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

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5 Abstract:

6 Lagged precipitation effect explains a large proportion of annual aboveground net
7 primary productivity in some dryland ecosystems. Using satellite-derived plant
8 productivity and precipitation datasets in the Northern Hemisphere drylands during
9 2000-2018, we identify 1111 pixels mainly located in the Tibetan Plateau, the western
10 US, and Kazakhstan where productivities are significantly correlated with previous-
11 year precipitation (hereafter, the lagged type). Differences in climatic and edaphic
12 factors between the lagged and unlagged (pixels where productivities are not correlated
13 with previous-year precipitation) types are evaluated. Permutational multivariate
14 analysis of variance shows that the two types differ significantly regarding six climatic
15 and edaphic factors. Compared to unlagged type, water availability, soil organic carbon,
16 total nitrogen, field capacity, silt content and radiation are more sensitive to changes in
17 precipitation in lagged type. Water availability is the most important factor for
18 distinguishing the two types, followed by soil organic carbon, total nitrogen, field
19 capacity, soil texture, and radiation. Our study suggests that the altered sensitivities of
20 several climatic and edaphic factors to precipitation collectively affect the lagged effect
21 of precipitation on productivity in drylands.

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

24 1 Introduction

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

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

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

55 The legacy effect of unusually dry or wet periods on biomass could last for less than
56 one year up to seven years, of which one year is the most commonly reported lag time
57 (Sherry et al., 2008). Previous-year precipitation has been found to drive the current-
58 year ecosystem process through lagged/legacy effect in multiple sites, e.g., the central
59 plains in north-central Colorado (Oesterheld et al., 2001), the Patagonian steppe
60 (Yahdjian and Sala, 2006), the Tallgrass Prairie in Oklahoma (Sherry et al., 2012) and
61 the Loess Plateau of China (Gong et al., 2020). At the interannual scale, the lagged
62 precipitation effect is defined as the impact of previous-year precipitation conditions on
63 the current structure and functioning of ecosystems (Monger et al., 2015; Sala et al.,
64 2012; Shen et al., 2016). A variety of mechanisms explaining the lagged precipitation
65 effect involve changes in the density of tillers, seeds and plant individuals (Oesterheld
66 et al., 2001; Reichmann et al., 2013; Yahdjian and Sala, 2006); the structural carry-
67 overs (e.g., leaf area and root biomass) between alternating wet and dry years

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

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

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

85 The lagged response to precipitation change results from drought and wetness legacies,
86 and the magnitude of drought and wetness legacies are proportional to the relative
87 precipitation change (Reichmann et al., 2013; Shen et al., 2016). However, we do not
88 know whether the lagged precipitation effect is associated with precipitation variability.
89 Sala et al. (2012) suggest that the sensitivity of productivity to precipitation might

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

107 2 Materials and methods

108 2.1 Precipitation

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

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

116 2.2 Primary productivity

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

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

135 2.3 Climatic and edaphic factors

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

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

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

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

158 To match the low-resolution TRMM precipitation dataset, all the above iEVI, climatic
159 and edaphic data were aggregated up to 0.25 °spatial resolution. The distribution of dry
160 domain was derived from the map of Bailey's four global ecoregion domains (Bailey,
161 1995).

162 2.4 Selection of lagged and unlagged ecosystems

163 For each pixel in the Northern Hemisphere drylands, linear regression and multiple
164 linear models between current-year iEVI and current-year precipitation (PPT_t) and/or
165 previous-year precipitation (PPT_{t-1}) were fitted (Table 1) using the linear model (lm)
166 function in R4.0.0. The lagged type fitted the multiple-year regression (i.e., $p < 0.05$ for
167 the multiple-year model [$iEVI_t = a \times PPT_t + b \times PPT_{t-1} + c$] and $p \geq 0.05$ for
168 current-year [t] model [$iEVI_t = a \times PPT_t + c$]), or previous-year ($t - 1$) regression
169 (i.e., $p < 0.05$ for previous-year model [$iEVI_t = a \times PPT_{t-1} + c$] and $p \geq 0.05$ for the
170 current-year model). The unlagged type only fitted current-year regression (i.e., $p <$
171 0.05 for the current-year model and $p \geq 0.05$ for the multiple-year model and
172 previous-year model).

