



Satellite-observed vegetation stability in response to changes in climate and total water storage in Central Asia

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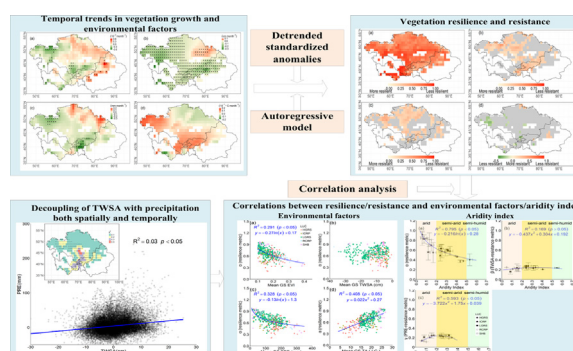
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HIGHLIGHTS

- Spatially vegetation resilience increased logarithmically with increasing mean annual precipitation or aridity index.
- Vegetation resilience was not correlated with TWSA due to the decoupling of TWSA with precipitation.
- Vegetation resistance to precipitation functioned nonlinearly along the aridity gradient.

GRAPHICAL ABSTRACT



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ABSTRACT

Ecosystems in arid and semi-arid regions are vulnerable to climatic and anthropogenic disturbances. However, our understanding of vegetation stability (including resistance and resilience, which are the abilities of ecosystems to resist perturbations and return to pre-disturbance structure or function, respectively) in response to environmental changes in dryland ecosystems remains insufficient, particularly in the absence of large-scale observations of water availability. Here we introduced GRACE monthly total water storage anomaly (TWSA) data into an autoregressive model with remote sensed EVI, air temperature and precipitation to investigate the short-term vegetation stability and its influencing factors in Central Asia (CA) during 2003–2015. The results showed that the grid-level vegetation resilience in CA increased logarithmically as mean annual precipitation ($R^2 = 0.33$, $P < 0.05$) but decreased linearly with increasing mean annual temperature ($R^2 = 0.41$, $P < 0.05$). Vegetation resilience was not correlated with TWSA, due to the decoupling of TWSA with precipitation both spatially and temporally in the majority of CA. At the biome level, vegetation resilience also increased as a logarithmical function of aridity index ($R^2 = 0.80$, $P < 0.05$). Vegetation resistance to TWSA showed minor difference across biomes, while vegetation resistance to precipitation functioned as a parabolic curve along the aridity gradient ($R^2 = 0.59$, $P < 0.05$). Our results suggest that accounting for the effects of total water column instead of precipitation only is critical in understanding vegetation–water relationships in drylands. The steep decrease in

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vegetation resilience in areas with high temperature and low water availability implies a high risk of collapse for these water-limited ecosystems if there are severe droughts. Furthermore, reduction in total water storage, induced by, e.g., large-scale extraction of surface runoff or shallow-layer groundwater for irrigation, can result in negative influences to natural biomes in dryland regions.

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1. Introduction

Drylands (including arid and semi-arid regions) occupy over 41% of the global land surface area and are inhabited by >2 billion people (Safriel et al., 2005). Ecosystems in these regions are fragile and sensitive to climate variability (Rotenberg and Yakir, 2010), especially to fluctuations in water availability. Given more frequent and severe extreme climate events such as heatwaves and droughts, which are projected for the future (Dai, 2012; Easterling et al., 2000), monitoring and quantifying the stability of dryland ecosystems to climatic variations, together with the understanding of underlying mechanisms, are essential.

However, there are two key issues to address before analyzing ecosystem stability in dryland regions. The first is how to describe ecosystem stability in a quantitative way. The “ecosystem stability” is a term with several different meanings, for instance, the inverse of variability in ecosystem biomass production (Bai et al., 2004) or the ecosystem efficiency in control or management of the destabilizing forces (Campos et al., 2013; Führer, 2000). The most common interpretation is the capacity of ecosystems to tolerate stress or perturbation and return to normal afterward (Harrison, 1979; Holling, 1973). Orians (1975) defined seven different aspects of stability: constancy, persistence, inertia, elasticity, amplitude, cyclical stability, and trajectory stability. Here, we focus on two of them: inertia and elasticity, denoting the ability of a system to resist perturbations and the ability to return to pre-stress or pre-disturbance structure or function following a perturbation, respectively. Webster et al. (1975) define the above two terms as resistance and resilience and we adopt their terminology. In general, resistance can be quantified using the magnitude of a vegetation response at the moment of the climate anomaly (Tilman, 1996; Tilman and Downing, 1994). Resilience can be quantified by the amount of time required to resume the normal after stress (Lhermitte et al., 2010; Tilman, 1996), or by autocorrelation or the persistence of trends in temporal changes of ecosystem properties (Harris et al., 2014; Simoniello et al., 2008). Of various methods, the autocorrelation model proposed by De Keersmaecker et al. (2015) can simultaneously calculate ecosystem resistance and resilience, by taking into account the standardized short-term climate anomalies and vegetation memory effects. We, therefore, apply this method to quantify ecosystem stability and the details will be introduced later.

The second issue is how to cover the spatial heterogeneity and temporal variability of the entire water column (including precipitation, surface runoff, soil moisture and groundwater) in dryland regions. Precipitation in arid or semi-arid area is scarce and thus groundwater and runoff are important or even major water supply for ecosystems there. The decrease in water table can reduce the water availability in the root zone of groundwater-dependent ecosystems (Eamus et al., 2015). Glacial meltwater-fed inland rivers are the major water sources for many natural oases and irrigated croplands (Barnett et al., 2005; Schaner et al., 2012). However, observations of groundwater and runoff are usually lacking because in situ measurements are sparse and difficult to access. Moreover, environmental changes, characterized by global warming, shifts of precipitation regimes and land use change, have been profoundly affecting the spatio-temporal patterns of water availability (Lioubimtseva and Henebry, 2009; Unger-Shayesteh et al., 2013). There is evidence that climate warming can decrease streamflow through shifting precipitation from snowfall to rainfall (Berghuijs et al.,

2014) and will decrease glacier runoff (Labat et al., 2004) in the 21st century among the majority of glacier-dominant regions (Bliss et al., 2014; Sorg et al., 2012). Therefore, analysis of vegetation stability in response to environmental changes must take into account the changes in total available water rather than that in precipitation only, particularly in oasis ecosystems.

