The Impacts of Interannual Climate Variability on the Declining Trend in Terrestrial Water Storage over the Tigris–Euphrates River Basin

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ABSTRACT: The Tigris–Euphrates dryland river basin has experienced a declining trend in terrestrial water storage (TWS) from April 2002 to June 2017. Using satellite observations and a process-based land surface model, we find that climate variations and direct human interventions explain $-61\%$ ($-0.57\text{ mm month}^{-1}$) and $-39\%$ ($-0.36\text{ mm month}^{-1}$) of the negative trend, respectively. We further disaggregate the effects of climate variations and find that interannual climate variability contributes substantially ($-0.27\text{ mm month}^{-1}$) to the negative TWS trend, slightly greater than the decadal climate change ($-0.25\text{ mm month}^{-1}$). Interannual climate variability affects TWS mainly through the nonlinear relationship between monthly TWS dynamics and aridity. Slow recovery of TWS during short wetting periods does not compensate for rapid depletion of TWS through transpiration during prolonged drying periods. Despite enhanced water stress, the dryland ecosystems show slightly enhanced resilience to water stress through greater partitioning of evapotranspiration into transpiration and weak surface “greening” effects. However, the dryland ecosystems are vulnerable to drought impacts. The basin shows straining ecosystem functioning after experiencing a severe drought event. In addition, after the onset of the drought, the dryland ecosystem becomes more sensitive to variations in climate conditions.

SIGNIFICANCE STATEMENT: The purpose of the research is to better understand climate impacts on terrestrial water storage over dryland regions with declining water storage. In our study, we disaggregate three components of climate impacts, namely, decadal climate change, interannual variability, and intra-annual variability. We then use observational datasets and a process-based model to quantify their individual effects on water storage. We find that interannual variability is the most significant climatic contributor to the declining water storage, mainly caused by prolonged drought periods and corresponding quick drying rates due to plant transpiration. We also find that the dryland ecosystem is sensitive and vulnerable to severe drought events. This study is important because 1) it provides a framework to investigate climate impacts on water fluxes and storages, 2) it highlights the importance of vegetation dynamics on dryland hydrology, and 3) it emphasizes the negative impacts of extreme hydroclimatological events on ecosystem functioning.

KEYWORDS: Climate variability; Evapotranspiration; Hydrology; Land surface model

1. Introduction

The Tigris–Euphrates river basin is known as the cradle of ancient civilization because river water and local alluvium allow agricultural development (FAO 2009; Macklin and Lewin 2015). Currently, people residing in the basin countries rely on water resources for agricultural, domestic, and industrial uses (UN-ESCA and BGR 2013). Water resources are also critically important for biological activities of local ecosystems (Delgado-Baquerizo et al. 2013). However, under a dry climate, the Tigris–Euphrates river basin has been experiencing water shortages due to relatively low precipitation and high atmospheric demand (FAO 2009). The water shortages are likely to be exacerbated under a warming climate because meteorological droughts may occur at a higher frequency and with a greater intensity (Mohamed 2020; Lelieveld et al. 2012; Kelley et al. 2015; Pokhrel et al. 2021). Despite the current water stress, extensive human water withdrawal due to rapid city development and population growth has been reported by previous research (Alipour et al. 2008; Motagh et al. 2008; Famiglietti et al. 2014; Gleeson et al. 2012; Wada et al. 2010). As a transboundary river basin, rising water scarcity may complicate political, economic, and social tensions, caused by a lack of effective water resource monitoring systems, efficient water management policies, and binding agreements between nations (Wolf 1998; Voss et al. 2013). In the long term, the water crisis may affect human settlement and population migrations in the region, and may even relate to civilization collapse (Best 2019; Kaniewski et al. 2012). Besides the human society, dryland ecosystems may experience nutrient depletion and increased vulnerability to climate change under prolonged water stress, thus straining ecosystem functions and services in the long run (Bozkurt and Sen 2013; Delgado-Baquerizo et al. 2013).

