**Lagged precipitation effect on plant productivity is influenced collectively by
climate and edaphic factors in drylands**

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Abstract:

Lagged precipitation effect explains a large proportion of annual aboveground net primary productivity in some dryland ecosystems. Using satellite-derived plant productivity and precipitation datasets in the Northern Hemisphere drylands during 2000-2018, we identify 1111 pixels mainly located in the Tibetan Plateau, the western US, and Kazakhstan where productivities are significantly correlated with previous-year precipitation (hereafter, the lagged type). Differences in climatic and edaphic factors between the lagged and unlagged (pixels where productivities are not correlated with previous-year precipitation) types are evaluated. Permutational multivariate analysis of variance shows that the two types differ significantly regarding six climatic and edaphic factors. Compared to unlagged type, water availability, soil organic carbon, total nitrogen, field capacity, silt content and radiation are more sensitive to changes in precipitation in lagged type. Water availability is the most important factor for distinguishing the two types, followed by soil organic carbon, total nitrogen, field capacity, soil texture, and radiation. Our study suggests that the altered sensitivities of several climatic and edaphic factors to precipitation collectively affect the lagged effect of precipitation on productivity in drylands.

Keywords: productivity, lagged precipitation effect, previous-year precipitation, water availability, dryland

1 Introduction

Global warming has intensified and accelerated the hydrologic cycle (Huntington, 2010; Trenberth, 2011), causing precipitation patterns shifting to higher variability and more frequent dry and wet years, which is almost ubiquitous globally (Collins et al., 2013; Min et al., 2011; Peng et al., 2018; Ye et al., 2018a). Increasing precipitation variability may profoundly affect ecosystem functioning and structure, especially primary productivity (Gherardi and Sala, 2015; Gherardi and Sala, 2019; Knapp et al., 2008; Rudgers et al., 2018; Ye et al., 2013). Therefore, understanding the relationship between plant productivity and precipitation is crucial to ecosystem function and also to humans who depend upon primary productivity for food, fiber and fuel (Haberl et al., 2007; Knapp et al., 2017).

The lags in the response of ecosystems to changes in precipitation and "asymmetries" in the productivity-precipitation relationship modulate the effect of precipitation variability on productivity (Knapp et al., 2017; Reichmann et al., 2013). First, the lags arise from the legacy effects of transitions from dry to wet years or the reverse (Reichmann et al., 2013). A previous dry year leads to a decrease in plant productivity in the following year (termed as drought legacy), while a wet year increases productivity in the next year, i.e., wetness legacy (Sala et al., 2012). Second, the productivity-precipitation relationship may be nonlinear, including concave-down and concave-up curves. Increasing precipitation has diminishing returns for productivity in "negative asymmetric" productivity-precipitation relationships (concave-down curves); in contrast, increasing precipitation has increasing returns for productivity in "positive

asymmetric" relationships (concave-up curves) (Dannenberg et al., 2019; Gherardi and Sala, 2015). The drivers of lagged response to precipitation and nonlinear productivity-precipitation relationship are valuable for accurately predicting the response of ecosystem function to global change. Ye et al. (2018b) find that concave-down nonlinear relationship ecosystems feature lower radiation and/or fewer soil nutrients than the linear type, suggesting a higher degree of limitation from resources other than precipitation in the nonlinear ecosystems (Huxman et al., 2004). However, it is still unclear how other environmental factors affect the lagged response of ecosystems to changes in precipitation.

The legacy effect of unusually dry or wet periods on biomass could last for less than one year up to seven years, of which one year is the most commonly reported lag time (Sherry et al., 2008). Previous-year precipitation has been found to drive the current-year ecosystem process through lagged/legacy effect in multiple sites, e.g., the central plains in north-central Colorado (Oesterheld et al., 2001), the Patagonian steppe (Yahdjian and Sala, 2006), the Tallgrass Prairie in Oklahoma (Sherry et al., 2012) and the Loess Plateau of China (Gong et al., 2020). At the interannual scale, the lagged precipitation effect is defined as the impact of previous-year precipitation conditions on the current structure and functioning of ecosystems (Monger et al., 2015; Sala et al., 2012; Shen et al., 2016). A variety of mechanisms explaining the lagged precipitation effect involve changes in the density of tillers, seeds and plant individuals (Oesterheld et al., 2001; Reichmann et al., 2013; Yahdjian and Sala, 2006); the structural carry-overs (e.g., leaf area and root biomass) between alternating wet and dry years

(Oosterheld et al., 2001); and the composition of species differ in rooting depth and phenology (Gong et al., 2020; Jobb gy and Sala, 2000). Within the context of climate change, lagged precipitation effect might result from feedbacks between biotic, edaphic, and geomorphic processes (Monger et al., 2015). Most studies focused on the biotic mechanisms; however, it remains largely uncertain how climatic and edaphic factors may interact with lagged precipitation effects.

