.

Nasher, N. M. R. and Uddin, M. N. Maximum and Minimum Temperature Trends Variation over Northern and Southern Part of Bangladesh, Journal of Environmental Science and Natural Resources, 6(2), 83–88, 2013.

Nievergelt, Y. Wavelets Made Easy. Birkhäuser (297pp), 2001.

Nury, A. H., Hasan, K. and Alam, J. B. Comparative study of wavelet-ARIMA and wavelet-ANN models for temperature time series data in northeastern Bangladesh, Journal of King Saud University – Science, 29, 47–61, 2017.

Nury, A. H., Hasan, K., Erfan, K. M. and Dey, D. C. Analysis of Spatially and Temporally Varying Precipitation in Bangladesh, Asian Journal of Water, Environment and Pollution, 13(3), 15–27, doi:10.3233/AJW-160023, 2016.

Partal, T. and Küçük, M. Long-term trend analysis using discrete wavelet components of annual precipitations measurements in Marmara region (Turkey). Physics and Chemistry of the Earth, 31(18), 1189–1200, 2006.

Partal, T. Modelling evapotranspiration using discrete wavelet transform and neural networks. Hydrological Processes, 23(25), 3545–3555, 2009.

Pathak, P., Kalra, A. and Ahmed, S. Wavelet-Aided Analysis to Estimate Seasonal Variability and Dominant Periodicities in Temperature, Precipitation, and Streamflow in the Midwestern United States. Water Resources Management, doi:10.1007/s11269-016-1445-0, 2016.

Percival, D. B. and Walden, A. T. Wavelet Methods for Time Series Analysis, 1106 Cambridge University Press, New York (594pp.), 2000.

Pereira, A. R. and Pruitt, W. O. Adaptation of the Thornthwaite scheme for estimating daily reference evapotranspiration. Agricultural Water Management, 66, 251–257, 2004.

Pišoft, P., Kalvová, J. and Brázdil, R. Cycles and trends in the Czech temperature series using wavelet transforms. International Journal of Climatology, 24, 1661–1670, 2004.

Priestley, C. H. B. and Taylor, R. J. On the assessment of surface heat flux and evaporation using large-scale parameters. Monthly Weather Review, 100(2), 81–92, 1972.

Rahman M. A., Yunsheng, L. and Sultana, N. Analysis and prediction of rainfall trends over Bangladesh using Mann–Kendall, Spearman's rho tests and ARIMA model. Meteorology and Atmospheric Physics, doi:10.1007/s00703-016-0479-4, 2016.

Rahman, A. T. M. S. Sustainable Groundwater Management in the Context of Climate Change in Drought Prone Barind Area, NW Bangladesh. Unpublished M.Phil. Thesis, Institute of Environmental Science, University of Rajshahi, Bangladesh, 2016.

Rahman, A. T. M. S., Jahan, C. S., Mazumder, Q. H., Kamruzzaman, M. and Hossain, A. Evaluation of spatio-temporal dynamics of water table in NW Bangladesh: An integrated approach of GIS and Statistics, Sustainable Water Resource Management, 2(3), doi:10.1007/s40899-016-0057-4, 2016.

Rahman, M. A. and Begum, M. Application of non-parametric test for trend detection of rainfall in the largest island of Bangladesh, ARPN Journal of Earth Sciences, 2(2), 40–44, 2013.

Rahman, M. R. and Lateh, H. Climate change in Bangladesh: a spatio-temporal analysis and simulation of recent temperature and rainfall data using GIS and time series analysis model. Theoretical and Applied Climatology, doi:10.1007/s00704-015-1688-3, 2015.

Rahman, M. R. and Lateh, H. Spatio-temporal analysis of warming in Bangladesh using recent observed temperature data and GIS, Climate. Dynamics, 46, 2943–2960, 2016.

Ravenscroft, P., Burgess, W. G., Ahmed, K. M., Burren, M. and Perrin, J. Arsenic in groundwater of the Bengal Basin, Bangladesh: Distribution, field relations, and hydrogeological setting, Hydrogeology Journal, 13, 727–751, 2005.