Due to sparse monitoring networks and intransparency of hydrological data (Voss et al. 2013; Bozkurt and Sen 2013), it is difficult to quantify the amount of available water resources over the Tigris–Euphrates river basin. However, the Gravity Recovery and Climate Experiment (GRACE) mission provides

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an unprecedented opportunity to detect variations in terrestrial water storage (TWS) over data-sparse regions. TWS anomaly derived from the GRACE twin satellites represents changes in water resources stored in aquifers, soils, glaciers, snowpacks, and biomass vertically (Landerer and Swenson 2012; Swenson 2012; Swenson and Wahr 2006; Reager et al. 2016). Using GRACE data, previous research indicated that the Tigris–Euphrates river basin has been experiencing a decadal decreasing trend of TWS due to the combined effects of meteorological droughts and human water withdrawal (Forootan et al. 2014, 2017; Rodell et al. 2018; Scanlon et al. 2018; Felfelani et al. 2017; Voss et al. 2013; Wada et al. 2014; Yi et al. 2016). Combining GRACE observations with numerical model simulations, researchers are able to separate and estimate impacts of climate variations and human activities on the negative TWS trend (Chang et al. 2020; Joodaki et al. 2014; Chao et al. 2018; Felfelani et al. 2017; Asoka and Mishra 2020).

Despite a plethora of research on the effects of climate variations and anthropogenic water withdrawal on water fluxes and subsequent water storage changes over the Tigris–Euphrates river basin (Özdögan 2011; Wada et al. 2014; Felfelani et al. 2017; Yi et al. 2016), few efforts have been made to disaggregate the impacts of various climate variations including long-term linear trend, interannual and intra-annual variabilities to understand the underlying mechanisms. Climate variations play an essential role in regulating TWS over the river basin, but quantifying the impacts of long-term climate change and climate variability on TWS variations and investigating ecosystem responses to the climate variations are still lacking. Long-term climate change has been documented to affect the long-term water availability as well as water demand (Döll 2002). With continuing decreasing precipitation and increasing air temperature, TWS is expected to decrease over the river basin (Özdögan 2011). Climate variability may also impact the TWS trend through precipitation and temperature anomalies, possibly caused by El Niño–Southern Oscillation (ENSO) and the North Atlantic Oscillation (NAO) (Chang et al. 2020; Cullen et al. 2002; Ni et al. 2018; Phillips et al. 2012). With continuing climate change and recurring variability (Chenoweth et al. 2011), it is important to quantify the impacts of climate change and variability (interannual and intra-annual variability) on TWS and investigate the ecosystem responses. In this study, we use GRACE satellite observations and a process-based land surface model to disaggregate the effects of climate variations by conducting virtual experiments with detrended climates and 3-hourly climatology. To understand the underlying mechanism, we examine the relationship between hydroclimatic variables of the river basin and varying climate conditions.

2. Data

The Gravity Recovery and Climate Experiment (GRACE) twin satellites use a K-band microwave ranging system to sense changes of intersatellite distance, indicative of variations of Earth’s gravity field (Tapley et al. 2004). The monthly variations of the gravity field are mainly caused by surface mass redistributions. After removing atmospheric and oceanic signals, time variations of the gravity field can then be interpreted as terrestrial water storage (TWS) fluctuations (Landerer and Swenson 2012). GRACE observations have been widely used in a variety of mass change studies, including but not limited to quantifying regional- and global-scale sea level rise (Milly et al. 2010; Jensen et al. 2013), studying glacier and ice mass loss (Jacob et al. 2012; Chen et al. 2009), investigating extreme hydroclimate events such as droughts and floods (Houborg et al. 2012; Thomas et al. 2014; Reager et al. 2014), evaluating groundwater depletion (Rodell et al. 2009, 2018; Thomas and Famiglietti 2019), and assessing ecosystem functioning under water stress (Humphrey et al. 2018).

In this study, we use GRACE Level 3 data with mascons solutions Release 6 (RL06). The data describe monthly estimates of TWS anomalies (TWSA) from April 2002 to June 2017. That means, at each grid cell, all monthly values are anomalies from its static field, defined as the mean value of all monthly data during 2004–09. We use ensemble mean TWSA values from data products processed at three groups, namely, the Center for Space Research (CSR), the Jet Propulsion Laboratory (JPL), and the NASA Goddard Space Flight Center (GSFC) to reduce data noise/error (Pokhrel et al. 2021; Sakumura et al. 2014; Scanlon et al. 2016). CSR mascons solutions are derived on equal-area geodesic tiles with a size of 1° × 1° at the equator (~120 km), but the RL06 data are released at 0.25° × 0.25° spatial resolution because the tiles across coastlines are split into ocean and land grids to reduce leakage errors (Save et al. 2016; Śliwińska et al. 2021). JPL data are available at 0.5° but the solutions are estimated on 3° equal area spherical cap mascons (Watkins et al. 2015). GSFC data are available at 0.5° with the native resolution at 1 arc degree (Loomis et al. 2019; Luthcke et al. 2013). To make GRACE datasets consistent in terms of spatial resolution, we upscale the CSR data to 0.5° × 0.5°.

