Annual water deficit in response to climate variabilities across the globe

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Keywords: water deficit, climate variabilities, Budyko framework, global water cycle

Supplementary material for this article is available online

Abstract

Severe water deficits due to abnormal climatic conditions can be observed in hydrology and agriculture and can be assessed by various characteristics of the water system that show different responses to climate variability. This paper comprehensively investigates the sensitivities of hydrological (i.e. streamflow and water storage) and agricultural (i.e. plant water availability) water deficits to climate variability at a global scale from a hydrological cycle perspective. The sensitivities of 77 large basins across the globe are quantified by both multiple linear regression (MLR) and the Budyko framework based on a newly released terrestrial water cycle dataset. We find that streamflow and water storage deficits are generally more sensitive to rainfall variation, while plant water availability is more responsive to variations of potential evapotranspiration. The climate sensitivities of the water deficit indices are shown to vary with the wetness index and are shaped by catchment surface properties like water storage capacity. The sensitivities of streamflow deficits to rainfall are higher in wetter regions, while the sensitivities of plant water availability to potential evapotranspiration are higher in drier regions. The findings about the divergent responses in water deficit indices can be conducive to developing region-dependent water resource management strategies to alleviate water deficits under a changing environment.

1. Introduction

In recent decades, severe water deficits have caused great adverse effects on regional agricultural production, eco-environmental health, and socioeconomic development (Zeng \textit{et al} \textit{2008}, van Dijk \textit{et al} \textit{2013}, Zampieri \textit{et al} \textit{2017}). Water deficits can occur in various systems (e.g. soil, vegetation, river, groundwater), and can be quantified by anomalies to the long-term mean status or the difference between the water demand and supply (Wada \textit{et al} \textit{2011}, Chirouze \textit{et al} \textit{2014}, Veldkamp \textit{et al} \textit{2016}). Climate variability (e.g. variations in precipitation and potential evapotranspiration) has been seen to strengthen water deficits in many regions in the world but with different performance in various systems (Chaplot \textit{2007}, Kelly \textit{et al} \textit{2016}, Berghuis \textit{et al} \textit{2017}).

Efforts have been made to investigate the responses of individual water deficit metrics to climatic variabilities at the local/regional scale (e.g. Wang and Alimohammadi \textit{2012}). For instance, a number of studies have assessed the sensitivities of streamflow to variations in precipitation, radiation, and other factors in various regions/basins such as the Amazon region and the Yellow River Basin (Liu and McVicar \textit{2012}, Guimberteau \textit{et al} \textit{2013}, Li \textit{et al} \textit{2021}). Some studies have also investigated the impacts of climatic variabilities on soil/vegetation water stress (Quetin and Swann \textit{2017}, Wang \textit{et al} \textit{2019}, Wu \textit{et al} \textit{2020}). Fewer studies have made the effort to explore
the influence of climatic variations on water storage (Lorenzo-Lacruz et al 2017, Chen et al 2018).

However, there have been limited studies that comprehensively explore the compounding sensitivities of various water deficits to climate variations at the global scale. One possible reason for this might be the lack of reliable terrestrial water cycle data. Recently, global gridded surface water budget datasets have been emerging, which include, for example, the Climate Data Record (CDR) developed by the Princeton University group and the Conserving Land–Atmosphere Synthesis Suite released by the University of New South Wales (Zhang et al 2018, Hobeichi et al 2019). With global water cycle data becoming more easily available among the hydrological community, it is now possible to conduct an initial exploration of the responses of water deficits to climatic variabilities from a global water cycle perspective.

In this study, we adopt the recently released CDR dataset and aim to investigate the sensitivities of annual water deficits to climatic variabilities for 77 large basins across the globe. We begin in section 2 by describing the climate and hydrologic data and the study basins, and then introduce definitions of water deficits and methodologies in section 3. In section 4, the sensitivities of water deficits to climatic conditions are demonstrated. We finish this section by investigating the potential factors affecting the climate sensitivities of the water deficit indices. In section 5, the consistency of the methods as well as the limitations are discussed, and main conclusions are summarized in section 6.