Ritter, A., Muñoz-Carpena, R. Performance evaluation of hydrological models: Statistical significance for reducing subjectivity in goodness-of-fit assessments. Journal of Hydrology, 480, 33–45. http://dx.doi.org/10.1016/j.jhydrol.2012.12.004, 2013.

Hydrology and Earth System Sciences
Open Access
Discussions

Sang, Y. -F. A practical guide to discrete wavelet decomposition of hydrologic time series. Water Resources Management, 26, 3345–3365, 2012.

Sang, Y. -F., Wang, Z., and Liu, C. Discrete wavelet-based trend identification in hydrologic time series, Hydrological Processes, 27, 2021–2031, 2013.

Scott, C. A. and Sharma, B. Energy supply and the expansion of groundwater irrigation in the Indus-Ganges Basin, International Journal of River Basin Management, 7(1), 1–6, 2009.

Sen, P. K. Estimates of the regression coefficient based on Kendall's tau, Journal of the American Statistical Association, 63(324), 1379–1389, 1968.

Shahid, S. and Behrawan, H. Drought risk assessment in the western part of Bangladesh, Natural Hazards, 46, 391–413, 2008.

Shahid, S. and Khairulmaini, O. S. Spatial and temporal variability of rainfall in Bangladesh, Asia-pacific Journal of Atmospheric Sciences, 45(3), 375–389, 2009.

Shahid, S. Recent trends in the climate of Bangladesh. Climatic Research, 42(3), 185–193, 2010.

Shamsudduha, M., Chandler, R. E., Taylor, R. G. and Ahmed, K. M. Recent trends in groundwater levels in a highly seasonal hydrological system: the Ganges-Brahmaputra-Meghna Delta, Hydrology and Earth System Science, 13, 2373–2385, 2009.

Smith, L. C., Turcotte, D. L. and Isacks, B. L. Stream flow characterization and feature detection using a discrete wavelet transform, Hydrological Processes, 12, 233–249, 1998.

Sneyers, R. On the Statistical Analysis of Series of Observations, Secretariat of the World Meteorological Organization, (192 pp), 1990.

Sperna Weiland, F. C., Tisseuil, C., Dürr, H.H., Vrac, M. and van Beek, L. P. H. Selecting the optimal method to calculate daily global reference potential evaporation from CFSR reanalysis data for application in a hydrological model study, Hydrology and Earth System Science, 16, 983–1000. 2012.

SRDI (Soil Resources Development Institute). Soil map of Bangladesh, Soil Resources Development Institute, 1998.

Sreekanth, P., Geethanjali, D. N., Sreedevi, P. D., Ahmed, S., Kumar, N. R. and Jayanthi, P. D. K. Forecasting groundwater level using artificial neural networks. Current Science, 96(7), 933–939, 2009.

Sun, S., Chen, H., Wang, G., Li, J., Mu, M., Yan, G., Xu, B. Huang, J., Wang, J., Zhang, F. and Zhu, S. Shift in potential evapotranspiration and its implications for dryness/wetness over Southwest China. Journal of Geophysical Research and Atmosphere, 121, 9342–9355, doi:10.1002/2016JD025276, 2016.

Syed, A. and Al Amin. Geospatial Modeling for Investigating Spatial Pattern and Change Trend of Temperature and Rainfall. Climate, 4, 21, doi:10.3390/cli4020021, 2016.

Team, R. C. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. ISBN 3-900051-07-0, 2016.

Thornthwaite, C. W. An approach towards a rational classification of climate, Geographical Review, 38, 55–94, 1948.

Thornthwaite, C. W. and Mather, J. R. Instructions and tables for computing potential evapotranspiration and the water balance. Publications in Climatology, 10(3), 183–311, 1957. Laboratory of Climatology, Drexel Institute of Technology, Centerton, New Jersey, USA.

