Spatial-temporal dynamics of cropland ecosystem water-use efficiency and the responses to agricultural water management in the Shiyang River Basin, northwestern China

Fei Tian\textsuperscript{a,b,\ast}, Yu Zhang\textsuperscript{a,b}, Saihong Lu\textsuperscript{a,b}

\textsuperscript{a} Center for Agricultural Water Research in China, China Agricultural University, Beijing 100083, China
\textsuperscript{b} Wuwei Experimental Station for Efficient Water Use in Agriculture, Ministry of Agriculture and Rural Affairs, Wuwei 733000, China

\textbf{ARTICLE INFO}

\textbf{Keywords:}
Water-use efficiency (WUE)  
Actual evapotranspiration (ET)  
Relative contribution  
Water-saving project  
Cropland  
MODIS

\textbf{ABSTRACT}

To deal with serious water resources crisis, the Shiyang River Basin (SRB) of Hexi Corridor in Northwestern China has been experiencing rehabilitation for water-saving since 2006. Water-use efficiency in cropland (WUE\textsubscript{c}) is a critical indicator to understand the response of carbon-water interactions. Because we currently lack a clear picture of how WUE\textsubscript{c} responds to climate and human activities factors in the SRB, here we applied Moderate Resolution Imaging Spectroradiometer (MODIS) satellite images to obtain a regional estimation of gross primary productivity in cropland (GPP\textsubscript{c}) and actual evapotranspiration in cropland (ET\textsubscript{c}), and analyzed the variations in WUE\textsubscript{c} and climate and human activities factors, then we evaluated the annual WUE\textsubscript{c} responses to climate and human activity factors and discussed major driving factors underlying the interannual variability (IAV) of WUE\textsubscript{c} from 2000 to 2014 in the SRB. Finally, we clarified the implications of the water saving project (WSP) on the water cycle. Results indicated that increased WUE\textsubscript{c} covered 97.25 \% of the cropland area, with a trend of 0.017 g C kg\textsuperscript{-1} H\textsubscript{2}O yr\textsuperscript{-1}. ET\textsubscript{c} decreased at 0.41 mm yr\textsuperscript{-1}. ET\textsubscript{c} decreasing pixel mainly occurred in the irrigation districts of WSP completed by 2010. The IAV of WUE\textsubscript{c} was mainly determined by ET\textsubscript{c} (68 \%) rather than GPP\textsubscript{c} (6\%). The relative contribution of human activities factors in the WSP to ET\textsubscript{c} was 77.5 \%, while that of climate factors was 22.5 \%. Which further proved water availability increase was mainly artificially controlled, an effect of the WSP rather than that of climate factors.

\section{1. Introduction}

Water-use efficiency (WUE) is a key parameter that quantifies the trade-off between photosynthetic carbon assimilation and transpiration at the leaf scale (Farquhar et al., 1980). Neither carbon assimilation nor transpiration can be observed directly at the ecosystem level. Ecosystem WUE (EWUE) is usually defined as the ratio of carbon assimilation (i.e., gross primary productivity [GPP]) to water consumption (i.e., actual evapotranspiration [ET]), which links carbon and water cycles over the terrestrial ecosystem (Reichstein et al., 2002; Beer and Ciais, 2009). Meanwhile climate change and human activities have significantly disturbed the global water balance (Teuling et al., 2013) and changed water availability conditions of the terrestrial ecosystem (Huntington, 2006). Hence, exploring the spatial and temporal patterns of EWUE sheds light on the interrelationship between carbon and water interactions in terrestrial ecosystems and supplies support in evaluating the response of ecosystem to changing environmental (Niu et al., 2011; Keenan et al., 2013; Kang et al., 2017). In recent years, forest and grassland ecosystems have attracted considerable attention and persistent interest in evaluating on EWUE variations and its driving factors (Niu et al., 2011; Christian-Smith et al., 2012; Huang et al., 2016; Yang et al., 2019). However, EWUE in cropland (WUE\textsubscript{c}, defined as the ratio of GPP in cropland [GPP\textsubscript{c}] to ET in cropland [ET\textsubscript{c}]) has few mentions (Du et al., 2019). Clearly, analyzing the variations and driving factors in WUE\textsubscript{c} under changing environments is of importance for the reasonable utilization of regional water resource management and allocation strategies. This is particularly true for sustainable development and agriculture in arid and semiarid areas that are experiencing severe water shortages (Bu et al., 2013).

