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Impact of prolonged drought on rainfall use efficiency using MODIS data across China in the early 21st century

Xin Zhang [a,b], M. Susan Moran [c,*], Xiang Zhao [a,d], Suhong Liu [a,b], Tao Zhou [e], Guillermo E. Ponce-Campos [c,f], Feng Liu [a,b]

[a] The State Key Laboratory of Remote Sensing Science, Jointly Sponsored by Beijing Normal University and Institute of Remote Sensing Applications of Chinese Academy of Sciences, Beijing, China
[b] School of Geography, Beijing Normal University, Beijing, China
[c] USDA ARS Southwest Watershed Research, Tucson, AZ 85719, USA
[d] College of Global Change and Earth System Sciences, Beijing Normal University, Beijing, China
[e] State Key Laboratory of Earth Surface Processes and Resource Ecology, Beijing Normal University, Beijing, China
[f] Soil, Water & Environmental Sciences, University of Arizona, Tucson, AZ 85721, USA

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ABSTRACT

Frequency and severity of droughts are projected to increase in many regions, and their effects on temporal dynamics of the terrestrial carbon cycle remain uncertain. Ecosystem net primary productivity (NPP) is a key component of the carbon cycle, and rainfall use efficiency (RUE = NPP/precipitation) is an important measure of ecosystem stability and resilience. Here we investigated the temporal patterns of NPP and RUE and their key driving climate factors, during the early 21st century drought for four biomes in China: Needleleaf forest, Broadleaf forest, Woody savannas, and Grassland. Estimates of regional-scale NPP were based on the NASA Moderate Resolution Imaging Spectroradiometer (MODIS) MOD17 NPP product. Our results confirmed recent findings that the impact of current-year precipitation on NPP was confounded by an array of biotic and abiotic factors. Whereas, the RUE responded strongly to variations in current- and previous-year drought for all the four biomes and the four biomes combined. We found that a dry year preceded by a wet year resulted in the highest RUE, and conversely, a wet year preceded by a dry year resulted in the lowest RUE. This was attributed to the legacy effect of precipitation changes in both wet and dry years, and to the resilience of the biomes in the dry years. Based on these results, we developed and validated a model of RUE based on the Palmer Drought Severity Index (PDSI) of both current and previous years which works well for these four biomes and all biomes combined. This model is particularly useful for understanding the impact of prolonged drought at the landscape scale because it is based on accessible satellite data and available meteorological data and the results have been tested across four major biomes.

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1. Introduction

Net primary productivity (NPP) is the rate at which all plants in an ecosystem produce net useful chemical energy (Melillo et al., 1993). As the foundation of energy flow and nutrient cycle for organisms, NPP plays an important role in the global carbon balance (Cramer et al., 1999), and alterations in ecosystem NPP greatly affect CO_2 exchange between land and atmosphere. Therefore, the interaction of NPP with climate has been a key focus of ecological study (Li & Guo, 2012; Yang, Fang, Ma, & Wang, 2008; Zhao & Running, 2010).

Ecologists generally agree that water availability is the primary factor limiting ecosystem function, and this is expressed as patterns of NPP across many regions and biomes (Lauenroth, 1979; Noy-Meir, 1973; Sala, Gherardi, Reichmann, Jobbagy, & Peters, 2012). Some studies have shown a very strong linear relationship between rainfall and aboveground net primary productivity (ANPP) through time at multiple sites (Bai et al., 2008; Jobbágy, Sala, & Paruelo, 2002; Sala, Parton, Joyce, & Lauenroth, 1988). Lieth (1975) developed a statistical model based on the relation between NPP and precipitation and temperature (called the Miami model) that has been applied globally. Other studies reported that an array of biotic and abiotic factors affect ANPP (Knapp & Smith, 2001; Running, Thornton, Nemani, & Glassy, 2000), where both current and previous precipitations controlled a significant fraction of current-year production (Reichmann, Sala, & Peters, 2012; Sala et al., 2012). Consequently, rainfall use efficiency (RUE), the ratio of NPP to precipitation, has been suggested as an effective integrating measure for evaluating the response of NPP to spatial and temporary changes in water availability (Bai et al., 2008). In general, RUE tends to increase spatially with increasing aridity. For example, Huxman et al. (2004) found that mean RUE increased with decreasing mean annually precipitation (MAP) in North and South America across nine different biomes from

* Corresponding author.
E-mail address: Susan.Moran@ARS.USDA.GOV (M. Susan Moran).

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desert grassland to tropical forest. Ponce-Campos et al. (2013) found that the lowest mean RUE was associated with the highest MAP across a diverse set of biomes in America and Australia.

Increased aridity and persistent droughts are projected in the 21st century for most of Africa, southern Europe and the Middle East, most of the Americas, Australia and Southeast Asia (Hogg, Brandt, & Michaelian, 2008; Lewis, Brando, Phillips, van der Heijden, & Nepstad, 2011; Phillips et al., 2009; Zeng, Qian, Roedenbeck, & Heimann, 2005). China suffered from a series of severe droughts during the first decade of the 21st century (Xiao et al., 2009). The drought in China in 2010 was the most severe in the last 50 years and was considered to be a 'once in a century drought' (Li, 2012).

Drought significantly affects ecosystem carbon exchange process, and has a direct impact on NPP and RUE (Pei, Li, Liu, & Lao, 2013). Most studies have focused on the response of NPP to the current-year drought and have shown different responses depending on the sites (Fay, Carlisle, Knapp, Blair, & Collins, 2003; Fay et al., 2002; Knapp et al., 2002). In a recent study, Sala et al. (2012) reported that current-year drought explained only a small proportion of the variation in annual ANPP, and the previous year drought contributed significantly to changes in ANPP. Reichmann et al. (2012) showed that there was a legacy effect in transition from dry years to wet years (or the reverse) resulting in lower ANPP than predicted if the previous-year precipitation was lower than current-year precipitation (and vice versa). They defined legacies as the difference between observed ANPP and expected ANPP deduced from a long-term precipitation–production relationship for a site, and found that the magnitude of the legacy was a function of the difference between previous and current-year precipitation. Further, Peters, Yao, Sala, and Anderson (2012) found that the response of ANPP to long-term variations in precipitation was different across biomes.

In this study, we investigated the temporal relation between RUE and drought for biomes from grassland to forest in China over the time period from 2000 to 2010. Estimates of regional-scale NPP were based on the NASA Moderate Resolution Imaging Spectroradiometer (MODIS) MOD17 NPP product, which accounts for climate conditions and biomes. It is the first continuous satellite-driven dataset monitoring global vegetation productivity at 1-km resolution (Zhao, Heinsch, Nemani, & Running, 2005). Our goal was to determine the impact of prolonged drought on RUE across large biomes, and generalize these results to model the variation of RUE with previous- and current-year drought.