Torrence, C. and Compo, G. P. A practical guide to wavelet analysis. Bulletin of American Meteorological Society, 79, 61–78, 1998.

Trajkovic, S. and Kolakovic, S. Evaluation of reference evapotranspiration equations under humid conditions. Water Resources Management, 23, 3057–3067, 2009.

Ukkola, A. M. and Prentice, I. C. A worldwide analysis of trends in water-balance evapotranspiration. Hydrology and Earth System Science, 17, 4177–4187, doi:10.5194/hess-17-4177-2013, 2013.

Valipour, M., Banihabib, M. B. and Behbahani, M. R. Comparison of the ARMA, ARIMA, and the autoregressive artificial neural network models in forecasting the monthly inflow of Dez dam reservoir, journal of hydrology 476 (2013) 433–441.

Venkata Ramana, R., Krishna, B., Kumar, S. R. and Pandey, N. G. Monthly rainfall prediction using wavelet neural network analysis, Water Resources Management, 27, 3697–3711, 2013.

Wang W., Ding, J. and Li, Y. Hydrologic Wavelet Analysis [in Chinese], Chemical Industry Press, Beijing, China, 2005.

Wang, D., Singh, V. P., Shang, X., Ding, H., Wu, J., Wang, L., Zou, X. Chen, Y., Chen, X., Wang, S. and Wang, Z. Sample entropy based adaptive wavelet de-noising approach for meteorological and hydrologic time series, Journal of Geophysical Research and Atmosphere, 119, 8726–8740, doi:10.1002/ 2014JD021869, 2014.

Wang, J., Lv, X., Wang, J. and Lin, H. Spatiotemporal Variations of Reference Crop Evapotranspiration in Northern Xinjiang, China, The Scientific World Journal, Volume 2014, http://dx.doi.org/10.1155/2014/931515, 2014.

WARPO (Water Resources Planning Organisation), National Water Management Plan: Topic Paper No 7, Land and Water Resources, and Draft Development Strategy Annex C: Land and Water Resources, Water Resources Planning Organisation, Dhaka, 2000.

Wolock, D. M. and McCabe, G. J. Effects of potential climatic change on annual runoff in the conterminous United States, Journal of the American Water Resources Association, 35, 1341–1350, 1999.

Xu, C. -Y. and Halldin, S. The effect of climate change in river flow and snow cover in the NOPEX area simulated by a simple water balance model, Proc. of Nordic Hydrological Conference, Alkureyri, Iceland, 1, 436–445, 1996.

Xu, C. -Y. and Singh, V. P. Cross comparison of empirical equations for calculating potential evapotranspiration with data from Switzerland, Water Resources Management, 16, 197–219, 2002.

Yue, S., Pilon, P., Phinney, B. and Cavadias, G. The influence of autocorrelation on the ability to detect trend in hydrological series, Hydrological Processes, 16, 1807–1829, 2002.

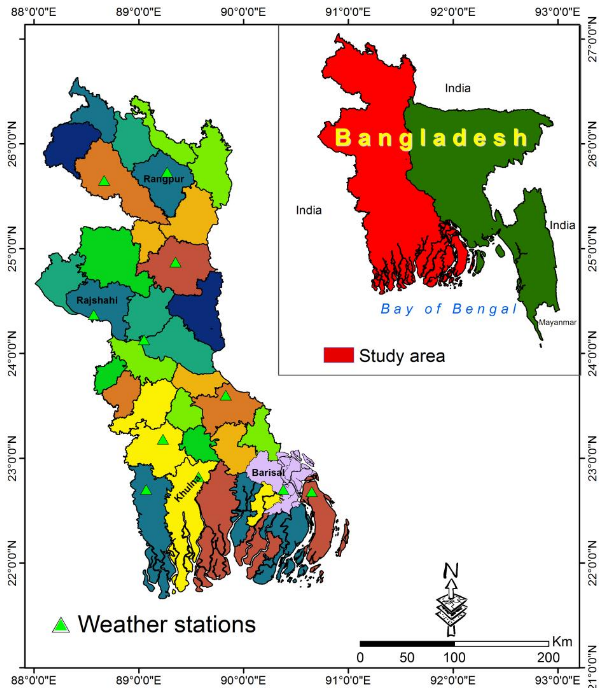

Figure 1: Study area western part of Bangladesh with locations of meteorological stations.