173 2.5 Hypotheses testing

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

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

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

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

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

209 3 Results

210 We identified 1111 lagged pixels and 1442 unlagged pixels among 16500 tested pixels
211 (0.25 spatial resolution) across drylands in the northern hemisphere (Fig. 1). Most of
212 them were found in grasslands, shrublands, and savanna biomes. The lagged pixels
213 were mainly located in the Tibetan Plateau of China, the western US, and Kazakhstan.
214 The sensitivities/slopes of productivity response to precipitation in the lagged were
215 significantly lower (slope and intercept difference: $p < 0.001$) than those in the unlagged
216 at the spatial scale (Fig. 2). Moreover, the differences in productivity sensitivities to
217 precipitation in the two types decreased with increasing MAP (Fig. 2). The two types
218 were not significantly different in terms of the variabilities of interannual precipitation
219 ($p = 0.11$) (Fig. S2). There were neither significant differences in occurrences of dry
220 (1SD: $p = 0.54$) and wet (1SD: $p = 0.8$, 2SD: $p = 0.13$) years in the two types, except
221 for the 2SD dry years (the occurrences in lagged type were less than those in the

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

223 PerMANOVA analysis indicated that the lagged and unlagged types differed
224 significantly when the climatic (water availability and radiation) and edaphic factors
225 (SOC, TN, VMC, and silt content) were collectively considered ($F = 12.96$, and $p <$
226 0.001). Moreover, the sensitivities of the six climatic and edaphic factors to MAP were
227 all higher in lagged type than those in the unlagged. Compared with the unlagged type,
228 water availability increased faster with increasing MAP in the lagged type (Fig. 3a and
229 Table 2). SOC, TN, and VMC raised across the MAP gradients in the two types, and
230 the slopes were significantly higher in the lagged type (Fig. 3b-d and Table 2). Silt
231 content was positively correlated with MAP in both types, and the slope of the
232 regression between them was greater in the lagged type than unlagged type (Fig. 3e and
233 Table 2). In contrast, radiation was negatively correlated with MAP in both types, and
234 the slope of the regression between them was lower in lagged type than unlagged type
235 (Fig. 3f and Table 2). However, air temperature did not significantly change with
236 increasing MAP in the lagged (Fig. S5). Water table depth, soil total carbon, and soil
237 phosphorus were higher in the lagged type than those in the unlagged; however, the
238 slopes between these regressions did not differ significantly (Fig. S6-7). Likewise, clay
239 content, sand content, and indicators of N and P availabilities (C/N and C/P ratios) did
240 not differ significantly between the two types (Fig. S8-9).

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

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

247 4 Discussion

248 Based on satellite-derived productivity and precipitation, we identify two types of
249 terrestrial ecosystems either with or without lagged precipitation effect in the Northern
250 Hemisphere drylands and evaluate the difference in climatic and edaphic factors
251 between them. Consistent with the first hypothesis, our results show that productivity
252 is less sensitive to precipitation in lagged type than unlagged type along the MAP
253 gradients. Previous studies attributed lagged precipitation effect to the differences in
254 productivity-PPT relationships among ecosystems (Bunting et al., 2017; Gong et al.,
255 2020; Petrie et al., 2018). Our results support this viewpoint that the lagged precipitation
256 effect plays a vital role in modifying the productivity-precipitation relationship.
257 Moreover, the differences between productivity responses to precipitation in the two
258 types decrease with increasing MAP, which is likely due to the limitation of resources
259 other than precipitation (Huxman et al., 2004). This observation is supported by recent
260 studies, which have reported the strength of vegetation water memory effects decreases
261 with increasing MAP (Liu et al., 2018), and the legacy effects of water deficits on trees
262 are highly reliance on MAP, with this effect being most pronounced in dry ecosystems
263 (Anderegg et al., 2015).