2. Data and methods

2.1. NPP, meteorological data and biome map

The annual NPP was derived from MODIS global data set (MOD17A3) at 1-km resolution over the time period from 2001 to 2010 (Fig. 1a). The MOD17A3 NPP product is based on a light-use efficiency model and provides annual NPP for evaluating spatial–temporal variations in productivity and terrestrial behavior at the annual scale. These products have been recently improved by temporally filling missing or cloud-contaminated FPAR/LAI, spatially interpolating coarse resolution meteorological data to the 1-km MODIS pixel level, and modifying the representation of autotrophic respiration in the algorithm. These data are comparable to the recent studies not only in magnitude but also in inter-annual variability (Zhao et al., 2005).

Four types of biomes, Needleleaf forest, Broadleaf forest, Woody savannas and Grassland (Fig. 1b) were selected from the biome map of China generated from the MODIS land cover product (MOD12Q1). Areas were chosen for this study if the biome type was consistent during the 10 years based on the MOD12Q1 classification. This analysis was limited to these four distinct biomes, and the four biomes combined.

Meteorological data including the monthly precipitation and the monthly temperature from 1985 to 2010 were available from 726 meteorological stations across China, provided by the Climate Database of China Meteorological Administration (CMA) (Fig. 1d). The annual precipitation (P) and temperature were obtained from the accumulated monthly data and then interpolated at 1-km resolution using a kriging method based on the digital elevation model (DEM) (Emery, 2005; Martínez-Cob, 1995).

2.2. PDSI and drought type

The degree of drought was determined from the self-calibrated Palmer drought severity index (PDSI). PDSI is a measure of the cumulative departure in the surface water balance based on latitude, precipitation, temperature and soil type; it has been proven to be an effective proxy for surface moisture conditions in measuring environment water stress (Alley, 1984; Palmer, 1965). The self-calibrated PDSI is based on a time series of measurements, and performs consistently with accurate comparisons in different areas (Wells, Goddard, & Hayes, 2004). In this case, PDSI was derived from an estimate of soil water holding capacity (θ) and self-calibrated with a 25-year record of monthly precipitation and temperature for each site (Dai, Trenberth, & Qian, 2004).

Monthly precipitation and monthly temperature during 25 years (1985–2010) were checked for quality, and sites were removed when their missing data were greater than five months. The soil water holding capacity was calculated from soil texture data based on the following equations (Saxton, Rawls, Romberger, & Papendick, 1986):

$$\begin{aligned}&\theta = (0.3333/A)^{\frac{1}{B}};\\ &A = \mathrm{Exp}\Big(-4.396-(0.0715\times C)-\big(4.88\times10^{-4}\times S^2\big)\\ &\quad -\big(4.285\times10^{-5}\times S^2\times C\big)\Big);\ \text{and}\\ &B = -3.14-\big(0.00222\times C^2\big)-\big(3.484\times10^{-5}\times S^2\times C\big).\end{aligned} \tag{1}$$

S is the percent sand *100 and C is the percent clay *100; and S and C were extracted from the 1 km soil texture map of China which was generated using the 1:1,000,000 scale soil map of China and 8595 soil profiles reordered in the second national soil survey data set (Shi et al., 2006; Wang, Tian, Liu, & Pan, 2003).

Based on the PDSI from years 2000 to 2010, all the cells were divided into wet years and dry years based on a threshold T (Table 1), where

$$\begin{aligned}&T_{dry} = PDSI_{mean} - 0.6745\times PDSI_{std};\ \text{and}\\ &T_{wet} = 0,\end{aligned} \tag{2}$$

where $PDSI_{mean}$ and $PDSI_{std}$ are the mean and the standard deviation of PDSI for each biome between 2000 and 2010, respectively. T_{dry} was computed to represent the threshold for the bottom 25th percentile of PDSI for 11-year record (at 0.6745 standard deviations below the mean). For each cell, the year with PDSI < T_{dry} was defined as a dry year, the year with PDSI > T_{wet} was defined as a wet year, and years with T_{wet} > PDSI > T_{dry} were considered the norm. Then for each year, a map was derived with each cell classified into one of four categories on drought type based on the current and previous-year drought type. The four categories are the dry year after wet year (W → D), the dry year after dry year (D → D), the wet year after wet year (W → W), and the wet year after dry year (D → W).

2.3. Study areas

In this work, we investigated the impact of drought on NPP across China. However, the accuracies of the MOD12Q1 land cover product are reported to be in the range of 70–80% (Zhao et al., 2005) and our results would be affected by a pixel with misclassified land cover. Therefore, a subset of this dataset was extracted for investigating the impact of prolonged drought on NPP and RUE and modeling the variation of RUE with previous- and current-year drought. Then, the results were validated with all the regional data in China (masked as illustrated in Fig. 1b). The data subset was chosen from the 726 meteorological sites in China (Fig. 1d). First, we determined the biome type for each site by masking all the sites on the MOD12Q1 biome map; 77 sites were associated with the four biomes. Of these, we confirmed that 54 sites were associated with the dominant biome by visual interpretation (Fig. 1d) with Google Earth. We averaged the NPP and RUE data over an area of 3 km $*$ 3 km (3 $*$ 3 pixels) based on the coordinates for each site. The P and PDSI data were derived from the meteorological data directly.

For clarification in next sections, the subset of all data limited to 54 stations will be referred to as the "station subset data". The complete dataset including all pixels in four biomes in China used largely for validation (N > 20,000 for each year), will be referred to as "all regional data".

2.4. Data processing

For analysis of the inter-annual variation of P, NPP and RUE in China, we defined P_i, NPP_i and RUE_i as values of P, NPP and RUE within year *i* from 2001 to 2010, respectively, and P_{10i}, NPP_{10i}, and RUE_{10i} as average