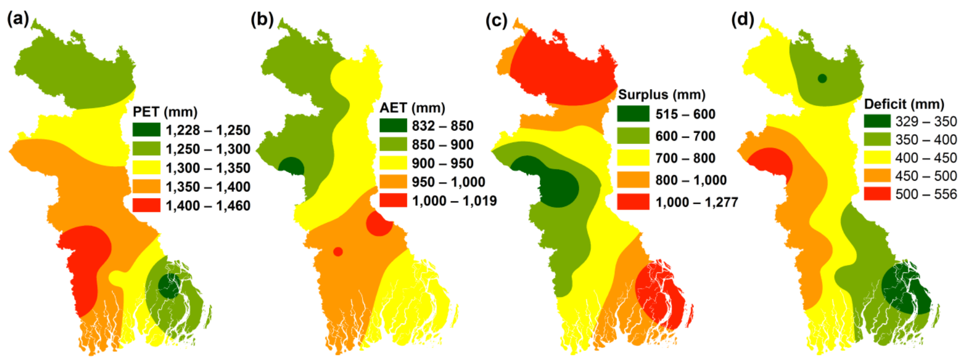

Figure 2: Distribution of mean annual (a) P_{ET}, (b) A_{ET}, (c) surplus and (d) deficit of water in the study area during the hydrologic year 1981-82 to 2012-13.

Hydrol. Earth Syst. Sci. Discuss., https://doi.org/10.5194/hess-2017-523
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Discussion started: 10 October 2017

Hydrology and Earth System Sciences
Discussions

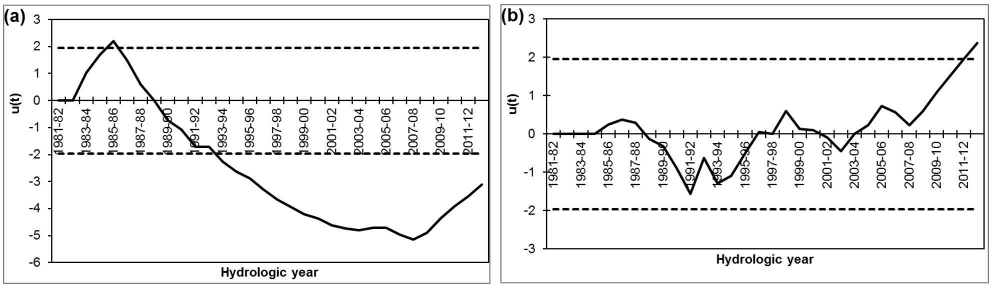

Figure 3: Sequential values of the statistics *u (t)* of (a) Satkhira station and (b) Bhola station.

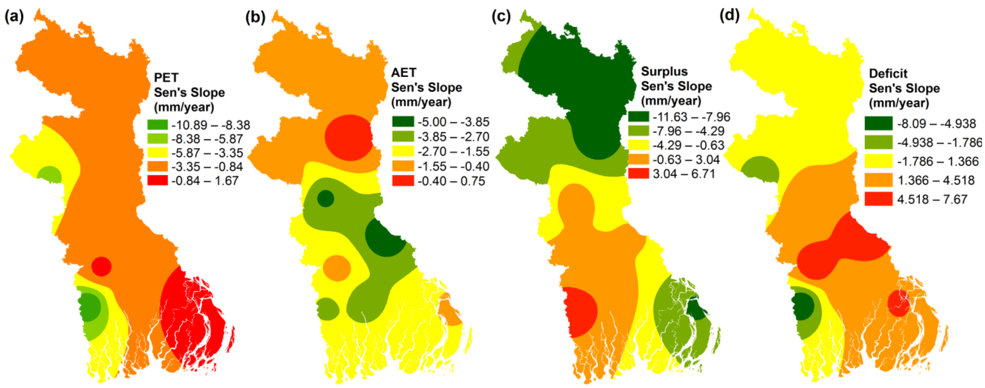

Figure 4: Distribution of rate of changes of WBC during the period of 1981-82 to 2012-13.