Drylands comprise 45% of the terrestrial earth surface (Prvlie, 2016), and precipitation is the most limiting factor to the functioning of dryland ecosystems (Lauenroth, 1979; Noy-Meir, 1973). Therefore, their responses to interannual precipitation variability have important consequences for global patterns of productivity (Ahlstrm et al., 2015; Gherardi and Sala, 2019; Yao et al., 2020).

Drylands are inherently slow in the dynamics of soil nutrient buildup and plant productivity compared to other ecosystems (Huang et al., 2017; Ye et al., 2019), we would expect strong lagged effects of past climate conditions such as precipitation on current functioning. However, our ability to forecast ecosystem responses to climate change is still hindered by our understanding of the mechanisms underlying the lagged precipitation effect (Kannenberget al., 2020; Yahdjian and Sala, 2006; Ye et al., 2019).

The lagged response to precipitation change results from drought and wetness legacies, and the magnitude of drought and wetness legacies are proportional to the relative precipitation change (Reichmann et al., 2013; Shen et al., 2016). However, we do not know whether the lagged precipitation effect is associated with precipitation variability.

Sala et al. (2012) suggest that the sensitivity of productivity to precipitation might

decrease due to the impact of previous-year precipitation. Besides, precipitation input is the determining factor of plant productivity in drylands, and other drivers of productivity may be indirectly influenced by precipitation amount and variability (Hsu and Adler, 2014; Noy-Meir, 1973; Ye et al., 2018b). Therefore, the productivity-precipitation relationship may be modified by changes in the responses of other environmental factors to precipitation. In these perspectives, we hypothesize that compared with the unlagged ecosystems, the lagged ones are characterized by (i) lower sensitivity of productivity response to precipitation, (ii) higher interannual precipitation variability and more occurrences of dry and wet years, and (iii) higher sensitivity of other environmental factors to precipitation. To test our hypotheses, we divide terrestrial ecosystems of the Northern Hemisphere drylands into the lagged and unlagged types. The lagged type has a significant lagged precipitation effect where productivities significantly correlate with previous-year precipitation, while productivities of the unlagged type do not significantly correlate with previous-year precipitation. To evaluate the difference between the two ecosystem types in terms of their climatic and edaphic factors, we explore their differences in the intercepts and slopes of liner regressions between these factors and mean annual precipitation.

2 Materials and methods

2.1 Precipitation

The Tropical Rainfall Measuring Mission (TRMM) product (TRMM 3B42) at 0.25° spatial and daily temporal resolution (<https://pmm.nasa.gov/data-access/downloads/trmm>) for the period of 1999-2018 were used. The product covers

the latitude range of 50°N-S. The daily rainfalls were cumulated to obtain annual precipitation. Previous studies have suggested that TRMM rainfall data are consistent with precipitation observations of weather stations at both local and global scales (Fang et al., 2019; Ye et al., 2018b).

2.2 Primary productivity

We used the enhanced vegetation index (EVI) to estimate primary productivity. The MOD13C2 version 6 EVI dataset (Didan, 2015) at 0.05 °spatial resolution and monthly compositing periods for the period from February 2000 to December 2018 was employed. As EVI data for January 2000 were not available, the average of values in January of 2001-2005 was used as a proxy. When no clear-sky observations were available, the corresponding pixels were excluded from the analysis. Pixels of croplands, built-up, water, snow and ice, barren or sparse vegetation, and land cover change were eliminated based on MCD12C1 IGBP land cover types between 2001 and 2018 (Friedl and Sulla-Menashe, 2015). We also excluded the wetland pixels due to the poor performance of EVI in estimating their productivity (Shi et al., 2017). An offset of 0.05 was extracted from each monthly dataset to reduce the soil background signal (Ponce Campos et al., 2013). Annual integrated EVI (termed iEVI) is a widely used satellite-derived measure of annual vegetation productivity across biomes (Ma et al., 2015; Shi et al., 2017). We thus used iEVI as the proxy of primary productivity. The iEVI was calculated in the software of TIMESAT 3.3 using the default parameters (Jönsson and Eklundh, 2017; Ponce Campos et al., 2013). We found a similar linear relationship between MODIS NPP (MOD17A3 product) and iEVI, consistent with Ponce Campos

et al. (2013) and Ye et al. (2018b) (Fig. S1).