Satellite observations provide a feasible method for monitoring water storage dynamics over world. The Gravity Recovery and Climate Experiment (GRACE) system, launched by NASA and the German Aerospace Centre (DLR) in March 2002, has since then provided global estimates of monthly changes in land total water storage (TWS, Chen et al., 2005). The TWS derived anomaly (TWSA) data, representing changes in vertically integrated water storage (including surface water, soil moisture, groundwater, snow/glacier meltwater, and biological water), have been widely used in hydrological and ecological fields such as changes in groundwater and drought impacts on ecosystems (Humphrey et al., 2018; Long et al., 2013; Rodell et al., 2018; Singh et al., 2012; Xie et al., 2016). Here we introduce GRACE TWSA into an autoregressive model and then apply it into the analysis of vegetation stability in response to short-term environmental changes in Central Asia (CA).

Central Asia is one of the largest dryland regions in the Northern Hemisphere (Cowan, 2007) and covers over 80% of global cold/temperate deserts and semi-deserts (Li et al., 2015a). Recently, climate change and rapid population growth have caused unprecedented large-scale disturbances to ecosystems in CA (e.g., glacier recession in Tianshan Mountains and increased irrigation water), resulting in extensive vegetation degradation and weakened ecosystem services (Jiang et al., 2017; Li et al., 2015b; Xu et al., 2016; Zhou et al., 2015).

Based on the Moderate Resolution Imaging Spectroradiometer (MODIS) enhanced vegetation index (EVI) data, we developed an autoregressive model integrating air temperature, precipitation and GRACE TWSA to estimate ecosystem stability in CA. Our aims are to (1) investigate the stability of a variety of biomes in CA in response to short-term disturbances of climate and total water column, and (2) identify the influences of vegetation types and hydrometeorological conditions on the spatial patterns of ecosystem short-term resilience and resistance.

2. Data and methods

2.1. Study area

In this study, Central Asia consists of five former Soviet Union republics (Kazakhstan, Kyrgyzstan, Tajikistan, Turkmenistan, and Uzbekistan) and the Xinjiang autonomous region in Northwest China (Fig. S1; Li et al., 2015a). The total area of CA is about 5.61 million km². Deserts are mainly distributed in Uzbekistan, Turkmenistan, Xinjiang as well as southern Kazakhstan. Located deep within the Eurasian continent, CA has a continental climate characterized by hot-dry summers and cold-moist winters. Mean annual temperature ranges between 10 and 15 °C in the north and around 20–25 °C in the south. Mean annual precipitation increases gradually from <50 mm per year at lowlands to about 400 mm per year at mountains. The growing season (GS) in most parts of CA lasts approximately from April to October (Gessner et al., 2013).

2.2. Data

2.2.1. Meteorological data

Monthly gridded temperature (TA) and precipitation (PRE) data ($0.5^\circ \times 0.5^\circ$) from 2003 to 2015 were obtained from the Climatic Research Unit (CRU TS4.0), University of East Anglia (<http://www.cru.uea.ac.uk/cru/data/hrg/>). Both TA and PRE data were resampled into the same spatial resolution as TWSA using the bilinear method.

2.2.2. GRACE derived total water storage anomaly

The GRACE TWSA data (available at <https://grace.jpl.nasa.gov>) during 2003–2015 used in this study are based on the release-5 spherical harmonics products from three independent centers (Jet Propulsion Laboratory, the Center for Space Research at University of Texas, and the German Research Center). All the three products use the historical mean values (2004–2009 time-mean) as the baseline (Chen et al., 2005). In generating these data, successive filters (including destriping, Gaussian and degree 60 filters) were applied to the observed gravity field anomalies to remove systematic errors that are induced by correlations between certain spherical harmonic coefficients and random errors in higher degree spherical harmonic coefficients (Landerer and Swenson, 2012). After these operations, the resolution of the GRACE data (originally at ~ 300 km) is smoothed to $1^\circ \times 1^\circ$ at the global scale (Swenson and Milly, 2006). However, these filters also modify the true geophysical signal of interest and thus a few techniques have been proposed to restore the signal attenuation (Longuevergne et al., 2010; Swenson and Wahr, 2007). One typical approach is the scaling factor method that is based on land surface models (Landerer and Swenson, 2012). To reduce the uncertainties arising from a single land surface model, an ensemble mean of scaling factors derived from six land surface models (Noah2.7, Mosaic, VIC, and CLM2.0 from GLDAS-1, WGHM2.2 and CLM4.0) was used (Long et al., 2015). Moreover, to minimize uncertainties associated with the different gravity-field solutions, the mean of the three TWSA products was calculated and used to represent the changes in total water storage in CA (Sakumura et al., 2014; Xie et al., 2016).

2.2.3. EVI data

The monthly MOD13C2 EVI product (Collection 6, $0.05^\circ \times 0.05^\circ$) from 2003 to 2015 was acquired from the NASA Land Processes Distributed Active Archive Centre (<https://lpdaac.usgs.gov>). MODIS EVI can effectively reduce soil background influences and atmospheric noise (Huete et al., 2002), and thus has been widely used in ecological studies. The singular spectrum analysis method was used to fill the gaps after QA filtering following Shi et al. (2017). Pixels with mean growing season EVI < 0.1 were treated as non-vegetated area and removed. To match the resolution of the TWSA data, the MODIS EVI data were resampled into a resolution of $1^\circ \times 1^\circ$ using the bilinear method.

2.2.4. Land cover map

The MCD12C1 land cover product (1×1 km, University of Maryland classification) in 2010 was obtained from the USGS website (<https://lpdaac.usgs.gov>). The major land use cover (LUC) types include barren lands, grasslands, shrublands and croplands (Fig. S1). Considering the differences in climate, topography and human managements, we

made further partitions of grasslands and croplands into highland or lowland grasslands, and irrigated or rainfed croplands (Supplementary Information). The statistics for the major land cover types are listed in Table S1. The reclassified LUC map was then aggregated into a $1^\circ \times 1^\circ$ resolution by the rule of maximum area.

