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RESEARCH ARTICLE

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Land use intensification affects the relative importance of climate variation and active land degradation: Convergence of six regions around the world

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Abstract

We explored the relative importance of climate oscillations and human-driven disturbances on the change in vegetation biomass in agroecosystems, and whether it is associated with land use. Our main contribution is a quantitative treatment of these factors in equivalent terms, i.e. not assuming any of them to be principal. The study was carried out in the drylands of the Iberian Peninsula, NW Maghreb, Palestinian West Bank, Mozambique, China and NE Brazil, using satellite time-series and the corresponding climate fields, at ten-year observation periods with spatial and temporal resolutions of 1000 m (250 m in Palestine) and one year, respectively. For each region, we separated the relative weights of climate and time by fitting multiple-stepwise regressions to a vegetation index as the dependent variable, and annual aridity (Aridity) and year number (Time) as predictors. The relative strength of the resulting standard partial regression coefficients was then compared by the Wilcoxon signed ranks test, and their combined associations with land uses were determined using Chi-square tests. Some points of convergence are as follows: (1) The relative weights of Aridity and Time depend on particular regional conditions and can be determined. (2) Such weights are associated with land use intensification, such that if vegetation increases over Time, Aridity increases its relative importance with intensification; if vegetation is degrading, Aridity is always more important than Time. (3) Aridity is an indicator of vulnerability to climate warming. Resilience can be improved by reducing land use intensification. 4. Vulnerability may worsen under constant climate if agriculture is intensified. These patterns enhance an integrated understanding of Sustainable Development Goals Indicator 15.3.1, particularly its land cover and productivity trend components.

KEYWORDS
desertification, drylands, global change, global warming, resilience, sustainability

1 | INTRODUCTION

Global change is the set of physical, ecological and socioeconomic transformations that operate on a planetary scale because of human activity. Two of the most important components are climate change and change in land use. There is evidence that these processes have been accelerating in the last decades. On one hand, climate tends to become progressively warmer, both in its means and in the frequency of extreme events (IPCC, 2014). On the other, demographic growth and growing globalization of the market economy intensify agroecological exploitation and favour the volatility of its types of use to adapt to yield demands (Kirkby, 2021; Martínez-Valderrama et al., 2021).

Drylands are zones with an arid, semiarid or subhumid-dry climate, where precipitation is from 3% to 65% of the atmospheric water demands (Trabucco, 2019). Those zones undergo global change with particular intensity, because due to their low natural productivity and their ecological functioning combined with weather events, they resist sustained pressure poorly. Desertification is the overexploitation of drylands beyond their capacity for resilience (Puigdefabregas, 1995). This always occurs as a consequence of socioeconomic syndromes that may adopt diverse forms depending on the particular configuration of uses, but with the common factor of exploiting a natural resource for which water is the limiting factor (Cherlet et al., 2018; D'Odorico et al., 2013).

Contrary to what its name suggests, desertification does not produce deserts (Verón et al., 2006); it causes land degradation. The ecosystems involved become simplified, opportunistic and less productive in the long term, causing poverty and migration in the human populations. Conservative estimates of worldwide prevalence of land degradation show that the net primary production (NPP) is lower than it would be under natural conditions in 23% of the terrestrial surface area, and that less than a fourth remains free of substantial human impact (IPBES, 2018; Krausmann et al., 2013). The importance of this figure, and its upward trend, have led to UN Sustainable Development Goal (SDG) 15.3: "By 2030…achieve a land degradation-neutral world" (UN General Assembly, 2015).

In this context, Earth observation systems have become very important for evaluating and monitoring land degradation (Higginbottom & Symeonakis, 2014). Most of them use a vegetation index calculated from spectral bands as a proxy for active vegetation at the time of observation. Of these, the normalized difference vegetation index (NDVI) is one of the most widely used, in spite of well-known problems of saturation in dense zones and sensitivity to barren land in arid zones (Price, 1993). In multi-temporal series, the mean and integral of NDVI for a specific period are parametric estimators of biomass and NPP, respectively (Fensholt et al., 2015; Hielkema et al., 1987).

Monitoring vegetation over a period of time without entering into causal details is useful, for example, to study its role as a carbon sink with regard to climate change. However, it is of little help in determining the human activity degradation component. For this, a conceptual framework is necessary to discriminate trends due to interannual climate variation from those due to land management, the two main sources of variation in a low spatial resolution perspective (Evans & Geerken, 2004).

Some NDVI time-series analysis methods follow that approach. For example, the residual trends (RESTREND) analysis (Evans & Geerken, 2004; Ibrahim et al., 2015; Wessels et al., 2007) identifies, first, the effect of climate variation by adjusting a linear regression that uses annual precipitation as the predictor, and second, by means of its residuals, identifies non-climatic trends attributable to human activity.

In RESTREND, the implicit assumption that climate is the main predictor may lead to confusion if the climate varies, in turn, over the course of time. To avoid this problem, 2dRUE (del Barrio et al., 2010) applies a multiple regression analysis, in which both predictors may be the main one, and the second is only included if it produces a specific determination increase. The following section describes this procedure in detail.

In a context of global change, it is essential to determine the trends in degradation caused by human activity and the response of vegetation to interannual climate variation properly (Mirzabaev et al., 2019; Xu et al., 2011). This is a prerequisite for evaluation of the need to make changes in land management and find signs of resilience in the ecosystems concerned. The concrete questions we asked in this study were: (1) What is the relative importance of climate variability and of human management acting together on the loss or gain in vegetation biomass? (2) Does this relative importance vary with land use intensification?

This study was undertaken in a selection of drylands from six regions around the world. It was based on extracting rates of variation in NDVI over time and under interannual variation in aridity using NDVI time-series and archived climate variables. These rates were then statistically compared, and their association with land uses was tested, to answer those questions.

2 | MATERIALS AND METHODS

2.1 | Study regions

This study was based on previous applications of 2dRUE in six regions around the world: the Iberian Peninsula, Northwest Maghreb, Palestine (West Bank), Mozambique, China and Northeast Brazil (Figure 1). The selection was conditioned by availability of results associated with previous studies and is, in some way, arbitrary. However, it is still valid, for three reasons: First, such studies share the same methodology, type of data and compatible periods. Second, respective land uses, even though they are not in a unified classification, reflect the patterns and syndromes of each region, highlighting the socioeconomic characteristics of each. And third, the six regions are independent of each other on a continental scale, and only data on their drylands were extracted. Therefore, they complement each other in terms of climate and land use systems, widening the spectrum for exploration of the study questions. All of them, except the Palestinian

