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Reconstructing annual groundwater storage changes in a large-scale irrigation region using GRACE data and Budyko model

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ABSTRACT

A two-parameter annual water balance model was developed for reconstructing annual terrestrial water storage change (ΔTWS) and groundwater storage change (ΔGWS). The model was integrated with the Gravity Recovery and Climate Experiment (GRACE) data and applied to the Punjab province in Pakistan for reconstructing ΔTWS and ΔGWS during 1980–2015 based on multiple input data sources. Model parameters were estimated through minimizing the root-mean-square error between the Budyko-modeled and GRACE-derived ΔTWS during 2003–2015. The correlation of ensemble means between Budyko-modeled and GRACE-derived ΔTWS is 0.68 with p-value <0.05. The ΔGWS was reconstructed by subtracting soil moisture storage change from the Budyko-modeled ΔTWS and was validated (i.e., $r = 0.74$, p-value < 0.05) against well observations during the pre-GRACE period (i.e., 1985–1994). The negative values of the cumulative sum of the reconstructed ΔGWS during 1980–2015 (i.e., -13.6 ± 9.7 cm) indicate that the aquifer in Punjab has experienced depletion. The estimated depletion rate is -0.3 ± 0.2 cm/year and it has a negative correlation (i.e., $r = -0.70$, p-value < 0.0001) with the total number of tube wells installed in Punjab. The integration of the developed Budyko model with GRACE data provides a new way for evaluating long-term groundwater depletion in large-scale irrigation regions with parsimonious models.

1. Introduction

Groundwater is the largest unfrozen freshwater source on Earth (Aeschbach-Hertig and Gleeson, 2012), and it is more widely accessible and less vulnerable to droughts than surface water (Foster and Chilton, 2003; Schwartz and Ibaraki, 2011). Approximately 37% of irrigated land area in the world depends on groundwater, and irrigation accounts for 56% of total groundwater withdrawal globally (Jury and Vaux, 2005; Siebert et al., 2010; Margat and Gun, 2013). The worldwide 'explosion' of groundwater exploitation has been instrumental for ensuring food supplies (Giordano, 2009), but led to severe groundwater depletion in many regions across the globe (Hanasaki et al., 2008). Groundwater depletion threatens the sustainability of food production in the long term and deteriorates groundwater-dependent ecosystems (Konikow and Kendy, 2005; Gleeson et al., 2010). Recently, efforts have been made to analyze this issue by incorporating irrigation into land surface models (Leng et al., 2014, 2015; Pokhrel et al., 2016).

The Gravity Recovery and Climate Experiment (GRACE) satellite mission, which was launched in 2002, provides an unprecedented opportunity to measure terrestrial water storage change (ΔTWS) and estimate groundwater storage change (ΔGWS) at large scale (i.e., area >200,000 km^2). The TWS information can be derived from the observed gravity field (Wahr et al., 1998; Swenson and Wahr, 2002; Jacob et al., 2012). The TWS variation captured by GRACE represents the vertical integration of changes in groundwater, soil moisture, surface water, snow, ice, and biomass (Tapley et al., 2004). Under certain circumstances, anthropogenic activities (e.g., mining, water diversion, and reservoir regulation) can alter land mass distribution in such a significant way that the resulted land mass re-distribution can be discerned by GRACE satellites (Tang et al., 2013). GRACE estimates are biased due to measurement noise, aliasing effects, and coarse spatial resolution (Wahr et al., 1998; Swenson and Wahr, 2002, 2006). The bias is corrected through spatial smoothing (Han et al., 2005). A leakage error is introduced during the spatial smoothing procedure which leads

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to the amplitude damping from mass variations inside and outside the basin (Klees et al., 2007; Longuevergne et al., 2010). A scaling factor is applied to restore the power attenuated by leakage error (Swenson and Wahr, 2002; Chen et al., 2007; Zhao et al., 2016). Several studies have shown that the GRACE-derived groundwater storage changes match ground-based observations (e.g., Yeh et al., 2006; Strassberg et al., 2009; Shamsudduha et al., 2012; Feng et al., 2013).

GRACE-derived data have been used to assess groundwater depletion in extensively irrigated regions around the world (Rodell et al., 2009; Panda and Wahr, 2016). Particularly, GRACE-based TWS anomalies have been integrated with regional groundwater and surface water models to estimate groundwater storage changes (Döll et al., 2014; Wada et al., 2014; Pokhrel et al., 2015) and quantify hydrologic responses to droughts and anthropogenic activities (Scanlon et al., 2012; Sun et al., 2012; Niu et al., 2014; Castle et al., 2014; Huang et al., 2015; Humphrey et al., 2016). However, the required intensive model development and computational burden of integrating GRACE-based TWS anomalies with sophisticated hydrologic models limits the opportunities of broader applications of reconstructing and predicting the long-term groundwater storage changes using GRACE-derived information. Therefore, parsimonious annual water balance models that can take advantage of GRACE data are practically needed to reconstruct groundwater storage changes for those large-scale irrigation region facing groundwater sustainability challenges.