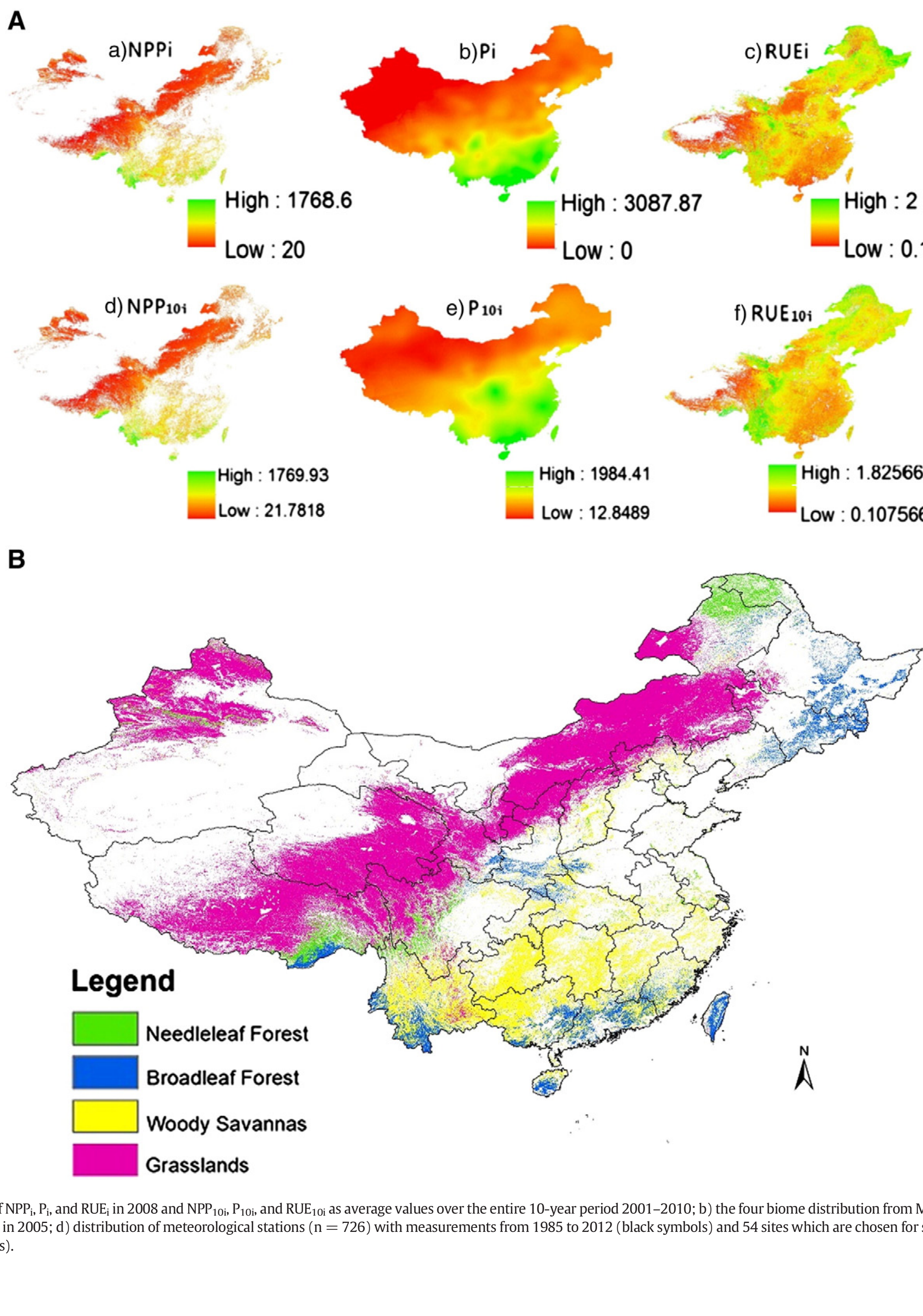

Fig. 1. a) Map of NPP_i, P_i, and RUE_i in 2008 and NPP_{10i}, P_{10i}, and RUE_{10i} as average values over the entire 10-year period 2001–2010; b) the four biome distribution from MOD12Q1; c) map of drought type in 2005; d) distribution of meteorological stations (n = 726) with measurements from 1985 to 2012 (black symbols) and 54 sites which are chosen for study areas (large colored symbols).

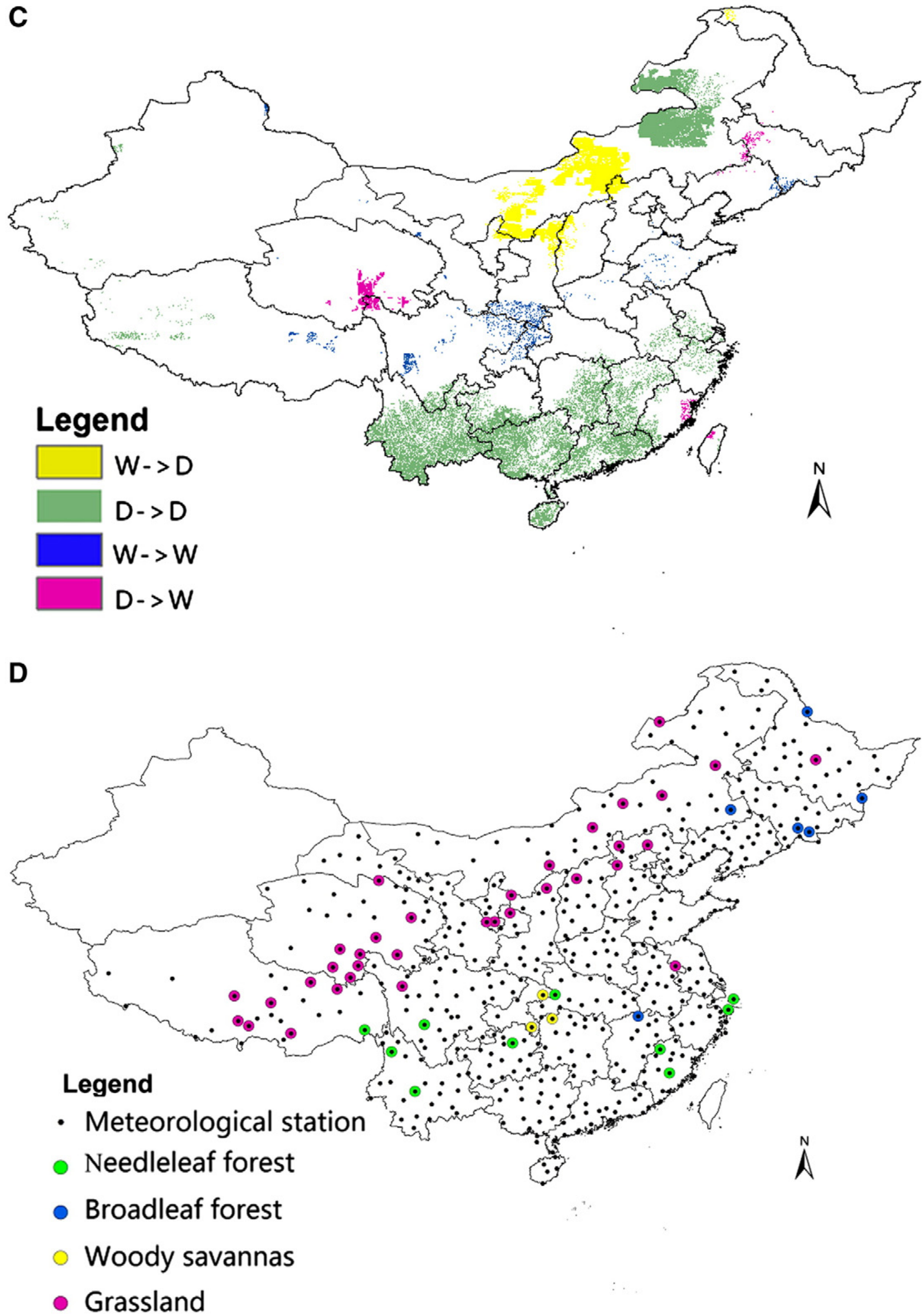

Fig. 1 (*continued*).