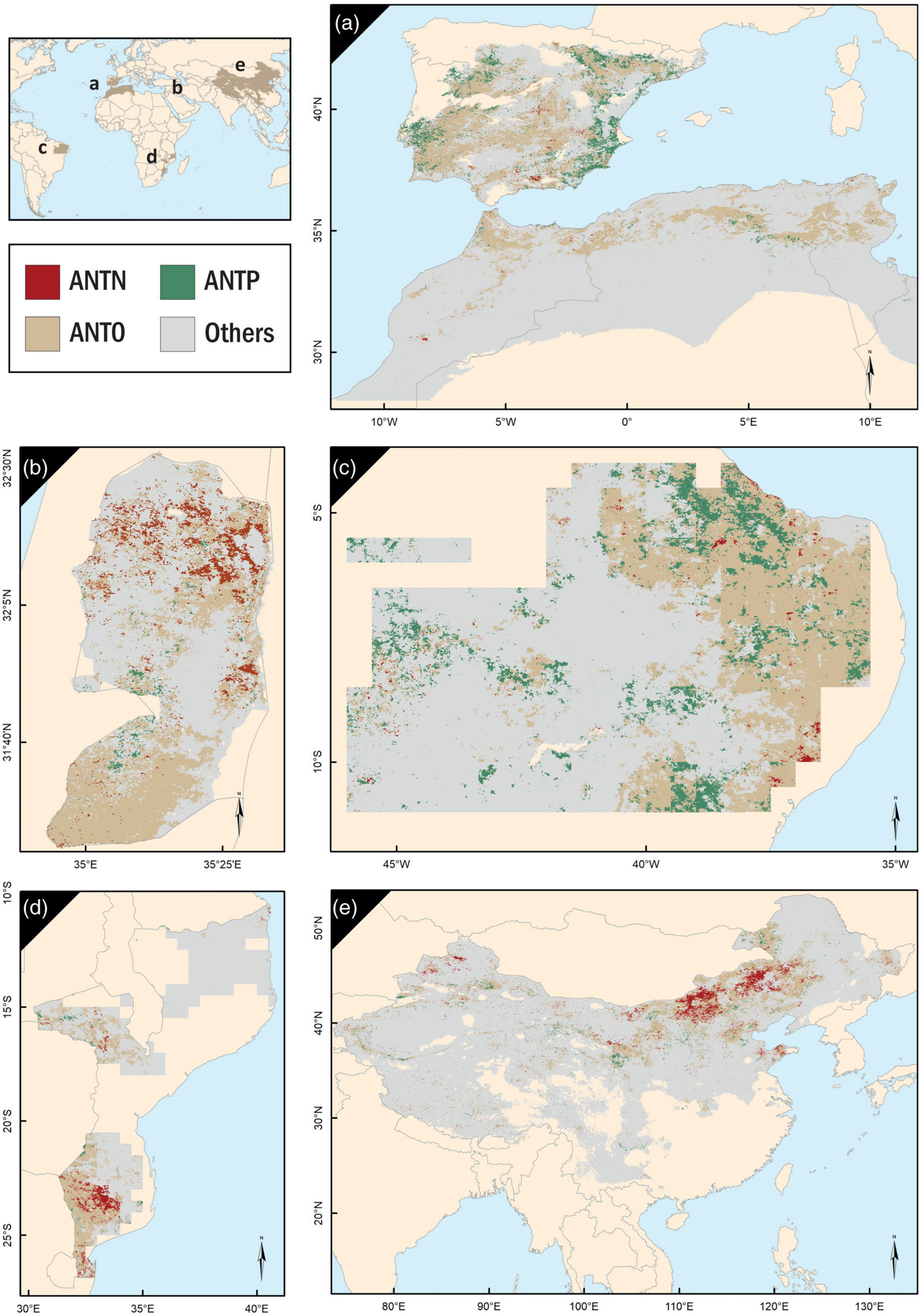

FIGURE 1 Response classes of vegetation biomass against aridity and time in drylands of Iberian Peninsula and NW Maghreb (a), Palestinian West Bank (b), NE Brazil (c), Mozambique (d) and China (e): ANTN: negative effects of both aridity and time; ANTP: negative effect of aridity, positive effect of time; ANT0: negative effect of aridity, no effect of time: OTHERS: any other effects combination, including lack of significant effects [Colour figure can be viewed at wileyonlinelibrary.com]

TABLE 1 Main metadata of the 2dRUE regional applications that provided input data for this study. Extent refers to the drylands subset within each region

Name	Area(km^2)	Resolution(m)	Period	Source
Iberian Peninsula	415,248	1000	2000–2010	Sanjuán et al., 2014; Zucca et al., 2012
NW Maghreb	1,142,503	1000	1998–2008	del Barrio et al., 2016
Palestinian West Bank	5630	250	2000–2010	Alkhouri, 2012
Mozambique	427,629	1000	1998–2006	Zucca et al., 2012
China	6,616,480	4000	2002–2012	del Barrio et al., 2020
NE Brazil	704,486	1000	1998–2006	Zucca et al., 2012

West Bank, cover wide areas, ensuring that their individual contributions are representative and complete. The special case of the Palestinian West Bank was included because its geopolitical conditions provide specific pressures on its agroecosystems. It is the region worked at the highest spatial resolution due to its comparatively small size.

Table 1 shows the main metadata in the regional applications. The complete results of each, including maps of condition states and trends, may be found in the corresponding references. The land use map for the Maghreb, Palestinian West Bank, Mozambique and Brazil was the product developed by the Land Degradation Assessment in Drylands (LADA) Project (Nachtergaele & Petri, 2013); the Iberian Peninsula and China have their own specific regional products, CORINE LC (EEA, 2016) and ChinaCover (Zhang et al., 2014), respectively. This land use map set was selected because it was compatible with the time periods in which 2dRUE was applied to those regions.

2.2 | Extraction of trends in vegetation over time and aridity

Variation in vegetation biomass over the course of time is an accepted indicator of the trend of ecosystem conditions. When low or medium-resolution terrestrial observation data are used in a large territory, the origin of these trends may be reduced to two factors: climate and ecological dynamics (Wessels et al., 2007). If the first of them can be determined, the second can be interpreted in terms of active degradation (if the rate of variation is negative) or growth (if it is positive). Therefore, vegetation surveillance covering periods of several years requires the effects of interannual variation in climate to be considered.

2dRUE is a geomatic procedure for indicating land condition states and trends. Its most recent version was described in del Barrio et al. (2016), and was programmed in the r2dRue R package (Ruiz et al., 2011). It uses monthly time series of an appropriate vegetation index and the corresponding climate files. Its typical spatial resolution is 1 km, and the period of analysis is about ten years.

The trends for this study were extracted using the monitoring function of r2dRue, as described in del Barrio et al. (2010). This routine fits hybrid multiple-stepwise regression to each location (pixel) using the mean annual NDVI as the dependent variable and the corresponding mean annual aridity index (ratio of potential evapotranspiration to precipitation; note that this formulation is the inverse of the FAO-UNEP aridity index) and the year number as predictors. First, the significance of the coefficient of multiple determination is evaluated. If it is significant, the predictors are arranged by the magnitude of the simple correlation coefficient with the dependent variable. Then, assuming that both are correlated (aridity would also vary over time), the additional increase in determination produced by the second predictor over the one produced by the first predictor alone is evaluated. The second predictor is only included in the regression model if the increase is significant. If not, simple regressions are explored for both predictors using their respective correlation coefficients. This process is rather restrictive in itself, so the level of significance applied is $p \leq 0.10$ to maintain its exploratory character.