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

266 years because both types possess similar precipitation variability and occurrences of
267 dry and wet years. Previous studies suggest that the magnitudes of the short-term
268 legacies of antecedent precipitation (i.e., drought and wetness legacies) are positively
269 related to relative precipitation changes between current and previous year (Reichmann
270 et al., 2013; Yahdjian and Sala, 2006), and greater variability in precipitation leads to
271 corresponding increases in legacy impacts (Shen et al., 2016). However, the lagged
272 precipitation effect may not be influenced directly by precipitation variability.
273 Precipitation amount and variability may indirectly alter other environmental factors,
274 thus influencing productivity (Hsu and Adler, 2014; Luo et al., 2017; Yahdjian and Sala,
275 2010).

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

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

288 terms of soil properties (such as SOC, TN, soil field capacity, and silt content,) and
289 water availability. Soil water availability is related to soil physical and chemical
290 properties (Cassel and Nielsen, 1986; Geroy et al., 2011). Low soil water holding
291 capacity might lead to low available soil water due to high loss of precipitation via
292 runoff or percolation, especially during large rain events (Ye et al., 2018b). Furthermore,
293 higher soil organic matter and silt content could increase water retention (Geroy et al.,
294 2011). Consistent with Wang et al. (2017), TN increases along the MAP gradients in
295 both types. Due to the higher sensitivity of TN to precipitation, changes in precipitation
296 may lead to more substantial fluctuation in soil N in lagged ecosystems, likely causing
297 N carry-over between interannual years. Recent studies report that previous-year
298 precipitation may influence litter dynamic, microbial mineralization and
299 immobilization, plant N uptake, and N leaching, causing soil mineral N pools to
300 accumulation or decrease (Dudney et al., 2017; Evans and Burke, 2012; Giese et al.,
301 2010; Shen et al., 2016; Yahdjian and Sala, 2010), thus promote or inhibit current-year
302 productivity.

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

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

311 5 Conclusion

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

327

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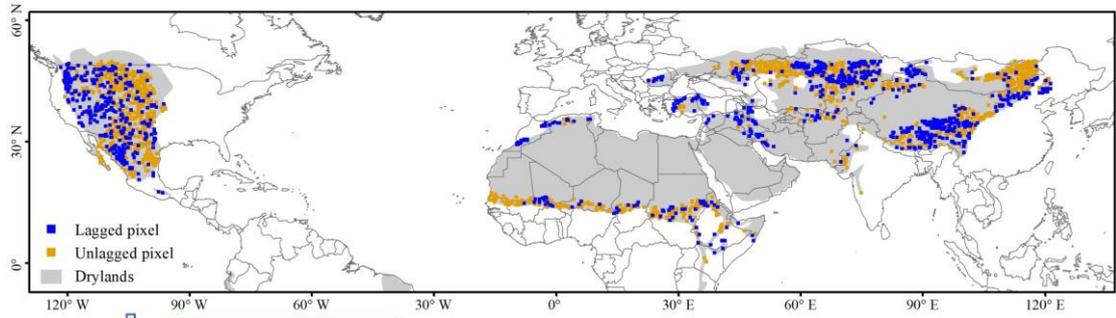
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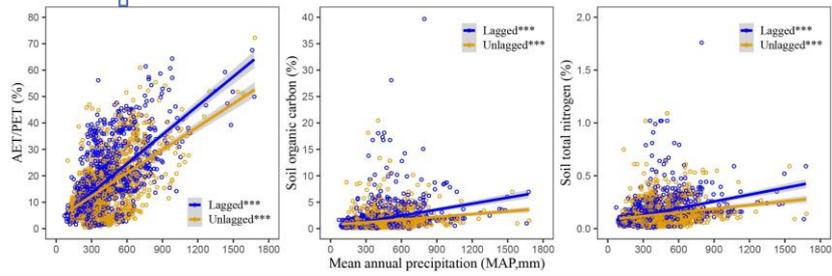
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542 Graphical abstract



Pixels with lagged precipitation effect in drylands have higher sensitivities of water availability, soil organic carbon, and total nitrogen to changes in precipitation than unlagged ones.