3. Methods

a. TWS linear trend estimate and uncertainty

In our study, we apply the seasonal trend decomposition based on LOESS (local regression) (STL) method to decompose time series of monthly TWS into long-term, seasonal, and remainder components (Cleveland et al. 1990). We then derive the trend by fitting a least-squares linear regression line to the long-term component. We use the same method to derive linear trends of time series of other hydrological and ecological variables.

To estimate TWS trend uncertainty, we follow Scanlon et al. (2018) and account for both solution uncertainty among the three GRACE datasets and regression uncertainty arisen from the trend analysis. The solution uncertainty, accounting for the difference in GRACE algorithms, is calculated as the square root of the mean squared departures of the three trends estimated using the CSR, JPL, and GSFC datasets. The regression uncertainty is calculated as the square root of the mean squared departures of the standard errors of the regression analysis. Finally, the trend uncertainty is calculated as the square root of the sum of squares of the solution uncertainty and the regression uncertainty.
b. Noah-MP land surface model (LSM)

The Noah-MP LSM is an augmented version of the original Noah LSM by implementing multiple parameterization options for key land surface processes (Niu et al. 2011). Noah-MP simulates fluxes of energy, water, and carbon between the land surface and the atmosphere. TWS simulated by Noah-MP equals the sum of canopy water, plant water storage in living plant tissues (Niu et al. 2020), snow water equivalent, soil moisture integrated over four soil layers, and groundwater storage in the unconfined aquifer.

The Noah-MP LSM represents canopy water dynamics through inputs from precipitation (snow and rain), dew and deposition formation, and outputs through drip, throughfall, and canopy interception loss (evaporation and sublimation). Plant water storage in living plant tissues is updated daily and canopy interception loss (evaporation and sublimation) at every time step by the residual of root water uptake minus transpiration loss (Niu et al. 2020). Noah-MP calculates snow water equivalent by accounting for snow interception, melting and refreezing, deposition and sublimation, and dew and evaporation processes (Niu et al. 2011). Noah-MP updates soil moisture at different layers by solving the Richard’s equation with the Clapp–Hornberger soil hydraulic model (Clapp and Hornberger 1978). Finally, groundwater storage fluctuates in the unconfined aquifer depending on the recharge rate from overlying soil layers and the discharge rate (Niu et al. 2007). The recharge rate is calculated following Darcy’s law. Noah-MP computes the discharge rate (or baseflow) as an exponential function of the water table depth based on a simple TOPMODEL runoff model (Niu et al. 2007).

In this study, we conduct a model experiment (denoted as “CTRL”) by driving the Noah-MP LSM using the 3-hourly, 1° × 1° gridded Global Land Data Assimilation System (GLDAS) near-surface climatic forcings (Rodell et al. 2004). We spun up the model for 20 times from year 2000 to 2017 until both soil moisture and groundwater reach steady states. We then use the last spinup outputs for our analysis. We calibrated our CTRL experiment against FLUXNET MTEs gross primary productivity (GPP) and evapotranspiration (ET) data (Jung et al. 2010, 2011), and reprocessed the MODIS leaf area index (LAI) products (Yuan et al. 2011) (GRACE TWSA not included). Descriptions of the GPP, ET, and LAI data and comparisons with model simulations can be found in the supplemental material (Text S1 and Fig. S3 in the online supplemental material). During our calibration, we adjust biophysiological parameters, such as temperature-related leaf-stress factor (SCEXP), maximum rate of carboxylation at 25°C (VCMAX25), leaf turnover rate (LTOVRC), foliage maintenance respiration rate at 25°C (RMF25), and leaf area per unit mass (SLA) to match the observational datasets. We also calibrated a key parameter controlling capillary fringe, i.e., the micropore volume fraction (FMIC < 1.0) representing the effects of macropores (reducing micropore volume and capillary rise) in the aquifers (Niu et al. 2011). To remain consistent and comparable with GRACE observations, we subtract the mean TWS field over 2004–09 to derive TWSA at each grid cell.

c. Disentangle impacts of contributing factors on the observed TWS trend

As GRACE satellites detect the combined effects of climate variations and human activities while CTRL is only driven by atmospheric forcings, we are able to isolate contributions of the two factors to the observed TWS trend over the Tigris–Euphrates river basin. Comparing the observed and simulated TWS trends, we attribute the simulated trend to climate variation effects, while the difference between GRACE and CTRL to direct human-induced factors (e.g., water withdrawal).