The purpose of those regressions is to identify the partial contributions of the two predictors to the variation in vegetation biomass, not to make predictions about it. Therefore, they are fit in standard mode, where the resulting partial regression coefficients express the increase, in standard deviation units, in the dependent variable for each unit of standard deviation increase in the predictor in question.

Those standard partial regression coefficients, also called beta (β) coefficients, were the metric used in this study. Their direct interpretation is the weight of the corresponding predictor, and as they are in the same units, the two predictors can be compared. The terms Time and Aridity (capitalized) hereinafter refer to the corresponding regression predictors as described above, while the same words (lower-case) refer to their common meanings. It is worth mentioning that the Time predictor has an implicit monotonous temporal sequence in the response of vegetation, while the Aridity predictor refers to variations in intensity associated with unordered values found during the study period. This study was not concerned with the evolution of aridity over time.

2.3 | Comparison of the relative effects of time and aridity

The β coefficients of Time and Aridity are found for each pixel, and therefore, the results are maps of their respective effects. Such maps were sampled to extract data without spatial autocorrelation. The sample had a stratified random design with a size of about 5% of the study area. We also imposed some conditions so the data would

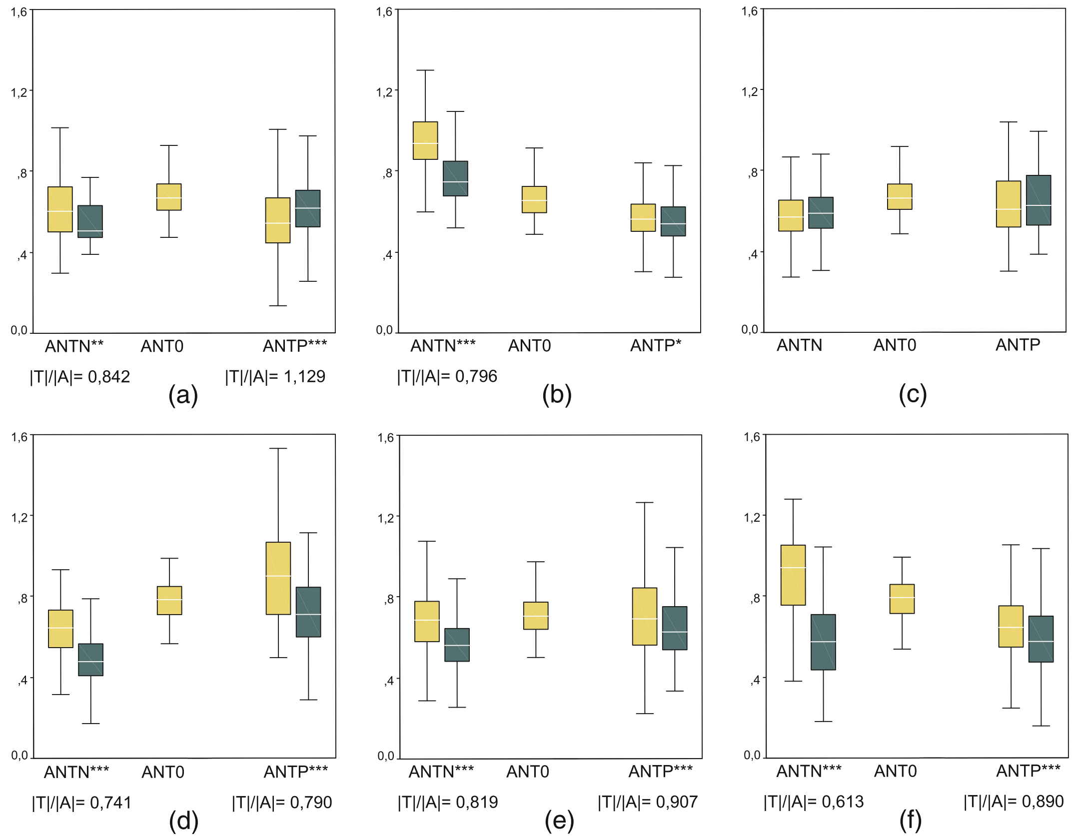

FIGURE 2 Statistical distributions of aridity (yellow) and time (green) β-coefficients, grouped by response class (ANTN, ANT0 and ANTP) in the study regions: (a) Iberian Peninsula; (b) NW Maghreb; (c) Palestinian West Bank; (d) Mozambique; (e) China; (f) NE Brazil. Boxes indicate the median (white bar) and the 25th and 75th percentiles. Whiskers show the non-outlier data range, defined as 1.5-times the interquartile range. Asterisks indicate significance level. The time to aridity ratio of absolute values of β-coefficients (|T|/|a|) is annotated for cases where $p \leq 0.05$ [Colour figure can be viewed at wileyonlinelibrary.com]

represent climate responses in a coherent domain for land uses that could vary in intensification. Specifically, this meant that the points must (i) be in drylands, (ii) not include irrigated or artificial land, and (iii) show a negative response to Aridity, whatever its response to Time. The last condition was intended to discard cold zone anomalies that might respond positively to Aridity due to the thermal component implicit in the index used, and which would require a specific approach outside of the scope of this study for its analysis. The condition that all the data show a climate response caused those with exclusively Time responses and no Aridity sign, to be omitted from the sample as well.

The data were then classified by response, according to the sign of their β coefficients for Aridity and Time, respectively: negative–negative (ANTN); negative–positive (ANTP); and negative- no response (ANT0) (Figure 1).

The relative weights of Aridity and Time in the ANTN and ANTP classes were compared using the Wilcoxon signed-rank test (Siegel & Castellan, 1988). Each class was considered a set of paired data, where each location contained its own responses to the two treatments, Aridity and Time. As the β coefficient sign was implicit in each class, we used their absolute values to simplify interpretation. After calculating the differences between the two treatments for each location, the test arranges them by absolute magnitude, and expects to find a regular distribution of the signs of the differences under the null hypothesis that the treatments are equivalent. To do this, it calculates a statistic for evaluating whether the sum of the ranks of the positive differences is too low or too high with regard to the negative differences, in which case the null hypothesis is rejected. In large samples, this statistic is normally distributed and can be approximated using *z* outliers, where $z \geq 1.96$ ($p \leq 0.05\%$) was the threshold for this study.