Climate change, which is a consequence of increased greenhouse gas emissions and global warming (IPCC, 2014; Karamouz et al., 2014), and the change in global precipitation regimes is considered to be caused by the warming air temperature in the northern hemisphere. These circumstances have greatly affected the relationship between...
GPP and ET (Huang et al., 2015). Meanwhile, water resource shortages and extreme environmental conditions (e.g., drought and extreme precipitation) are occurring more frequently in China under global warming (Yu et al., 2008; Niu et al., 2008; Wang et al., 2017), which also affects regional carbon and water cycles. Generally, EWUE responds positively to warming in the northern hemisphere due to relatively higher photosynthetic capacities (Piao et al., 2007, 2013; Richardson et al., 2010). However, under different conditions (dry and wet), the trend of EWUE in relation to climate change and its response to climate factors will probably be inconsistent (Yu et al., 2008; Liu et al., 2015; Zhou et al., 2016). For example, Bai et al. (2008) concluded that EWUE increased with increasing annual precipitation, while Li et al. (2008) found an opposite result. And WUE is usually considered to be decreased with increasing vapor pressure deficit (VPD) across different time scales (Law et al., 2002). Similarly, in some conditions such a response of WUE to VPD may only exist seasonally (Eamus et al., 2013), or even does not exist at all due to extreme environmental conditions (Reichstein et al., 2002). In addition to climate change, EWUE is one of the fundamental trade-offs governing plant growth and is widely used to indicate the influence of human activities (e.g., vegetation performance). Previous studies have shown that large-scale vegetation changes due to Grain for Green Programs implemented in North China have significantly influenced the terrestrial ecohydrology (Yu et al., 2008). Similar studies have been conducted using the public domain MODIS Reprojection Tool (MRT) package. This tool in ArcMap 10.2. The MODIS data format (HDF) was converted to the relevant geographical coordinates, and World Geodetic System (WGS) 84 data with 2 tiles (h25v05, h26v05) were mosaic together using the public domain MODIS Reprojection Tool (MRT) package. This study only focused on cropland ecosystem. Based on the annual crop cover of MCD12Q1 datasets by the extracting tool in ArcMap 10.2 to generate GPPc, ETc, PET (potential evapotranspiration in cropland), NDVIc (NDVI in cropland) and EVIc (EVI in cropland). The analysis was performed for the period from 2000 to 2014, except for the MODIS annual land cover type product providing temporal coverage from 2001–2014. Only pixels with a constant crop cover between 2001–2014 are included for analysis.

2. Materials and methods

2.1. Study area

The SRB lies in the east part of the Hexi Corridor in the arid and semiarid regions of northwest China (101°41′E–104°16′E, 37°41′N–42°42′N). The total basin area is about 4000 km². Elevation varies from 1244 m to 5220 m, with an average elevation of 1910 m above mean sea level (Fig. 1). Annual mean temperature is 7.4 °C, with a range of -12.3 °C-22.0 °C, and it increases from the snowy mountains upstream to the deserts downstream in the SRB (Fig. 1). Natural landscape ecosystems of the SRB comprise glacial areas, forestland, grassland, cropland, and deserts. Cropland accounts for about 10 % of the SRB area. Locally generated precipitation in the cropland is normally insufficient (i.e., the mean is 259 mm yr⁻¹; Fig. 1) for supporting agricultural irrigation. Streamflow and groundwater are the main water resources for irrigation in the cropland. Before the CTSRB, the over-exploitation of groundwater seriously destroyed the ecohydrology and ecosystem environment of the basin and led to ecological degradation (e.g., salinization, desertification, and vegetation degradation; Zhang and Li, 2016; Hao et al., 2017). Meanwhile, an obvious turning point in the year of 2000 that moving average value of mean air temperature exceeded the average of the year 1970–2015 in the Hexi Corridor was detected by Fu et al. (2019), indicating that the region has faced a more challenging environment since the new millennium.