To isolate the effects of climate variations on the observed TWS trend, we follow the method of Green et al. (2019). We design two additional virtual experiments: DETREND and CLIM to further disentangle the impacts of climate variations to decadal linear climate change, interannual climate variability, and intra-annual climate variability on terrestrial ecohydrological processes. “DETREND” uses the linearly detrended GLDAS meteorological forcings. Here, due to the short period of GRACE observations (15 years), we only account for linear climate change while excluding nonlinear change in our study. “CLIM” repeatedly uses the 3-hourly, year-long climatological forcings (18-yr average of the 3-hourly GLDAS data from 2000 to 2017).

CTRL, using the original atmospheric forcings, accounts for effects of all three aspects of climate variations on the TWS trend. DETREND retains the impacts of interannual and intra-annual climate variabilities but excludes those of decadal climate change on land surface processes. CLIM only includes the intra-annual climate variability impacts. Therefore, we quantify the effects of decadal climate change by subtracting the TWS trend resulting from DETREND from that of CTRL. Similarly, we calculate the difference of TWS trends between DETREND and CLIM to estimate the interannual climate variability effects. Finally, the TWS trend resulting from CLIM is used to evaluate the intra-annual climate variability effects. A schematic diagram is provided (Fig. 1) to illustrate the disaggregation and attribution processes on the TWS trend.

d. Relationship between monthly TWS changes (dTWS) and climate aridity conditions

Climate variations impact the water fluxes exchanging between the land surface and the atmosphere, thus contributing to the TWS variations. To understand how the Tigris–Euphrates river basin responds to changing atmospheric conditions and how the responses regulate TWS variations, we evaluate the relationship between monthly TWS change (dTWS) and aridity index (AI) using both observational data and Noah-MP simulations.

To quantify atmospheric water availability (or dryness), we adopt the concept of aridity index (AI), defined as the ratio of long-term mean precipitation (PRCP) to potential evapotranspiration (PET) (Middleton and Thomas 1997). Areas with AI < 0.65 are defined as dryland regions. Here, we generate monthly AI time series, computed as the ratio of monthly PRCP to monthly PET using the GLDAS 2.0 Land Information
System (LIS) outputs (Rodell et al. 2004). Monthly AI describes temporal variations of the contrast between atmospheric water supply (PRCP) and demand (PET). We define humid and arid months as when \( AI > 0.65 \) and \( AI < 0.65 \), respectively. Arid months are subdivided to hyperarid (\( AI < 0.05 \)), arid (\( 0.05 \leq AI < 0.20 \)), semiarid (\( 0.20 \leq AI < 0.50 \)), and dry subhumid periods (\( 0.50 \leq AI < 0.65 \)).

Monthly TWS change, \( dTWS_t \), is computed as temporal derivations of TWSA (Forootan et al. 2017), i.e., the difference of TWSA between two consecutive months. The \( dTWS_t \) reflects the integral budget of water fluxes entering (PRCP) and leaving (ET, runoff \( Q_t \), and human water withdrawal \( W_t \)) the basin within the month \( t \) [Eq. (1)]. We use \( dTWS_t \), instead of TWSA because \( dTWS_t \) is a flux term, which responds readily to the changing atmospheric conditions while TWSA is a state variable that cumulates previous water fluxes over time. To understand the collective nature of \( dTWS_t \) to climatic variations over the river basin, we compute the basin-wide area-weighted time series of \( dTWS_t \) and AI. To account for the missing data in observations, we linearly interpolate GRACE TWSA data before generating the \( dTWS_t \) time series. To evaluate consistency of gridcell and basin-scale behaviors, we analyze grid scale relationship in our supplemental material (Text S2):

\[
dTWS_t = TWSA_{t+1} - TWSA_t = PRCP_t - ET_t - Q_t - W_t.
\]

(1)