The relationship between land uses and response types represented by the ANTN, ANTP and ANT0 classes was explored using the Chi-square (χ^2) test. It compares the frequencies of the different combinations of land use classes by response type with what could be expected under the null hypothesis that there is no association between variables. Significance was calculated using Monte Carlo simulations to avoid the asymptotic distribution problems of the χ^2 statistic. Interpretation, if the null hypothesis was rejected ($p \leq 0.05$), was done by examining the magnitude and sign of the outliers between observed and expected frequencies. These outliers were standardized, that is, transformed into standard deviation units following a normal distribution to facilitate their comparison. Only those with an absolute value equal to or higher than $|1.96|$ ($p \leq 0.05$) were interpreted.

TABLE 2 Wilcoxon signed rank test to determine differences between absolute values of the β coefficients of time and aridity, in the ANTN and ANTP response classes. The differences were evaluated for ($|\beta_{Time}| - |\beta_{Aridity}|$). Table entries, by response class and region, show the sample size (N), sums of positive (T^+) and negative (T^-) ranks, z score of T^+ and two-tailed significance (p)

Response	Region	N	T^+	T^-	z	p
ANTN						
	Iberian Peninsula	50	398	877	−2.312	**0.021**
	NW Maghreb	47	207	921	−3.778	**0.000**
	Palestinian West Bank	340	30,310	27,660	−0.731	0.465
	Mozambique	459	19,356.5	86,213.5	−11.757	**0.000**
	China	661	52,845	165,946	−11.514	**0.000**
	NE Brazil	252	2562.5	29,315.5	−11.549	**0.000**
ANTP						
	Iberian Peninsula	2717	2,264,988	1,427,415	10.241	**0.000**
	NW Maghreb	195	8237.5	10,872.5	−1.670	0.095
	Palestinian West Bank	42	431	472	−0.256	0.798
	Mozambique	117	1317.5	5585.5	−5.804	**0.000**
	China	327	19,833	33,795	−4.080	**0.000**
	NE Brazil	4943	4,425,429	7,793,667	−16.785	**0.000**

3 | RESULTS

3.1 | Relative effects of time and aridity

Figure 2 shows the distribution of the weights of Aridity and Time in the study regions by response class. The results of comparing their relative weights are shown in Table 2. The case of the Iberian Peninsula in Class ANTN illustrates interpretation of the Wilcoxon test. After organizing the 50 differences ($|\beta_{Time}| - |\beta_{Aridity}|$) in ascending order of magnitude and regardless of their sign, the sum of ranks of positive differences (T^+) is 398, while that of the ranks of negative differences (T^-) is 877. If there were no differences between β coefficients (H_0), it would be expected for $T^+ \approx T^-$. However, the z outlier associated with T^+ if H_0 were true is −2.312, with a two-tailed probability of $p = 0.021 < 0.05$. Therefore, H_0 is rejected. Admitting the difference, the negative sign of z indicates that $|\beta_{Time}| < |\beta_{Aridity}|$.

Thus, in the Iberian Peninsula, if both Aridity and Time have negative effects on biomass, Aridity has significantly more weight than Time. Figure 2a confirms that absolute medians of Aridity and Time are 0.6 and 0.5, respectively, and a calculation performed with the native accuracy of the β coefficients results in a |Time|/|Aridity| ratio of 0.842. This result is similar for the rest of the ANTN responses, except in the Palestinian West Bank, where there are no significant differences between predictors.

For the ANTP responses in Mozambique, China and NE Brazil, the weight of Aridity is greater than Time. In the Iberian Peninsula it is the opposite, and in the Palestinian West Bank and Maghreb there is no significant difference. However, restoring the signs to the β coefficients, it should be kept in mind that in this class the effects are the contrary. That is, vegetation tends to accumulate biomass over Time, but that effect is counteracted by interannual increments in Aridity.

In general, in the regions where significant differences were found between Aridity and Time, they were in both the ANTN and ANTP classes. Moreover, in such regions, the |Time|/|Aridity| ratio was consistently higher in ANTP than in ANTN (Figure 2).

TABLE 3 Chi-square test to determine association between land uses and response classes: Iberian Peninsula. $\chi^2 = 797.197$, $N = 9805$, $df = 28$, $p < 1E\text{-}3$. Only residual frequencies with standardized value greater than |1.96| are shown, corresponding to $p < 0.05$

Denomination	ANTN	ANT0	ANTP
Complex cultivation patterns		−2.1	2.2
Agro-forestry areas		5.2	−5.3
Broad-leaved forest		2.9	−3.2
Coniferous forest		−15.4	15.3
Mixed forests		−8.3	8.4
Natural grasslands	−2.9	18.1	−17.8
Moors and heathland		−4.9	5.1
Sparsely vegetated areas		−12.4	12.8

3.2 | Relationship between response class and land use

Tables 3–8 show the association patterns between response class and land use for each of the regions studied. The sign and magnitude of the standardized residuals express their affinity or repellence between the attributes corresponding to each combination.

Class ANTN generally has highly significant positive associations with strong intensification of grazing in the Maghreb, Palestinian West Bank and Brazil. On the contrary, in Mozambique, the significant association is with unmanaged forests and with agriculture in protected areas. The map used for China reflects more types of cover than land uses, and there, this class is associated strongly with steppes. In the Iberian Peninsula there is no significant positive association at all with use or cover.

Class ANT0 follows a similar pattern up to a point. It shows significant positive associations with intensive uses (Maghreb, Palestinian

TABLE 4 Chi-square test to determine association between land uses and response classes: NW Maghreb. $\chi^2 = 135.923$, $N = 5464$, $df = 28$, $p < 1E\text{-}3$. Only residual frequencies with standardized value greater than |1.96| are shown, corresponding to $p < 0.05$

Denomination	ANTN	ANT0	ANTP
Forestry—Grazing moderate or higher	2.9	−2.0	
Forest—Agroforestry with scattered plantations		2.0	−2.6
Shrubs—Not used/not managed			2.2
Shrubs—Intensive grazing		2.7	−2.6
Bare areas—Not used/not managed		−4.1	4.8
Bare areas—Extensive grazing		−7.4	8.3

TABLE 5 Chi-square test to determine association between land uses and response classes: Palestinian West Bank. $\chi^2 = 336.099$, $N = 2282$, $df = 28$, $p < 1E\text{-}3$. Only residual frequencies with standardized value greater than |1.96| are shown, corresponding to $p < 0.05$

Denomination	ANTN	ANT0	ANTP
Grasslands—Not used/not managed			7.5
Grasslands—Moderately intensive grazing	12.6	−11.7	
Grasslands—Intensive grazing	4.3	−4.3	
Shrubs—Not used/not managed	−2.3	2.5	
Shrubs—Moderately intensive grazing	−3.6	3.8	
Shrubs—Intensive grazing	−5.1	5.4	
Agriculture—Rainfed agriculture (Subsistence/Commercial)	−3.0	2.3	
Agriculture—Crops and moderately intensive grazing	2.8	−3.1	
Agriculture—Crops and intensive grazing	5.3	−5.4	
Bare areas—Moderately intensive grazing or higher	−4.7	4.9	

