A Study of Bangladesh's Sub-surface Water Storages Using Satellite Products and Data Assimilation Scheme

M. Khaki[a,1], E. Forootan[b], M. Kuhn[a], J. Awange[a], F. Papa[c,d], C. K. Shum[e,f]

[a]*Department of Spatial Sciences, Curtin University, Perth, Australia.*
[b]*School of Earth and Ocean Sciences, Cardiff University, Cardiff, UK.*
[c]*LEGOS, Universit de Toulouse, IRD, CNES, CNRS, UPS, Toulouse 31400, France.*
[d]*Indo-French Cell for Water Sciences (IFCWS), IRD-IISc-NIO-IITM Joint International Laboratory, Bangalore 560012, India.*
[e]*Division of Geodetic Science, School of Earth Sciences, The Ohio State University, Columbus, OH, USA.*
[f]*Institute of Geodesy and Geophysics, Chinese Academy of Sciences, Wuhan 430077, China.*

Abstract

Climate change can significantly influence terrestrial water changes around the world particularly in places that have been proven to be more vulnerable such as Bangladesh. Its impacts, together with those of excessive human water use, in the past few decades have changed the country's water availability structure. In this study, we use multi-mission remotely sensed measurements along with a hydrological model to separately analyze groundwater and soil moisture variations for the period 2003–2013, and their interactions with rainfall in Bangladesh. To improve the model's estimates of water storages, terrestrial water storage (TWS) data obtained from the Gravity Recovery And Climate Experiment (GRACE) satellite mission are assimilated into the World-Wide Water Resources Assessment (W3RA) model using the ensemble-based sequential technique of the Square Root Analysis (SQRA) filter. We investigate the capability of the data assimilation approach for using a non-regional hydrological model for studying water storage changes. Based on these estimates, we investigate connections between the model derived sub-surface water storage changes and remotely sensed precipitations, as well as altimetry-derived river level variations in the area by applying the empirical mode decomposition (EMD) method. A larger correlation is found between river level heights and rainfalls (78% on average) in comparison to groundwater storage variations and rainfalls (57% on average). The results indicate a significant decline in groundwater storage (∼32% reduction) for Bangladesh between 2003 and 2013, which is equivalent to an average rate of 8.73±2.45 mm/year.

Keywords: Bangladesh, Groundwater storage, Data assimilation, Hydrological modelling, GRACE

Email address: Mehdi.Khaki@postgrad.curtin.edu.au (M. Khaki)
[1]Contact details: Western Australian Centre for Geodesy and The Institute for Geoscience Research, Curtin University, Perth, Australia, Email: Mehdi.Khaki@postgrad.curtin.edu.au, Tel: 0061410620379

1. Introduction

South Asia, and in particular Bangladesh, is amongst the most water vulnerable regions of the world exhibiting an increase in droughts and floods due to climate change (McCarthy et al., 2001). Groundwater is the main source of drinking and irrigation water (almost 90%) in the country (Islam et al., 2013). Any considerable change in climate will, therefore, affect Bangladesh's available water, which is stored in different forms including aquifers, soils, surface waters as rivers, lakes, man-made reservoirs, wetlands and seasonally inundated areas (Papa et al., 2015). Understanding the interaction between precipitation (mainly provided during the Monsoon season) and water storage changes is important to relate climate variability to hydrology. An in-depth understanding of this interaction can be more difficult in Bangladesh due to the changing behavior of monsoonal precipitation (Wang and Ding, 2006) as well as the lack of knowledge on their influence on the hydrology of the region (Shahid, 2010; Rafiuddin et al., 2010).

Groundwater accessibility has made Bangladesh an agro-based country with the main product being rice, making it one of the world's largest rice producer (Abdullah Aziz et al., 2015). The excessive groundwater usage during the last two decades has resulted in serious problems of both rapid falling of groundwater levels and the deterioration of its quality (Qureshi et al., 2015). Groundwater depletion has been reported by Shamsudduha et al. (2009) between 1985 and 2005 within different regions in Bangladesh such as north-central, northwestern, and southwestern parts of the country. This has also been shown by Shamsudduha et al. (2012) for the period of 2003 to 2007. Moreover, Sengupta et al. (2013) reported that groundwater in 63 (out of 64) districts of Bangladesh are seriously contaminated with arsenic, which is partly attributed to its depletion. A number of studies attribute the drop in groundwater level since 1972 to the rainfall decrease and increase in human water usage (see, e.g., Mainuddin, 2002; Ahmed, 2006; McBean et al., 2011; Dey et al., 2011; Adhikary et al., 2013). The Groundwater Monitoring Survey Report of Bangladesh Agricultural Development Corporation (BADC) and Institute of Water Modeling (IWM) showed a three-meter drop of groundwater levels in Dhaka (Sumon and Abul Kalam, 2014). Knappett et al. (2016) claimed that an excess extraction caused the groundwater level to decline more than one meter near the Buriganga River, which passes in the southwest outskirts of Dhaka resulting in insufficient resources available for the rapidly growing population.

Soil water storage variation is another important factor that worsens the situation and affects agriculture. Furthermore, a considerable amount of surface water from rainfall is consumed by human and thus is not able to recharge the groundwater (e.g., Kanoua and Merkel, 2015; Qureshi et al., 2015; Alimuzzaman, 2017), which can aggravate the conditions mentioned above. Apart from efforts by these studies, a comprehensive study is missing to account for both groundwater and soil moisture variations and their connections to climate variability and change over the entire Bangladesh.

In this regard, hydrological models are important tools for simulating and predicting sub-surface water storages with high saptio-temporal resolutions (e.g., Wooldridge and Kalma, 2001; Döll et al., 2003; van Dijk et al., 2013). However, imperfect modeling of complex water cycle processes, data deficiencies on both temporal and spatial resolutions (e.g., limited ground-based observations), and uncertainties of (unknown) empirical model parameters, inputs and forcing data cause some degrees of deficiencies in them (Vrugt et al., 2013; van Dijk et al., 2011, 2014). These limitations are addressed through data assimilation, which is a technique that incorporates additional observations into a dynamic model to improve its state estimations (Bertino et al., 2003; Hoteit et al., 2012). The technique has been widely applied and validated in the fields of oceanography, climate, and hydrological science (Garner et al., 1999; Elbern and Schmidt, 2001; Bennett, 2002; Moradkhani et al., 2005; van Dijk et al., 2014; Reager et al., 2015). Several studies indicate that terrestrial water storage (TWS) derived from the Gravity Recovery And Climate Experiment (GRACE) can play a significant role in better understanding surface and sub-surface processes related to water redistribution within the Earth system (e.g., Huntington, 2006; Chen et al., 2007; Kusche et al., 2012; Forootan et al., 2014; van Dijk et al., 2014). In particular, Shamsudduha et al. (2012) showed a high capability of GRACE measurements for studying water storage variations in the Bengal Basin. A growing number of studies have also assimilated GRACE TWS in order to constrain the mass balance of hydrological models (e.g., Zaitchik et al., 2008; Thomas et al., 2014; van Dijk et al., 2014; Eicker et al., 2014; Tangdamrongsub et al., 2015; Reager et al., 2015; Khaki et al., 2017c; Schumacher et al., 2017).

The present study aims at assimilating GRACE TWS into the World-Wide Water Resources Assessment (W3RA) hydrological model (van Dijk, 2010) to analyze groundwater and soil moisture changes within Bangladesh. While the main focus is on groundwater and soil moisture, surface water as an important water source in Bangladesh is also studied since some surface water sources (e.g., lakes and rivers, except major ones) are not modeled in W3RA. Moreover, since GRACE TWS reflects the summation of all water compartments, for the first time, we use three different scenarios to account for surface water storage changes before data assimilation (see details in Section 3.1). The main reason for using the W3RA model to perform our investigations is to rely on the physical processes implemented in the model equations to consistently separate GRACE TWS (since both model and observation errors are considered) into different water compartments that includes groundwater and soil moisture. As hydrological models are usually better resolved than GRACE data during the assimilation procedure, observations are downscaled, and therefore, higher spatial resolution estimations of water storages will be available within the study region (see, e.g., Schumacher et al., 2016). Here, we use the ensemble-based sequential technique of the Square Root Analysis (SQRA) filtering scheme (Evensen, 2004) to assimilate GRACE TWS into W3RA. SQRA is preferred over the traditional ensemble Kalman filter since it offers a higher computational speed, simplicity, and independence of observation perturbations. Besides, Khaki et al. (2017a) showed that this method is highly capable of assimilating GRACE TWS data into a hydrological model.

After data assimilation, we investigate the connections between the estimated groundwater and soil moisture storages (from improved model) and both surface water level variations and rainfall from multi-mission satellite remote sensing data over Bangladesh. Satellite radar altimetry products of Jason-1 and -2, and Envisat are used in this study to provide 19 virtual river gauge stations for the period 2003 to 2013 distributed across Bangladesh. Since satellite altimetry was initially designed for ocean studies (Fu and Cazenave, 2013), its observations over inland water bodies must be carefully post processed (Birkett, 1998; Calmant et al., 2008; Khaki et al., 2015). Therefore, the Extrema Retracking (ExtR) technique, proposed by Khaki et al. (2014), is applied to retrack satellite waveform data to improve range estimations and consequently derive better water level estimations.