4. Results

a. Declining terrestrial water storage

The river basin has experienced a statistically significant (two-tailed Student’s \( t \) test with alpha at 0.05) drying trend over the GRACE period as indicated by the decreasing TWSA of GRACE (\( -0.93 \pm 0.089 \text{ mm month}^{-1} \)) and CTRL (\( -0.57 \text{ mm month}^{-1} \)) (Fig. 2). We also compare individual GRACE mascon products and find the data are consistent in terms of TWS seasonality and trend values (Fig. S1 and Table S1). TWSA increases before 2006, but starts to decrease afterward, consistent with a decline in AI mainly caused by precipitation reduction (Fig. S2). Following TWSA, monthly runoff (\( Q_t \) also decreases with time (Fig. S3 and Table S2). The transition from the wetting to drying conditions may be caused by the onset of a 3-yr drought, during which the decreased precipitation results in a reduction in soil moisture and groundwater storage (Fig. S4), and consequently contributes to the declines in TWS (Mohamed 2020; Rodell et al. 2018; Yi et al. 2016; Rateb et al. 2021). The 2007–10 drought is the most severe and longest drought based on instrumental records, resulting in massive crop failure and human migration from rural areas to city centers (Kelley et al. 2015; Hoegh-Guldberg et al. 2018; Trigo et al. 2010). Previous research indicated that the drought may be related to La Niña events (Barlow et al. 2016). Consistently, we also find a greater value of correlation coefficient between precipitation and ENSO index at 0.40 during drought years (2007–10) than predrought (2002–06) and postdrought (2011–17) periods at 0.07 and −0.03, respectively (Table S3). However, the correlation coefficient between monthly precipitation and NAO index during drought is small (0.096). Besides climate impacts, human water withdrawal from surface and groundwater due to the high demands for water resources may further deplete TWS, exacerbating the drought impacts (Voss et al. 2013). Groundwater abstractions can exert negative impacts on water storage over dryland regions (Yuan et al. 2019). Over the Tigris–Euphrates river basin, previous research has reported depletion of TWS caused by unsustainable rates of groundwater exploitation (Alipour et al. 2008; Motaghi et al. 2008; Döll et al. 2014; Felfelani et al. 2017).
b. Impacts of climate variations on the TWS trend

We compare the TWS trends using GRACE observations and the Noah-MP CTRL experiment to isolate the impacts of climate variations. CTRL underestimates the TWS trend (−0.57 mm month⁻¹), explaining only 61% of the GRACE trend (−0.93 mm month⁻¹) (Fig. 2 and Table 1). As CTRL is driven only by climatic forcings without accounting for direct anthropogenic impacts, we attribute the remaining 39% of GRACE trend (0.36 mm month⁻¹) to direct human interventions, such as groundwater pumping and surface water withdrawal. Our estimate is comparable to previous studies. Yi et al. (2016) estimated the human-induced rate of groundwater storage changes at 0.38 mm month⁻¹ over the Tigris–Euphrates river basin during 2003–14. Using groundwater level data in Iran from 2002 to 2015, Ashraf et al. (2021) reported a decline of groundwater storage at 0.27 mm month⁻¹ and attributed 90% of the decline (0.24 mm month⁻¹) to direct human water withdrawals.

To further understand the climatic influences on the negative TWS trend, we disaggregate the climate variations into decadal climate change (linear trend), interannual variability, and intra-annual variability (3-hourly climatology). CTRL includes all the three variations, DETREND removes the linear decadal change, and CLIM, driven by the 3-hourly climatology repeated annually, represents the intra-annual variability. After disaggregation, we find that the linear decadal change causes a negative TWS trend mainly due to the decreasing trend in the supply (PRCP) and the increasing trend in the atmospheric demand (PET) as reflected from the decadal declining AI (Fig. S2).

<table>
<thead>
<tr>
<th>Experiment</th>
<th>TWS trend (mm month⁻¹)</th>
<th>Climatic impacts (mm month⁻¹)</th>
<th>Water balance (mm month⁻¹)</th>
</tr>
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<tbody>
<tr>
<td></td>
<td></td>
<td>Cause of effects</td>
<td>ΔTWS</td>
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<tr>
<td>CTRL</td>
<td>−0.57</td>
<td>Climate change</td>
<td>−0.25</td>
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<tr>
<td>DETREND</td>
<td>−0.32</td>
<td>Interannual variability</td>
<td>−0.27</td>
</tr>
<tr>
<td>CLIM</td>
<td>−0.05</td>
<td>Intra-annual variability</td>
<td>−0.05</td>
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FIG. 2. Time series of TWSA using GRACE observations and Noah-MP model simulations.

c. Relationship between monthly dTWS and AI

Our study indicates that the interannual climate variability appears a dominant contributor to the declining TWS trend at a rate of −0.27 mm month⁻¹, which is slightly greater than that of the decadal climate change at −0.25 mm month⁻¹ (Table 1). But the impacts of the intra-annual (or seasonal) variability are negligible (−0.05 mm month⁻¹). The impacts of interannual climate variability on the negative TWS trend can be explained by the empirical probability density function (PDF) of AI and the relationship between AI and dTWS.