TABLE 6 Chi-square test to determine association between land uses and response classes: Mozambique. $\chi^2 = 167.471$, $N = 3580$, $df = 32$, $p < 1E\text{-}3$. Only residual frequencies with standardized value greater than |1.96| are shown, corresponding to $p < 0.05$

Denomination	ANTN	ANT0	ANTP
Forest—Not used/not managed (Natural)	7.4	−6.1	
Forestry—In Protected Areas			−2.5
Forest—Agro forestry with scattered plantations	−2.5		2.9
Forest—Scattered Plantations	−2.4	2.0	
Grasslands—Not used/not managed			2.0
Grasslands—In Protected Areas	2.9	−2.1	
Grasslands—Extensive grazing	−6.8	5.8	
Grasslands—Moderately intensive grazing		2.8	−2.1
Agriculture—Rainfed agriculture (Subsistence/Commercial)			2.2
Agriculture—Crops and moderately intensive grazing	−2.2		
Agriculture—Crops and intensive grazing			2.9
Agriculture—Protected	3.1	−2.7	

West Bank, Mozambique and Brazil), but all of them have sparse plant cover: shrubs, grasslands, agro-grazing systems or bare land. The Iberian Peninsula shows this response class in grasslands, agro-forestry areas and to a lesser extent, broad-leaved forests. In this class, China is the exception, showing only association with broad-leaved deciduous forests.

Finally, the pattern in Class ANTP is the opposite of the others. Several vegetation covers are associated: forests (Iberian Peninsula, Mozambique, Brazil), grasslands Palestinian West Bank, China, Brazil), agro-forestry or agro-grazing systems (Mozambique, Brazil) and even bare areas or with sparse vegetation (Iberian Peninsula, Maghreb, Brazil). However, in most of the cases where land use intensification is qualified, it appears as extensive or unmanaged.

4 | DISCUSSION

The above results may be examined on a hierarchy of levels progressing toward the answers to our research questions. Thus, we examine the meaning of the Time and Aridity change variables first. Then, the meaning of their associated response classes, ANTN and

TABLE 7 Chi-square test to determine association between land uses and response classes: China. $\chi^2 = 242.999$, $N = 4225$, $df = 24$, $p < 1E\text{-}3$. Only residual frequencies with standardized value greater than $|1.96|$ are shown, corresponding to $p < 0.05$

Name	ANTN	ANT0	ANTP
Steppe	10.5	−3.1	−9.4
Grassland	−3.1		5.7
Cropland	−4.6		4.1
Sparse shrub	−2.7		3.8
Sparse grass	−4.4		3.6
Rock	−2.4		
Bare soil			2.9
Sand	2.0		
Deciduous broadleaf forest	−2.2	2.7	
Evergreen needleleaf forest	−2.4		
Deciduous needleleaf forest			2.1
Deciduous broadleaf shrub	−2.5		

ANTP. Those elements are then interpreted in view of concrete land use systems found in the various regions, and some limitations of this scope are commented. Finally, we discuss the relevance of the outcome for the SDG indicator 15.3.1.

4.1 | Interpretation of aridity and time

Time is what remains of the change in vegetation after having separated the climate component. In this frame, a negative response implies loss of biomass, and therefore, degradation attributable to human activity, as discussed in Section 2.2 above. The trend in active degradation is a variable of flow, as distinguished from the state of degradation, which is a stock variable. This distinction, which seems obvious, has only recently begun to be applied in international initiatives (IPBES, 2018; Orr et al., 2017) and has caused much confusion in previous evaluations of land degradation, leading to overestimation of around 70% in drylands (UNCOD, 1977). Not all that is degraded is degrading. For example, in the Maghreb, 21% of the territory was found to be degraded or very degraded, while only 0.7% is undergoing active degradation (del Barrio et al., 2016).

Reciprocally, a positive response means growth of vegetation. Under natural conditions, this trend would reflect the development of a secondary ecological succession. However, the increase in NDVI may also reflect the replacement of the reference ecosystem after its degradation by another opportunistic one (Verón et al., 2006). This is the case of substitution of alpha grass (*Machochloa tenacissima*) by others dominated by *Artemisia* or *Salsola* in the Maghreb (Hirche et al., 2011). Finally, that growth may be due to startup of agricultural production in a zone with natural vegetation. Therefore, this trend must be interpreted with caution.

Aridity with a negative response is simpler to interpret: vegetation grows less in drier years, and more when they are wetter. The values are extracted from a period, but lack temporal dimension. Therefore, the use of Aridity in this study only reflects sensitivity to interannual variations, not loss of biomass due to an increase in sustained aridity over time.

This consideration leads to anticipation of an interesting problem posed by the ANTN and ANTP response classes: Should their respective effects be interpreted in terms of the balance to determine the change expected in vegetation? For example, a hypothetical pixel in Class ANTP could show β coefficients of -0.7 and $+0.3$ for Aridity and Time, respectively. Then it might be supposed that the final balance would be -0.4; hence, its internal ecological dynamics would be neutralized by the stronger effect of aridity.

The response is negative. For that to be possible, the cumulative effects of both predictors would have to refer to a period. Time is

TABLE 8 Chi-square test to determine association between land uses and response classes: NE Brazil. $\chi^2 = 873.016$, $N = 21{,}733$, $df = 32$, $p < 1E\text{-}3$. Only residual frequencies with standardized value greater than $|1.96|$ are shown, corresponding to $p < 0.05$

Name	ANTN	ANT0	ANTP
Forestry—Not used/not managed	4.0	−10.6	9.8
Forestry—Pastoralism moderate or higher		4.8	−4.5
Forestry—Pastoralism moderate or higher with scattered plantations	−2.7		
Herbaceous—Extensive pastoralism		−7.5	7.7
Herbaceous—Moderately intensive pastoralism		8.3	−8.0
Herbaceous—Intensive pastoralism	4.4	7.5	−8.7
Rainfed Agriculture		−14.8	15.4
Agro-pastoralism—Moderately intensive	−2.0	−7.5	8.1
Agro-pastoralism - Intensive	4.3	9.8	−11.0
Agriculture—Protected areas		−4.4	4.2
Bare areas—Not used/not managed (Natural)		2.6	−2.8
Bare areas—Extensive pastoralism		−5.8	5.8
Bare areas—Moderately intensive pastoralism or higher	−2.5	9.0	−8.5

interpreted as a proxy for other ecological or human processes, and that is exactly what it does when the regression is explored (leaving Aridity constant) for several years. However, Aridity only comes from a spectrum of values that occurred during the years studied, not in order over time. So, when the effect of a value of the aridity index is explored in the regression (leaving Time constant), what results is instantaneous sensitivity to that value, not its integration in a dimension of time.