Further, we apply the statistical method of empirical mode decomposition (EMD, Chen et al., 2007) to explore connections between the groundwater and surface water from the model, rainfall data from the Tropical Rainfall Measuring Mission (TRMM), and retracked surface water heights. EMD is an efficient approach to extract cyclic/semi-cyclic components and is preferred over the classical techniques such as the Fourier analysis (Chen et al., 2007; Pietrafesa et al., 2016).

The remainder of this study is organized as follows: in Section 2, the study area, and datasets are presented. Section 3 provides a brief overview of the data assimilation filtering methods, the ExtR retarcking method as well as the EMD approach. Results and discussion are presented in Section 4, and the study is concluded in Section 5.

2. Study Area and Data

2.1. Bangladesh

Bangladesh is located in the Bengal Basin, where the Ganges, Brahmaputra, and the Meghna rivers converge. The average temperature of the country ranges from 17°C to 20.6°C during winter and 26.9°C to 31.1°C during summer (Rajib et al., 2011). Bangladesh is placed in the sub-tropical region with a humid, warm, and tropical climate, which is dominated by a subtropical monsoon originating over the Indian Ocean, which carry warm, moist, and unstable air (Ahmed, 2006; Khandu et al., 2017). An average drought frequency in the country is reported to be equivalent to 2.5 years (Adnan, 1993; Hossain, 1990) when rainfall, as the most important water supply, drops by almost 46% (Dey et al., 2011). The annual precipitation ranges from less than 1500 to ∼5000 mm and varies over different parts of the country, e.g., 1276 mm and 1337 mm in the central and western regions, respectively (see, e.g., Hasan et al., 2013; Islam et al., 2014).

FIGURE 1

2.2. W3RA Hydrological Model

The globally distributed 1°×1° World-Wide Water Resources Assessment system (W3RA) model is used to simulate water storage over Bangladesh. W3RA is a daily grid distributed biophysical model developed in 2008 by the Commonwealth Scientific and Industrial Research Organisation (CSIRO). The model simulates water storage and flows to monitor, represent, and forecast terrestrial water storages (van Dijk, 2010; Renzullo et al., 2014). The meteorological forcing data sets for the model include minimum and maximum temperature, downwelling short-wave radiation, and precipitation from Princeton University (see detail in Sheffield et al., 2006). Effective soil parameters, including water holding capacity, and soil evaporation, related greenness and groundwater recession, and saturated area to catchment characteristics are the model parameters (van Dijk et al., 2013). The model states used in this study include the top, shallow, and deep root soil layers, groundwater storage, and surface water storage in a one-dimensional system (vertical variability). More detailed information on W3RA can be found in van Dijk et al. (2013).

2.3. Remotely Sensed Observations

2.3.1. GRACE

The GRACE level 2 (L2) monthly Stokes' coefficients up to degree and order 90 and their full error information (2003-2013) are obtained from the ITSG-Grace2014 gravity field model (Mayer-Gürr et al., 2014) and used in the data assimilation process. The monthly full error information of the Stokes' coefficients is used to construct an observation error covariance matrix for the GRACE TWS fields (Eicker et al., 2014; Schumacher et al., 2016). Note that different GRACE products from various centers can lead to different results depending on their data processing strategies (Shamsudduha et al., 2017). However, for the sake of data assimilation, in addition to GRACE observations, we also need full error information associated with the observations. Schumacher et al. (2016) and Khaki et al. (2017b) show that it is important to consider GRACE full error covariance matrix to conduct data assimilation experiments. A more comprehensive analysis of different GRACE products has already been performed in a recently published paper of Schumacher et al. (2017). Their results indicate that while using the full covariance matrix in the data assimilation procedure, differences between the GRACE products do not significantly change to affect the final results. Therefore, we only use ITSG-Grace2014 data for which we are sure that the full covariance field is well representative of the GRACE data's error structure.

Degree 1 of Stokes' coefficients are replaced with those estimated by Swenson et al. (2008) to account for the change in the Earth's center of mass. Degree 2 and order 0 (C20) coefficients are replaced by those from Satellite Laser Ranging solutions due to unquantified large uncertainties in this term (e.g., Cheng and Tapley, 2004; Chen et al., 2007). Colored/correlated noises in the L2 products are reduced using the DDK2 smoothing filter following Kusche et al. (2009). This smoothing causes some degree of signal attenuation (Klees et al., 2008) and moving anomalies from outside the region (e.g., Bay of Bengal) (Chen et al., 2007; Khaki et al., 2017d). To mitigate this issue, following Swenson and Wahr (2002), we apply an isotropic kernel using a Lagrange multiplier filter to decrease leakage errors over the entire Bangladesh. This filter uses a basin averaging kernel method expanded in terms of spherical harmonics and subsequently combined with L2 potential coefficients to improve the GRACE estimates (see details in Swenson and

Wahr, 2002). The L2 gravity fields are then converted to 1°×1° TWS fields following Wahr et al. (1998). Note that the GRACE data provide changes in TWS while W3RA produces absolute TWS. Accordingly, the mean TWS for the study period is taken from W3RA and is added to the GRACE TWS change time series to obtain absolute values and make them comparable with model outputs (Zaitchik et al., 2008).

2.3.2. Satellite Radar Altimetry

Satellite radar altimetry data of Jason-1 and -2, i.e., 20-Hz sensor geographic data records (SGDR), and Envisat, i.e., 18-Hz SGDR products are applied in this study. The data includes 260 cycles of Jason-1 covering 2002–2008, 166 cycles of Jason-2 covering 2008–2013, and 113 cycles of Envisat covering 2002–2012. Jason-2 is a follow-on mission of Jason-1 with a similar temporal resolution of ∼9.915 days and the ground cross-track resolution of ∼280 km (over the equator), with the same characteristics as Topex/Poseidon altimetry mission (Benada, 1997; Papa et al., 2010). Jason-1 and-2 data are obtained from the Physical Oceanography Distributed Active Archive Center (PO.DAAC) and AVISO, respectively. Additionally, Envisat RA2 products with a 35 days repeat cycle (30 days for new orbit after October 2010) are derived from ESA (Table 1).

Altimeter ranges should be corrected for atmospheric impacts such as ionospheric, tropospheric, and electromagnetic effects (Benada, 1997). We apply geophysical correction, including solid earth tide, pole tide, and dry tropospheric (Birkett, 1995) to correct the ranges. The ExtR post-processing technique (Khaki et al., 2014) is applied on waveforms to retrack datasets and improve range measurements. The retracked altimetry data are then used to build virtual time series for 19 different points (Figure 1) located on the satellite ground tracks and distributed throughout the study area. At each virtual point, several points belonging to the same satellite cycle are considered, and the median value of the retracked altimetry-based water levels is computed to address the hooking effect (Frappart et al., 2006). While a satellite is passing above a water body, it is locked over a spatially limited part of the water, which can result in an error. The hooking effect results in incorrect range measurements, known as off-nadir measurements (Seyler et al., 2008; Boergens et al., 2016). Afterwards, time series of water level variations from Jason-1 and -2 are combined with those of Envisat products to produce monthly surface levels. Details of the datasets, model, and pass numbers of the altimetry missions used in this study are presented in Table 1.

2.3.3. Precipitation

We use precipitation data of the Tropical Rainfall Measuring Mission Project (TRMM-3B43 products; version 7, TRMM, 2011; Huffman et al., 2012) to assess climate variability over Bangladesh. Incorporating more microwave sounding and imagery records as well as implementing better processing algorithms have caused a large improvement in this version of data (Huffman et al., 2012; Fleming and Awange, 2013). The data sets, validated by Khandu et al. (2017) over the study region showed promising performance. The gridded ($0.25^\circ \times 0.25^\circ$) precipitation products (2003 to 2013) are converted to $1^\circ \times 1^\circ$ and used to investigate their connection to water storage changes.

2.4. Surface Storage Data

For the objective of data assimilation, considering that many surface water sources (in different forms, e.g., lakes and rivers except few major ones) are not modeled in W3RA, surface water storages should be removed from GRACE TWS data. To this end, we use satellite-derived surface water data in the Ganges–Brahmaputra River Basin (as the main source of surface water in Bangladesh) provided by Papa et al. (2015). The data is based on a multi-satellite approach that combines surface water extent from the Global Inundation Extent from Multi-Satellite (GIEMS, Papa et al., 2006, 2010; Prigent et al., 2012) and level height variations of water bodies from Envisat radar altimetry to estimate surface water storage (Frappart et al., 2012) covering the period from 2003 to 2007. Since study period is 2003 to 2013, canonical correlation analysis is applied to extend the data from 2007 to 2013. Satellite derived river height fluctuations of Section 2.3.2 that are distributed across the study area are used in the process of extending the surface water storage of Papa et al. (2015). More details on the canonical correlation analysis are provided in Section 3.4.