2. Data and study area

2.1. Data

We use the global terrestrial water cycle budget dataset known as the CDR (Zhang et al 2018) to characterize water deficits. The CDR dataset integrates multi-source observations and model outputs, and is firstly and specifically designed for the terrestrial water cycle. It includes four water cycle variables (precipitation ($P$), evapotranspiration ($E$), streamflow ($R$), and total water storage change (TWSC)), with the spatial resolution of 0.5° and monthly time series from 1984 to 2010. The basic hydrologic concepts of mass balance have been enforced in the dataset, and numerous tests of the dataset have also been reported by the authors. Yin and Roderick (2020) have augmented those original tests by independently using data from 32 FLUXNET tower sites, two evapotranspiration datasets, and a European runoff dataset.

The global surface radiation data is from the NASA GEWEX-SRB project (SRB; Stackhouse et al 2011), and is used to estimate the potential evapotranspiration $E_{0}$ (defined as the net radiation $R_{n}$ expressed as an equivalent depth of liquid water $R_{n}/\lambda$, with $\lambda$ the latent heat of vaporization; Budyko 1974). It includes four components (surface incoming/outgoing, shortwave, and longwave) with the spatial resolution of 1° and monthly time series from 1984 to 2007. In this study, we use the period 1984–2007, in which the CDR and SRB datasets overlapped, as the study period. The global basin boundary has been obtained from the Global Composite Runoff Fields (GCRF) product (Fekete et al 2002).

In addition, we anticipate two important factors, the characteristics of the underlying surface conditions in the study basins (represented by the parameter $n$ in the Budyko framework; see equation (4) in section 3.3) and the water storage capacity $S_{\text{max}}$, which are likely to have potential effects on the water deficit responses. The value of $n$ in each study basin is inversely calculated by using the $E$ and $P$ data in the CDR dataset based on equation (4). The $S_{\text{max}}$ in each study basin is estimated by the active range of the monthly water storage variation (i.e. $S_{\text{max}} = \text{Max}(S_{t}) - \text{Min}(S_{t})$, with $S_{t}$ as the water storage at time step $t$ assuming $S_{0}$ equals zero) using the TWSC data in the CDR dataset (for details, refer to section 2 in Yin and Roderick 2020).

2.2. Study basins

In total, 77 large basins (with an area of more than 200 000 km$^2$) across the globe are selected based on the GCRF product (figure 1). The study basins cover around 60% of global land area (except the north and south poles). The wetness index ($WI = P/E_{0}$) defined as the ratio of mean annual rainfall ($P$) to potential evapotranspiration ($E_{0}$) (Budyko 1974) is used to measure the aridity in the selected basin. The $WI$ is widely used in representing surface dryness (e.g. Roderick et al 2015, Greve et al 2019). Based on the $WI$, the study basins are divided into 30 arid ($WI < 0.5$), 36 semi-arid ($0.5 \leq WI \leq 1.0$), and 11 humid ($WI > 1.0$) basins (figure 1). The detailed characteristics of each basin (e.g. name, area) are shown in table S1 (available online at stacks.iop.org/ERL/17/054021/mmedia). It can be seen from figure 1 that the arid basins are primarily located in central Africa and near 30° N-S latitude, and with all selected basins in Australia in arid environments. The semi-arid basins are mainly located at higher latitudes in the northern hemisphere, as well as between 0° and 30° in the southern hemisphere; e.g. central South America and Africa. The humid basins are primarily distributed in the Amazon region and southern Asia.

3. Methods

3.1. Water deficit indices

Three water deficit indices are considered in this study. It includes two hydrological water deficit indices defined according to the annual anomalies (i.e. the difference to the long-term mean) of runoff and total water storage, denoted as $\Delta R$ and

$$R_{n} = \lambda \Delta R$$

where $\lambda$ is the latent heat of vaporization; and $S_{\text{max}}$ which is the water storage capacity at each study basin.
Figure 1. The selected 77 basins in this study.

$\Delta T W S C$, respectively. The two indices are widely used in hydrology representing the deficit in the renewable water flux (i.e. runoff) and the status of water budget (i.e. water storage). The third water deficit index is investigated herein to reflect the agricultural water deficit ($W_a = E_0 - E$), which is the evapotranspiration deficit defined as the difference between potential water demand (represented by $E_0$) and the actual water supplied (represented by $E$) for vegetation. The larger the $W_a$, the more severe the agricultural water stress is. The definition of $W_a$ is adopted to quantify the crop water stress index commonly used in measuring agricultural water stress (Idso et al. 1981, Jackson et al. 1981, Berni et al. 2009, Wu et al. 2019).