First, the dry periods are much longer than the humid periods (Figs. 3c, d) over the region. About 81% of the total months from January 2000 to December 2017 are classified as arid months (AI < 0.65). The distribution of monthly AI is skewed toward the hyperarid end, indicating a high frequency of extreme climatic water deficit due to the imbalanced atmospheric supply and demand. Accordingly, monthly dTWS values are negative over more than half of the time period, with GRACE data and CTRL reporting 52% and 57% of the period, respectively (Fig. 3b). However, CTRL tends to underestimate negative values and annual amplitudes of dTWS than the GRACE observations (Figs. 3a, b), possibly explaining the underestimation of the negative TWS trend (due to human activities) (Fig. 2). A closer inspection of the time series of AI and dTWS reveals a relationship between the two variables. The monthly time series of dTWS and AI are close in phase (Fig. S5). In addition, the correlation coefficient between dTWS and AI is 0.77 using the GRACE dTWS and 0.85 using the simulated dTWS. An increase in water storage relative to the previous month is closely related to the increase in humidness of the atmosphere of the region, and vice versa.

Second, the declining TWS is further attributed to a nonlinear relationship between monthly dTWS and AI (Fig. 4a).
The dTWS declines sharply toward more negative values as the basin becomes more arid (more apparent for the arid and hyperarid conditions with AI being smaller than 0.2). However, during the wetting events (AI increase) within less arid months (AI > 0.2), the recovery of dTWS slows down, with gradual positive slopes (Fig. 4a). Both GRACE data and Noah-MP simulations support this nonlinear relationship, with GRACE observations detecting a greater sensitivity of dTWS to the varying AI under arid conditions than the CTRL. Combining the distribution of aridity and dTWS responses, we infer that slow recovery of water storage over the shorter humid periods is not able to replenish storage deficit depleted during longer arid periods, contributing to a negative TWS trend.

As dTWS represents monthly residuals of water fluxes entering and leaving the system, negative values indicate that the river basin not only uses up PRCP for ET and Q but also some water stored in the soil columns and aquifers to meet additional demands for ET due to high PET. Therefore, investigating partitioning of water fluxes under various aridity conditions is critical for understanding the TWS dynamics. Figure 4b illustrates that the nonlinear relationship between dTWS and AI is mainly caused by ET dynamics. Consistent with the AI-dTWS relationship, monthly partitioning of PRCP to ET is highly nonlinear as suggested by both FLUXNET MTEs data and Noah-MP model simulations. Monthly ET easily exceeds precipitation as the basin approaches hyperarid and arid conditions as indicated by the ratio of ET to PRCP (ET/PRCP) (Fig. 4b). However, as the basin becomes more humid, the ratio gradually decreases below 1 and remains stable. Humid climatic conditions allow precipitation excess to infiltrate and to be stored in the subsurface for future uses but hardly allow water storage to recover from antecedent drying events. In other words, gradual water storage increments by precipitation residuals during short humid seasons cannot compensate for quick ET depletion during long arid seasons.

A closer inspection of ET partitioning indicates that plant transpiration (T) is the dominant contributor to the fast growing ET/PRCP ratio and depleting TWS during dry seasons (Fig. 4c). As the basin becomes more arid, T/ET ratio increases sharply, with a larger fraction of ET partitioned to plant T than soil E. The pattern is largely caused by the suppression of E from the drying surface soil and enhancement of T due to root water uptake of subsurface water (Fig. S6). During arid periods, the dryland ecosystem enhances its resilience to water stress by using antecedent precipitation stored in subsurface more efficiently (Fig. 4d). The rain use efficiency (RUE; GPP/PRCP) increases monotonically with decreasing AI, supported by both the FLUXNET MTEs data and Noah-MP simulations. RUE reaches its maximum value at the extremely dry conditions. Similarly, the water use efficiency (WUE = GPP/ET) increases monotonically as the river basin becomes more arid and converges to its maximum value under extremely hyperarid conditions.

Previous observational studies also support the enhancement of ecosystem rain use efficiency under hydrological stress. Ponce-Campos et al. (2013) suggests an increase of ecosystem RUE and WUE during droughts across all biomes. Huxman et al. (2004) also suggest that ecosystems enhance tolerance and resilience to water stress under dry conditions and tend to reach a common maximum RUE across biomes during the driest years. However, compared with the FLUXNET MTEs data, our CTRL model experiment produces lower RUE and WUE (Figs. 4d,e), possibly...
due to underestimation of ET by the FLUXNET MTEs (Fig. S7) or generally weaker ecosystem resilience commonly represented by large-scale land surface models (LSMs). For instance, Zhu et al. (2019) reported that LSMs tend to generate smaller RUE than observations during low-precipitation conditions.