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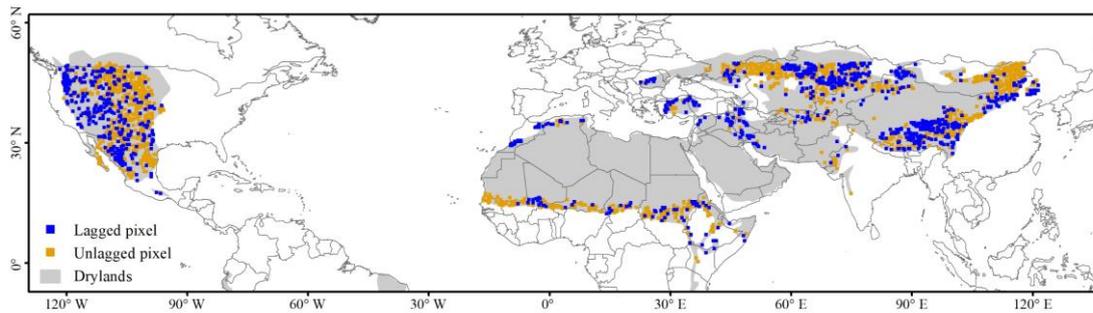
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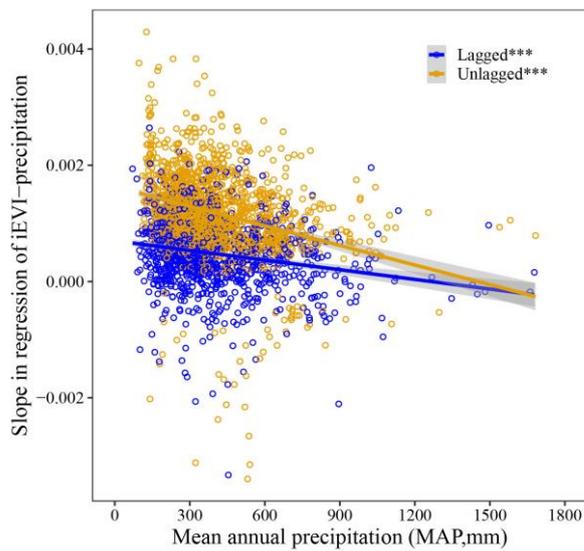
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557 Fig. 1. Distributions of lagged ecosystems where productivities are significantly correlated with
 558 previous-year precipitation and unlagged ecosystems where productivities are not correlated with
 559 previous-year precipitation in Northern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