2.2. Materials

2.2.1. Remote sensing data

The digital elevation model data set was obtained from the NASA Shuttle Radar Topography Mission website (http://www.golf.umd.edu/) at a 1 km resolution. MODIS GPP data (MOD17A2) and ET/potential evapotranspiration (MOD16A2) were acquired from the Numerical Terradynamic Simulation Group of the University of Montana at an 8-day interval with a 1 km resolution (http://www.ntsg.umt.edu/). Monthly vegetation index information (i.e., the normalized difference vegetation index, NDVI) and enhanced vegetation index, (EVI) were derived from the Moderate Resolution Imaging Spectroradiometer (MODIS) Terra MOD13A3 Version 6 product. It was provided by the NASA Land Processes Distributed Active Archive Center (LP DAAC) with a spatial resolution of 1 km (https://lpdaac.usgs.gov/). The MODIS Land cover type product (MCD12Q1) was downloaded from the NASA LP DAAC at a 500 m resolution. The Land cover type product was resampled and categorized into a 1 km resolution using the Resample Tool in ArcMap 10.2. The MODIS data format (HDF) was converted to the Digital Elevation Model, and World Geodetic System (WGS) 84 data with 2 tiles (h25v05, h26v05) were mosaic together using the public domain MODIS Reprojection Tool (MRT) package. This study only focused on cropland ecosystem. Based on the annual crop cover of MCD12Q1 datasets by the extracting tool in ArcMap 10.2 to generate GPPc, ETc, PET (potential evapotranspiration in cropland), NDVIc (NDVI in cropland) and EVIc (EVI in cropland). The analysis was performed for the period from 2000 to 2014, except for the MODIS annual land cover type product providing temporal coverage from 2001–2014. Only pixels with a constant crop cover between 2001–2014 are included for analysis.

2.2.2. Meteorological data

Meteorological data, including daily air temperatures (T), precipitation (P), and relative humidity (RH) were collected from meteorological stations of the SRB and the surrounding area (Table 1), in 2000–2014, and they were acquired from the China Meteorological Data Service Center (http://data.cma.cn). We used thin plate smoothing splines algorithms based on the elevation information derived from the digital elevation model, and applied them in the Anusplin package to process the daily meteorological data (T and P) into grid
The vapor pressure deficit (VPD) can be calculated in terms of T and RH by the following formula (Jiao et al., 2019):

\[ VPD = 0.611e^{\frac{17.502}{T}} + 0.611e^{\frac{240.970}{T}} \times (100\% - RH) \] (1)

where VPD is the vapor pressure deficit (kPa), T is the monthly average air temperature (°C), and RH is the monthly average relative humidity (%).

2.3. Data analysis

All spatial data was simulated at the same spatial resolution of 1 km. Our data analysis methods mainly include temporal Pearson correlation analysis, spatially Sen’s trend test and partial correlation analysis on each pixel from 2000 to 2014.

2.3.1. Spatial trend test and partial correlation analysis

In the Mann–Kendall test, another very useful index is Sen’s slope, which is an unbiased estimator of monotonic trend magnitude extended by Hirsch et al. (1982) from the one proposed by Sen (1968). The slope was performed to detect the spatial variation of trends in GPPc, ETo, and WUEc during 2000–2014 on each pixel. To explore the response of annual variations of each driving factor to WUEc on each pixel, we also chose partial correlation analysis between WUEc and one driver after
statistically controlling changes in the other drivers. For example, the partial correlation coefficient between WUEc and NDVIc was controlled the interrelationship between NDVIc, P, and T.

### 2.3.2. Temporal correlation analysis

To quantify the IAV of GPPc, ETC, WUEc, climatic variables (i.e., T, P, and VPD), and human agricultural activities variables (i.e., NDVIc, EVIc, and IWU), the following equation was used:

\[
\Delta X = X_{(i+1)} - X_{(i)} (i = 2000, ..., 2013)
\]

where \(X_{(i+1)}\) was the following-year variable, \(X_{(i)}\) was the current-year variable, and \(\Delta X\) was the IAV of the variables.