3.2. Estimating the climate sensitivity of water deficits based on regression

To quantify the response of water deficits to climate variation, firstly, statistical models based on multiple linear regression (MLR) are developed to demonstrate the connections between the water deficit indices and the two dominant climate variables, i.e. rainfall and potential evapotranspiration. The statistical models assume linear relationships exist between the dependent and the independent variables and are expressed as:

$$\Delta R = a_1 \Delta P + b_1 \Delta E_0$$

(1)

$$\Delta T W S C = a_2 \Delta P + b_2 \Delta E_0$$

(2)

$$W_a = a_3 \Delta P + b_3 \Delta E_0 + c,$$

(3)

where $a_1$, $a_2$, $a_3$, $b_1$, $b_2$, $b_3$, and $c$ are regression coefficients of the statistical models. The regression coefficients except for the constant $c$ in equation (3) can then be considered as the sensitivity coefficients quantifying water deficits in response to climate variations. It should be noted that there is no constant term (i.e. interception in regression) in both equations (1) and (2). This is because, in equations (1) and (2), both the dependent and independent variables are the annual anomaly, which can be considered as the difference between their corresponding differential equations. In principle, for a linear system assuming that $y = ax + b$, its corresponding first order differential equation is $dy = a \cdot dx$, and hence the difference equation should be $\Delta y = a \cdot \Delta x$, suggesting no constant term is needed in the empirical relationship between $\Delta y$ and $\Delta x$.

3.3. Estimating the climate sensitivity of water deficits based on the Budyko framework

The climate sensitivity of the abovementioned water deficit indices can also be estimated according to the Budyko framework (Budyko 1974), which has stronger physical bases and is widely used in hydroclimate research (e.g. Zheng et al. 2009). The Budyko framework assumes that actual evapotranspiration ($E$) is a function of wetness and has various forms. To derive the climate sensitivity coefficients based on the Budyko framework, here, the Mezentsev-Choudhury-Yang form (Mezentsev 1955, Choudhury 1999, Yang et al. 2008) is used, which can be expressed as:

$$E = \frac{P \cdot E_0}{(P^n + E_0^n)^{1/n}},$$

(4)

where $n$ is a parameter reflecting compounding effects of the catchment.

Based on the mass balance of the surface water cycle and the Budyko equation (equation (4)), by
ignoring changes in $n$, the impact of changes in precipitation ($\Delta P$) and potential evapotranspiration ($\Delta E_0$) on evapotranspiration ($\Delta E$) and runoff ($\Delta R$) can be expressed as (Roderick and Farquhar 2011):

$$
\Delta E = \frac{\partial E}{\partial P} \Delta P + \frac{\partial E}{\partial E_0} \Delta E_0
$$

(5)

$$
\Delta R = \left(1 - \frac{\partial E}{\partial P}\right) \Delta P - \frac{\partial E}{\partial E_0} \Delta E_0,
$$

(6)

where

$$
\frac{\partial E}{\partial P} = \frac{E}{P} \left( \frac{E_0}{P^0 + E_0} \right)
$$

(7)

$$
\frac{\partial E}{\partial E_0} = \frac{E}{E_0} \left( \frac{P_0}{P^0 + E_0} \right).
$$

(8)

Since the agricultural water availability term $W_a$ can be represented as

$$
W_a = E_0 - E = (E_0 + \Delta E_0) - (E + \Delta E),
$$

(9)

substituting equation (5) into equation (9), we can obtain the relationship between the agricultural water deficit index and the climate variables expressed as:

$$
W_a = -\frac{\partial E}{\partial P} \Delta P + \left(1 - \frac{\partial E}{\partial E_0}\right) \Delta E_0 + (E_0 - E).
$$

(10)

Equations (6) and (10) derived from the Budyko framework can then be used to assess the climate sensitivity of runoff and the agricultural water deficit, respectively. One may notice that equation (6) is similar to equation (1), while equation (10) is similar to equation (3) in terms of their mathematical forms. In other words, the coefficients in equations (6) and (10), namely $1 - \partial E/\partial P$, $-\partial E/\partial E_0$, and $-\partial E/\partial P$, are equivalent to $a_1$, $b_1$, $a_3$, $b_3$, and $c_3$ in equations (1) and (3), respectively, and are denoted as $a_{1, \text{Budyko}}$, $b_{1, \text{Budyko}}$, $a_{3, \text{Budyko}}$, $b_{3, \text{Budyko}}$, and $c_{\text{Budyko}}$ in the following sections.