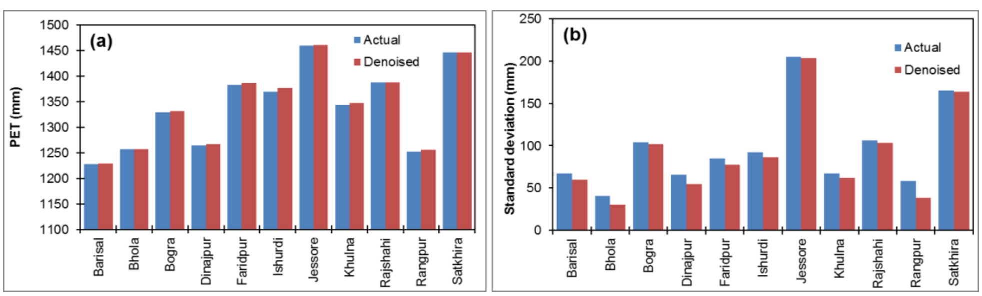

Figure 5: Comparison between actual and denoised P_{ET} time series (a) mean and (b) standard deviation.

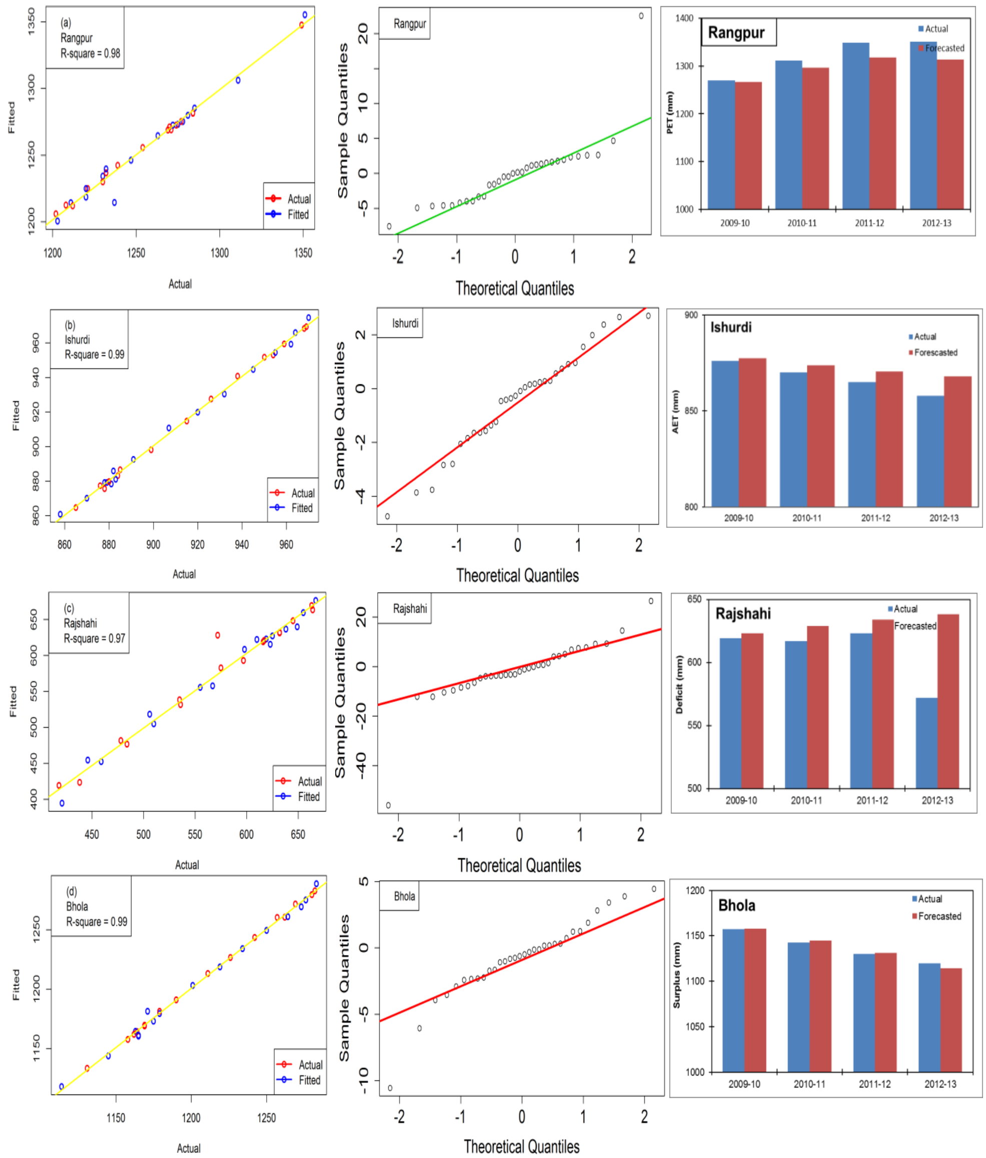

Figure 6: Plot of best wavelet ARIMA model first panel represents actual versus fitted values for the period of 1981-82 to 2012-2013, second panel is normal Q-Q plot of residuals of the model, and third panel shows actual, fitted and forecasted values for 2009-2010 to 2012-13 (a) P_{ET} of Rangpur station located in north; (b) A_{ET} of Ishurdi station located in the central part, (c) deficit of Rajshahi station located in NW Bangladesh and (d) surplus of Bhola station located in south of the study area.

Table 1: ***Z*** statistic of MK or MMK of original time series, approximation and different models PET of DWT (the dominant components are bold and asterisk for significant at 5% level)

Stations / Models	Barisal			Bhola			Bogra			Dinajpur		
	Z	*Co*	MSE	*Z*	*Co*	MSE	*Z*	*Co*	MSE	*Z*	*Co*	MSE
Original	0.72			2.37*			-0.20			-0.98		