When TWS change is negligible over a long period of time for river basins under natural condition, mean annual precipitation ($\bar{P}$) is partitioned into mean annual evapotranspiration ($\bar{E}$) and runoff ($\bar{Q}$). This partitioning can be described by a parsimonious water balance model (i.e. Budyko equation), $\bar{E}/\bar{P} = f(\overline{E_p}/\bar{P})$, where $\overline{E_p}$ refers to mean annual potential evapotranspiration (Mezentsev, 1955; Budyko, 1958; Pike, 1964; Fu, 1981; Choudhury, 1999; Zhang et al., 2001; Donohue et al., 2007; Yang et al., 2008; Wang and Tang, 2014). As a function of catchment size (Liu et al., 2016), the interannual water storage changes can be significant in semi-arid and arid basins (Wang and Alimohammadi, 2012), or in basins with intensive anthropogenic activities (Du et al., 2016). When annual ΔTWS is not negligible, the amount of water available for competition between evapotranspiration (E) and runoff (Q) is the difference between precipitation (P) and ΔTWS, which is defined as effective precipitation, i.e., $P_e = P - \Delta TWS$ (Wang, 2012). Precipitation in the Budyko equation is then replaced by P_e (Chen et al., 2013). Therefore, ΔTWS can be incorporated into a Budyko-type equation, leading to a parsimonious model for estimation of long-term ΔTWS.

The objectives of this paper are to: 1) integrate the GRACE data with a parsimonious Budyko model to reconstruct the long-term time series of ΔTWS and ΔGWS for the Punjab province of Pakistan; and 2) quantify the groundwater depletion in the study area based on the reconstructed ΔGWS. The remaining of the paper is organized as follows. Section 2 introduces the study area and data sources. Section 3 describes the methodology including the annual Budyko model, parameters estimation, and the reconstruction of ΔTWS and ΔGWS. Results and discussion are presented in Section 4 and Section 5, and conclusions are drawn in Section 6.

2. Study area and data sources

2.1. Study area

With an area of 205,344 km^2 in northern Pakistan, the Punjab province is traversed by the Indus River and its five tributaries including Chenab, Sutlej, Jhelum, Ravi, and Punjnad (Fig. 1). Its climate is characterized by significant seasonal fluctuations in temperature and precipitation. Average annual temperature in Punjab is 23.3 °C, with a maximum of 32.8 °C occurring in the summer from May to August (MoWP, 2012). The mean annual precipitation during 1971–2000 is 58 cm/year, and 70% of the rainfall occurs during the monsoon season from June to September (MoWP, 2012). Correspondingly, 60 percent of the river flow is concentrated in the monsoon season. The topographic slope declines from north to south and southwest, and the soils are moderately or highly permeable (Greenman et al., 1967). Punjab contains a large unconfined aquifer with negligible lateral flow crossing the boundary (Swarzenski, 1968; Khan et al., 2016).

The Punjab province produced 76% of wheat, 83% of gram, and 65% of sugarcane in Pakistan during 2013–2014 (PDS, 2015). Irrigation has become a prerequisite for intensive agriculture in this semi-arid region, and a persistent increase in both surface water and groundwater withdrawal has been reported (Wada et al., 2014). During the early years, water was transferred from the Indus and its tributaries to irrigation fields through the extensive network of irrigation canals (i.e., Indus Basin Irrigation System); meanwhile, dams and reservoirs were built. It is difficult to store water in canals for irrigation in dry seasons (i.e., October to March) due to the high permeability of soil (Siddiqi and Wescoat, 2013; Biemans et al., 2016; Mekonnen et al., 2016). The Chashma Reservoir on the Indus River (Fig. 1) is the major reservoir in the area with a live capacity of 0.75 billion m^3 (MoWP, 2012). Water transfers exist within the Punjab province, but transfers across the Punjab provincial boundaries are negligible (PDS, 2015). Due to the low reliability of surface water supply and increasing water scarcity caused by rapid population growth, groundwater has been used to supplement surface water supply since the 1960s (Ullah et al., 2002). From 1965 to 2002, annual groundwater abstraction increased from 10 billion m^3 to 68 billion m^3; and over 80 percent of groundwater was extracted by private tube wells (Bhutta and Alam, 2005). The number of private tube wells increased rapidly from 2700 in 1960 to over 600,000 in 2001. Groundwater was used in approximately 69% of irrigated areas, either alone or in conjunctive use with canal water (PDS, 2015). The continuous overdraft due to unregulated pumping led to groundwater depletion (Mekonnen et al., 2016).

2.2. Precipitation

Precipitation data were obtained from two sources: 1) the precipitation reconstruction over land (PREC/L), and 2) the meteorological forcing for land surface models (LSMs) in the Global Land Data Assimilation System (GLDAS-1). Both PREC/L and forcing in GLDAS-1 contain monthly precipitation with a spatial resolution of 1 degree. The PREC/L dataset was generated by interpolating observations from more than 17,000 stations in the Global Historical Climatology Network (GHCN) version 2 dataset and the Climate Anomaly Monitoring System (CAMS) dataset (Chen et al., 2002). The forcing dataset was derived by combining reanalysis data and observations (Sheffield et al., 2006). The spatial averages of monthly precipitation within the study area were computed for each dataset during 1980–2016. Precipitation data from GLDAS-1 during 1995–1997 were excluded for the analysis due to high uncertainty in the forcing dataset (Rui, 2015).

2.3. Potential evapotranspiration

A physically-based method has been recommended to estimate potential evapotranspiration for higher reliability (Donohue et al., 2010; McVicar et al., 2012). In this study, the Penman equation (Penman, 1948; Shuttleworth, 1993; Donohue et al., 2010; McMahon et al., 2013) was used to estimate potential evapotranspiration based on meteorological data from GLDAS-1. This dataset