values over the entire 10-year period 2001–2010 (Fig. 1a). Then, for each site, the inter-annual variation in P, NPP, and RUE relative to the 10-year average by year was computed,

$$\Delta P_i = P_i \text{-} P_{10i},\quad \Delta NPP_i = NPP_i \text{-} NPP_{10i},\ \text{and}\quad \Delta RUE = RUE_i \text{-} RUE_{10i}, \tag{3}$$

and the normalized values were computed as

$$\text{Normalized } \Delta P_i = \Delta P_i / P_{10i},\quad \text{Normalized } \Delta NPP_i = \Delta NPP_i / NPP_{10i},\ \text{and}\quad \text{Normalized } \Delta RUE_i = \Delta RUE_i / RUE_{10i}. \tag{4}$$

Table 1
The thresholds of each biome for determining the drought type, where T_{dry} is the threshold for the bottom 25th percentile of PDSI for 11-year record and T_{wet} equals zero. The PDSI < T_{dry} and PDSI > T_{wet} are defined as a dry year and wet year, respectively.

Biome type	T_{dry}
Needleleaf forest	−1.0700
Broadleaf forest	−0.9994
Woody savannas	−0.9719
Grassland	−1.1736
All combined	−1.1179

$$\text{Normalized } \Delta\overline{\text{NPP}}_{j,k} = \sum\nolimits_{i=2001}^{2010} \left(\text{Normalized } \Delta\text{NPP}_{i,j,k}\right) / \sum\nolimits_{i=2001}^{2010} \text{N}_{i,j,k}, \tag{5}$$

where $\sum_{i=2001}^{2010}$(Normalized $\Delta NPP_{i,j,k}$) is the sum of all the normalized ΔNPP_i in a certain biome and drought type in 2001–2010. $N_{i,j,k}$ is the number of sites in a certain year, biome and drought type. Similarly,

$$\text{Normalized } \Delta\overline{\text{RUE}}_{j,k} = \sum\nolimits_{i=2001}^{2010} \left(\text{Normalized } \Delta\text{RUE}_{i,j,k}\right) / \sum\nolimits_{i=2001}^{2010} \text{N}_{i,j,k}. \tag{6}$$

2.5. Modeling method and validation

Based on a previous study reporting that RUE was affected by the current-year drought (Bai et al., 2008), we assumed that the normalized ΔRUE_i was a function of $PDSI_i$, where

$$\text{Normalized } \Delta\text{RUE}_i = a + b \times \text{PDSI}_i. \tag{7}$$

Other studies have reported that the drought legacy affects the current-year production, especially in circumstances transitioning from a dry to a wet year, and vice versa. Sala et al. (2012) created a multiple regression model of ANPP with current-year P and previous-year ANPP, where $ANPP_i = a + b \times P_i + c \times ANPP_{i-1}$. Based on this model, we derived a logical relation between normalized ΔRUE_i

$$\text{Normalized } \Delta\text{RUE}_i = a + b \times \text{PDSI}_i + c \times \text{PDSI}_{i-1}. \tag{8}$$

Unlike the model by Sala et al. (2012), we used normalized ΔRUE_i instead of current-year ANPP. We then used previous-year PDSI instead of previous-year ANPP to eliminate the effects of different biomes and locations on RUE.

Akaike Information Criterion (AIC) analysis was used to evaluate the benefit of adding the previous-year PDSI to this model in Eq. (8) (Sakamoto, Ishiguro, & Kitagawa, 1986). We assumed that the new model (Eq. 8) was an improvement over the old one (Eq. 7) if the AIC reduced more than 2.0 (Burnham & Anderson, 2002). We also reported regression correlation coefficients (R^2) as an absolute measure of model fit. The hierarchical partitioning algorithm was used to calculate the independent effects of current- and previous-year PDSI on RUE as a percentage contribution to the goodness of fit of the model (Chevan & Sutherland, 1991). Finally, the validation was based on all regional data in China by comparing the predicted and the measured normalized ΔRUE_i.

3. Results

3.1. The relation between the annual precipitation and NPP in China

As expected, for the four biomes combined across China using the station subset data, there was no discernible trend in the inter-annual variations between normalized ΔNPP_i and normalized ΔP_i from 2001 to 2010. The linear regression between the normalized ΔNPP_i and the normalized ΔP_i was weak (Normalized ΔNPP_i = 0.1724 × Normalized ΔP_i + 0.0037, $R^2 = 0.0799$, $P < 0.05$) (Fig. 2a). Across the biomes of Needleleaf forest, Broadleaf forest, Woody savannas and Grassland, the linear relations between the normalized ΔNPP_i and the normalized ΔP_i were still weak ($R^2 < 0.2$) (Fig. 2b, Table 2). This negative result supported the use of RUE as an integrative measure of NPP and P related to ecosystem stability and resilience in the next analyses. That is, Normalized ΔP_i explained only a small part of Normalized ΔNPP_i, whereas RUE integrates both into a single index of ecosystem efficiency that can be related to prolonged drought.

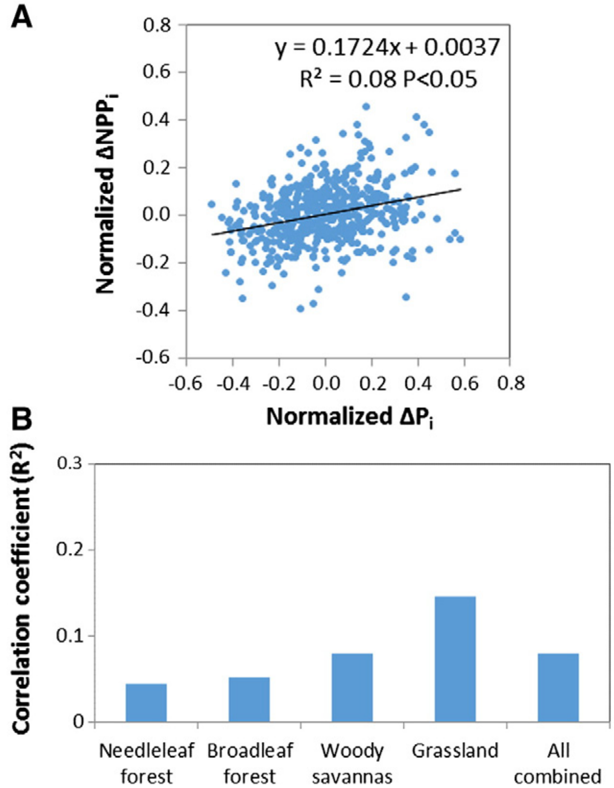

Fig. 2. a) The linear relationship between the inter-annual variations of NPP and P in the four biomes combined based on the station subset data (N = 54 sites by 10 years); b) correlation coefficients (R^2) between normalized ΔNPP and normalized ΔP_i for each four biomes and four biomes combined.