Therefore, that hypothetical pixel could well be one of the 10,941 km^2 of the Iberian Peninsula's Mediterranean zone which were ANTP in a previous 2dRUE application (del Barrio et al., 2010). This would have been interpreted as degrading under the conventional scheme of observing variation in vegetation over time using simple regressions, but a more appropriate interpretation of what is happening in such pixels would be that the dry years simply had negative effects on the growth of vegetation, and after the removal of these effects, biomass kept increasing over time. That is, the true value of the β coefficients is to facilitate comparison of their relative weights on the vegetation biomass variation rates.

4.2 | Response classes by region

Tables 3 to 8 show association between the ANTP, ANTN and ANT0 response classes by region and land use. Here we explore them in detail, as a previous step to generalizing patterns. To do this, we also consider the relative weights of Aridity and Time within each response class (Table 2).

There are three scenarios in Class ANTP. In the first, Aridity had less weight than Time in determining the variation in vegetation biomass, and its only representative was the Iberian Peninsula. In Spain, the positive trend of Time prevailed in 33% of the territory, and the related landscape types were forests and woods or scrub (Sanjuán et al., 2014). In Portugal, this prevalence was 32%, with similar covers (Rosario et al., 2015). Spain went through historic global change events that placed pressure on the natural vegetation. Some examples are the *Mesta* (historic merino livestock guild), the Spanish confiscation (seizure and sale for profit of land owned by the Catholic Church), 19th century mining, etc. (del Barrio, Sainz, et al., 2021). However, the most recent (entry in the EU in 1986) has led to relaxation of human pressure on agroecosystems (Martínez-Valderrama et al., 2021). Here, therefore, this response class included both recently abandoned territories and those with historic desertification. Assuming that those places experienced the same fluctuations in climate as others in different response classes, it may be concluded that the vegetation there has had a longer time to recover and is therefore less affected by such fluctuations.

The second scenario in Class ANTP occurred in the Palestinian West Bank and the Maghreb, where we found no significant differences between Aridity and Time. In these regions, the increases in vegetation over time were related to unmanaged or extensively managed zones. It should be highlighted that the Maghreb, where this trend prevails in 24% of its territory (del Barrio et al., 2016), has a considerable expanse of historic desertification associated with its more recent global change event, European colonization during the 19th and 20th centuries.

The third ANTP scenario is where Aridity had more weight than Time, which occurred in Brazil, Mozambique and China. In all these cases, the most significant associations were land uses involving intensive exploitation. In Brazil, rainfed crops may have led to a decrease in the relative weight of Time because of annual harvesting. In more naturalized areas of Brazil and Mozambique, the ANTP response took place in vegetation under extensive grazing (Zucca et al., 2012). In China, the increase in vegetation was more diversified. On one hand, it has involved pastures and woody formations that could be related to large government protection and restoration projects together called the Six Key Forest Programs (Wang et al., 2007). On the other hand, and similar, as mentioned above in the case of Brazil, China is still pursuing an active policy of transforming natural vegetation into new agricultural areas, and intensifying existing agriculture, all of which produced positive signs in Time for a limited period (del Barrio et al., 2020).

In Class ANTN, both Aridity and Time showed negative effects on vegetation. In all the regions, except the Palestinian West Bank, the weight of Aridity was higher. The associated land uses always showed higher levels of intensification, whatever the plant cover is. For example, 'Forest—Grazing moderate or higher' in NW Maghreb or 'Herbaceous—Intensive pastoralism' in NE Brazil. Furthermore, the negative effect of human exploitation was often coupled with drought, a combination for which vegetation does not seem to be resilient. Mozambique is a good example. Our results for this region showed that the uses associated with negative trends in Time were unmanaged forests, and agriculture or grazing in protected areas. This finding seems to contradict the above statement on intensification. However, a close inspection reveals that most degradation in Time occurs on the periphery of the Banhine National Park and territories in the Great Limpopo Transfrontier Park. These are savannahs with mopane trees (*Colophospermum mopane*). Their inhabitants live in disperse family units near their fields, pastures and springs, and land use has been subsistence exploitation since ancestral times. From 2003 to 2006, a severe drought led to poor crops and famine. Consequently, pressure on forests for survival increased (Dear & McCool, 2010). This event falls within our study period (1998–2006) and is reflected in our results. Therefore, this example reinforces the case for intensification (or overexploitation) in Class ANTN.

In China, the only association with Class ANTN was in the steppes of Inner Mongolia (Figure 1b). This could be related to two recent parallel developments: a gradual increase in aridity and the expansion of urban areas, coupled with the rise of mining (Batunacun et al., 2019).

The Palestinian West Bank is exceptional in this class because of its particular territorial organization. The rural Palestinian communities live essentially from goat and sheep herding, and this use showed the strongest positive association with Class ANTN in our study. This situation occurs notably in the agricultural areas of the Jordan Valley, Eastern Slopes and Central Highlands, the latter often on eroded soils.

However, most of the land suitable for grazing is classified as military zones in Area C by the Israeli government, and only 225 km^2 remain available to local inhabitants (Alkhouri, 2012). The low carrying capacity of these residual territories leads to active degradation by overgrazing, especially during drought. In this case, intensification may be interpreted as reduction from shrinking of space rather than expansion or change in human activity, and that could explain the similarity in weights of Aridity and Time.

Class ANT0 provides a certain reference for the others. In this class, the ecosystems do not show the effects of the internal dynamics of their management, or more likely, these effects could not be detected during the study periods. Such lack of response could happen under two extreme circumstances: either because ecosystems are in mature states of their ecological succession, therefore favouring gross primary productivity over net primary productivity, or because they have arrived at their final simplification, due to maximum renovation turnover (annual harvests) or extreme degradation. Our results support this interpretation. Only in the Iberian Peninsula (due to abandonment) and China (due to protection policies) is this class associated with forests. In the rest of the regions, it is related to intensive uses.

A pattern emerging from this discussion is that the intensification of land use tends to diminish the relative weight of Time with respect to Aridity; that is, to increase dependence of agroecosystems on climate. The fact that that pattern occurs over widespread regions not related to each other suggests independent convergence of the biomes involved. This has already been observed at other levels of organization. For example, Wan et al. (2021) demonstrated that microbiological biomass changes proportionately to total biomass in a given biome under natural conditions, but all biomes converge toward a gradual reduction with the intensification of livestock raising, which is worsened by global warming.

It is interesting to examine the |Time|/|Aridity| ratios for the various regions (Figure 2). In all cases where these values were significantly different, these ratios were higher in ANTP than in ANTN. Considering their signs, this suggests that in a growing agroecosystem (ANTP), the tendency to complete the ecological succession is stronger than the effect of droughts. Nevertheless, as it degrades, that trend decreases, and becomes negative if the climatic pressure on it is strong enough (ANTN). Under these conditions, unfavorable weather events operate in the same direction, albeit more markedly, than degradation. That is, the agroecosystem concerned would lose resilience. We cannot support this interpretation with concrete results, since the set of land uses in each region remains grouped in the response classes. However, we know now that in the Iberian Peninsula, most of Class ANTP is related to secondary successions in forests and shrubland (del Barrio et al., 2010; Sanjuán et al., 2014). There the |Time|/|Aridity| ratio was the highest we found (1.129). That supports the interpretation and reinforces the need for further research on this topic.