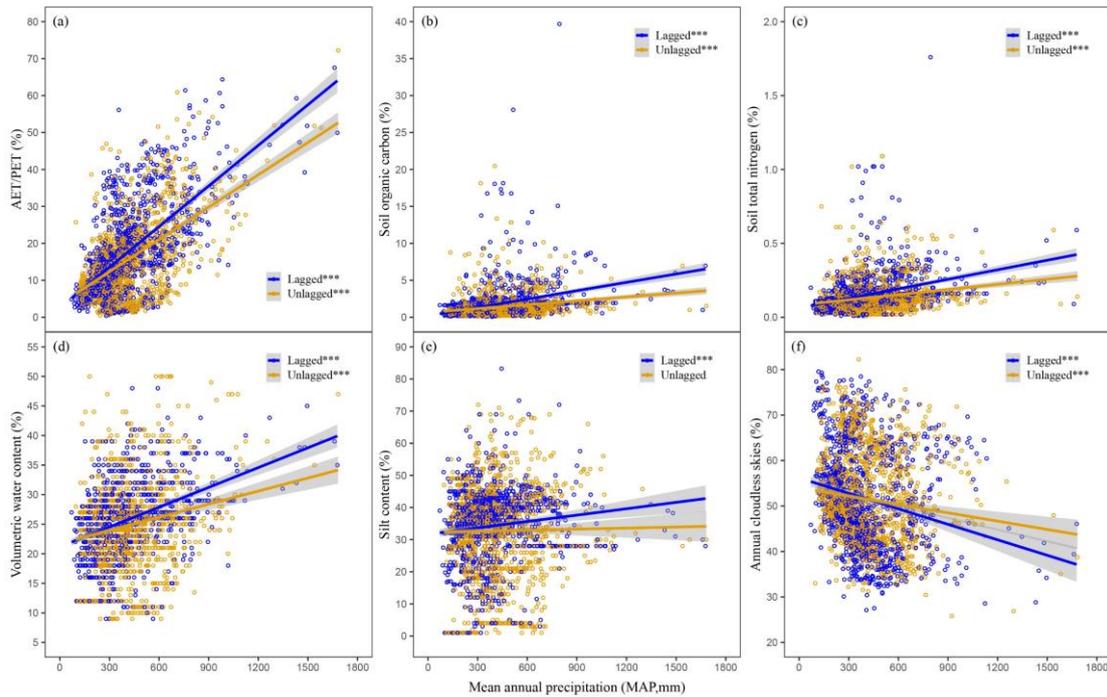


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561 Fig. 2. The response of iEVI (annual integrated EVI) to annual precipitation across MAP gradient
 562 in the lagged and unlagged types (slope difference: $p < 0.001$). Significant codes for linear
 563 regressions: ***, $p < 0.001$.

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567 Fig. 3. Comparisons of six climatic and edaphic factors between the lagged and unlagged types. (a)

568 The lagged type has higher sensitivity in AET/PET (a measure of water availability), (b) soil organic

569 carbon content, (c) soil total N content, (d) volumetric water content (at -10 kPa), (e) silt content,

570 and (f) annual cloudless skies (a measure of radiation) in comparison with the unlagged type along

571 gradients of MAP. Significant codes for linear regressions: ***, $p < 0.001$. Statistical differences in

572 the slopes and intercepts of linear regression lines between the two types are shown in Table2.

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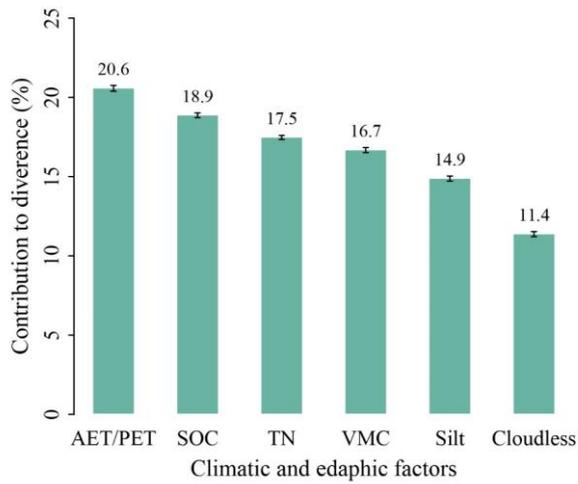
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581 Fig. 4. Percentage contributions of six climatic and edaphic factors to the divergence between the
 582 lagged and unlagged types based on SIMPER analysis. The bars are the average percentage
 583 contribution of selected pixels ($n = 100$ randomly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

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597 Table 1 Method for dividing pixels of the Northern Hemisphere dry landmass into lagged and
 598 unlagged types. The lagged pixels fitted the multiple-year regression (i.e., $p < 0.05$ for the multiple-
 599 year model [$iEVI_t = a \times PPT_t + b \times PPT_{t-1} + c$] and $p \geq 0.05$ for current-year [t] model [$iEVI_t =$
 600 $a \times PPT_t + c$]), or previous-year ($t - 1$) regression (i.e., $p < 0.05$ for previous-year model [$iEVI_t =$
 601 $a \times PPT_{t-1} + c$] and $p \geq 0.05$ for the current-year model). The unlagged pixels only fitted current-
 602 year regression (i.e., $p < 0.05$ for the current-year model and $p \geq 0.05$ for the multiple-year model
 603 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 | $p < 0.05$ | $p \geq 0.05$ | $p \geq 0.05$ |

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615 Table 2 Regressions between mean annual precipitation and climatic-edaphic factors, as shown in
 616 Fig. 3. Statistical differences in the slopes and intercepts of regression lines between the lagged and
 617 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 | $y=-0.012x+56.2$ $p < 0.001$ | $y=-0.006x+54$ $p < 0.001$ | $p < 0.01$ | $p = 0.42$ |

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

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