3.2. The impact of prolonged drought on NPP and RUE

Normalized $\Delta\overline{NPP}_{j,k}$ for the station subset data did not change significantly with current- and previous-year drought (Fig. 3a, Table 3). Across every drought type, the variations of normalized $\Delta\overline{NPP}_{j,k}$ between different drought types were not significant statistically for each biome and all biomes combined ($P > 0.05$, Table 3).

Unlike the influence of drought on NPP, for each biome and all biomes combined, normalized $\Delta\overline{RUE}_{j,k}$ showed a significantly declining trend with the variations in current and previous-year drought, where the highest normalized $\Delta\overline{RUE}_{j,k}$ appeared in a dry year preceded by a wet year, and conversely, a wet year preceded by a dry year resulted in the lowest normalized $\Delta\overline{RUE}_{j,k}$ ($P < 0.05$) (Fig. 3b, Table 3). This finding was validated with the normalized $\Delta\overline{RUE}_{j,k}$ derived from all regional data in China (Fig. 3c, Table 3).

Table 2
The relations between normalized ΔNPP_i and normalized ΔP_i for years 2001–2010 for each biome and all biomes combined for station subset data.

Biome type	The linear relationship	R^2	P
Needleleaf forest	Normalized $\Delta NPP_i = -0.0818 \times$ Normalized $\Delta P_i + 0.0020$	0.0442	<0.05
Broadleaf forest	Normalized $\Delta NPP_i = 0.1382 \times$ Normalized $\Delta P_i - 0.0042$	0.0514	<0.05
Woody savannas	Normalized $\Delta NPP_i = 0.1223 \times$ Normalized $\Delta P_i + 0.0108$	0.0791	<0.05
Grassland	Normalized $\Delta NPP_i = 0.2511 \times$ Normalized $\Delta P_i + 0.0052$	0.1457	<0.05
All combined	Normalized $\Delta NPP_i = 0.1724 \times$ Normalized $\Delta P_i + 0.0037$	0.0799	<0.05

3.3. The model of variation of annual RUE by previous- and current-year PDSI

Based on this trend of normalized $\Delta\overline{RUE_{j,k}}$, we created an empirical equation of normalized ΔRUE_i by previous- and current-year PDSI (Eq. 8, Table 4). The model predicted the variation of RUE by the two consecutive years of drought in four biomes combined (Fig. 4a). In Needleleaf forest, Broadleaf forest, Grassland and all biomes combined, the model based on previous- and current-year PDSI reduced AIC by more than 2.0 relative to the model based on only current-year PDSI (Eq. 7). In Woody savannas, the AIC for the two-year PDSI model was lower, but was reduced by only 0.45 and the R^2 of these two models were close (Fig. 4b, Table 5).

The hierarchical partitioning algorithm showed that the previous-year PDSI contributed more than 20% to the goodness of fit in Needleleaf forest, Grassland and all biomes combined; in Broadleaf forest and

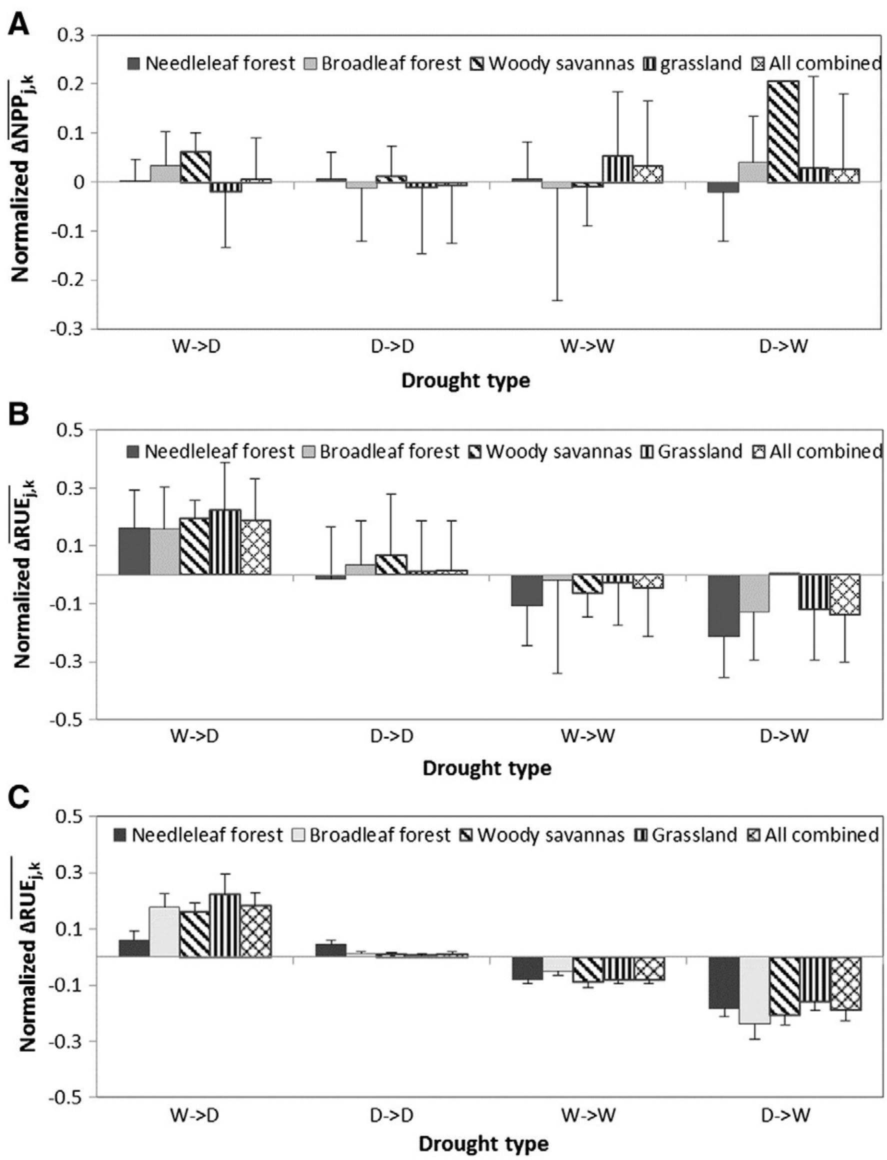

Fig. 3. For the station subset data, a) the variation of normalized $\Delta\overline{NPP_{j,k}}$ for each biome and drought type; and b) the variation of normalized $\Delta\overline{RUE_{j,k}}$ for each biome and drought type. For all regional data (N > 20,000 for each year), c) the variation of normalized $\Delta\overline{RUE_{j,k}}$ for each biome and drought type.