A	-1.80	0.24	11.56	-1.80	-0.15	17.15	-1.80	0.83	4.66	-1.80	0.83	3.47
D1	0.91	0.50	0.50	2.02*	0.25	0.68	1.16	-0.42	5.10	-		
D2	-0.03	0.17	1.51	0.61	0.21	0.94	0.16	0.60	3.70	0.43	0.63	8.82
D3	0.45	0.17	1.51	0.46	0.21	0.94	1.08	0.60	3.70	0.90	0.63	8.82
D4	**0.76**	0.37	3.93	1.20	0.80	7.28	1.14	0.13	3.76	2.10*	-0.03	13.35
D1+A	-0.89	0.35	0.71	1.58	0.11	0.72	-2.35*	0.90	0.54	-1.70	0.95	0.44
D2+A	-1.51	0.14	2.75	0.48	0.13	1.05	-1.54	0.89	0.62	-2.05*	0.93	1.25
D3+A	-0.66	0.50	1.90	0.31	0.14	1.23	-1.91	0.89	5.72	-1.56	0.95	3.03
D4+A	0.06	0.53	9.99	0.90	0.77	8.71	-0.34	0.58	7.32	-1.79	0.85	2.41
D1+D2+A	-0.89	0.35	0.82	0.73	0.39	0.68	-1.12	0.88	0.77	-1.76	0.97	0.18
D1+D3+A	-0.81	0.58	0.88	0.79	0.31	0.69	-1.33	0.87	0.89	-1.51	0.98	0.38
D1+D4+A	0.91	0.63	1.16	2.29*	0.83	0.35	0.24	0.87	0.53	-1.15	0.97	0.20
D2+D3+A	-0.46	0.43	1.24	1.01	0.08	2.42	-1.33	0.89	1.10	-1.37	0.96	1.35
D2+D4+A	0.54	0.50	2.84	**2.36***	0.77	0.68	0.10	0.88	0.60	**-1.27**	0.94	0.85
D3+D4+A	0.56	0.85	2.04	1.83	0.90	0.74	**-0.30**	0.87	1.37	-1.54	0.96	2.10