d. Drought impacts on the relationships between ecohydrological variables and AI

In our study, we also investigate ecohydrological responses to varying AI conditions during different time periods, i.e., predrought (2002–06), during drought (2007–10), and postdrought (2011–17) to understand drought impacts on TWS dynamics over the dryland river basin (Fig. 5). AI and dTWS values are generally small during and after the drought compared with those during the predrought period (Fig. 5a). Before the drought, the curve spans a larger range in both the x and y axes, indicating a more complete seasonal cycle of losing water (negative dTWS) under dry conditions (small AI values) and replenishing water (positive dTWS) under wetter conditions (large AI values). However, climate conditions are drier, and dTWS values are more negative during and after the drought, implying a prolonged period of losing water after the onset of the drought.

The drought also modifies the ecohydrological responses to climate conditions. During and after the drought, the dryland ecosystem conserves limited water resource under arid climate conditions, indicated by larger values of dTWS (Fig. 5a). Possibly due to impaired ecosystem functioning influenced by the drought, the dryland basin shows lower values of T/ET and WUE (Figs. 5c,e).

In addition, the ecosystem may become more sensitive and vulnerable to changing climate conditions (varying AI) when experiencing and recovering from the severe drought. During arid months ($0.20 \leq AI < 0.50$), the slope of dTWS to AI is sharper during and after the drought than before drought period. Moreover, during the less arid months when AI is greater than 0.5, the river basin recovers more slowly during the drought event.
e. Greening and ecosystem resilience

Despite the increasing water stress, the basin becomes slightly “greener” with positive trends of GPP and LAI due to elevated CO₂ concentration (Fig. S3 and Table S3), agreeing and complementing with previous research on the dryland “greening.” Using LAI observations, Zhu et al. (2016) find a global pattern of enhanced greenness under a warming climate. Ahlström et al. (2015) report increasing net biome production over global semiarid regions despite a drying trend. Using satellite observations, Fensholt et al. (2012) find a positive trend in the normalized difference vegetation index (NDVI) over global semiarid areas. The enhanced ecosystem productivity over dryland regions under increasing water stress may be attributed to the extended plant rooting systems to access deep soil moisture and groundwater (Fan et al. 2017). Despite increasing GPP and LAI values, both observational data and our model simulations show weak trends, with annual rates smaller than 2% of decadal mean values (Table S3). In addition, our simulated LAI and GPP trends may be overestimated as compared to observational datasets given the relatively low NSE values (0.11 for LAI and 0.35 for GPP).

Our CTRL experiment also produces a slightly positive trend [0.008 g C (kg H₂O)⁻¹ yr⁻¹] in WUE to quantify ecosystem sensitivity to water availability. Consistently, RUE shows a positive trend [0.032 g C (kg H₂O)⁻¹ yr⁻¹] during the simulation period. Using the same Noah-MP version, Zhang et al. (2022) project extensive greening with enhanced WUE in the western United States (except regions with hot droughts) from 2016 to 2099 under the highest RCP 8.5 CO₂ growth rate. Although the increasing WUE and RUE indicate enhanced ecosystem resilience during prolonged drying conditions (Ponce-Campos et al. 2013; Huxman et al. 2004), the evidence may be weak as the trend values are smaller than their decadal mean values and seasonal amplitudes. WUE and RUE only increase by 1.24% and 1.64% of their mean values per year, respectively.

5. Discussion

The decadal declining TWS over the Tigris–Euphrates river basin is largely controlled by varying climatic conditions. In this study, we find a close relationship between area-weighted
time series of dTWS and AI, indicating the impacts of the contrast between atmospheric supply and demand on the changes of monthly water fluxes over the river basin. The relationship is consistent across spatial scales. The nonlinearity exists not only in the basinwide area-weighted time series, but also in the time series of a majority of the grid cells in the basin, supported by the Noah-MP model simulations (Fig. S8). All grid cells exhibit positive correlations between dTWS and AI. In addition, the nonlinear responses of dTWS, precipitation partitioning, ET partitioning, RUE, and WUE to varying aridity conditions hold not only for the integrated river basin using area-weighted time series, but also for individual grid cells using standardized time series (Fig. S9). During extremely dry conditions, dTWS at a majority of grid cells declines sharply due to a quick increase in ET caused by plant $T$. Despite these drying events, both RUE and WUE increase as the atmospheres becomes drier at the gridcell scale. Therefore, we conclude that the nonlinear relationship between ecohydrological variables and climatic conditions are spatially consistent and coherent over the river basin across scales.