2.5. In-situ measurements

To evaluate the performance of data assimilation, in-situ measurements are used. To this end, we use groundwater (198 stations) and soil moisture (12 stations) in-situ measurements of different stations (see Figure 1) provided by the Bangladesh Water Development Board (BWDB) and Institute of Water Modelling (IWM) in The Asian Development Bank (2011). Figure 2 shows the sample products of different groundwater stations, as well as soil moisture variations measured at various depths. Specific yields ranging from 0.01 to 0.2 (Shamsudduha et al., 2011; BWDB, 1994) are used to convert well-water levels to variations in groundwater storage. Details of the datasets used in this study are outlined in Table 1.

FIGURE 2

TABLE 1

3. Method

3.1. Data Assimilation

3.1.1. Filtering Method

The square root analysis (SQRA) scheme for the Ensemble Kalman Filter (EnKF), presented in Evensen (2004) is used to assimilate the GRACE TWS into W3RA. SQRA, which is a deterministic form of ensemble-based Kalman filters uses a statistical sample of state estimates and unlike traditional Kalman filtering method, does not need an observation perturbation (Burgers et al., 1998; Sakov and Oke, 2008; Khaki et al., 2017a). Instead, by introducing a new sampling scheme, SQRA uses unperturbed observations without imposing any additional approximations like uncorrelated measurement errors (Evensen, 2004) . The update stage in SQRA includes two steps starting with updating the ensemble-mean as,

$$\bar{X}^a = \bar{X}^f + K(y - H\bar{X}^f), \quad i = 1 \ldots N, \tag{1}$$

$$K = P^f(H)^T(HP^f(H)^T + R)^{-1}, \tag{2}$$

where 'f' stands for forecast, 'a' for analysis, and N is the ensemble number. $\bar{X}^a$ is the mean analysis state, K represent the Kalman gain, and y is the observation vector. The transition and observation covariance matrices are indicated by H and R, respectively. $\bar{X}^f$, the forecast ensemble mean, and the model state forecast error covariance (P^f) are derived by,

$$\bar{X}^f = \frac{1}{N}\sum_{i=1}^{N}(X_i), \tag{3}$$

$$P^f = \frac{1}{N-1}\sum_{i=1}^{N}({X_i}^f - \bar{X}^f)({X_i}^f - \bar{X}^f)^T. \tag{4}$$

(5)

The model state (X) contains N different vectors of the model state variables. Note that $A^f = [A_1{}^f \dots A_N{}^f]$ is the ensemble of anomalies, the deviation of model state ensembles from the ensemble mean ($A_i{}^f = X_i{}^f - \bar{X}^f$). In the second update step, SQRA computes the ensemble perturbations through.

$$A^a = A^f V \sqrt{I - \Sigma^T \Sigma \Theta^T}, \tag{6}$$

where Σ and V are result from singular value decomposition of A^f ($A^f = U \Sigma V^T$). Γ refers to the singular value decomposition and Θ is a random orthogonal matrix (e.g., the right singular vectors from a singular value decomposition of a random $N \times N$ matrix) for ensemble redistribution of the variance reduction (cf. Evensen, 2004, 2007; Khaki et al., 2017a).

3.1.2. Assimilation of GRACE data

To assimilate GRACE TWS into the model, we use a summation of model's vertical water compartments (e.g., soil moisture, groundwater, and surface water) at 13 grid points. This summation is then updated by the GRACE TWS at the same location at every assimilation step (whenever a new observation is available). Initial ensemble members are generated by perturbing the meteorological forcing fields following Renzullo et al. (2014). In this regard, the three most important forcing variables; precipitation, temperature, and radiation are perturbed using Monte Carlo sampling of multivariate normal distribution (with the errors representing the standard deviations) to produce an ensemble (with 72 members as suggested by Oke et al., 2008). The perturbed meteorological forcing datasets are then integrated forward with the model from 2000 to 2003 to provide a set of state vectors at the beginning of the study period.

Two widely used tuning techniques of ensemble inflation and localization are applied to enhance the assimilation performance especially when a limited ensemble size is assumed. Ensemble inflation uses a small coefficient (i.e., 1.12 in our study; Anderson et al., 2001) to inflate prior ensemble deviation from the ensemble-mean to increase their variations and alleviate the inbreeding problem (Anderson et al., 2007). For localization, the Local Analysis (LA) scheme (Evensen, 2003; Ott et al., 2004; Khaki et al., 2017b) is applied. LA restricts the impact of a given measurement in the update step to the points located within a certain distance (3° following Khaki et al., 2017b) from the measurement location. We also implement three different cases to deal with surface water storage during data assimilation.

- Case 1: Assimilating the GRACE TWS data after removing surface storages into the model states except for the surface water compartment.

- Case 2: Adding surface water storage to model surface water compartment and using the GRACE TWS to update the summations of all water compartments.
- Case 3: Assimilating the GRACE TWS to update the summations of all water compartments (including surface water compartment).

In Section 4.1, the results of all the case scenarios are compared with each other and evaluated against in-situ groundwater measurements.

3.2. Empirical Mode Decomposition (EMD)

The empirical mode decomposition (EMD) proposed by Chen et al. (2007) is used for analyzing multivariate datasets of this study. EMD establishes different frequencies and trends within time series, which are called Intrinsic Mode Functions (IMFs), by considering local oscillations (Rilling et al., 2003; Flandrin et al., 2004). The idea is that a signal is composed of fast oscillations superimposed by slow oscillations (Flandrin et al., 2004). Thus, EMD decomposes any complicated data set into a finite and often small number of IMFs hidden in the observations (Huang et al., 1998). We apply EMD on all available time series of this study to extract different frequencies and also to find local trends for a better understanding of their interrelationships.

3.3. Retracking Scheme

In this study, we use the retracking method to improve altimetry estimations of river height variations. The retracking process is essential since complex waveform patterns are usually observed over rivers. To this end, Extrema Retracking (ExtR) post-processing technique (Khaki et al., 2014, 2015) is used. The ExtR is a three step filter that starts by applying a moving average filter to reduce the random noise of the waveforms. It then identifies extremum points of the filtered waveforms, and finally, extracts the main leading edge amongst the established extremum points. The method is applied to process different types of waveforms and improve level estimations as demonstrated in Khaki et al. (2014, 2015). The filter is employed here to retrack satellite radar altimetry data for extracting surface storage from TWS (in Section 3.4).Figure 12 shows river level fluctuations for different parts of Bangladesh (Figure 3a) and the entire area of the country (Figure 3b).

FIGURE 3

3.4. Canonical Correlation Analysis (CCA)

Canonical correlation analysis (CCA) seeks to find the linear relationship between two sets of multidimensional variables x and y. The process extracts canonical coefficients u and v such that $X = x^T u$ and $Y = y^T v$ (X and Y are canonical variates) possess a maximum correlation coefficient (Chang et al., 2013) using the following function,

$$
\begin{aligned}
P &= \frac{E[XY]}{sqrt(E[X^2]E[Y^2])} \\
&= \frac{E[u^T x y^T v]}{sqrt(E[u^T x x^T u]E[v^T y y^T v])} \\
&= \frac{u^T C_{xy} v}{sqrt(u^T C_{xx} u v^T C_{yy} v])},
\end{aligned}
\tag{7}
$$

where C_{xx} and C_{yy} are covariance matrices of x and y respectively and the objective in above function is to maximize the correlation P. Once the coefficients are calculated, they can be used to find the projection of x and y onto u and v as canonical variates with maximum correlation. Here, x contains the vectors of surface water storages from Papa et al. (2015) at each grid point and y includes river heights variations from satellite radar altimetry in a same temporal scale as the former data (2003 to 2007). After performing canonical correlation analysis, the computed canonical coefficient of u and v, and a new set of variables y (from 2007 to 2013) are used to estimate the canonical variate of x. The combination of surface water storages (x) using the extracted u from the first part has the maximum correlation to the altimetry-derived river heights variability. Hence, this coefficient vector can be used to transform river heights into surface waters at each grid point.

4. Results

4.1. Data Assimilation

Before discussing groundwater and soil moisture variations within Bangladesh, the effect of data assimilation on terrestrial water storage time series and its capability to improve model simulations are investigated. Figure 4 shows average TWS time series over Bangladesh before (model-free run) and after data assimilation. The figure also contains GRACE TWS time series. It can be seen that data assimilation largely reduces misfits between model-free run and observations by incorporating GRACE TWS into the states.

FIGURE 4

To assess whether data assimilation (e.g., in Figure 4) can result in better water storage estimates, in-situ groundwater and soil moisture measurements are used for validation. Time series of groundwater and soil moisture anomalies are generated for each station. Groundwater and soil moisture results from all the three assimilation cases (cf. Section 3.1.2) are spatially interpolated using the nearest neighbour (the closest four data values) to the location of the in-situ measurements. This is also done for outputs of the WaterGAP Global Hydrology Model (WGHM; more details on Döll et al., 2003; Müller et al., 2014), as well as estimated storages by van Dijk et al. (2014), indicated here by W3, who merged GRACE observations with a hydrological multi-model ensemble. The comparison between these products and data assimilation results allows us to better investigate any achieved improvements. For this purpose, the RMSE and correlations between in-situ and estimated time series are calculated.