4. Results

4.1. Annual water deficit characteristics in the study basins

Figure 2 shows the temporal variation of water conditions for nine representative basins for the period 1984–2007, where the time series of annual water availabilities ($R$, TWSC and $W_a$) as well as the climatic water conditions (represented by $P$) are presented. The time series of all the other basins are shown in figures S1–S3. It can be seen that, in arid basins, the TWSC ($W_a$) basically (slightly) varies with the fluctuation of $P$, and there are slight differences in the variation of $R$ with $P$ in different basins. In the basin with a larger $R$, the $R$ generally changed with $P$ (e.g. the Indus Basin, labeled as 22), while in the basin with a smaller $R$, the variation of $R$ is lower (e.g. the Murray Basin, labeled as 18). In semi-arid basins, both $R$ and the TWSC change with $P$ (e.g. the Huai Basin, labeled 62, and the Mississippi Basin, labeled 47), with limited influence of $P$ on $W_a$. In humid basins (e.g. the Ganges Basin, labeled as 68), the variation in $P$ seems primarily to cause fluctuations in $R$, with a slight impact on TWSC and almost no influence $W_a$.

4.2. Climate sensitivity of water deficits

The statistical distribution of the MLR sensitivity coefficients (equations (1)–(3)) for arid, semi-arid, and humid basins is shown in figure 3, which is similar to those based on the Budyko framework (figure S5). The values of the coefficient for all the study basins are shown in figure S4. It can be seen that, in the study basins, the sensitivities of $\Delta R$ to $\Delta P$ (i.e. coefficient $a_1$) are positive and relatively high, which indicates that variation in $P$ has a great impact on streamflow. The coefficient $a_1$ increases gradually from the arid to the humid basins, approaching 1.0 in the humid basins (figure 3(a)). The sensitivities (i.e. coefficient $b_1$) of $\Delta R$ to $\Delta E_0$ are generally negative with absolute values lower than $a_1$. The absolute values of $b_1$ gradually decrease from the humid to the arid basins, being close to zero in the arid basin (figure 3(b)).

The sensitivity coefficients $(a_2)$ of the TWSC to $P$ change in arid and semi-arid basins are relatively higher than that in humid basins (figure 3(c)). This indicates that water storage is more affected by rainfall variations in arid and semi-arid basins than in humid basins. The sensitivity coefficients $(b_2)$ of the TWSC to $E_0$ change are largely negative with absolute values lower than $a_2$. The absolute value of $b_2$ is relatively high in some semi-arid basins (e.g. the Volga Basin, labeled as 52), indicating that water storage deficits in those basins are affected by changes in $E_0$.

The sensitivity coefficient of $W_a$ to $P$ $(a_3)$ is found to be generally negative (figure 3(e)). The absolute value of $a_3$ decreases gradually from the arid to the humid basins and approaches zero in some humid basins (e.g. the Ogooue Basin, labeled as 72), suggesting that agricultural water deficits in arid basins are more responsive to rainfall compared to humid basins. Variation in rainfall may have a very limited impact on agricultural water deficits in humid basins. The sensitivity coefficient of $W_a$ to $E_0$ $(b_3)$ is positive, and shows higher absolute values than $a_3$, which means that $W_a$ is more affected by potential evapotranspiration than by rainfall. The magnitude of the sensitivity coefficient $b_3$ increases gradually from humid to arid basins (figure 3(f)), implying that $E_0$ plays a more important role in agricultural deficits in arid basins than in humid basins.
4.3. Divergent climate sensitivity of water deficit across the globe

The results show divergent responses of water deficits to climate variations across the globe (figures 3 and 4). This means that rainfall is the dominant climate factor affecting streamflow deficits in humid basins (figures 4(g)–(i)) and storage deficits in arid and semi-arid basins (figures 4(d)–(f)), while potential...
Sensitivity coefficients of the MLR in typical basins. The red, orange, and blue colors represent results in arid, semi-arid, and humid basins.

4.4. Factors shaping water deficit responses to climate variations

Climate sensitivity of water deficits is not solely dependent on regional climate conditions represented by the WI, it can also be shaped by physical properties of the catchments. Two critical factors including the parameter \( n \) in the Budyko framework and the water storage capacity \( (S_{\text{max}}) \) are investigated here to explore their potential impact on water deficit responses to climate variabilities. The parameter \( n \) is calculated based on the Budyko framework (equation (4)), while the estimation of \( S_{\text{max}} \) is described in section 2.1.