In our study, we calibrate our CTRL experiment against FLUXNET GPP and ET data, and reprocessed MODIS LAI products (GRACE TWSA not included). The CTRL simulations capture the seasonality of observed data but with 1-month phase lag in the time series of GPP and LAI (Fig. S3). However, the trend values of observed and simulated LAI are the same (0.0001 m$^2$ m$^{-2}$ month$^{-1}$). Our simulated ET exceeds observed FLUXNET data, possibly due to underestimated FLUXNET ET (Fig. S7). During the overlap period (April 2002–December 2011), the monthly mean ET value of the CTRL experiment (20.60 mm month$^{-1}$) is closer to the water-balance derived ET from observed precipitation and runoff (26.56 mm month$^{-1}$) than the FLUXNET value (15.64 mm month$^{-1}$).

In our study, we attribute the difference between the two trends to direct human interventions on TWS, such as groundwater and surface water withdrawal. However, the discrepancy between the two trends may also arise from uncertainties in model structures and parameters. Due mainly to uncertainties imbedded in model structures, using different models to quantify contributing factors to TWS changes may result in different interpretations. For instance, Haddeland et al. (2014) suggest that the dryland region loses water mainly due to anthropogenic effects followed by climate impacts. The study mainly uses the WaterGAP model to directly estimate human water use while our study estimates the anthropogenic effects indirectly.

While process-based LSMs allow explorations of mechanisms contributing to TWS changes, simulation results should be interpreted carefully by accounting for model uncertainties. During our calibration processes, we experimented with different carbon allocation schemes, one with priority allocation to leaves to facilitate photosynthesis and the other with priority to fine roots to enhance water acquisition in drylands. We also explore dynamic (with root hydrotropism and more carbon allocation to roots during dry conditions; Niu et al. 2020) and static rooting systems. In addition, groundwater storage represented in Noah-MP may also contribute to simulation uncertainty. Currently, the Noah-MP LSM only includes a simple unconfined aquifer to represent groundwater without accounting for confined aquifer systems. However, confined aquifers have been reported in our study region by previous research (Saleh et al. 2020; Taylor et al. 2013). The difference in hydraulic properties between confined and unconfined aquifers may bring changes to simulated water fluxes and resultant TWS values.

6. Conclusions

Over the Tigris–Euphrates river basin, TWS has been declining at a rate of $-0.93 \pm 0.089$ mm month$^{-1}$ from April 2002 to June 2017 observed by the GRACE twin satellites. To interpret the contributing factors and quantify their effects on the decreasing TWS over the dryland river basin, we conduct three virtual experiments using the Noah-MP LSM, namely, CTRL driven by original GLDAS near-surface atmospheric forcings, DETREND driven by the detrended forcings, and CLIM driven by annually repeated, 3-hourly climatological forcings. Including all climate variations, CTRL indicates that climate variations explain 61% of the negative TWS trend of GRACE, while the remaining 39% of the trend may be attributed to direct human interventions.

We further disaggregate the effects of the climate variations to decadal climate change, interannual variability, and intra-annual climate variability. Among the three variations, interannual climate variability is the largest contributor to the decreasing TWS, greater than the decadal climate change, while the contribution of intra-annual variability may be negligible. The decadal climate change depletes TWS by reducing the atmospheric supply of water (PRCP) and enhancing the atmospheric demand (PET). The interannual climate variability affects TWS mainly through a nonlinear relationship between TWS changes and variations in aridity. TWS declines quickly during prolonged dry periods but recovers slowly during shorter humid periods; the asymmetric drying and wetting processes contribute to the overall declining TWS. The relationship between dTWS and climatic aridity is largely controlled by the ET dynamics. Under dry conditions, ET easily exceeds precipitation at monthly scale mainly through the rooting systems to uptake water stored in deep soil and aquifers while the soil surface evaporation is suppressed. The enhanced ecosystem resilience over the dryland river basin allows a greater partitioning of ET to $T$ and weak ecosystem greening under elevated CO$_2$ concentration and a warmer but drier climate. However, the dryland ecosystem shows impaired ecosystem functioning after experiencing a severe drought event with a decline in the $T$/ET ratio and WUE. After the onset of the drought, the ecosystem becomes more sensitive to changing aridity conditions.

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Data availability statement. GRACE land data are available to download at https://grace.jpl.nasa.gov/data/get-data/. Multivariate ENSO index data can be found at https://www.esrl.noaa.gov/psd/enso/mei/. The authors declare no competing financial interests.

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