Table 2 summarizes the average RMSE and correlation for each of the three data assimilation case. From Table 2, it can be seen that the groundwater results are more correlated to in-situ measurements after the application of every assimilation case (0.81 on average), 0.39 larger than model simulations without applying data assimilation (model-free run). An average RMSE improvement of 51.16% (at 0.95 confidence level) in case 1 shows a significant influence of the data assimilation scheme, approximately 4.44% and 39.11% larger than cases 2 and 3, respectively. It is also evident from Table 2 that data assimilation results, especially cases 1 and 2 outperform groundwater estimates of WGHM. Note that the provided W3 does not include groundwater and therefore we use it for soil moisture comparison only. Table 2 emphasizes that model groundwater estimations can be successfully improved with respect to the in-situ measurements if they are fine tuned by GRACE data through the assimilation especially for cases 1 and 2.

TABLE 2

Furthermore, correlation analysis is carried out between in-situ soil moisture measurements at various depths and data assimilation results from different scenarios, as well as soil moisture estimates of WGHM and W3 (Table 3). In-situ measurements at different depths are compared with different layers from data assimilation results. For this purpose, in-situ soil moisture time series of 0–10 cm, 0–30 cm, and 0–50 cm depths are compared to the model top, shallow, and deep soil moisture layers. While the model soil moisture of top layer corresponds to the thickness between 5 and 10 cm, the model shallow and deep-root soil layers broadly represent 10–21 cm and 3–6 m soil thicknesses (see also Renzullo et al., 2014; Tian et al., 2017). Here, we compare W3RA's top layer estimations with in-situ of 0–10 cm, top layer plus shallow-root simulations with in-situ of 0–20 cm, and summation of the top, shallow, and a portion of deep-root soil layers with 0–50 cm in-situ measurements. Note that WGHM and W3 outputs are provided at a single aggregated layer and correspondingly are compared with in-situ soil time series at the depth 0–50 cm. Table 3 shows that the highest correlation improvements, 18.31% (on average) for all layers and 25.25% for the deep layer. Case 2 also represents considerable improvements slightly smaller than case 1, still 11.57% larger than case 3, 6.97% larger than WGHM, and 9.25% larger than W3. Both Table 2 and Table 3 demonstrate a high capability of data assimilation in improving model simulations of different compartments. These tables also indicate a better performance of the implemented data assimilation, specifically cases 1 and 2, compared to WGHM and W3.

TABLE 3

To better analyze the differences between each assimilation case, we compare their RMSE during 2007. In 2007, a major flooding (following ENSO rains) occurred across South Asia affecting Bangladesh (Gaiha et al., 2010). This phenomenon can help us to monitor performances of each case in such an extreme situation and their ability to distribute observed TWS between all water compartments. Groundwater estimates from each case and in-situ measurements are used to calculate RMSE for each assimilation case (Figure 5), where the least errors are estimated by cases 1 and 2. Assimilating the GRACE TWS without considering surface water storage within the area (case 3) causes larger errors especially in April and September. The largest error, however, is obtained for the model-free run. Hereafter, we use the result of data assimilation for case 1 since it performed slightly better than case 2 and significantly better than case 3 in terms of the RMSE (see Figure 5).

FIGURE 5

The model's water storage variations computed by assimilating GRACE TWS data into

W3RA are presented in Figures 6 and 7. Temporal averages of soil moisture and groundwater storage variations for each grid point from data assimilation, WGHM, and W3 in the study area are displayed in Figures 6 and 7, respectively. We find large correlations between assimilation results and WGHM (0.76 on average for soil moisture and 0.82 on average for groundwater) and W3 (0.71 on average for soil moisture) outputs. The results show more negative groundwater variations within different parts of Bangladesh than soil water storage variations (see Figure 6). Both water compartments indicate larger signals (in terms of amplitude) in the central and northwestern parts of Bangladesh. A positive soil moisture variations are found in the centre toward east and north within the study period, especially for the assimilation and WGHM maps. Larger groundwater variations are also captured in the same area. While assimilation results show negative groundwater changes over the central, eastern, and to a lesser degree southern parts, WGHM only indicates negative variations in the southern and eastern parts. Figure 7 indicate that smaller water storage variations in the northwestern and northeastern parts of Bangladesh during 2003–2013.

FIGURE 6

FIGURE 7

The average time series of soil moisture and groundwater storages from data assimilation are shown in Figures 8a Figure 8b, respectively. We estimate spatial averages for all the time series at grid points for this figure. Figure 8a shows slight declines in the soil water storage after 2007, which can be related to variations of surface water storage in the same period. The correlation between the surface water storage and soil moisture time series (after removing seasonal effects) is found to be 0.92 (for a 95% confidence interval), 34% higher than the correlation between groundwater and soil moisture. This indicates that a stronger connection exists between the surface water storage and soil moisture over the area. Annual variations of groundwater storages, however, show a larger decline in comparison to soil moisture storage variations, especially between 2008 and 2012. A significant decrease in groundwater storage is seen in Figure 8b with an average rate of 8.73 ± 2.45 mm/year, showing an overall $\sim$46% reduction. The decline in water availability can be due to over-extraction of groundwater resources since such a decrease is not seen in precipitation (see Section 4.2 for more details).

FIGURE 8

4.2. Statistical Analyses

First, the precipitation and TWS over Bangladesh is analyzed. To explore the climate variability and its relationship with water storages, precipitation will be compared to the data assimilation results. Principal component analysis (PCA Lorenz, 1956) is applied on GRACE TWS and precipitation time series at each grid point to explore their spatio-temporal variations. The first three most dominant empirical orthogonal functions (EOF1, EOF2, EOF3) for each variable are presented in Figure 9. The spatial distribution of precipitation within Bangladesh indicates larger rainfall in south-eastern parts. TWS distribution in EOF2 follows the same pattern. A large water storages are captured by EOF3 in the northwest. More information can be extracted from precipitation and TWS time series. The first three principal components (PC1, PC2, and PC3) of each data set are shown in Figure 10. Large precipitation impacts are found in 2003 and 2007. A negative anomaly in rainfall is found in 2010 and 2012, as well as in the period between 2005 and 2007 (PC1). TWS time series demonstrate declines between 2005 and 2007, and particularly after 2009 following a drop event (Mondol et al., 2017). Results, however, show an increase in 2007 in agreement with ENSO rainfall. The overall average of TWS variations during the study period is negative ($\sim$11.48$\pm$3.19 mm/year) for the entire country. A similar trend, however, is not observed in precipitation even though there is a shorter period negative decline in 2005 and after 2010. Figure 10 illustrates that although in some cases a variation in precipitation results in a changes in TWS, continuous TWS reduction possibly has different explanations that could become clear through the separation of the groundwater and surface water storages (cf. Section 3.4).

FIGURE 9

FIGURE 10

Details on surface and groundwater storage variations and their relationship to precipitation and rivers' level heights are presented in Table 4. For each grid point in the study area, we calculate water storage variation rates and depletions, and also a correlation coefficient between their time series and both precipitation and river height variations. Note that we use lagcorrelation (cross correlation) to achieve the maximum correlation between each two time series. Table 4 illustrates that there is a water decline in both surface and groundwater storages at different rates. This can be inferred from the negative storage variation rates. An approximately 32% depletion in groundwater storage causes a significant decrease in TWS as shown in Figure 10. This remarkable water reduction, unlike the rainfall pattern, is highly related to excessive groundwater usages, especially for irrigation. It can be concluded from Table 4, therefore, that groundwater storages are less correlated (16.5%) to river height variations and precipitation, respectively, in comparison to surface water storage. Consequently, variations in rainfalls and river heights are more reflected in surface storage variations.

TABLE 4

To better analyze groundwater storage changes, we apply empirical mode decomposition (EMD) on time series in each grid point. EMD is used to extract Intrinsic Mode Functions (IMFs) of time series that are found to be most representative of the initial signals. The relationships between the groundwater IMFs and those of precipitation, TWS, and surface river fluctuations are shown in Figure 11, which contains scatter bi-plots and the interpolated line representing the correspondence between two variables. The trend lines in the sub-figures show that the computed IMFs for the different variables are close to each other. The concentration of distributed points after applying EMD is more symmetric than for the initial time series especially for the groundwater and TWS, as well as the groundwater and water level variations. Table 5 contains the average correlation between the time series of groundwater and the variables of precipitation, TWS, and river height variation. The more symmetric distributed points in between the groundwater IMF and that of GRACE TWS shows the greater relationship between these two variables corresponding to a higher correlation presented in Table 5. The reason for this can be due to the use of GRACE TWS in data assimilation. A higher correlation is also obtained between the IMF of groundwater and those of river height. The least relationship is obtained for the groundwater IMF and precipitation, that implies the different pattern in variations of these two variables, which could be related to the non-climatic effects in the groundwater.