For temporal correlation analysis, the Pearson correlation coefficient was used. In this study, the correlation analysis was used to investigate the relationships between the IAV of the variables.

### 2.3.3. Temporally relative contribution assessment

Temporally, to quantify the relative contribution of human activities factors in the WSP to ETC, its mutation period was determined according to the MK mutation test (Kendall, 1938; Mann, 1945). EVIc and IWU variations represent the influence of human activities in WSP.

Using the basic idea of the partial differential equation, all variables were normalization by the zero-mean method, and the ETC variation \(n\) could be decomposed as follows:

\[
\frac{d\Delta ETC}{dt} = \frac{\Delta ETC}{\Delta EVIc} \Delta EVIc + \frac{\Delta ETC}{\Delta IWU} \Delta IWU + \frac{\Delta ETC}{\Delta \text{lim ate}} \Delta \text{lim ate}
\]

where \(\Delta ETC\), \(\Delta EVIc\), and \(\Delta IWU\) are the difference of variables, respectively.

Then, based on first-order approximation, the equation can be written as:

\[
\Delta ETC = \frac{\Delta ETC}{\Delta EVIc} \Delta EVIc + \frac{\Delta ETC}{\Delta IWU} \Delta IWU + \frac{\Delta ETC}{\Delta \text{lim ate}} \Delta \text{lim ate}
\]

where \(\Delta ETC\), \(\Delta EVIc\), and \(\Delta IWU\) are the difference of variables, respectively.

The sum of the first and second terms is approximately the indication of the contribution of human activities factors to ETC variation, and the temporally relative contribution of ETC can be expressed as follows:

\[
R_{\text{climate}} = \frac{\Delta ETC_{\text{climate}}}{\Delta ETC_{\text{lim ate}}} \times 100\%
\]

\[
R_{\text{lim ate}} = 100\% - R_{\text{climate}}
\]

### 3. Results and discussion

#### 3.1. Verification of the EWUE estimated from the MODIS products

Upon comparing the results of this study with other estimates in the literature to verify the effectiveness of the MODIS-EWUE. The variation of the MODIS-EWUE was consistent with the results of the remote sensing calculations and model estimations (Xiao et al., 2013; Gao et al., 2014; Zhu et al., 2015; Du et al., 2019). Xiao et al. (2013) reported ranges of the EWUE in China were about 0.37–3.10 g C kg\(^{-1}\) H\(_2\)O from 2003 to 2010, and Zhu et al. (2015) found approximately 0.36–3.89 g C kg\(^{-1}\) H\(_2\)O from 2001 to 2010, all of which were consistent with our results, which ranged from 0.00–4.68 g C kg\(^{-1}\) H\(_2\)O. Recently, Du et al. (2019) compared the two EWUE datasets derived from the MODIS GPP and ET products and from the GLASS GPP and ET datasets for the North China. The result concluded a high degree of consistency between the MODIS-EWUE and GLASS-EWUE (RMSE = 0.21, \(R^2 = 0.72\), \(p < 0.001\)). There was highest consistency between the values in the western-central of North China (\(R^2 = 0.83\)), SRB is located in the region. Hence, the EWUE values estimated using the MODIS products in this study were similar to the results of previous studies, supporting the use of the MODIS products.

#### 3.2. Variation of climate and human activities factors and WUEc

##### 3.2.1. Variations of climate and human activities factors

The seasonal patterns of the climate variables are shown in Fig. 2. The monthly P was 15.6 mm on average through all the year. It was about 24.8 mm during the growing season (between April and October) on average, with the peak value reaching 41.4 mm in July. On the other hand, it was only 2.3 mm during the nongrowing season on average, with the lowest value reaching 1.1 mm in December. The monthly T ranged from -12.3 °C–22.0 °C with a mean value of 7.4 °C, and the highest mean value occurred in July (20.4 °C). Meanwhile, the annual mean VPD showed an increased trend and varied between 0.55 kPa (in 2007) and 0.68 kPa (in 2013), with a mean value of 0.60 kPa. The monthly mean VPD showed the highest mean value occurred in April (0.77 kPa) and the lowest value in January (0.18 kPa). Overall, it is obvious that the variations of P, T, and VPD from 2000 to 2014 represented typically seasonal trends for the SRB, which implied warm and wet growing seasons and cool and dry nongrowing seasons.