Figure 5 shows the relations between the regression coefficients (from MLR) and the WI, with the points colored by the values of parameters \( n \) or \( S_{\text{max}} \). We also show the relations between the coefficients from the Budyko framework and the WI colored by parameters \( n \) or \( S_{\text{max}} \) in figure S7. It can be seen that the sensitivity coefficients of \( R \), TWSC, and \( W_a \) to variation in \( P \) (i.e. \( a_1, a_2 \), and \( a_3 \), respectively) are affected by parameter \( n \), showing a decrease of \( a_1 \) and \( a_3 \) but an increase of \( a_2 \) with the increase of \( n \) (figures 5(a), (c), and (e)). The sensitivity coefficients related to \( E_0 \) changes (i.e. \( b_1, b_2, b_3 \)) are basically not influenced by parameter \( n \) (figures 5(b), (d), and (f)). Research has shown that the parameter \( n \) reflects compounding effects of physical properties in the catchments, including vegetation coverage and average slope (Yang et al. 2007, Li et al. 2013). With distinct changes of land surface conditions under climate change and human activities (Mankin et al. 2019, Fiao et al. 2020), the above results imply that water deficit responses to climatic conditions could also vary in a changing environment (Kelly et al. 2016).

The climate sensitivity coefficients (\( a_i \) and \( b_i \) in equations (1)–(3)) are found to not be directly related to catchment storage capacity \( (S_{\text{max}}) \). The constant term \( c \) in equation (3), however, tends to increase with higher \( S_{\text{max}} \) (figure 5(g)). This result means that catchment storage capacity does not have a direct effect on the climate sensitivities of water deficits; however, higher \( S_{\text{max}} \) could strengthen evapotranspiration deficits under abnormal climate conditions. This could be because a larger proportion of rainfall is more likely partitioned into groundwater in unconfined aquifers and then discharges to rivers for basins with higher storage capacity, which could then result in a lower portion of rainfall available to meet the evapotranspiration demand and...
hence a higher evapotranspiration deficit rate ($W_a$ in equation (3)).

5. Discussion

5.1. Climate sensitivities based on MLR and the Budyko framework

A comparison of the sensitivity coefficients from the MLR (equations (1)–(3)) and the Budyko framework (equations (6) and (10)) in arid, semi-arid, and humid basins is shown in figure 6. The same comparison in all study basins but colored by the WI in each basin is shown in figure S6. It is found that the coefficients estimated using the two methods generally agree with each other, showing consistent variation patterns from arid to humid basins (figure S5). In arid and semi-arid basins, the sensitivity coefficients of $R$ to $P$ variation estimated using the Budyko framework ($a_{1,\text{Budyko}}$) are generally higher than those using MLR ($a_1$). Meanwhile, in humid basins, the coefficients $a_{1,\text{Budyko}}$ are lower than those of $a_1$ (figure 6(a)). Most of the sensitivity coefficients of $R$ to $E_0$ changes from the Budyko framework ($b_{1,\text{Budyko}}$) are stronger than those using MLR ($b_1$), especially in humid basins (figure 6(b)). Compared to those from MLR, the Budyko framework...
also shows stronger sensitivities of $W_a$ to $P$ ($a_{3,\text{Budyko}}$) but lower coefficients of $W_a$ to $E_0$ change ($b_{3,\text{Budyko}}$). This could be because of the steady state assumption in the Budyko framework ignoring the inter-annual variation of water storage, which is found, however, to be prominent in some regions (e.g. Yin and Roderick 2020).

5.2. Limitations and uncertainties
Water deficits can be assessed at temporal scales from weeks, months, years to decades, and the spatial scales from tens to tens of millions of square kilometers (Stahl and Hisdal 2004, Van Loon 2013). It should be noted that water deficits in response to abnormal climate could perform substantially differently among various spatial-temporal scales. This study focuses on annual water deficits at a basin scale. The findings together with the approaches could be conducive to large-scale water resource management and planning but could need further investigation when applied to a much smaller spatial-temporal scale, where more detailed processes about water cycles should be considered (e.g. the dynamics of soil moisture that contributes substantially to agricultural and ecological water deficits).