FIGURE 11

TABLE 5

The extracted first two IMFs for the groundwater time series are illustrated in Figure 12. In the both subfigures, a decline in groundwater storages is observed. Such a trend, however, is more significant for IMF 2. We also plot the first and second precipitation's IMFs for comparison. The precipitation's IMF 1 in Figure 12, better indicates rainfall variation from Figure 10. Two periods with larger rainfall can be seen for the years 2006 and 2009. A decrease in rainfall over Bangladesh is found from 2010 onwards, with smaller amplitudes during 2010 and 2012. This may impact the groundwater levels during similar temporal periods. There are several similar patterns in both time series (groundwater and precipitation) especially for IMF 1. Both groundwater and precipitation IMFs increase during 2006 and mid-2008 to mid-2009. Figure 12b, presenting IMF 2 time series of assimilated groundwater, clearly shows the groundwater depletion despite having minimum changes in precipitations. This suggests that other factors (e.g., human impacts) affect groundwater storages in Bangladesh.

FIGURE 12

5. Conclusion

Terrestrial waters, as an essential factor for both human life and environment, can be affected by climate changes, especially over the south Asian areas. Bangladesh, in particular, is a highly vulnerable region in facing climate changes suffering from serious water issues, especially for irrigation. In this study, we analyze groundwater variations within Bangladesh using multi-mission satellite measurements, as well as by running a hydrological model during 2003 to 2013. The the Gravity Recovery And Climate Experiment (GRACE) terrestrial water storage (TWS) data after removing surface water storages is assimilated into W3RA model using the ensemble-based sequential technique of the Square Root Analysis (SQRA) filter. This is done to improve the World-Wide Water Resources Assessment system (W3RA) simulations of groundwater, as well as soil water storages. We also apply the empirical mode decomposition (EMD) on water storages, precipitation, and altimetry-derived rivers level variations time series to explore the relationship between them in the area. The larger correlation is found between river level heights and rainfalls (78% average) in comparison to groundwater storage variations and rainfalls (57% average). The considerable difference between correlation coefficients indicates a different impact of rainfall on surface and groundwater variations, which could imply influences of groundwater depletion by population (especially for excessive irrigations) across the country. The results show an approximately 26%, groundwater depletion with a remarkable influence on a total water stored in the area. A significant decline in groundwater storage (∼32% reduction over the study period) over the country is found by the assimilation results with an average rate of 8.73 mm/year. In the absence of any considerable decrease in precipitation over the region, a remarkable groundwater reduction is observed from the first and second Intrinsic Mode Functions (IMFs), which can be referred to human impacts. High spatio-temporal resolution remote sensing products along with the data assimilation methodology show a high capability for studying water storages in Bangladesh. Developing Earth observation missions dedicated to hydrology (GRACE follow-on and SWOT) can be very important to pursue and improve such modeling and assimilation studies.

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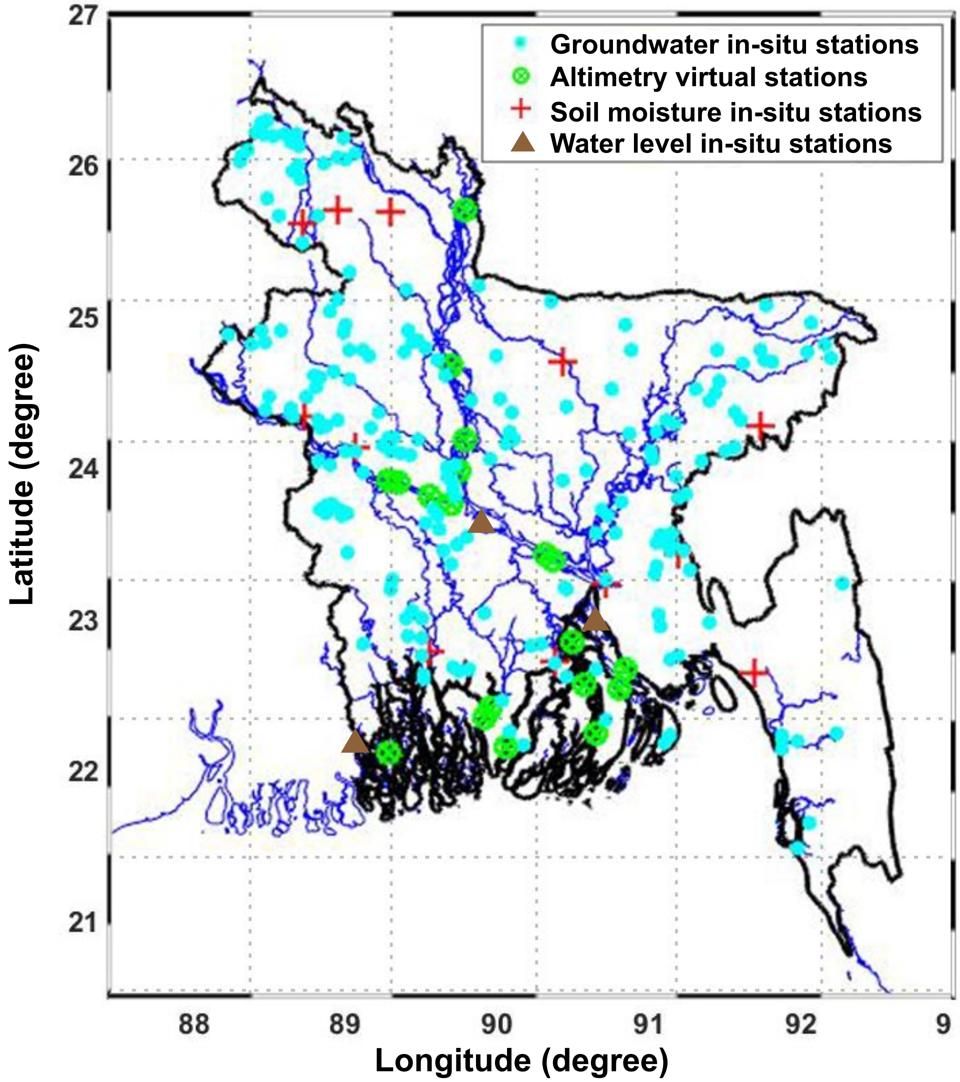

Figure 1: The study area is represented by black solid line. The figure also contains the locations of virtual stations for satellite altimetry time series and various in-situ stations.

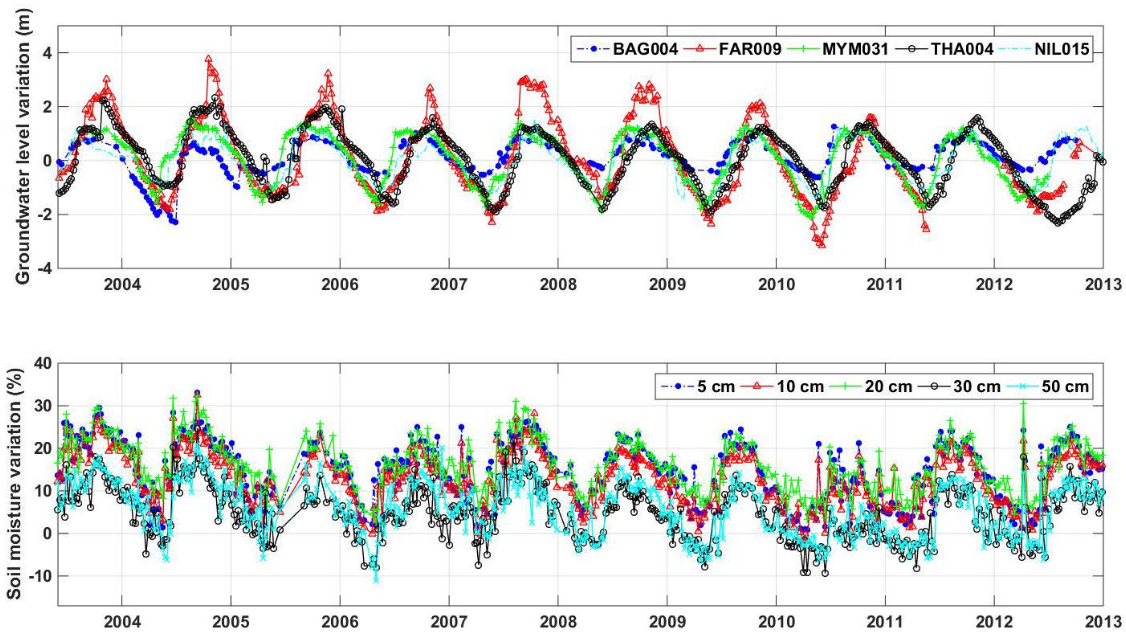

Figure 2: (a): In-situ groundwater level variations of various stations. (b): Soil moisture variations at deferent depths belong to Rajshahi in-situ station.