Table 3
The P values of the t-test of the difference between normalized $\Delta\overline{\mathrm{NPP}_{j,k}}$ (and normalized $\Delta\overline{\mathrm{RUE}_{j,k}}$) for drought types (shown in Fig. 3), where (W → D) means the dry year after wet year, (D → D) means the dry year after dry year, (W → W) means the wet year after wet year and (D → W) means the wet year after dry year. The terminology for change in drought type is expressed as, for example, (W → D) → (D → D), where the change is from the drought type (W → D) to drought type (D → D). For $P < 0.05$, the changes in normalized $\Delta\overline{\mathrm{NPP}_{j,k}}$ or normalized $\Delta\overline{\mathrm{RUE}_{j,k}}$ between two drought types are significant statistically and are shown in boldface.

The change of drought type	Needleleaf forest	Broadleaf forest	Woody savannas	Grassland	All combined
Normalized $\Delta\overline{NPP_{j,k}}$ *for station subset data*					
(W → D) → (D → D)	0.4054	0.1815	0.1508	0.4393	0.3072
(W → D) → (W → W)	0.4135	0.3328	0.1284	**0.0486**	0.1597
(W → D) → (D → W)	0.3041	0.4524		0.2398	0.2759
(D → D) → (W → W)	0.4726	0.4989	0.2569	0.0501	**0.0027**
(D → D) → (D → W)	0.1572	0.1243		0.1249	0.0728
(W → W) → (D → W)	0.2139	0.2859		0.2393	0.3919
Normalized $\Delta\overline{RUE_{j,k}}$ *for station subset data*					
(W → D) → (D → D)	**0.0089**	**0.0244**	**0.0504**	**0.0001**	**0.0000**
(W → D) → (W → W)	**0.0001**	**0.0341**	**0.0011**	**0.0000**	**0.0000**
(W → D) → (D → W)	**0.0001**	**0.0021**		**0.0000**	**0.0000**
(D → D) → (W → W)	**0.0252**	**0.1059**	0.1579	**0.0456**	**0.0017**
(D → D) → (D → W)	**0.0044**	**0.0039**		**0.0012**	**0.0000**
(W → W) → (D → W)	**0.0476**	**0.1411**		**0.0133**	**0.0032**
Normalized $\Delta\overline{RUE_{j,k}}$ *for all regional data*					
(W → D) → (D → D)	**0.0316**	**0.0056**	**0.0008**	**0.0030**	**0.0003**
(W → D) → (W → W)	**0.0000**	**0.0237**	**0.0001**	**0.0002**	**0.0000**
(W → D) → (D → W)	**0.0000**	**0.0000**	**0.0000**	**0.0000**	**0.0000**
(D → D) → (W → W)	**0.0096**	0.16787	**0.0122**	**0.0110**	**0.0025**
(D → D) → (D → W)	**0.0001**	**0.0000**	**0.0001**	**0.0000**	**0.0000**
(W → W) → (D → W)	**0.0029**	**0.0261**	**0.0402**	**0.0243**	**0.0388**

Woody savannas, the independent effects were less than 20%. Considering that the ΔAIC between the two models in Broadleaf forest was only 3.28, the results of dependent effects were the same as the AIC analysis (Fig. 4c). That is, the impact of previous-year drought on RUE was less important for Broadleaf forest and Woody savannas than for Needleleaf forest and Grassland. Nonetheless, for all biomes combined, both current-year and previous-year drought had strong and significant impact on RUE.

The calibrated model was tested with all regional data in China. By comparing the predicted and the measured normalized $\Delta\mathrm{RUE}_i$, the R^2 based on two-year PDSI and current-year PDSI were reported (Fig. 5). In four biomes and all biomes combined, the R^2 based on two year PDSI were greater than the current-year PDSI model. In addition, for most of years, the linear correlations between measured normalized $\Delta\mathrm{RUE}_i$ and predicting normalized $\Delta\mathrm{RUE}_i$ by two-year PDSI were significant ($P < 0.05$, Eq. 8), except in 2001, 2008 and 2010 for all biomes combined, 2001, 2003–2005 and 2010 for Needleleaf forest, 2008 for Broadleaf forest, and 2001, 2003, 2004, 2006 and 2008 for Grassland. In contrast, the linear relationships based on current-year PDSI (Eq. 7) were significant for only 1–4 years for the Needleleaf forest, Broadleaf forest, Grassland and all biomes combined. For Woody savannas, there were 7 years of significant relationships based on current-year PDSI (Eq. 7).

4. Discussion

Results for Needleleaf forest, Broadleaf forest, Woody savannas, Grassland and the four biomes combined showed that the temporal linear relations between NPP and precipitation were weak. This is because precipitation is only one of an array of biotic and abiotic factors affecting NPP, including temperature, nutrient availability, physical properties of soil, and intertwining biotic interactions (Knapp & Smith, 2001; Sala et al., 1988; Zhao & Running, 2010). The MODIS NPP product was based on a light use efficiency model which relies primarily on MODIS spectral measurements, but also includes current-year precipitation, temperature, and solar radiation (Running et al., 2000). Sala et al. (2012) and Reichmann et al. (2012) reported that current-year precipitation explained only a small proportion of annual ANPP, and that previous-year precipitation and ANPP controlled a significant fraction of current-year production. By dividing ANPP by P to obtain RUE, we were then able to determine the impact of current- and previous-year drought on ecosystem stability and resilience.

We found that the variations of RUE were significantly related to the prolonged drought. In our results, the normalized $\Delta\overline{\mathrm{RUE}_{j,k}}$ in dry years was positive for each one of the four biomes and the four biomes combined. Further, RUE was even higher in the dry year after a wet year (W → D) indicating a biome-scale sensitivity to drought where ecosystems sustained NPP by increasing their RUE. Thus, these results suggest that the ecosystem resilience, defined as the capacity to absorb disturbances and retain the same function, feedbacks and sensitivity (Holling, 1973; Walker, Holling, Carpenter, & Kinzig, 2004), allowed biomes to retain NPP by increasing annual RUE. In addition, we found that the normalized $\Delta\overline{\mathrm{RUE}_{j,k}}$ decreased in a dry year after dry year (D → D) supporting previous results from Ponce-Campos et al. (2013) where they found that the resilience decreased with prolonged warm drought.