In terms of human activities factors (Fig. 3). The monthly NDVIc and EVIc were 0.29 and 0.20 on average through all the year (Fig. 3a). They were about 0.40 and 0.28 during the growing season on average, with the peak value reaching 0.60 and 0.45 in July. On the other hand, they were only 0.13 and 0.08 during the nongrowing season on average, with the lowest value reaching 0.08 and 0.07 in December. Consistent with the seasonal patterns of P and T. Which also indicated
the better vegetation performance in growing season compared with nongrowing season. The annual IWU is shown in Fig. 3b. Although IWU was decreased with rate of 0.03 billion m$^3$ yr$^{-1}$ from 2000 to 2014. The inter-annual fluctuation is relatively greater, especially from 2007–2014. The IWU increased slightly during the period 2000–2007, the highest IWU occurred at 2005 of 2.40 billion m$^3$, with 0.18 billion m$^3$ higher than the multi-year average IWU. The annual IWU decreased dramatically during the period 2007–2014, with a decreased rate of 0.064 billion m$^3$ yr$^{-1}$. The lowest value of the growing season IWU appeared in 2013 with a value of 1.83 billion m$^3$ (0.39 billion m$^3$ less than the multi-year average IWU), which may be attributed to the effect of human activities factors in WSP and climate factors on water cycle.

### 3.2.2. Variations of GPPc, ETc, and WUEc

The monthly GPPc reached its maximum value in July, with a mean value of 126.59 g C m$^{-2}$ month$^{-1}$ (Fig. 4a). Similarly, the highest value of the monthly ETc also occurred in July, ranging from 33.55 mm month$^{-1}$ to 63.06 mm month$^{-1}$ (Fig. 4b), with a mean value of 38.96 mm month$^{-1}$. During the growing season, the mean ETc was 29.19 mm month$^{-1}$, which was about 60 % higher than that during the nongrowing season (19.38 mm month$^{-1}$). The monthly WUEc ranged from 2.67 g C kg$^{-1}$ H$_2$O to 4.68 g C kg$^{-1}$ H$_2$O during the growing season; the monthly WUEc peaked in May (Fig. 4c). In addition, the mean, maximum and minimum values of WUEc in the growing season were higher than those in the nongrowing season. For example, the mean values of WUEc in growing seasons and nongrowing seasons were 2.33 g C kg$^{-1}$ H$_2$O and 0.10 g C kg$^{-1}$ H$_2$O, respectively. Clearly, GPPc, ETc, and WUEc showed a synchronized seasonal variation trends.

To describe the spatial patterns of GPPc, ETc, and WUEc variations, their changing trends were analyzed pixel by pixel from 2000 to 2014. This showed GPPc increased at a mean rate of 2.42 g C m$^{-2}$ yr$^{-1}$ (Fig. 5a), and ETc slightly declined at a mean rate of 0.41 mm yr$^{-1}$; the negative trend of ETc mainly occurred in the ID where the WSP was completed by 2010 (Fig. 5b). The negative trend of ETc occupied approximately 51.28 % of cropland area, and that for the positive GPPc covered about 62.89 % of cropland area. Meanwhile, the spatial pattern of annual GPPc, ETc, and WUEc were correlated with climate and human activities in the SRB. Uneven changes in environmental factors resulted in the variance in WUEc tendencies over the 15-year period. The positive WUEc trend covered about 97.25 % of the total cropland area, with a slope of 0.017 g C kg$^{-1}$ H$_2$O yr$^{-1}$ (Fig. 5c). The spatial distribution of the mean annual WUEc from 2000 to 2014 was shown in Fig. 5d. The mean annual WUEc was about 1.575 g C kg$^{-1}$ H$_2$O yr$^{-1}$ and varied from 0.710 g C kg$^{-1}$ H$_2$O yr$^{-1}$ to 2.927 g C kg$^{-1}$ H$_2$O yr$^{-1}$. The spatial variation of WUEc indicated obvious regional heterogeneity (Fig. 5d), with relatively lower values located in the upstream cropland, while higher values mainly occurred in the oasis in the middle and lower reaches. The result also implies that water availability for cropland was limited, the land was forced to respond to the water stress more efficiently (Miranda Fernandes et al., 2018).