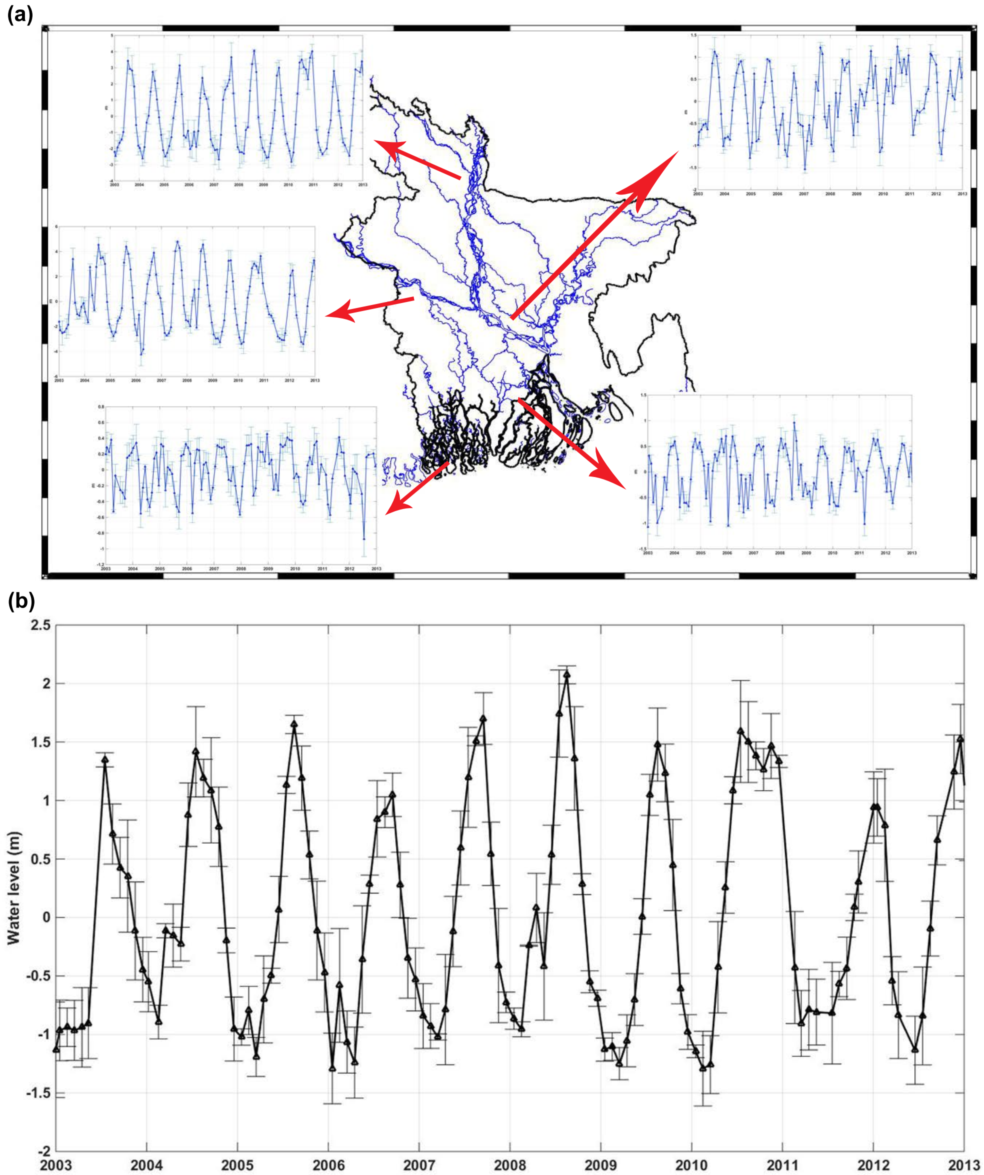

Figure 3: Average river height variation time series from satellite radar altimetry for different parts (a) and for the entire area (b) of Bangladesh. The average error for each measurement is presented as error bars.

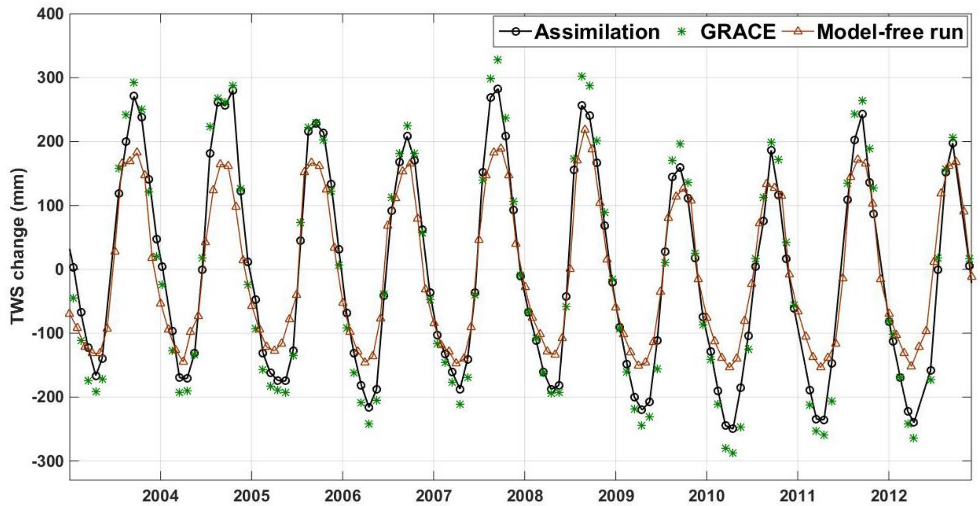

Figure 4: Average TWS change time series from data assimilation (case 1), model-free run, and GRACE.

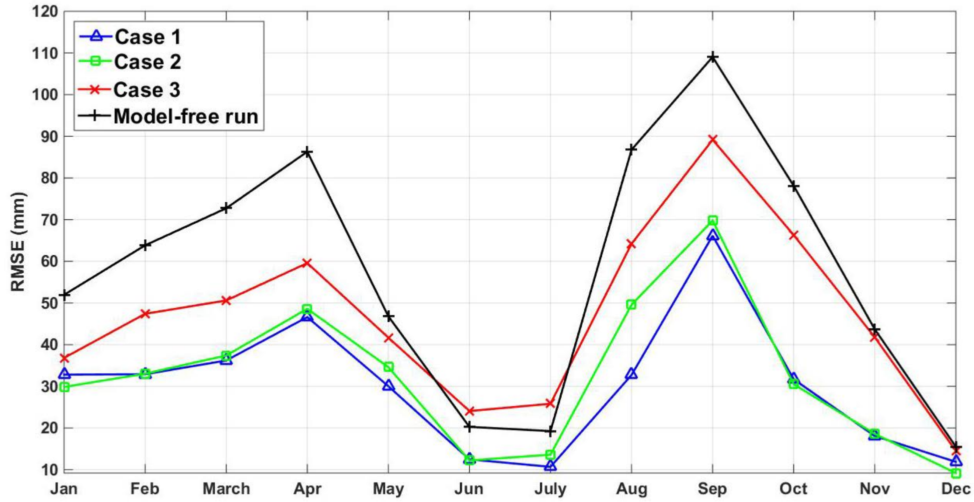

Figure 5: Comparison between RMSE achieved from implementing each data assimilation scenario as well as model-free run during 2007. In case 1, surface storages is removed from GRACE TWS, in case 2, surface storages is added to W3RA surface water, and case 3 refers to the data assimilation with no surface storage correction.

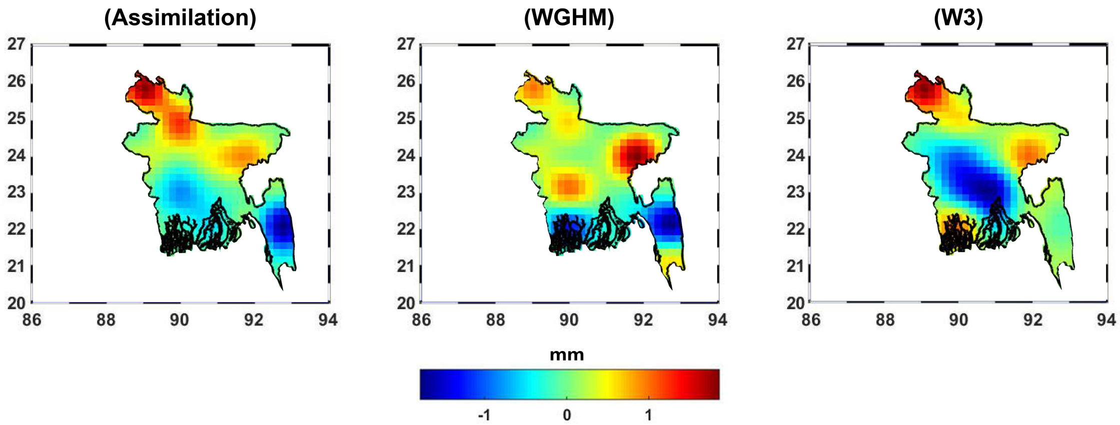

Figure 6: Spatial distribution of average soil water storage variations from data assimilation, WGHM, and W3.