2.2.5. Aridity index

The aridity index (AI) is used to represent the degree of climatic dryness and is defined as the ratio of annual precipitation to potential evapotranspiration (PET). Here, we calculated AI using CRU TS4.0 climatic dataset during 2003–2015 in CA as the following:

$$AI = \frac{PRE}{PET} \quad (1)$$

where PRE is mean growing season precipitation (mm), and PET is mean growing season potential evapotranspiration (mm). PET was estimated using CRU TS4.0 temperature dataset and based on the Thornthwaite equation (Thornthwaite, 1948). According to the United Nations Environment Program (1992), we defined “arid” as $0 < AI < 0.2$, “semiarid” as $0.2 < AI < 0.5$, “semi-humid” as $0.5 < AI < 0.65$, and “humid” as $AI > 0.65$.

2.3. The autoregressive model

As we focus on the short-term stability of vegetation in response to environmental variations, both the long-term trends and the seasonal components were removed. Firstly, the monthly anomalies of EVI and environmental factors were calculated by subtracting the long-term monthly mean from the monthly observations. Secondly, the long-term linear trend was subtracted from the anomaly time-series if there was one. Thirdly, the seasonality of detrended anomalies was removed through the z-score standardization:

$$z_{i,j} = \frac{x_{i,j} - \bar{x}_j}{\sigma_j} \quad (2)$$

where $x_{i,j}$ is the detrended anomaly in the j th month of the i th year, $\bar{x}_j$ and σ_j are the mean and standard deviation of the variable x in the j th month of all years, respectively (A et al., 2017; Zhao et al., 2017).

The autoregressive model was built referring to the method by De Keersmaecker et al. (2015) but introduced TWSA and substituted the standardized precipitation-evapotranspiration index in their model by precipitation. It can be represented as:

$$Y_t = \alpha \times Y_{t-1} + \beta \times TWSA_t + \gamma \times PRE_t + \delta \times TA_t + \varepsilon_t \quad (3)$$

where Y_t is the standardized EVI anomaly at time t , Y_{t-1} is the standardized EVI anomaly at time $t-1$, $TWSA_t$ is the standardized TWSA anomaly at time t , TA_t is the standardized temperature anomaly, PRE_t is the standardized precipitation anomaly at time t , ε_t is the residual term at time t , and α , β , γ and δ are coefficients.

Each of α , β , γ and δ is a metric of ecosystem stability (Table 1; De Keersmaecker et al., 2015). α indicates ecosystem resilience. When α is large, current EVI anomaly is strongly associated with the previous EVI anomaly, and the ecosystem resilience is low, indicating vegetation

Table 1
Interpretation of the coefficients in the autoregressive model.

Coefficient	Meaning of absolute value	Meaning of sign
α	A large absolute value indicates low resilience, which means that vegetation slowly recovers from previous disturbance.	Positive value of α shows EVI anomaly is similar to the previous anomaly. Negative value of α shows EVI anomaly is similar to the previous anomaly but with the opposite trend.
$\beta/\gamma/\delta$	Large absolute values indicate low resistance to TWSA/precipitation/temperature anomalies.	Positive Higher TWSA/precipitation/temperature than average induces a positive EVI response (higher EVI). Negative Lower TWSA/precipitation/temperature than average induces a negative EVI response (lower EVI).

recovers slowly and vice versa. The coefficients β , γ and δ indicate the resistances of EVI anomaly to changes in TWSA, precipitation and temperature, respectively. The larger the absolute values of β , γ and δ are, the more sensitively vegetation responds to variations in environmental variables and the smaller the vegetation resistance is. The autoregressive model with the four predicting variables was applied to all the pixels in CA. The predicting variables with insignificant coefficients ($P > 0.05$) were filtered out, and we fitted again the autoregressive model using the retained variables only.

We also applied the partial correlation method to identify the major factors influencing monthly vegetation growth. In the comparison of vegetation stability among different land covers, we first conducted ANOVA analysis and then applied a “post hoc” Tukey’s test.

3. Results

3.1. Controls for monthly vegetation growth in Central Asia

Moderate or strong memory effects were observed in vegetation growth across the whole CA with the mean $|R|$ value of 0.64 ± 0.15 (Fig. 1a). The memory effects in southern deserts of CA were stronger than those in the steppes of northern Kazakh and in the meadows of eastern Tianshan Mountains (Figs. 1a and S2). Compared to monthly precipitation, vegetation growth was more correlated with TWSA (Fig. 1b and c). There were about 46% and 36% of vegetated pixels that had significant relationships ($P < 0.05$) with TWSA ($|R| = 0.56 \pm 0.22$) and precipitation ($|R| = 0.41 \pm 0.23$), respectively. Specifically, vegetation showed significant positive responses to TWSA and precipitation in steppes, northern semi-deserts or deserts, open woodlands in southern CA, and meadows in eastern Tianshan Mountains. (Figs. 1b, c and S2). Monthly temperature exhibited weak or insignificant influence on vegetation growth in the majority of CA (Fig. 1d). Only 12% of the vegetated pixels showed significant response to monthly temperature, and most of them were negative, particularly in western and northern deserts,

open woodlands in southern CA, and Junggar desert in northern Xinjiang (Figs. 1d and S2).