In addition, the RUE decreased with the increasing water availability in the wet year. However, the normalized $\Delta\overline{\mathrm{RUE}_{j,k}}$ was even lower in a wet year when the previous year was a dry year. Reichmann et al. (2012) hypothesized that lags in the response of ecosystems to changes in RUE explain this result. The legacy effects result from transitions from dry to wet years or the reverse. In the wet year after dry year, because of the legacy effects from the previous drought, NPP was lower than in the normal wet year, and then normalized $\Delta\overline{\mathrm{RUE}_{j,k}}$ was lower in D → W than in W → W. Meanwhile, the legacy effects also appeared in the dry year after wet year (W → D). NPP was higher than in the normal dry year because the previous wet year, the resilience and legacy effects combined together to cause the normalized $\Delta\overline{\mathrm{RUE}_{j,k}}$ to be higher in dry year after wet year.

Based on the patterns of normalized $\Delta\overline{\mathrm{RUE}_{j,k}}$ with the prolonged drought, we created an empirical model of normalized $\Delta\mathrm{RUE}_i$ based on previous- and current-year PDSI using the station subset dataset. This model could explain the impact of prolonged drought on RUE. Our results showed that the normalized $\Delta\mathrm{RUE}_i$ was better predicted by the model with two-year drought (Eq. 8) than by the model with current-year drought (Eq. 7) for all biomes except Woody

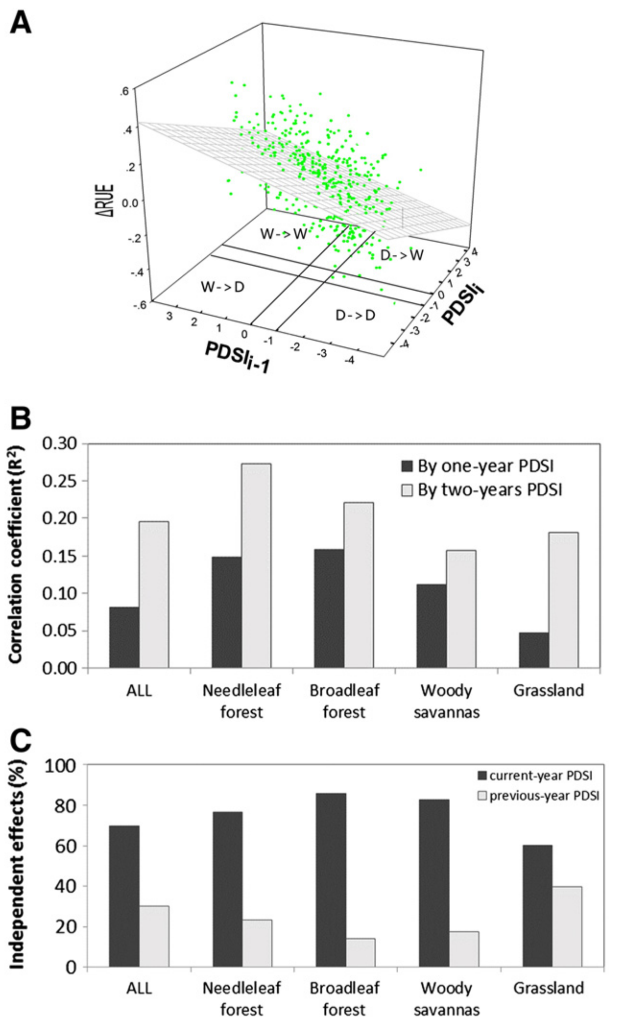

Fig. 4. Using the station subset data, a) the model of RUE by two consecutive years of drought in four biomes combined, where Normalized $\Delta RUE_i = -0.0109 + (-0.0537PDSI_i) + 0.0419PDSI_{i-1}$; b) the correlation coefficient (R^2) of the normalized ΔRUE_i model by current-year PDSI (Eq. 7) and by two-year PDSI (Eq. 8); and c) the independent effects of two year PDSI on the goodness of fit.

savannas. In the latter case, the improvement associated with adding the previous year was marginal. Because the transpiration water consumption of Broadleaf forest and Woody savannas was larger than other biomes (Woodward, 1992), the variation of RUE was mainly affected by the current-year drought, and the impact of previous-year drought was less.

There are two factors that affected the validation accuracy of the predicted normalized ΔRUE_i. First, the validation data were distributed widely in China; the Needleleaf forest and Broadleaf forest were grown both in the north and south, the Grassland was distributed throughout the west, and only Woody savannas were distributed in the south central. The same biome in different areas had different sensitivity to drought (Hall, Carroll, Vandermeer, & Rosset, 1990; Wu & Wang, 2000). The mean annual precipitation in the south is greater than in the north in China, and biomes in drought areas generally have a higher RUE. This led to a decrease in the accuracy of the predicted normalized ΔRUE_i in different areas. Second, MOD12Q1 land cover accuracies are known to fall in the range of 70–80%. Through the process of selecting the study areas using visual interpretation with Google Earth for the station subset, we found that the MOD12Q1 biome designations were only about 70% (54/77 ∗ 100) accurate. At the regional scale of the validation dataset, the many mixed and misclassified pixels affected our assessment of the accuracy of the predicted normalized ΔRUE_i.

5. Conclusions

Our results support the view that the relation between annual NPP and current-year precipitation is weak, and RUE is a better indicator of the biome sensitivity to water availability (Huxman et al., 2004; Ponce-Campos et al., 2013). Results also concur with recent work in other locations that showed how extreme climate change not only affected the carbon cycle concurrently, but also initiated lagged responses (Arnone et al., 2008; Reichstein et al., 2013). Due to the ecosystem resilience in dry years and the legacy effect of precipitation in both dry and wet years, RUE showed a significant, predictable trend with the prolonged drought. We quantified the impact of severe prolonged drought on RUE and created a model of RUE based on previous- and current-year PDSI. These findings are useful because they are based on satellite data across four biomes. The model can be used to assess the impacts of climate change on terrestrial ecosystems in China, especially if prolonged drought continues. This work is a first step in understanding the impact of prolonged drought on RUE at the regional scale across a heterogeneous landscape.

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Table 4
The models of normalized ΔRUE_i as a function of two-year drought and current-year drought for station subset data (illustrated in Fig. 4b), where $P < 0.05$ for all models.