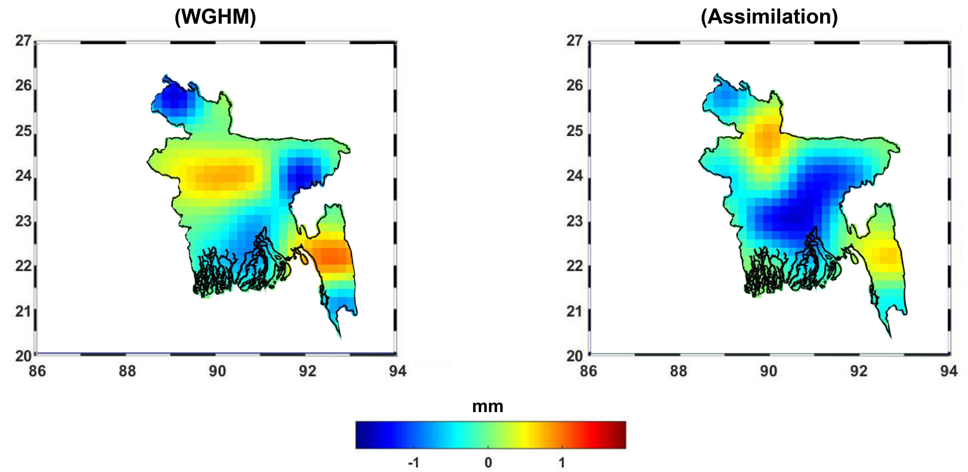

Figure 7: Spatial distribution of average groundwater storage variations from data assimilation and WGHM.

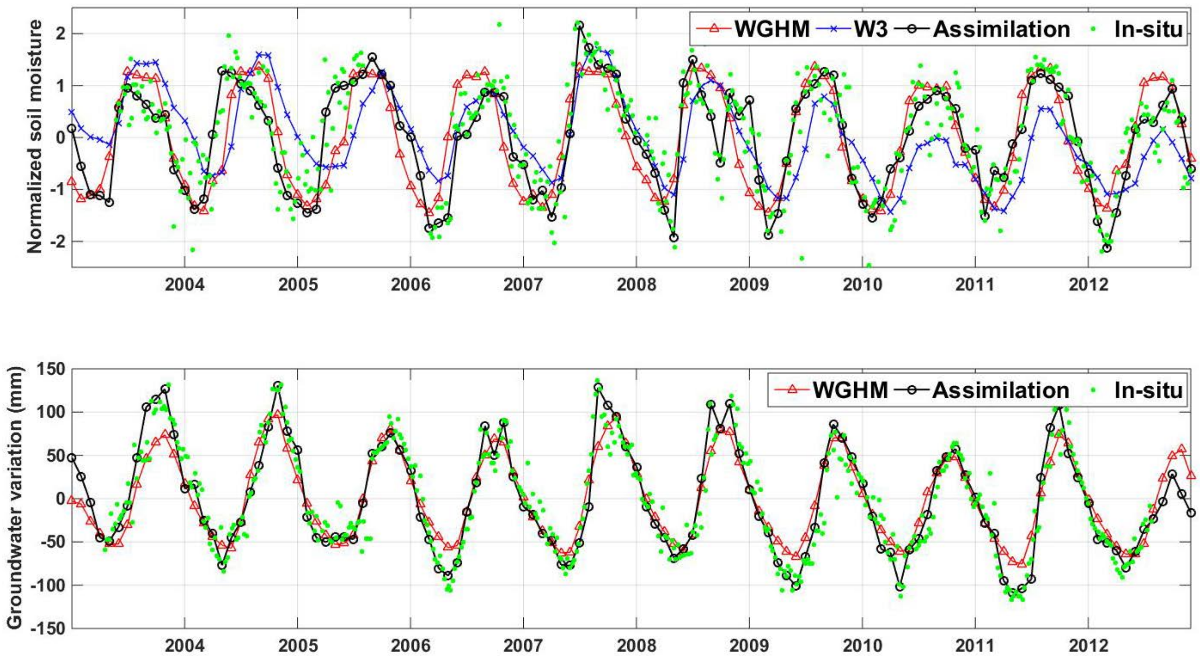

Figure 8: Average soil moisture storage (a) and groundwater storage (b) time series from assimilation, WGHM, W3, and in-situ measurements.

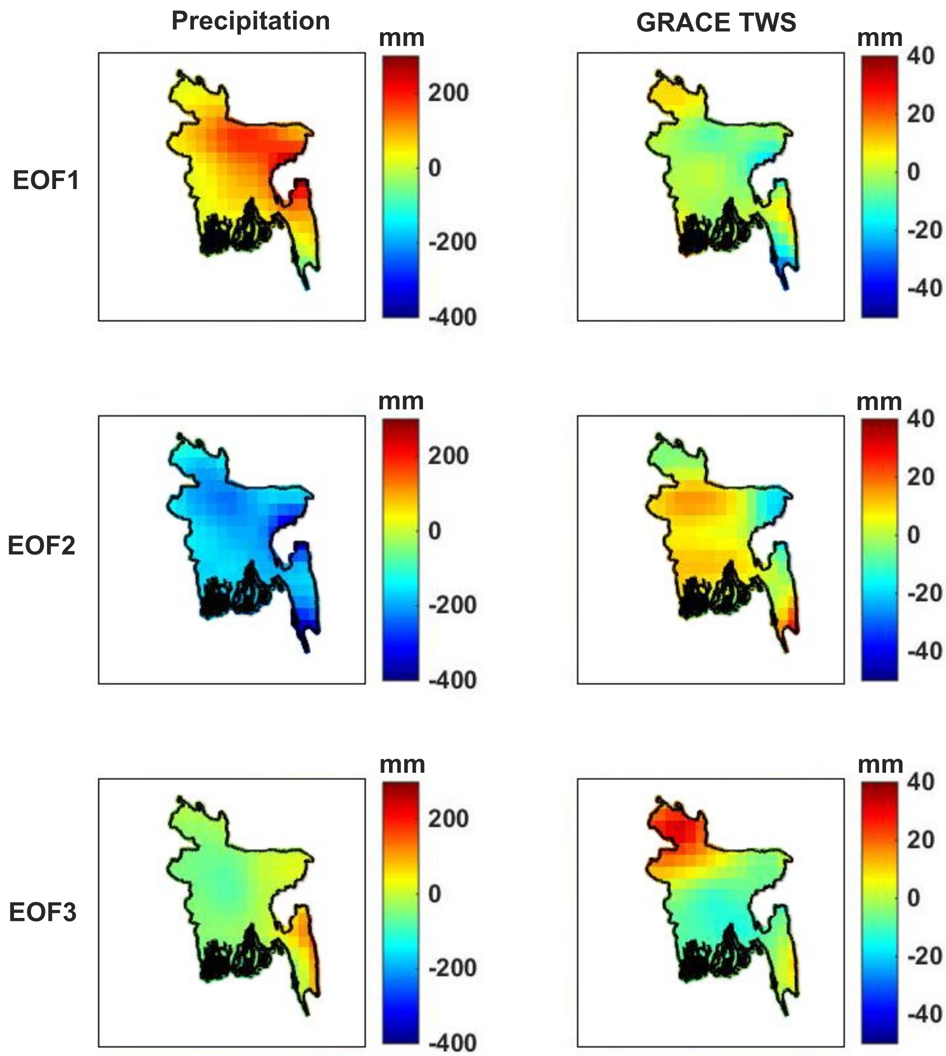

Figure 9: Spatial distribution of of EOF1, EOF2, and EOF3 from applying PCA on precipitation and GRACE TWS.

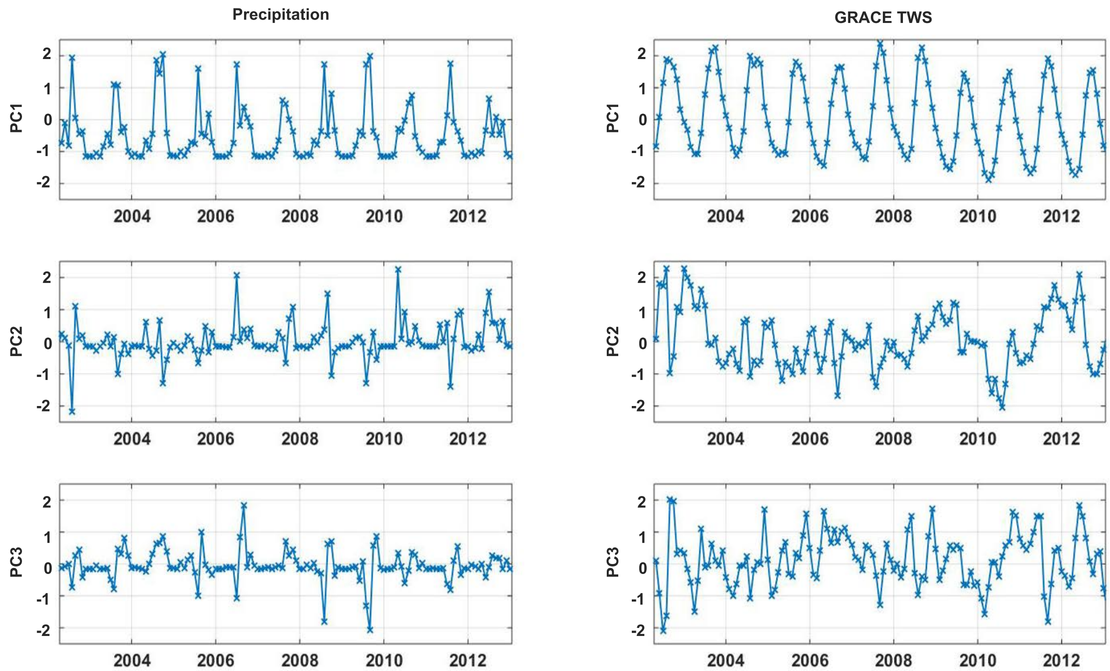

Figure 10: The first three principal components from applying PCA on precipitation and GRACE TWS.