3.2. Vegetation resilience and resistance in CA

Vegetation showed significant resilience across almost the whole CA (99.5% of the vegetated pixels, Fig. 2a). The metric of vegetation resilience (α) was largest in highland grasslands (0.56 ± 0.12) in the north-east Tianshan Mountains and smallest in shrublands (0.78 ± 0.19) in the southwest (Figs. 2a and 3a). Lowland grasslands (0.68 ± 0.12), irrigated croplands (0.60 ± 0.15) and rainfed croplands (0.58 ± 0.12) showed intermediate resilience, with α of lowland grasslands significantly different from the latter two land covers (Fig. 3a). Approximately 45% and 44% of the vegetated pixels showed significant resistance to TWSA and precipitation, respectively (Fig. 2b and c). Almost all land covers showed strong capability to resist variations in TWSA (Figs. 2b and 3b). The metric of vegetation TWSA-resistance (β) showed no significant difference among rainfed croplands, irrigated croplands and shrublands (Fig. 3b). In addition, no significant β was found in areas around Balkhash Lake and Aral Sea, and in parts of northern Xinjiang (Figs. 2b and S2). Similarly, the metric of precipitation-resistance (γ) in these areas were not significant, either (Fig. 2c). Of all land covers, the metric of the precipitation resistance in shrublands was the lowest (0.12 ± 0.01), while it showed no significant difference (ranging from 0.22 ± 0.03 to 0.24 ± 0.05) in other land covers (Fig. 3c). About 10% of vegetated pixels in CA showed significant temperature resistance (Fig. 2d).

3.3. Spatial controls of vegetation resilience and resistance

To identify the controlling factors for vegetation resilience and resistance across different land covers, we regressed vegetation resilience and resistance metrics against mean growing season EVI, TWSA, precipitation and temperature during 2003–2015. The results showed that the

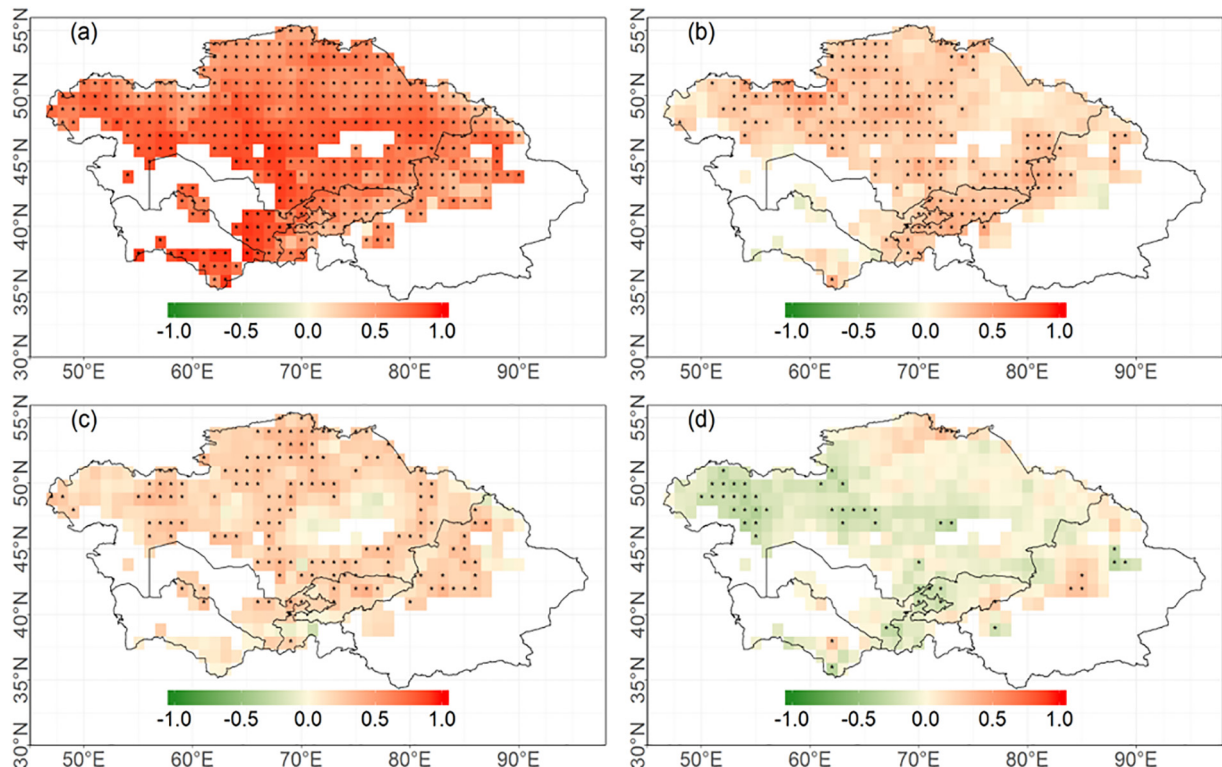


Fig. 1. Spatial distribution of partial correlation coefficients between monthly EVI and (a) its previous monthly EVI ($R_{EVI-EVI(i-1)}$), (b) TWSA ($R_{EVI-TWSA}$), (c) precipitation ($R_{EVI-PRE}$), and (d) air temperature (R_{EVI-TA}) in growing seasons (April–October) during 2003–2015 in Central Asia. The asterisk symbols (*) represent trends at a significant level of $P < 0.05$.