2.3 Climatic and edaphic factors

Radiation, air temperature, water availability, nitrogen (N), phosphorus (P), soil organic carbon (SOC), soil texture, soil field capacity, and water table depth are important drivers of productivity (Epstein et al., 1997; Huang et al., 2019; Ye et al., 2018b).

Therefore, we selected these climatic and edaphic factors to analyze their respective contribution to the lagged precipitation effect on plant productivity. The annual average climatic factors were obtained from Seddon et al. (2016). Radiation was measured by the proportion of clear-sky to cloudy days in a given pixel based on the MODIS Cloud Mask product (MOD35_L2) (Ackerman and Frey, 2015). MOD07_L2 Atmospheric Profile product was used as a measure of air temperature (Borbas and Menzel, 2015). Pixels from the highest available pressure level, corresponding to the temperature nearest to the Earth's surface, were selected. We used the ratio of actual evapotranspiration to potential evapotranspiration (AET/PET) as an indicator of water availability. A higher value suggests sufficient water supply to plant, while a lower one indicates higher water deficit or aridity. AET and PET were both derived from the MOD16 Global Evapotranspiration product, which estimates evapotranspiration through the Penman-Monteith equation (Mu et al., 2011).

We obtained edaphic factors from the gridded Global Soil Dataset for use in Earth System Models (GSDE), including total nitrogen (TN), total phosphorus (TP), total carbon, SOC, volumetric water content (VMC), and soil texture. The dataset provides soil properties, such as soil texture, organic carbon, and nutrients, with 30 arc-seconds

spatial resolution, which are quality controlled (Shangguan et al., 2014). The water table depth dataset at 30 arc-second grid was obtained from Fan et al. (2013).

To match the low-resolution TRMM precipitation dataset, all the above iEVI, climatic and edaphic data were aggregated up to 0.25 °spatial resolution. The distribution of dry domain was derived from the map of Bailey's four global ecoregion domains (Bailey, 1995).

2.4 Selection of lagged and unlagged ecosystems

For each pixel in the Northern Hemisphere drylands, linear regression and multiple linear models between current-year iEVI and current-year precipitation (PPT_t) and/or previous-year precipitation (PPT_{t-1}) were fitted (Table 1) using the linear model (lm) function in R4.0.0. The lagged type fitted the multiple-year regression (i.e., $p < 0.05$ for the multiple-year model [$iEVI_t = a \times PPT_t + b \times PPT_{t-1} + c$] and $p \geq 0.05$ for current-year [t] model [$iEVI_t = a \times PPT_t + c$]), or previous-year ($t - 1$) regression (i.e., $p < 0.05$ for previous-year model [$iEVI_t = a \times PPT_{t-1} + c$] and $p \geq 0.05$ for the current-year model). The unlagged type only fitted current-year regression (i.e., $p < 0.05$ for the current-year model and $p \geq 0.05$ for the multiple-year model and previous-year model).

2.5 Hypotheses testing

To test the first hypothesis, i.e., the lagged type had a lower sensitivity of productivity response to precipitation. We fitted the regressions between iEVI and precipitation for each pixel. We measured the sensitivities as the slopes of the liner regression between iEVI and precipitation. We then compared the sensitivities of the lagged and unlagged

types across the mean annual precipitation (MAP) gradients based on the procedure of Zar (2009).

To test the second hypothesis, i.e., the lagged type had higher interannual precipitation variability and more occurrences of dry and wet years. We calculated the coefficient of variation (CV) of annual precipitation and the occurrences of dry and wet years for each pixel based on 19-year annual precipitation data. We defined a dry year as one and two SDs (standard deviations) of precipitation lower than the average and wet year as one and two SDs higher than the average during the study period.