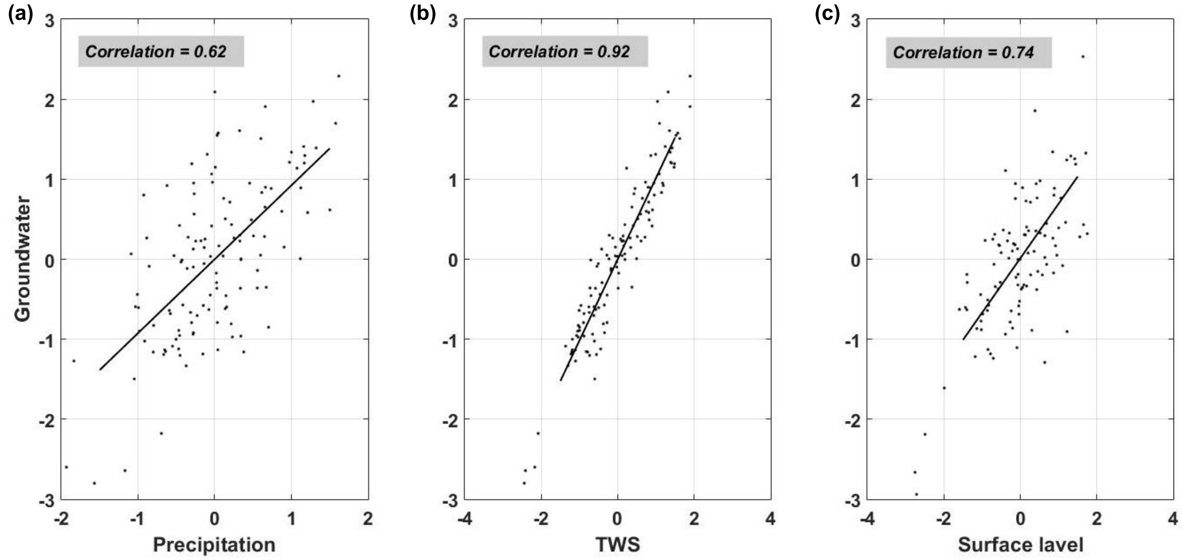

Figure 11: Relationships between normalized Intrinsic Mode Functions (IMF) time series of groundwater and precipitation, TWS, and surface river height.

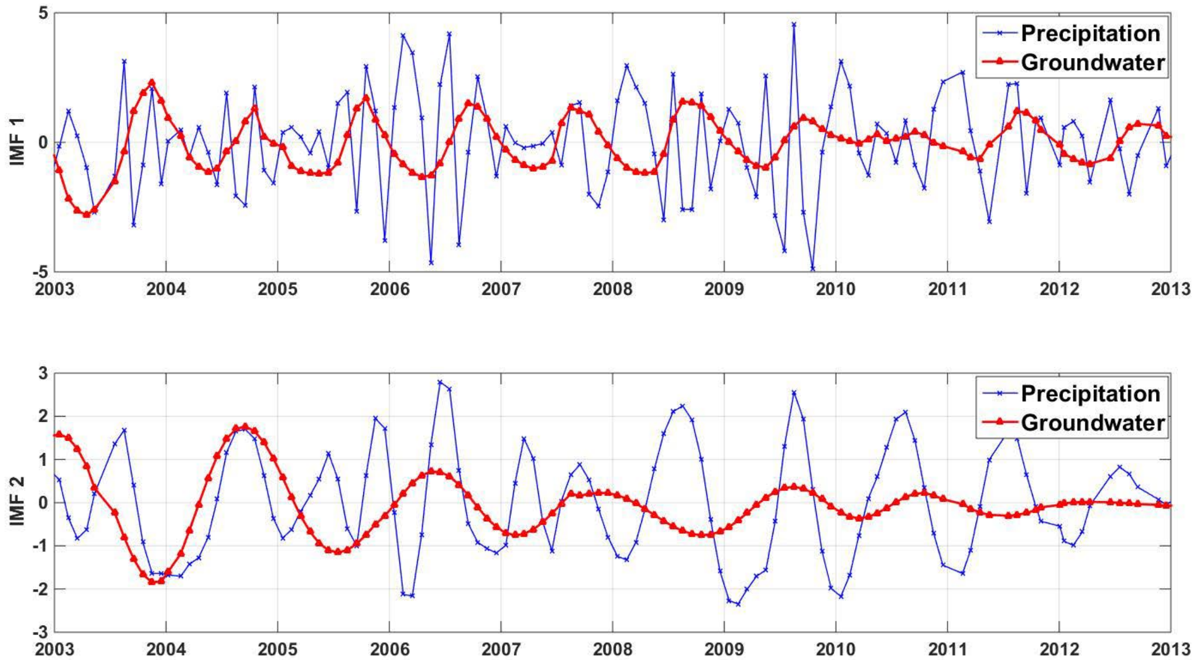

Figure 12: The first and second extracted Intrinsic Mode Functions (IMF) time series of the groundwater storage (red) and precipitation (blue).

Table 1: A summary of the datasets used in this study.

Description	Platform	Detail	Data access
Terrestrial water storage (TWS)	GRACE	GRACE level 2 (L2)	https://www.tugraz.at/institute/ifg/downloads/gravity-field-models/itsg-grace2014/
Altimetry-derived level height	Jason-1	Pass numbers 90 and 231	http://podaac.jpl.nasa.gov
	Jason-2	Pass numbers 90 and 231	http://avisoftp.cnes.fr/
	Envisat	Pass numbers 337, 438, 795, 896, and 982	http://envisat.esa.int/dataproducts/ra2-mwr/
Precipitation	TRMM-3B42	Daily accumulated precipitation	http://disc2.gesdisc.eosdis.nasa.gov/data/TRMM_L3/TRMM_3B42_Daily.7
Hydrological model	W3RA	The Commonwealth Scientific and Industrial Research Organisation (CSIRO)	http://www.wenfo.org/wald/data-software/
Surface water storage		Satellite-derived surface water storage in the GangesBrahmaputra River Basin	Papa et al. (2015)
In-situ measurements	BWDB	http://www.ffwc.gov.bd/	

Table 2: Statistics of groundwater errors. For each case, the RMSE average and its range (±XX) at the 95% confidence interval is presented. Improvements in data assimilation results are calculated with respect to the groundwater storages from the model without implementing data assimilation.

			Improvement (%)	
Assimilation scenario	**Correlation**	**RMSE (mm)**	**Correlation**	**RMSE (mm)**
Case 1 [Removed surface storages from GRACE TWS]	0.86	35±5.65	51.16	57.36
Case 2 [Added surface storages to W3RA surface water]	0.82	39±5.18	48.78	52.92
Case 3 [No surface storage correction applied]	0.75	68±7.72	44.02	18.25
WGHM	0.79	57±5.37	46.83	30.89
Mode-free run	0.42	83±9.29	–	–

Table 3: Average correlations improvements (at 95% confidence interval) between in-situ and soil moisture estimates with respect to model-free run.

Filter	**0-10 cm**	**0-20 cm**	**0-50 cm**
Case 1	10.42	19.27	25.25
Case 2	11.10	17.88	24.48
Case 3	5.25	8.34	12.91
WGHM	–	–	17.51
W3	–	–	15.23

Table 4: Statistics of water storage variations.

		Depletion (%)			**Correlation (95% confidence interval)**	
Water storage	**Variation rate (mm/year)**	**Min**	**Max**	**Mean**	**Precipitation**	**Water level height**
Surface water	-1.54	0	38	11	0.74	0.81
Groundwater	-8.73	12	41	32	0.59	0.63

Table 5: Groundwater storage correlation to precipitation, TWS, and river level height variations.

	Precipitation	**GRACE TWS**	**River level height**
Before EMD	0.57	0.73	0.63
After EMD	0.71	0.88	0.77
Improvement(%)	12	15	14