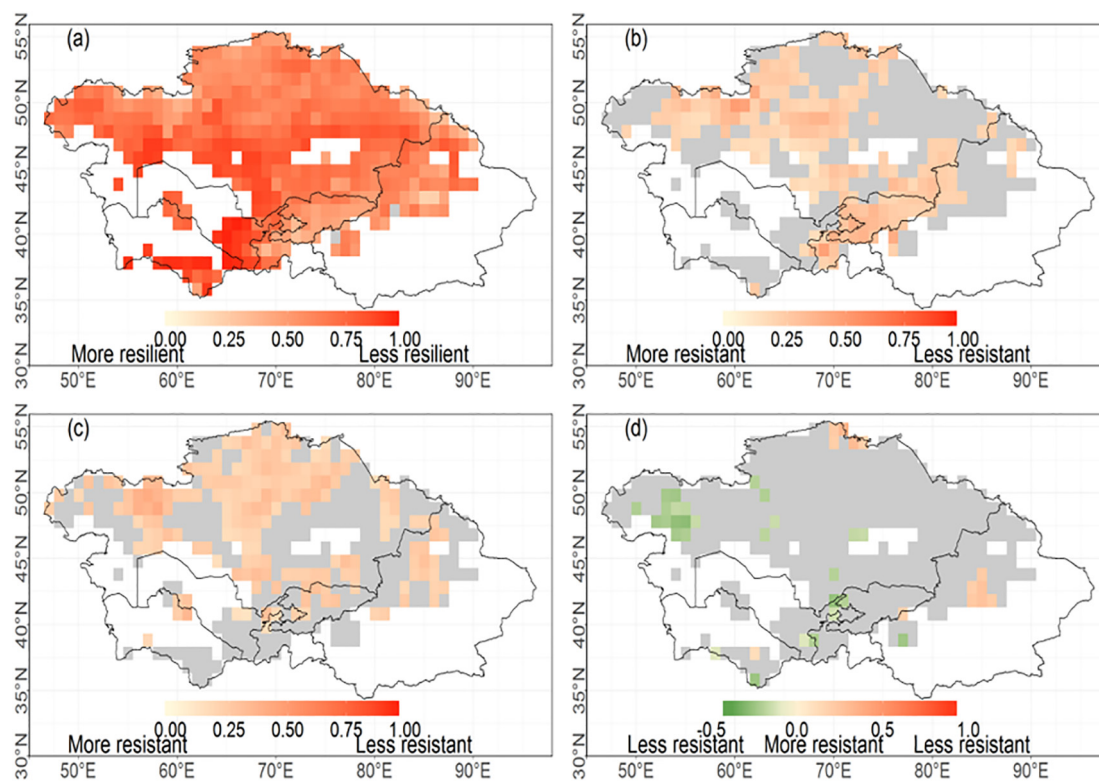


Fig. 2. Spatial distribution of (a) α (resilience-metric), (b) β (TWSA-resistance metric), (c) γ (PRE-resistance metric) and (d) δ (TA-resistance metric) in Central Asia during growing seasons (April–October) of 2003–2015. Vegetated pixels with insignificant ($p > 0.05$) resilience or resistance metric values are shown in gray color.

metric of vegetation resilience was high in the area with sparse vegetation and decreased logarithmically as mean growing season EVI increased ($R^2 = 0.29$, Fig. 4a). Although the metric of vegetation resilience had no significant correlation with mean growing season TWSA (Fig. 4b), it was correlated with both mean growing season

precipitation and temperature ($R^2 = 0.33$ and $R^2 = 0.41$, respectively; Fig. 4c and d). Specifically, the metric of vegetation resilience decreased logarithmically as precipitation increased and linearly increased with increasing temperature. The difference of the vegetation resilience in responding to mean growing season TWSA and precipitation

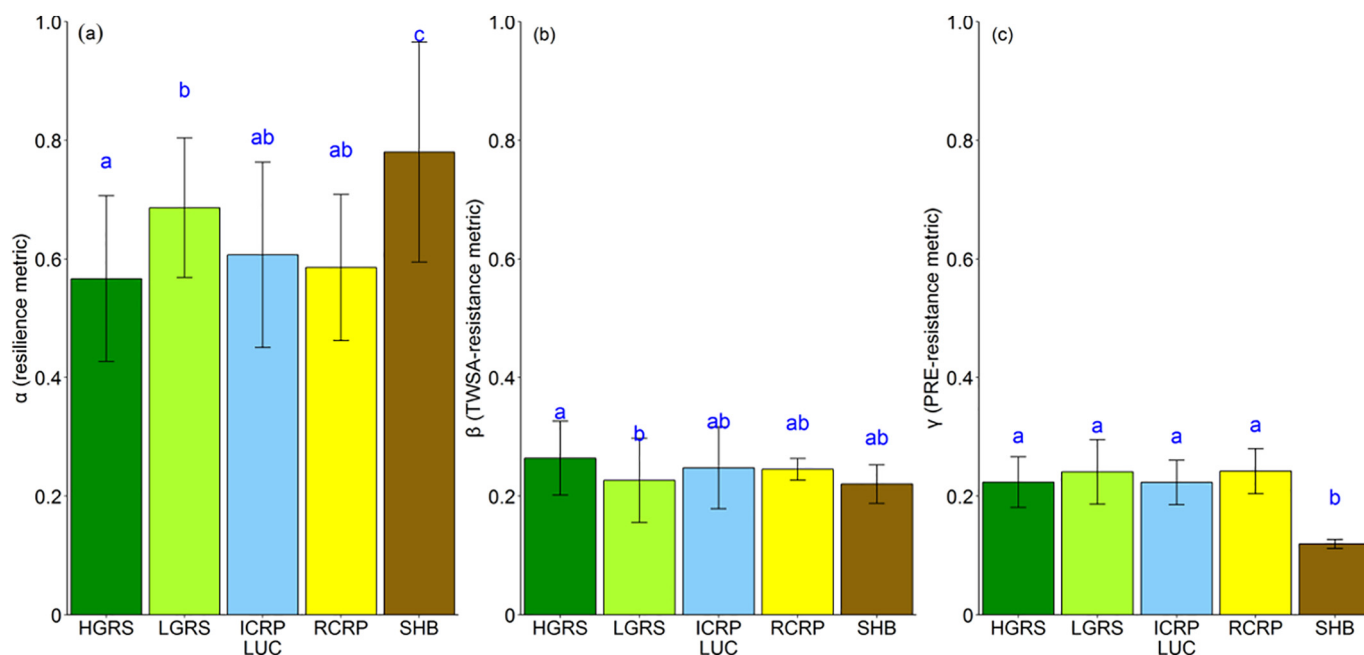


Fig. 3. Land cover-specific (a) α (resilience metric), (b) β (TWSA-resistance metric) and (c) γ (PRE-resistance metric). The land cover types include highland grasslands (HGRS, elevation >1000 m), lowland grasslands (LGRS, elevation <800 m), irrigation croplands (ICRP), rainfed croplands (RCRP) and shrublands (SHB).