Table 2: Comparison of performance of ARIMA model and wavelet ARIMA model

Stations	P_{ET}				A_{ET}		Surplus		Deficit	
	ARIMA		Wavelet ARIMA		Wavelet ARIMA		Wavelet ARIMA		Wavelet ARIMA	
	NSE	R^2	NSE	R^2	NSE	R^2	NSE	R^2	NSE	R^2
Barisal	0.42	0.43	0.95	0.57	0.58	0.58	0.99	0.99	0.87	0.87
Bhola	-0.57	0.10	0.95	0.61	0.98	0.59	0.99	0.99	0.56	0.67
Bogra	0.52	0.50	0.68	0.63	0.97	0.97	0.99	0.99	0.95	0.95
Dinajpur	0.54	0.52	0.99	0.79	0.98	0.98	0.84	0.95	0.95	0.94
Faridpur	0.32	0.30	0.65	0.50	0.99	0.99	0.99	0.99	0.87	0.88
Ishurdi	0.34	0.31	0.39	0.57	0.99	0.99	0.98	0.56	0.88	0.89
Jessore	0.81	0.81	0.76	0.67	0.82	0.82	0.96	0.96	0.82	0.77
Khulna	0.31	0.29	0.45	0.41	0.98	0.97	0.99	0.99	0.94	0.94
Rajshahi	0.58	0.56	0.60	0.61	0.99	0.99	0.98	0.98	0.97	0.97
Rangpur	0.19	0.20	0.98	0.98	0.84	0.92	0.47	0.49	0.86	0.84
Satkhira	0.77	0.20	0.95	0.98	0.99	0.99	0.99	0.99	0.99	0.99
Avg.	**0.38**	**0.38**	**0.76**	**0.67**	**0.92**	**0.89**	**0.92**	**0.90**	**0.88**	**0.88**

Hydrol. Earth Syst. Sci. Discuss., https://doi.org/10.5194/hess-2017-523
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Discussion started: 10 October 2017

Table 3: Accuracy of wavelet ARIMA models of WBC for validation of the models predictive ability for the period of 2009-10 to 2012-2013

Stations	P_{ET}		A_{ET}		Surplus		Deficit	
	ME	E_{MP}	ME	E_{MP}	ME	E_{MP}	ME	E_{MP}
Barisal	0.07	-0.02	-5.36	-0.70	-0.70	-0.10	0.80	0.29
Bhola	0.75	0.06	-0.10	-0.01	-0.80	-0.10	0.80	0.29
Bogra	-0.75	-0.19	0.19	0.02	-1.10	-0.10	-0.07	-0.03
Dinajpur	-0.16	-0.01	-0.19	-0.02	-0.10	0.00	-0.17	-0.10
Faridpur	-2.22	-0.25	-0.77	-0.07	-0.10	0.00	1.05	0.39
Ishurdi	0.34	-0.16	-0.45	-0.05	-0.20	0.00	0.72	0.25
Jessore	0.11	-0.02	0.26	0.02	0.70	0.00	1.52	-2.42
Khulna	-1.56	-0.22	-0.53	-0.05	0.60	0.10	0.01	-0.01
Rajshahi	-3.34	-0.35	-0.11	-0.01	-0.60	-0.10	-0.14	0.08
Rangpur	-0.11	-0.01	-0.40	-0.05	-8.50	-7.90	-0.05	-0.14
Satkhira	0.54	0.04	-0.36	-0.04	0.50	0.10	-0.43	0.12
Avg.	**-0.57**	**-0.10**	**-0.71**	**-0.09**	**-0.95**	**-0.75**	**0.37**	**-0.12**