To test the third hypothesis, i.e., the lagged type had a higher sensitivity of other environmental factors to precipitation. We compared the difference between the two types in terms of climatic-edaphic factors, to explore what factors were responsible for the lagged precipitation effect. Firstly, the linear regressions between each factor and MAP were conducted for the two types, respectively. We then tested the statistical differences in the slopes and intercepts of these linear fittings based on the procedure of Zar (2009). To ensure that the lagged type was sensitive to the selected climatic-edaphic factors, we used the two criteria: (1) the regression between climatic-edaphic factor and MAP in lagged type was significant; and (2) the slopes between regressions in lagged and unlagged types differed significantly. Secondly, permutational multivariate analysis of variance (perMANOVA, "vegan" package in R) was applied to determine whether the two types differed significantly when all selected climatic-edaphic factors were taken into account collectively. The perMANOVA is a non-parametric multivariate statistical test to evaluate whether the centroids and dispersions

of some groups (lagged and unlagged types in this study) are equivalent. It requires no assumption regarding the number of variables (or distributions) within the groups (Anderson, 2001). To allow for a comparison of the climatic-edaphic factors with different units, the normalized values were used in the perMANOVA test. The random intercept model was further used to compare the difference in the intercepts between the two types when fixing the slope of linear regression ("lmerTest" package in R). A Euclidean distance-based similarity percentage (SIMPER) analysis (Clarke, 1993; Ye et al., 2018a) was employed to determine the contribution of each climatic-edaphic factor to the overall dissimilarity between the two types.

3 Results

We identified 1111 lagged pixels and 1442 unlagged pixels among 16500 tested pixels (0.25 spatial resolution) across drylands in the northern hemisphere (Fig. 1). Most of them were found in grasslands, shrublands, and savanna biomes. The lagged pixels were mainly located in the Tibetan Plateau of China, the western US, and Kazakhstan. The sensitivities/slopes of productivity response to precipitation in the lagged were significantly lower (slope and intercept difference: $p < 0.001$) than those in the unlagged at the spatial scale (Fig. 2). Moreover, the differences in productivity sensitivities to precipitation in the two types decreased with increasing MAP (Fig. 2). The two types were not significantly different in terms of the variabilities of interannual precipitation ($p = 0.11$) (Fig. S2). There were neither significant differences in occurrences of dry (1SD: $p = 0.54$) and wet (1SD: $p = 0.8$, 2SD: $p = 0.13$) years in the two types, except for the 2SD dry years (the occurrences in lagged type were less than those in the

unlagged type, $p < 0.01$) (Fig. S3-4).

PerMANOVA analysis indicated that the lagged and unlagged types differed significantly when the climatic (water availability and radiation) and edaphic factors (SOC, TN, VMC, and silt content) were collectively considered ($F = 12.96$, and $p < 0.001$). Moreover, the sensitivities of the six climatic and edaphic factors to MAP were all higher in lagged type than those in the unlagged. Compared with the unlagged type, water availability increased faster with increasing MAP in the lagged type (Fig. 3a and Table 2). SOC, TN, and VMC raised across the MAP gradients in the two types, and the slopes were significantly higher in the lagged type (Fig. 3b-d and Table 2). Silt content was positively correlated with MAP in both types, and the slope of the regression between them was greater in the lagged type than unlagged type (Fig. 3e and Table 2). In contrast, radiation was negatively correlated with MAP in both types, and the slope of the regression between them was lower in lagged type than unlagged type (Fig. 3f and Table 2). However, air temperature did not significantly change with increasing MAP in the lagged (Fig. S5). Water table depth, soil total carbon, and soil phosphorus were higher in the lagged type than those in the unlagged; however, the slopes between these regressions did not differ significantly (Fig. S6-7). Likewise, clay content, sand content, and indicators of N and P availabilities (C/N and C/P ratios) did not differ significantly between the two types (Fig. S8-9).

The random intercept model showed that the lagged type might have higher TN, VMC, and silt content than the unlagged when fixing the slope (Table S1), and the differences between the two types in the means of these environmental factors were small (Fig. 3

and Table S1). SIMPER analysis showed that water availability was the most important factor for distinguishing between the two types, followed by SOC, TN, VMC, and silt content (Fig. 4). The radiation had a minimal contribution.