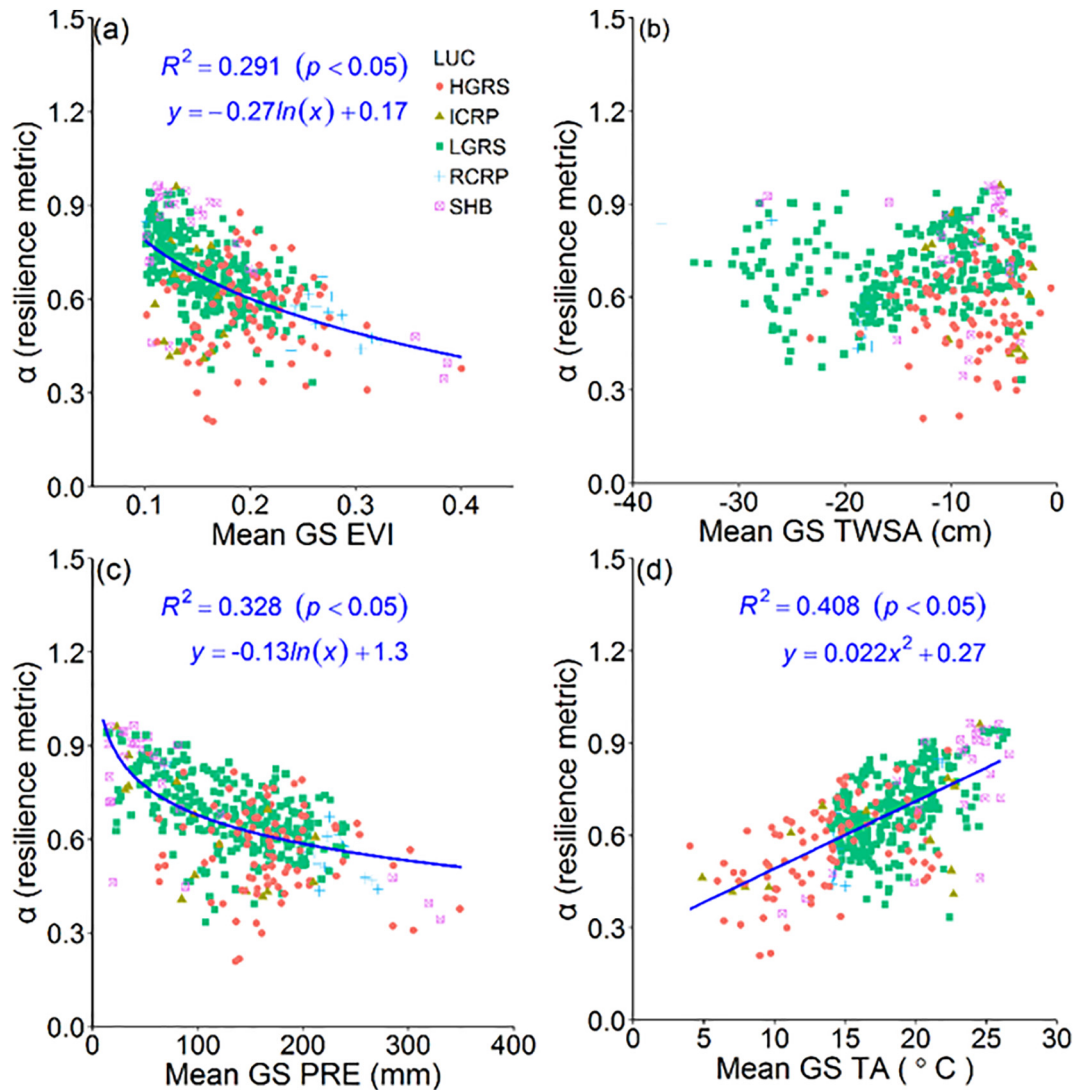


Fig. 4. Correlations between α (resilience metric) and mean growing season (a) EVI, (b) TWSA, (c) precipitation (MAP) and (d) temperature (MAT) during 2003–2015 in Central Asia. The blue curves indicate the regression lines using data of all land covers. HGRS denotes highland grasslands, ICRP denotes irrigated croplands, LGRS denotes lowland grasslands, RCRP denotes rainfed croplands, and SHB denotes shrublands.

enlightened us to further investigate the contribution of precipitation to the changes in total water storage. Consequently, we found that TWSA was decoupled with precipitation both spatially and temporally in the majority of CA (Fig. 5). Within each land cover, the vegetation resilience also varied with changing climatic variables (Fig. 4c and d). The vegetation resistance to TWSA and precipitation showed no significant or minor correlation with any of TWSA, precipitation and temperature (Fig. S3). The metric of temperature resistance was positively correlated with both mean growing season EVI ($R^2 = 0.33$, Fig. S3a) and precipitation ($R^2 = 0.30$, Fig. S3c), but showed a decreasing trend as mean growing season temperature increased ($R^2 = 0.34$, Fig. S3d).

Considering the interaction effects of temperature and precipitation on vegetation, pixel resilience or resistance of different land covers was averaged according to bins of aridity index (every 0.1 increment) (Fig. 6). The vegetation resilience showed a logarithmic relationship with the aridity index ($R^2 = 0.80$, Fig. 6a) from arid to semi-humid ecosystems. The metric of TWSA-resistance nearly converged across different hydrothermal conditions (Fig. 6b). In contrast, the metric of precipitation-resistance functioned as a parabolic curve across arid to semi-arid regions ($R^2 = 0.60$, Fig. 6c), and it peaked around 0.23 of aridity index.

4. Discussion

4.1. Environmental effects on monthly variations in vegetation growth

The monthly variations of EVI were primarily controlled by short-term memory effects, changes in TWSA and precipitation in CA (Fig. 1). Vegetation memory effects have been widely reported in water-limited ecosystems at various time-scales (e.g., Los et al., 2006; Schwinning et al., 2004). Because ecosystems have the ability to store water, carbon and nitrogen in various pools, the vegetation status in the previous period can greatly affect the physiological and morphological readiness of plants for resource use in the following period (Ogle and Reynolds, 2004). The memory effects commonly observed in CA (Fig. 1a) suggest that vegetation memory for previous environmental changes can last at least a month in this area and thus shape the intra-annual patterns of vegetation growth.