In the literature, water deficits at the regional scale can be measured by different indices based on hydroclimatic variables (e.g. rainfall, runoff, soil moisture, groundwater storage) or agricultural/ecological variables (e.g. leaf area index, crop yield). Each individual index is valuable in quantifying water deficits for a certain application purpose. For a broader assessment of regional water deficits, however, it is practically necessary to investigate the compounding performances represented by multiple water deficit indices. With such a consideration, in this study, three different indices (defined in equations (1)–(3)) are used to investigate hydrological water deficits ($\Delta R$ in equation (1) and $\Delta TWSC$ in equation (2)) and agricultural water deficits ($W_a$ in equation (3)) based mainly on variables like runoff, water storage, and evapotranspiration. The three indices, though all affected by regional climate conditions (e.g. rainfall and potential evapotranspiration), are complementary in assessing regional water deficits. For instance, the agricultural water deficit defined in equation (3) is the difference between the actual water consumed by plants (represented by actual evapotranspiration) and the potential water demand of the plants (represented by potential evapotranspiration). However, it should be noted that water can be withdrawn from a river or from a groundwater system for agricultural irrigation. Hence, a comprehensive assessment of agricultural
water deficits should also take into account the availability of runoff and groundwater (i.e. hydrological and hydrogeological water deficit represented by $\Delta R$ and $\Delta$TWSC).

It should be noted that, in this study, a water deficit is defined to reflect water stress under natural conditions across global large basins, where precipitation and potential evapotranspiration are the two dominant variables affecting water availability and water demand, respectively. In practice, however, water deficits could also be affected by water supply capacity (e.g. irrigation infrastructures), water use efficiency, and water-management strategies (e.g. water allocation priorities). The issues are out of the scope of the study, but are important for enhancing regional drought resilience and developing adaptive water-management strategies under a changing climate.

In this study, two different approaches have been used to quantify the climate sensitivities of the water deficit indices. The two approaches generally show consistent results across the studied basins. However, uncertainties exist in the estimated sensitivity coefficients due to the availability and quality of the dataset. For example, the potential evapotranspiration $E_0$ is estimated using the radiation-based method in this study; therefore, the estimated impact of $E_0$ on water deficits is mainly from radiation. Though radiation is the most important variable determining the $E_0$, other factors (e.g. temperature) might also play considerable roles in $E_0$ estimation and hereafter impact water deficits (Allen et al. 1998, Milly and Dunne 2016, Yang and Roderick 2019). The increase of temperature under global warming could have a potential impact on regional water deficits, which deserves further investigation in the future.

### 6. Conclusions

In this study, we have investigated the sensitivities of annual water deficits (i.e. the streamflow, water storage, and agricultural water availabilities) to climatic variabilities (including precipitation and potential evapotranspiration variations) across the globe from the perspective of the hydrological cycle by using the newly released terrestrial water cycle dataset. Water deficits in response to climatic variations during 1984–2007 in 77 large basins across the globe were quantified based on MLR and the Budyko empirical framework. Critical factors (i.e. parameter $n$ from the Budyko framework and water storage capacity $S_{\text{max}}$) shaping the spatial difference in the climate sensitivities were also investigated.

It is found that deficits in streamflow and water storage are generally more sensitive to precipitation variations, while the evapotranspiration deficit is more responsive to potential evapotranspiration variations. The climate sensitivities of water deficits show considerable geospatial differences mainly due to climate wetness (represented by the WI) but are shaped by catchment properties (represented by parameter $n$ in the Budyko framework and water storage capacity). Streamflow and water storage deficits are more responsive to rainfall variation in wetter regions, while evapotranspiration deficits are more sensitive to potential evapotranspiration variation in drier regions. The findings in this study provide overall understanding of the connections between annual water deficits and climatic variations across the globe and can be conducive to developing region-dependent water resource management strategies to alleviate water deficits under a changing environment.

### Data availability statement

The data that support the findings of this study are openly available at the following URL/DOI: https://asdc.larc.nasa.gov/project/SRB.

### Acknowledgments

This research was supported by the National Natural Science Foundation of China (42171024, 51609122), the Natural Science Foundation of Qinghai Province in China (2022-ZJ-933Q), the Open Research Fund Program of the State Key Laboratory of Hydroscience and Engineering (sklhse-2020-A-07), and the Joint Open Research Fund Program of the State Key Laboratory of Hydroscience and Engineering and the Tsinghua-Ningxia Yinchuan Joint Institute of Internet of Waters on Digital Water Governance (sklhse-2021-Iow06). We thank the anonymous reviewers for constructive comments that improved the manuscript. The authors declare that there is no conflict of interests regarding the publication of this paper.

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