4 Discussion

Based on satellite-derived productivity and precipitation, we identify two types of terrestrial ecosystems either with or without lagged precipitation effect in the Northern Hemisphere drylands and evaluate the difference in climatic and edaphic factors between them. Consistent with the first hypothesis, our results show that productivity is less sensitive to precipitation in lagged type than unlagged type along the MAP gradients. Previous studies attributed lagged precipitation effect to the differences in productivity-PPT relationships among ecosystems (Bunting et al., 2017; Gong et al., 2020; Petrie et al., 2018). Our results support this viewpoint that the lagged precipitation effect plays a vital role in modifying the productivity-precipitation relationship. Moreover, the differences between productivity responses to precipitation in the two types decrease with increasing MAP, which is likely due to the limitation of resources other than precipitation (Huxman et al., 2004). This observation is supported by recent studies, which have reported the strength of vegetation water memory effects decreases with increasing MAP (Liu et al., 2018), and the legacy effects of water deficits on trees are highly reliance on MAP, with this effect being most pronounced in dry ecosystems (Anderegg et al., 2015).

Our study does not support the second hypothesis that the lagged type is characterized by higher interannual precipitation variability and more occurrences of dry and wet

years because both types possess similar precipitation variability and occurrences of dry and wet years. Previous studies suggest that the magnitudes of the short-term legacies of antecedent precipitation (i.e., drought and wetness legacies) are positively related to relative precipitation changes between current and previous year (Reichmann et al., 2013; Yahdjian and Sala, 2006), and greater variability in precipitation leads to corresponding increases in legacy impacts (Shen et al., 2016). However, the lagged precipitation effect may not be influenced directly by precipitation variability. Precipitation amount and variability may indirectly alter other environmental factors, thus influencing productivity (Hsu and Adler, 2014; Luo et al., 2017; Yahdjian and Sala, 2010).

In our study, climatic and edaphic factors in lagged ecosystems are more sensitive to precipitation at a spatial scale, supporting the third hypothesis. A similar difference pattern between the two types is also found in the Southern Hemisphere dry landmass (Fig. S10-11). Compared to the unlagged type, higher sensitivity in water availability to precipitation in the lagged type could lead a more deteriorated water condition when precipitation decreases, resulting in more changes in the plant structure (e.g., leaf and root), plant reproduction (e.g., seed production and tillers), litter dynamics, and community composition (Dudney et al., 2017; Reichmann and Sala, 2014; Yahdjian and Sala, 2006), thus exerting a negative influence on following-year productivity. In contrast, ecosystems with high sensitivity in water availability may benefit more with precipitation increasing.

We find that dissimilarity patterns between lagged and unlagged types are consistent in

terms of soil properties (such as SOC, TN, soil field capacity, and silt content,) and water availability. Soil water availability is related to soil physical and chemical properties (Cassel and Nielsen, 1986; Geroy et al., 2011). Low soil water holding capacity might lead to low available soil water due to high loss of precipitation via runoff or percolation, especially during large rain events (Ye et al., 2018b). Furthermore, higher soil organic matter and silt content could increase water retention (Geroy et al., 2011). Consistent with Wang et al. (2017), TN increases along the MAP gradients in both types. Due to the higher sensitivity of TN to precipitation, changes in precipitation may lead to more substantial fluctuation in soil N in lagged ecosystems, likely causing N carry-over between interannual years. Recent studies report that previous-year precipitation may influence litter dynamic, microbial mineralization and immobilization, plant N uptake, and N leaching, causing soil mineral N pools to accumulation or decrease (Dudney et al., 2017; Evans and Burke, 2012; Giese et al., 2010; Shen et al., 2016; Yahdjian and Sala, 2010), thus promote or inhibit current-year productivity.

In addition, our results show that water availability is the most important factor in distinguishing between the two types. Water availability is the most determining and limiting factor to the functioning of arid and semiarid ecosystems (Lauenroth, 1979; Noy-Meir, 1973). Soil properties (e.g., soil field capacity, soil texture, and soil organic carbon) have an association with water availability; in turn, the changes in water availability could influence the dynamics of soil organic carbon and nitrogen. The importance of water availability in these connections among environmental factors in

drylands may explain its highest contributions to the lagged precipitation effects.

5 Conclusion

Lagged precipitation effect plays an essential role in the productivity-precipitation relationship. In our study, we found the ecosystems with a significant lagged precipitation effect had lower sensitivity of productivity response to precipitation than those of unlagged ones, and the differences in productivity sensitivities to precipitation in the two types decreased with increasing MAP. Moreover, the increase in the sensitivities of environmental factors to precipitation might contribute to the lags in the response of productivities to changes in precipitation at the interannual scale. With increasing interannual precipitation variability and frequency of dry and wet years, it is necessary to consider would the sensitivity of other environmental factors to precipitation be significantly influenced by changes in precipitation in dryland. Moreover, current land surface models have a weak ability to represent the lagged precipitation effects on plant growth and the carbon cycle (Jiang et al., 2019; Kolus et al., 2019). Thus, consideration of other climatic and edaphic factors may be necessary to better predict terrestrial ecosystem productivity in model simulation, and to study the productivity-precipitation relationship in precipitation manipulation experiments.