The relatively weak influence of precipitation on monthly vegetation growth was unexpected. Many studies have highlighted the important roles of precipitation on influencing the seasonal variations of vegetation activity in CA (Jiang et al., 2017; Xu et al., 2016). However, in these studies the effects of precipitation were generally analyzed

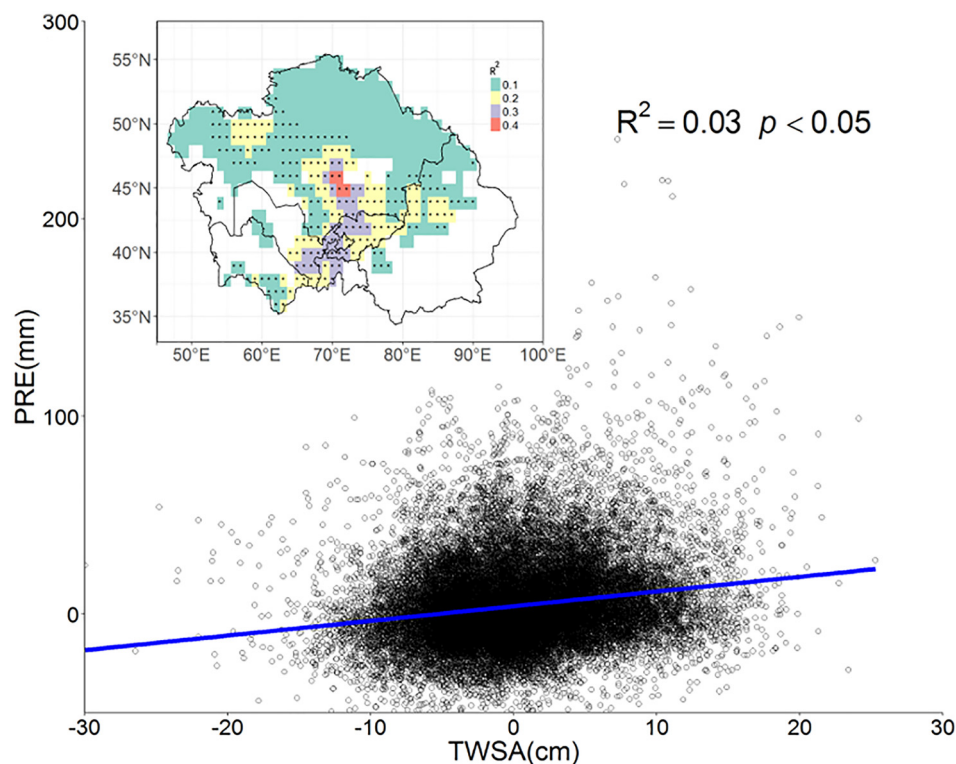


Fig. 5. The spatial relationship between mean growing season TWSA and precipitation anomalies. The inset shows the spatial pattern of correlation between monthly TWSA and precipitation anomalies.

without distinguishing the effects of increased temperature as this study. Moreover, both Gessner et al. (2013) and Epstein et al. (1997) reported a temporal lag between vegetation reaction and precipitation events of 1–3 months in CA, suggesting the effects of precipitation on current monthly vegetation growth are limited. The other deficit is that previous studies did not take into account the effects of other available water, which can bias the estimates of precipitation role in regulating semi-arid and arid ecosystems. For example, non-precipitation water sources (e.g. soil water, groundwater and snow meltwater) are

critical in supporting plants living in deserts where summer precipitation is scarce (Xu et al., 2017). Our result indicated that TWSA performed better than precipitation in explaining the seasonal variations in vegetation activity is consistent with similar studies that employ TWSA as an indicator of available water (e.g., Yang et al., 2014). The observed decline of TWSA in the majority of CA in the past 13 years implies a threat of vegetation degradation in this region.

The observed influence of monthly temperature, primarily in mountains, was consistent with previous studies (e.g., Jiang et al., 2017;

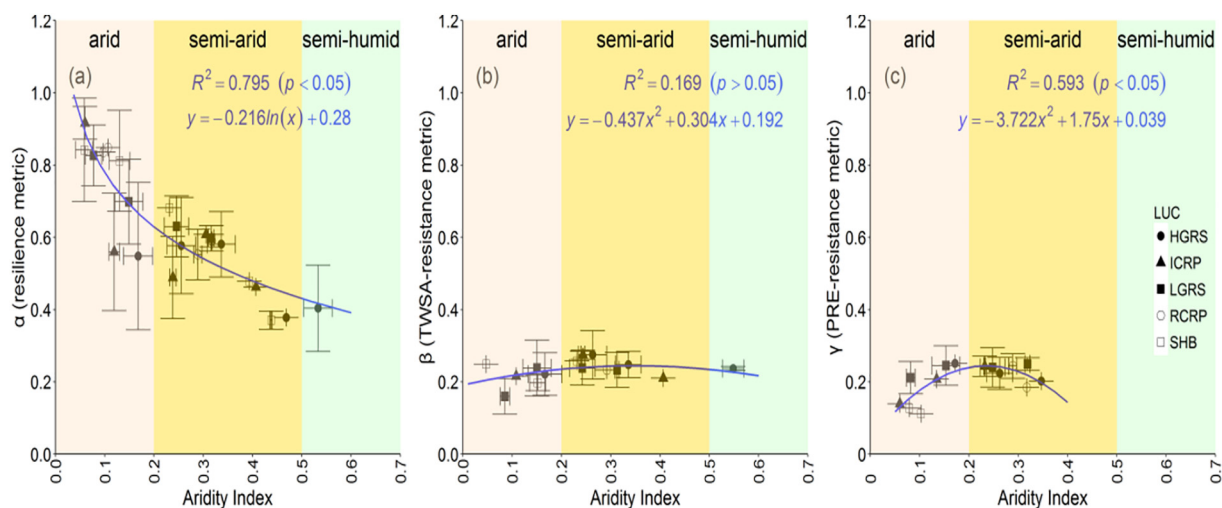


Fig. 6. Distribution of (a) α (resilience metric), (b) β (TWSA-resistance metric) and (c) γ (PRE-resistance metric) along aridity gradient. The blue curves indicate the regression lines using data of all the five land covers.