### 3.3. The response of WUEc variation to climate and human activities factors

#### 3.3.1. The response of WUEc variation to T and P

T (Wang et al., 2014) and P (Poulter et al., 2014; Jung et al., 2017) have been reported as the most important climate factors controlling the GPP and ET variations. Trend analysis showed WUEc increased during the period of 2000–2014, and spatially, partial correlation analysis was used to further explore the individual effects of T and P on WUEc from 2000 to 2014 (Fig. 6). The partial correlation of WUEc and T showed a positive relationship in most regions, covering 82.5 % of cropland area. Generally, T mainly affects crop photosynthesis and
evapotranspiration (Zhang et al., 2012; Xue et al., 2015; Sun et al., 2016). For photosynthesis, if the ambient T is lower than the optimal T of photosynthesis, then increased T will promote photosynthesis and vice versa. T affected the evapotranspiration process mainly by adjusting the stomatal conductance of crop. Below the threshold of T, the stomatal conductance of crop is more open with an T increased, and the effect of photosynthesis is greater than that of evapotranspiration. Meanwhile, as an important part of climate change, P significantly influenced the water cycle of the ecosystem. P had a negative correlation with WUEc in most regions, accounting for 90.6 % of the SRB area. High negative partial coefficients were found in the ID of the WSP completed by 2010. Recently, numerous researches have discussed the effect of P on WUE (Yu et al., 2008; Hu et al., 2008, 2010; Guo et al., 2019). Yu et al. (2008) also showed WUE was negatively correlated with P variation. In addition, there are many studies that have shown that with the aggravation of drought, WUE first gradually increases and then decreases after the drought reaches a threshold (Xu et al., 2019). Overall, in the cropland ecosystem of the SRB, WUEc was negatively correlated with P; however, it showed a positive correlation with T in most regions. For the downstream area, a positive relationship between WUEc and P was found in the north of the Hongyashan ID, where the climate was warmer and drier (Fig. 1). This is in accordance with Huang et al. (2015), who indicated that positive partial correlations of WUE and P mainly occurred in warmer and drier regions due to water being the main limitation on GPP, forcing a positive correlation between WUE and annual P by enhance GPP (Knapp and Smith (2001); Nemani et al., 2003; Bai et al., 2008).

3.3.2. The response of WUEc variation to NDVic and EVIc

Previous EC-based and process-based model EWUE studies have showed that vegetation strongly affected EWUE and even primarily determined the seasonal and annual variations of EWUE (Hu et al., 2008; Zhang et al., 2014). For example, based on the model experiments (scenario analysis), Zhang et al. (2014) concluded that the increased WUE over East Asia during 1982–2006 was first attributed to the vegetation greening, followed by the effects of climate factors. However, many studies have explored the T and P directly drive the water and energy cycle and further affect vegetation performance (Bagnoud et al., 2001; Blanken et al., 2004; Ding et al., 2014). In contrast, our partial correlation analysis explored the relationship between WUEc and vegetation variations to remove the covariate effects of vegetation performance and climate factors (T and P). Spatially, a positive partial correlation coefficient for WUEc and NDVic/EVIc mainly occurred in the region of the WSP completed by 2010 (Fig. 7). Thus, the WSP has successfully achieved the purpose of increasing low WUEc by promoting advanced irrigation technology and adjusting crop planting structure; some water-intensive crops have been converted into cash crops.