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Fig. 1. Distributions of lagged ecosystems where productivities are significantly correlated with previous-year precipitation and unlagged ecosystems where productivities are not correlated with previous-year precipitation in Northern Hemisphere drylands.

Fig. 2. The response of iEVI (annual integrated EVI) to annual precipitation across MAP gradient in the lagged and unlagged types (slope difference: $p < 0.001$). Significant codes for linear regressions: ***, $p < 0.001$.

Fig. 3. Comparisons of six climatic and edaphic factors between the lagged and unlagged types. (a) The lagged type has higher sensitivity in AET/PET (a measure of water availability), (b) soil organic carbon content, (c) soil total N content, (d) volumetric water content (at -10 kPa), (e) silt content, and (f) annual cloudless skies (a measure of radiation) in comparison with the unlagged type along gradients of MAP. Significant codes for linear regressions: ***, $p < 0.001$. Statistical differences in the slopes and intercepts of linear regression lines between the two types are shown in Table2.

Fig. 4. Percentage contributions of six climatic and edaphic factors to the divergence between the lagged and unlagged types based on SIMPER analysis. The bars are the average percentage contribution of selected pixels ($n = 100$ randomly sampled, repeated 10000 times). The error bars are the average standard errors of 100 randomly selected pixels in 10000 times. The contribution of each climatic-edaphic factor is significantly different from those of another factor.

Table 1 Method for dividing pixels of the Northern Hemisphere dry landmass into lagged and unlagged types. The lagged pixels fitted the multiple-year regression (i.e., $p < 0.05$ for the multiple-year model [$iEVI_t = a \times PPT_t + b \times PPT_{t-1} + c$] and $p \geq 0.05$ for current-year [t] model [$iEVI_t = a \times PPT_t + c$]), or previous-year ($t - 1$) regression (i.e., $p < 0.05$ for previous-year model [$iEVI_t = a \times PPT_{t-1} + c$] and $p \geq 0.05$ for the current-year model). The unlagged pixels only fitted current-year regression (i.e., $p < 0.05$ for the current-year model and $p \geq 0.05$ for the multiple-year model and previous-year model).

	Regression models		
	$iEVI_t, PPT_t$	$iEVI_t, PPT_{t-1}$	$iEVI_t, PPT_t, PPT_{t-1}$
Lagged type	$p \geq 0.05$	$p < 0.05$	$p < 0.05$
Unlagged type	$p < 0.05$	$p \geq 0.05$	$p \geq 0.05$

Table 2 Regressions between mean annual precipitation and climatic-edaphic factors, as shown in Fig. 3. Statistical differences in the slopes and intercepts of regression lines between the lagged and unlagged types were compared based on the procedure of Zar (2009).

Factors ^a	Regression of lagged type	Regression of unlagged type	Slope difference	Intercept difference
AET/PET	$y=0.037x+2.6$ $p < 0.001$	$y=0.029x+3.6$ $p < 0.001$	$p < 0.001$	$p < 0.001$
SOC	$y=0.0038x+0.2$ $p < 0.001$	$y=0.0017x+0.65$ $p < 0.001$	$p < 0.001$	$p < 0.001$
TN	$y=0.00022x+0.06$ $p < 0.001$	$y=0.0001x+0.08$ $p < 0.001$	$p < 0.001$	$p < 0.001$
VMC	$y=0.011x+21.2$ $p < 0.001$	$y=0.007x+21.7$ $p < 0.001$	$p < 0.01$	$p < 0.001$
SILT	$y=0.0066x+31.7$ $p < 0.001$	$y=0.0011x+32.3$ $p = 0.56$	$p < 0.05$	$p < 0.001$
Cloudless	$y=-0.012x+56.2$ $p < 0.001$	$y=-0.006x+54$ $p < 0.001$	$p < 0.01$	$p = 0.42$

^a AET/PET is the ratio of actual to potential evapotranspiration (%); SOC is soil organic carbon content (%); TN is soil total nitrogen contents (%); VMC is the volumetric water content at -10 kPa (%), a proxy of soil field capacity; and SILT is silt content of soil (%); and Cloudless is annual cloudless skies (%), a measure of radiation.