4.3 | Limitations

The land use products in this study are consistent with each other only in a limited way. It was fortunate that the world map produced by the LADA Project was available for the study period in Maghreb, Mozambique, Palestinian West Bank and Brazil. Its land use legend explicitly qualifies their positions on the extensive-intensive polarity, which is recognized as a cause of desertification and has been relevant in clarifying the problems posed here. In the Iberian Peninsula and China, we used specific regional products to which this polarity can only be attributed implicitly or through the literature. This heterogeneity was the reason we decided not to unify the land cover classifications using a standard physiognomic system such as the Land Cover Meta Language (ISO, 2012), and avoid entering interpretations in the input data. However, the set of all the regional applications has shown sufficient convergence to extract general patterns in the relationships explored.

It was those patterns, and not the monographic analysis of each region, that we pursued here, and that explains the conditions for selecting the points described under Methods. This caused some land uses, important for understanding a particular region, to be left out of the analysis. For example, in the Iberian Peninsula, land abandonment, which feeds the ANTP response largely, was accompanied by agricultural intensification involving stabling animals and increasing irrigated crops. Irrigation, excluded here, may have a limited lifetime in drylands due to subsoil salinity mobilization, saline intrusion in coastal plains and groundwater depletion (FAO, 2021), and end up losing productivity or being abandoned (Postel, 1999). This is a major cause of 1% of degrading land detected in the Iberian Peninsula, and explains Class ANTN to a great extent, but to evaluate the complete irrigated land cycle would require management details (for example, growing contributions of water and fertilizers or added agricultural value of harvests) beyond the experimental design of this study. We have observed the same process in the Maghreb and in China, and it is likely that this or other equivalent uses are crucial to explain the ecological history of each region. Therefore, the scope of this study, in this particular geographical sense, is limited.

4.4 | Relevance for SDG indicator 15.3.1

Progress in SDG 15.3 is measured by Indicator SDG 15.3.1, "Proportion of land that is degraded over total land area", which, in turn, consists of three sub-indicators on Land Cover and Land Cover Change, Land Productivity and Carbon Stocks Above and Below Ground. Indicator 15.3.1 reports in units of spatial area of the binary condition "not degraded/degraded", but its sub-indicators are based on quantitative trends, and only if the three are positive is the unit evaluated considered not degraded (Sims et al., 2021).

The methodology supporting Indicator 15.3.1 is unequivocal in its application, and the three sub-indicators are considered separately. This, which is an advantage, can become a problem if its execution becomes automatic. Some evidences found in this study could help to point out hidden paradoxes or synergies coming from a simplistic computation of SDG 15.3.1.

Among the paradoxes, the greatest is that SDG 1 5.3.1, by focusing almost exclusively on the detection of land degradation trends, ignores the compound effects of climate on land degradation. It acknowledges the need for climate calibration and recommends RESTREND as a suitable technique for extracting productivity change beyond climate. However, as mentioned earlier in the Introduction, assuming that climate is always the first predictor and finding human effects through its residual trends might be effective at the expense of oversimplification. The approach followed here is more balanced because it enables any of the predictors to become first, second or none at explaining vegetation change. In turn, this allows subtle variations in their relative weight as some climatic or human driver proceeds, to be explored. This feature has been relevant here to investigate the effect of land use intensification or even to anticipate the impact of climate warming, and therefore, adds some value as an early warning.

With respect to synergies, the One Out, All Out (1OAO) principle facilitates rough overall evaluation based on qualitative relationships between land use and vegetation productivity. Nonetheless, it does not account for feedback between these variables by which one may influence the other to a point that affects land suitability and subsequent loss of management options (del Barrio, Sanjuán, et al., 2021). In general, that diverges from the paradigm relating desertification to change of state within concrete land uses (Bestelmeyer et al., 2015), rather than between them. In particular, our results show that the degree of intensification of land use increases sensitivity to Aridity, and therefore, decreases the relative importance of intrinsic trends in vegetation biomass.

It is not the purpose of this study to criticize, not even comparatively, SDG Indicator 15.3.1. However, the comments in this section suggest that, in parallel to its application, some complementary tests could be made to make the complexity of land degradation more visible. More so, this type of test is based on the same data as the SDG 15.3.1 itself.

5 | CONCLUSIONS

This study assumed that the response to interannual variations in aridity (Aridity), and the course of time, as a proxy of ecological dynamics (Time), are the main sources of regional-scale variation in vegetation biomass. It extracted the relative weights of both factors, and compared them statistically. The data are from a wide representation of drylands in six regions distributed over four continents, and therefore provide sufficient variety and robustness to extract some generalizable convergences. The main conclusions are:

1. The weights of Aridity and Time for causing changes in vegetation biomass are variable and may be delimited using appropriate statistical methods. Their values may be significantly different when these predictors are grouped by response class.
2. These weights are significantly associated with the degree of intensification of land use such that if vegetation increases over Time, Aridity increases its relative importance with intensification; if vegetation is degrading, Aridity is always more important than Time.
3. The weight of Aridity, by definition, is an indicator of vulnerability to climate warming. Given the relationships found, management of land use tending to curb its intensification would probably increase its resilience to such climate change.
4. If climate change were the main source of variation in agroecosystem boundary conditions, only through management changes could some resilience be achieved. Reciprocally, vulnerability may increase under a constant climate if management is intensified. Therefore, global change is the only conceptual framework that can address this type of socioecological issue.

AUTHOR CONTRIBUTIONS

María E. Sanjuán: formal analysis, conceptualization, data curation, methodology, writing.
Original draft, writing—review and editing. Alberto Ruiz: software, display. Jaime Martínez-Valderrama: conceptualization, research, writing—review and editing. Gabriel del Barrio: acquisition of data collections, conceptualization, writing—original draft, writing—review and editing, supervision.