3.3.3. Factors underlying WUEc interannual variations

We quantified the major driving factors of WUEc variation, and the effects of major drivers on WUEc were also estimated by calculating the IAV of human activities (vegetation change and so on) and climate (air temperature, precipitation, and VPD) factors to the variation of WUEc (Fig. 7). Results show that both GPPc and ETc were negatively
correlated with WUEc by a correlation coefficient of -0.06, and -0.68, respectively, indicating that the IAV in WUEc was mainly ascribed to the changes in ETc and not determined by NDVIc and EVIc by a correlation coefficient of -0.04 and -0.19, respectively. The IAV of GPPc has a strongly positive correlation with NDVIc and EVIc (0.84, 0.85), indicating that the IAV in GPPc was mainly ascribed to the vegetation performance. There is debate about whether variations in annual GPP would be positively or negatively correlated with that of WUE; some research indicates that plants in environments with and without sufficient water supply may have distinct water-use strategies (Hu et al.,...
2008). Niu et al. (2011) indicated that EWUE responded negatively to climate warming while responding positively to increasing precipitation based on a 4-year manipulative field experiment in a temperate steppe in northern China. But WUE may decrease or increase with annual precipitation increasing in different ecosystems depending on water condition and vegetation types (Tian et al., 2010). In the cropland ecosystem of the SRB, the IAV of WUEc was positivity correlated with T (0.54) but negatively correlated with P (-0.64). This is in accordance with Hu et al. (2008). Under drier conditions with warming, however without other water sources, more water evaporated into the atmosphere, decoupled from vegetation productivity with high GPPc. The IAV of ETc has a strong correlation with VPD (-0.81), followed by P (0.80). This is because that water was the main limitation on ETc. Irrigation was applied to maintain crop growth for agriculture in the arid and semiarid regions. In such cases, irrigated crop may transpire at its actual rate defined by atmospheric moisture demand. Because atmospheric moisture demand is also represented by VPD as a factor influencing the vegetation-moisture relationship (Geruo et al., 2020). Thus, VPD became the dominant factors that control the water cycle process. Furthermore, the IAV of VPD has a strongly negative correlation with P, ETc, GPPc, NDVIc and EVIc (-0.91−0.81, -0.63, -0.60, -0.62), indicating that VPD closely connected carbon-water cycle and vegetation performance. Meanwhile, in the water-limited SRB, the response of VPD would be considerably more important in variations of the water cycle process compared with the carbon cycle in the cropland of the SRB. It is likely that VPD determines the IAV in ETc and, hence WUEc, which is in accordance with Hu et al. (2008). The high VPD-driven transpiration water loss, decoupled from vegetation productivity, may lead to high WUEc (Guo et al., 2019), and the increasing of WUEc will ultimately result in decreasing in water consumption, which will alleviate water shortages in the SRB. In addition, WUEc formulation could be considered to link WUEc and VPD in SRB, such as an inherent WUE (IWUE = GPP × VPD/ET) at the ecosystem scale was proposed by Beer and Ciais, 2009, and Zhou et al., 2014, 2015, 2016) introduced the concept of underlying WUE, given by uWUE = GPP × VPD^{0.5}/ET.

In terms of human activities factors, the IAV of IWU had a negative correlation with WUEc variation (-0.48) but positively correlated with ETc (0.52); therefore, the improved irrigation technology had probably played a significant role in promoting WUEc mainly by reducing water consumption. Although IAV in WUEc was mainly ascribed to the changes in ETc and not determined by NDVIc and EVIc, the IAVs of NDVIc and EVIc had a very high correlation coefficient with GPPc and ETc. They even explained 63 % and 73 % of ETc variation and of 84 % and 85 % GPPc variation, respectively. Corresponding to Fig. 5 and Fig. 7, vegetation performance was closely connected with GPPc and ETc variations; therefore, adjusting crop planting structure is also very important in this region in improving WUEc. As a conclusion, WSP had probably played an important role in promoting WUEc by improving irrigation technology and adjusting crop planting structure.

3.4. Implications of water-saving project on water cycle

Hao et al. (2017) showed that the implementation of the GTSRB had a significantly positive effect in regard to the groundwater resource recovery in the Minqin during the first decade of the program and also verified the effects of watershed groundwater restoration polices. Corresponding measures of the WSP involve promoting advanced water-saving technologies and adjusting crop plant pattern to increased WUEc in the SRB. And the IAV in WUEc was mainly ascribed to the changes in ETc (Fig. 8b). Water consumption decreased in the cropland, mainly occurred in the ID where the WSP was completed by 2010 (Fig. 5b). Especially, a large proportion of the cropland of SRB showed wet trend in the last decades (Fu et al., 2019), due to the effect of human activities and climate change in the SRB. To further clarify the relative contribution of climate change and human activities to ETc variation, we figured out the mutation point of ETc decrease. As shown in Fig. 9, ETc decline started in 2007. This finding is consistent with the annual variation of IWU for the SRB (Fig. 3b).