Xu et al., 2016). In the western CA where it is relatively dry, increase of temperature can intensify the water deficit through elevated evaporation (Epstein et al., 1997) and thus causes a negative response of EVI. In contrast, in eastern Tianshan Mountains where it is relatively wet, elevated temperature can promote plant photosynthetic activity and thus lead to a positive response of vegetation growth.

4.2. Effects of hydrothermal conditions on vegetation resilience and resistance

Because resilience measures the rate of ecosystem returning to its normal state, the capability of ecosystems recovering from disturbances to favored conditions of vegetation growth becomes the determinant factor for the spatial pattern of vegetation resilience. In those areas with more precipitation, soil moisture has the larger probability to be recharged in a short time thus ecosystem shows high vegetation resilience (Fig. 4c). For hot and dry areas, high temperature inhibits the vegetation growth, resulting low vegetation resilience in the majority of shrublands and lowland grasslands (Fig. 4d). As for TWSA, although it can well reflect the temporal variation of the whole water column (Rodell, 2004; Rodell and Famiglietti, 2001), it is not good at indicating the spatial variations of short-term water recharge rates typically characterized by precipitation (Fig. 5). This is because that each storage component of TWSA has different time-scales of variability (A et al., 2017; Vicente-Serrano et al., 2010; Vicente-Serrano et al., 2013). Therefore, vegetation resilience showed no spatial correlation with TWSA (Fig. 4b).

The difference among land covers in vegetation resilience (Fig. 3a) may also be related to traits of different land covers. Shrublands in arid and semi-arid regions have relatively deep perennial rooting systems to access groundwater, and thus can sustain photosynthesis during long dry periods (Guswa, 2010; Noy-Meir, 1973). For example, the two typical shrubland species in Gurbantonggut desert of CA, *ramosissima Ledeb.* and *Haloxylon persicum* have main roots extending to a soil depth of 2.8–3.1 m (Liu et al., 2012) and 1.5 m (Xu and Li, 2006), respectively. In contrast, grasslands have relatively short rooting systems with the main roots around 0–0.5 m long in CA (Liu et al., 2012). Such evolved traits and inter-species competition enable the prosperity of a land cover type in a specific environment. For example, shrublands dominate the area with low precipitation and high temperature while highland grasslands are mainly located in the area with contrasting hydrothermal conditions (Fig. 4c and d). Wu et al. (2018) also reported that the shrublands exhibited longer drought legacy response with reduced growth than grasslands did, indicating the lower resilience of shrublands over the temperate Northern Hemisphere. However, it is noted that when different land covers are in similar hydrothermal conditions, they can show similar vegetation resilience (Figs. 4c, d and 6a).

The differed rooting traits of land covers also determined their different water-use strategies, which can effectively explain the different susceptibilities of shrublands to precipitation in comparison with grasslands and croplands (Fig. 3c). The drought-tolerant shrublands can adapt to maximize usage of deeper soil water by large root: shoot ratio, lower leaf conductance with low stomatal sensitivity, therefore they don't show significant photosynthetic response to drought or precipitation pulses (Xu and Li, 2006; Xu et al., 2007). For example, as one important species in the lower reaches of Tarim River of Northwest China, *Populus euphratica* can take advantage of water in the deep soil layers through the hydraulic redistribution process (Hao et al., 2010). However, the herbaceous plants have shallow root systems which limit access to stable groundwater source, and thus they are more sensitive to precipitation, even small rewetting events after severe droughts in semi-arid or arid regions (Hu et al., 2008; Scott et al., 2010).

Across the aridity gradient, the unimodal distribution of precipitation-resistance (Fig. 6c) was like that of hydroclimatic sensitivity of vegetation productivity to SPEI observed in southeastern Australia (Ma et al., 2015). The high adaptability of plants in dry area (Grime et al.,

2000) and the higher soil water storage and the potential carry-over effect in relatively wet area (Ma et al., 2015) are possibly the main causes for the skewed precipitation-resistance curves for vegetation. Moreover, the increase in the metric of temperature-resistance along precipitation (Fig. S3c) suggests that the temperature effects on vegetation response are modulated by water availability, as found in a semi-arid grassland (Huang et al., 2015).

4.3. Implications for ecosystem management and future studies

The steep rise of the metric of vegetation resilience along decreasing aridity index (Fig. 6A) implies a huge risk for ecosystem collapse at the areas with extremely low water availability and significant warming. Verbesselt et al. (2016) suggested that the critical slowing down of recovery from disturbances is related to the proximity of a tipping point of plant dying. Seddon et al. (2016) also found that the vegetation responses to climate variability became more sensitive in steppe and prairie regions of CA.

Considering the significant role of total water storage in determining vegetation growth in CA, reducing current water extraction is important for preventing arid and semi-arid ecosystems towards an irreversible state and thus their sustainable developments. Agriculture (especially irrigation agriculture), which is highly dependent on human inputs of water, energy and nutrients, can significantly alter the spatial patterns of water availability (more water for agriculture and less water for natural ecosystems; Piao et al., 2010; Scanlon et al., 2007). Large-scale decrease in groundwater due to agricultural irrigation has been reported in Badain Jaran Desert, northwest China (Zhang et al., 2018), and in Aral Sea Basin and Tarim River Basin (Deng and Chen, 2017). Jiang et al. (2017) also reported that the excessive exploitation of water resources in the upstream areas of the Amu Darya Basin has caused great loss of shrubs in southern CA and wetland delta of the Large Aral Sea. Since all land covers showed similar TWSA-resistance (Fig. 3b), the decrease of TWSA would result in common damage to natural vegetation in CA. From this perspective, the large-scale abandonment of croplands in the five CA countries after the collapse of Soviet Union may relieve water stress in local natural ecosystems. This reminds us that much care should be taken in developing irrigation agriculture in arid and semi-arid regions.

Another implication of our study is that it should consider the influence of total water storage in analysis of vegetation growth in drylands where non-precipitation water resources are important. Our finding of the decoupling of TWSA and precipitation provides a new insight to investigating vegetation-water relationship in CA, where there exist large-scale human disturbances on water resources.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.scitotenv.2018.12.418>.

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