Biome	Model	R^2
Needleleaf forest	Normalized $\Delta RUE_i = -0.0430 + (-0.0553PDSI_i) + (0.0367PDSI_{i-1})$	0.2734
	Normalized $\Delta RUE_i = -0.0452 + (-\ 0.0322PDSI_i)$	0.1479
Broadleaf forest	Normalized $\Delta RUE_i = -0.0242 + (-0.0546PDSI_i) + (0.0332PDSI_{i-1})$	0.2206
	Normalized $\Delta RUE_i = -0.0442 + (-0.0376PDSI_i)$	0.1587
Woody savannas	Normalized $\Delta RUE_i = 0.0057 + (-0.0409PDSI_i) + (0.0240PDSI_{i-1})$	0.1569
	Normalized $\Delta RUE_i = 0.0053 + (-0.0244PDSI_i)$	0.1122
Grassland	Normalized $\Delta RUE_i = 0.0019 + (-0.0547PDSI_i) + (0.0482PDSI_{i-1})$	0.1816
	Normalized $\Delta RUE_i = -\ 0.0108 + (-0.0203PDSI_i)$	0.0475
All combined	Normalized $\Delta RUE_i = -0.0109 + (-0.0537PDSI_i) + (0.0419PDSI_{i-1})$	0.1968
	Normalized $\Delta RUE_i = -0.0218 + (-0.0256PDSI_i)$	0.0806

Table 5
Comparison of models which predicted normalized ΔRUE_i as a function of both previous- and current-year PDSI (Eq. 8) and current-year PDSI (Eq. 7). The AIC is the Akaike Information Criterion value of the models. According to AIC criteria, the most parsimonious models are shown in boldface. N is the number of samples for each biome.

Biome type	Model	N	AIC	ΔAIC	R^2
Needleleaf forest	Eq. (8)	**100**	**−368.06**	**0.00**	**0.27**
	Eq. (7)		−354.29	13.77	0.15
Broadleaf forest	Eq. (8)	**70**	**−241.39**	**0.00**	**0.22**
	Eq. (7)		−238.11	3.28	0.16
Woody savannas	Eq. (8)	30	−107.74	0.00	0.16
	Eq. (7)		**−107.29**	**0.45**	**0.11**
Grassland	Eq. (8)	**340**	**−1230.10**	**0.00**	**0.18**
	Eq. (7)		−1180.90	49.2	0.05
All combined	Eq. (8)	**540**	**−1955.80**	**0.00**	**0.20**
	Eq. (7)		−1886.00	69.80	0.08

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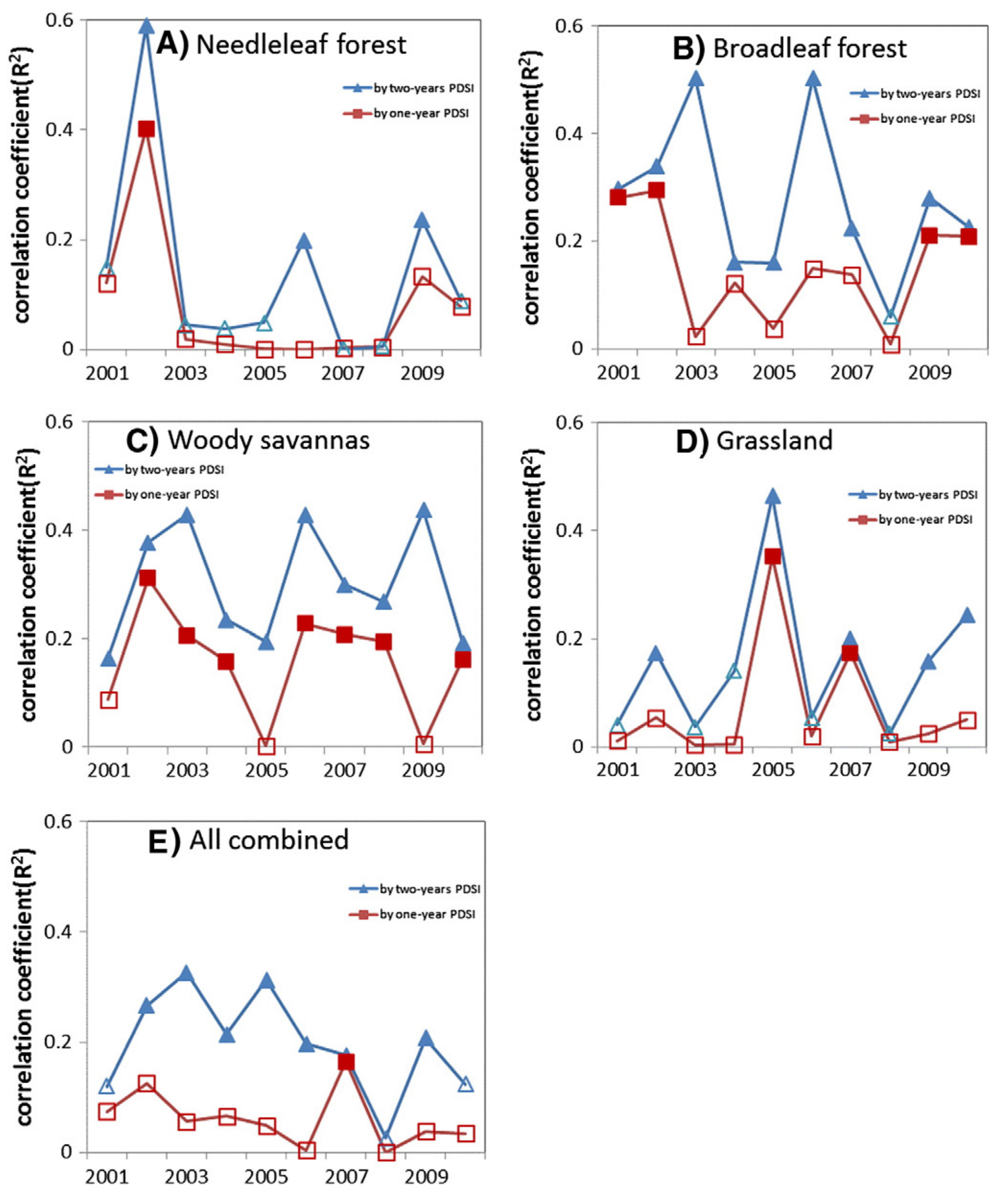

Fig. 5. Using all regional data for validation, the R^2 in the four biomes and the four biomes combined by comparing the predicted and measured normalized ΔRUE_i in when applying two-year PDSI model (Eq. 8) and one-year PDSI model (Eq. 7), respectively. The solid markers represent the case when $P < 0.05$.

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