Besides, annual ETc was plotted against potential evapotranspiration in cropland (PETc) revealed in Fig. 10. Further regression analysis of pre-2007 and post-2007 point to human activities factors rather than climate factors, as the dominant factors of driving regional crop consumptive water use. For similar PETc, lower ETc is noticeable from the regression lines after 2007. That is, similar water demand or maximum water at large scale, lower the actual amount of water evaporated from the entire region, after years of water saving technology popularization. Hence, water-saving measures probably changed the hydrological cycle through adjusting ETc after WSP. Furthermore, to quantify the contribution of human activities factors in WSP to the ETc variation, IWU and vegetation index were used to represent the human activities factors in WSP due to the aim of WSP. IWU was used to represent the improving irrigation technology. Regarding the vegetation index, as mentioned above, the IAVs of NDVIc and EVIc explained 63 % and 73 % of ETc variation, respectively (Fig. 8). EVIc was used to represent the adjusting crop planting structure due to its better explained the variation of ETc. Results indicated that the relative contribution of human
Fig. 8. The color-coded correlation matrices in interannual variation (IAV) (a), and structural model analysis examining the major driving factors of underlying the IAV (b). WUEc: ecosystem water use efficiency in cropland, GPPc: gross primary productivity in cropland, ETc: actual evapotranspiration in cropland, NDVIc: normalized difference vegetation index in cropland, EVIc: enhanced vegetation index in cropland, VPD: vapor pressure deficit, P: precipitation, T: air temperature, and IWU: irrigation water used.
activities factor in water-saving management was extremely low before the mutation point, only accounting for 26.3%, while after the mutation point, human activities in WSP contribution to ETc increased to 77.5% (Fig. 11). This further proves that water availability increase was mainly artificially controlled by the effect of the WSP rather than that of climate factors.

4. Conclusions

In this study, we explored the variations and major driving factors in WUEc under the changing environment to clarify the effects of the WSP in the SRB. It was revealed that increased WUEc area occupied 97.25% of the total cropland area of the SRB since 2000. ETc decreasing pixel mainly occurred in the irrigation districts of WSP completed by 2010. Then, we explained the effects of climate and human activities factors on the variations of WUEc and its major driving factors. The IAV of WUEc was mainly determined by ETc (68%) rather than GPPc (6%). Thus, the study quantified the contribution of human activities factors in the WSP to ETc variation. Further clarified water availability increase is mainly artificially controlled by the effect of WSP rather than that of climate factors. Overall, which serves as a valuable reference for the effectiveness of a WSP and the reasonable utilization of regional water resource management and allocation strategies in the SRB.

The VPD was shown to play a more important role in the underlying WUEc interannual variations. Further studies are also required, WUEc formulation could be considered to link WUEc and VPD. Namely using the developed WUEc formulation, to better assess spatial-temporal dynamics of developed WUEc and its response to agricultural water management. In addition, given the improvement in WUEc being related to the change in crop biomass production in different crop types, not only in the SRB, it is also of great necessity to explore the spatial variations of crop biomass production in different crop types by remote sensing in the future.

Fig. 9. The M-K mutation point test of actual evapotranspiration in cropland (ETc) with forward-test–solid red line, the backward-trend–dashed blue line, and dotted horizontal lines represent critical values corresponding to the 95% confidence level.

Fig. 10. Comparison and relationship between actual evapotranspiration (ETc) and potential evapotranspiration in cropland (PETc) in the Shiyang River Basin (SRB) during the period of 2000 and 2014.


OECD, 2015. Drying Wells, Rising Stakes Towards Sustainable Agricultural Groundwater
Niu, S.L., Wu, M.Y., Han, Y., Xia, J.Y., Li, L.H., Wan, S.Q., 2008. Water-mediated re-
Niu, S.L., Wu, M.Y., Han, Y., Xia, J.Y., Li, L.H., Wan, S.Q., 2008. Water-mediated re-