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CONFLICT OF INTEREST

The authors have no conflict of interest to declare.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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REFERENCES

Alkhouri S. 2012. *Monitoring of land condition in the Occupied Palestinian Territory (2000–2010).* Jerusalem: Applied Research Institute (ARIJ). https://www.arij.org/publications/special-reports/special-reports-2012/monitoring-of-land-condition-in-the-occupied-palestinian-territory-2000-2010/

Batunacun, W. R., Lakes, T., Yunfeng, H., & Nendel, C. (2019). Identifying drivers of land degradation in Xilingol, China, between 1975 and 2015. *Land Use Policy*, *83*, 543–559. https://doi.org/10.1016/j.landusepol.2019.02.013

Bestelmeyer, B. T., Okin, G. S., Duniway, M. C., Archer, S. R., Sayre, N. F., Williamson, J. C., & Herrick, J. E. (2015). Desertification, land use, and the transformation of global drylands. *Frontiers in Ecology and the Environment*, *13*, 28–36. https://doi.org/10.1890/140162

Cherlet, M., Hutchinson, C., Reynolds, J., Hill, J., Sommer, S. & von Maltitz, G. (Eds). (2018). *World atlas of desertification. Rethinking land degradation and sustainable land management*. Brussels: Publication Office of the European Union. https://doi.org/10.2760/9205

Dear, C., & McCool, S. (2010). Causes and consequences of displacement decision-making in Banhine National Park, Mozambique. *Conservation and Society*, *8*, 103–111. https://doi.org/10.4103/0972-4923.68910

del Barrio, G., Puigdefabregas, J., Sanjuán, M. E., Stellmes, M., & Ruiz, A. (2010). Assessment and monitoring of land condition in the Iberian Peninsula, 1989-2000. *Remote Sensing of Environment*, *114*, 1817–1832. https://doi.org/10.1016/j.rse.2010.03.009

del Barrio, G., Sainz, H., Sanjuán, M. E., Sánchez de Dios, R., Martínez-Valderrama, J., & Ruiz, A. (2021). Abrupt fragmentation thresholds of eight zonal forest types in mainland Spain. *Forest Ecology and Management*, *482*, 1-9. https://doi.org/10.1016/j.foreco.2020.118788

del Barrio, G., Sanjuán, M. E., Hirche, A., Yassin, M., Ruiz, A., Ouessar, M., Martínez-Valderrama, J., Essifi, B., Puigdefabregas, J., Valderrama, J. M., Essifi, B., & Puigdefabregas, J. (2016). Land degradation states and trends in the northwestern Maghreb drylands, 1998–2008. *Remote Sensing*, *8*, 1–25. https://doi.org/10.3390/rs8070603

del Barrio, G., Sanjuán, M. E., Martínez-Valderrama, J., Ruiz, A., & Puigdefábregas, J. (2021). Land degradation means a loss of management options. *Journal of Arid Environments*, *189*, 104502. https://doi.org/10.1016/j.jaridenv.2021.104502

del Barrio, G., Zhihai, G., Martínez-Valderrama, J., Li, X., Sanjuán, M. E., Sun, B., Ruiz, A., Wang, B., & Puigdefábregas, J. (2020). Comparing land degradation and regeneration trends in China drylands. *Journal of Geodesy and Geoinformation Science*, *3*, 89–97. https://doi.org/10.11947/j.JGGS.2020.0409

D'Odorico, P., Bhattachan, A., Davis, K. F., Ravi, S., & Runyan, C. W. (2013). Global desertification: Drivers and feedbacks. *Advances in Water Resources*, *51*, 326–344. https://doi.org/10.1016/j.advwatres.2012.01.013

EEA. 2016. CORINE Land Cover (CLC) 2006, Version 18. https://land.copernicus.eu/pan-european/corine-land-cover

Evans, J., & Geerken, R. (2004). Discrimination between climate and human-induced dryland degradation. *Journal of Arid Environments*, *57*, 535–554. https://doi.org/10.1016/S0140-1963(03)00121-6

FAO. (2021). *The state of the World's land and water resources for food and agriculture—Systems at breaking point (SOLAW 2021)*. Rome: FAO. https://doi.org/10.4060/cb7654en

Fensholt, R., Horion, S., Tagesson, T., Ehammer, A., Grogan, K., Tian, F., Huber, S., Verbesselt, J., Prince, S. D., Tucker, C. J., & Rasmussen, K. (2015). Assessing drivers of vegetation changes in drylands from time series of earth observation data. In C. Kruenzer, S. Dech, & W. Wagner (Eds.), *Remote sensing time series* (pp. 183–202). Cham, CH: Springer. ISBN: 978-3-319-15966-9. https://doi.org/10.1007/978-3-319-15967-6_9

Hielkema, J. U., Prince, S. D., & Astle, W. L. (1987). Monitoring of global vegetation dynamics for assessment of primary productivity using NOAA advanced very high resolution radiometer. *Advances in Space Research*, *7*, 81–88.

Higginbottom, T. P., & Symeonakis, E. (2014). Assessing land degradation and desertification using vegetation index data: Current frameworks and future directions. *Remote Sensing*, *6*, 9552–9575. https://doi.org/10.3390/rs6109552

Hirche, A., Salamani, M., Abdellaoui, A., Benhouhou, S., & Valderrama, J. M. (2011). Landscape changes of desertification in arid areas: The case of South-West Algeria. *Environmental Monitoring and Assessment*, *179*, 403–420. https://doi.org/10.1007/s10661-010-1744-5

Ibrahim, Y. Z., Balzter, H., Kaduk, J., & Tucker, C. J. (2015). Land degradation assessment using residual trend analysis of GIMMS NDVI3g, soil moisture and rainfall in sub-Saharan West Africa from 1982 to 2012. *Remote Sensing*, *7*, 5471–5494. https://doi.org/10.3390/rs70505471

IPBES. (2018). *The IPBES assessment report on land degradation and restoration*. Bonn.

IPCC. (2014). *Climate change 2014 impacts, adaptation, and vulnerability*. Working Group II Contribution to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge, UK: Cambridge University Press. https://doi.org/10.1017/CBO9781107415379

ISO. (2012). ISO 19144-2:2012 Geographic information - Classification systems — Part 2: Land Cover Meta Language (LCML). *Geneva*. https://www.iso.org/standard/44342.html

Kirkby, M. (2021). Desertification and development: Some broader contexts. *Journal of Arid Environments*, *193*, 104575. https://doi.org/10.1016/j.jaridenv.2021.104575

Krausmann, F., Erb, K. H., Gingrich, S., Haberl, H., Bondeau, A., Gaube, V., Lauk, C., Plutzar, C., & Searchinger, T. D. (2013). Global human appropriation of net primary production doubled in the 20th century. *Proceedings of the National Academy of Sciences of the United States of America*, *110*, 10324–10329. https://doi.org/10.1073/pnas.1211349110

Martínez-Valderrama, J., Sanjuán, M. E., del Barrio, G., Guirado, E., Ruiz, A., & Maestre, F. T. (2021). Mediterranean landscape re-greening at the expense of South American agricultural expansion. *Land*, *10*, 204. https://doi.org/10.3390/land10020204

Mirzabaev, A., Wu, J., Evans, J., García-Oliva, F., Hussein, I. A. G., Iqbal, M. H., Kimutai, J., Knowles, T., Meza, F., Nedjraoui, D., Tena, F., Türkeş, M., Vázquez, R. J., & Weltz, M. (2019). Desertification. In P. R. Shukla, J. Skea, E. C. Buendia, V. Masson-Delmotte, H.-O. Pörtner, D. C. Roberts, P. Zhai, R. Slade, S. Connors, R. Diemen, M. Ferrat, E. Haughey, S. Luz, S. Neogi, M. Pathak, J. Petzold, J. Pereira Portugal, P. Vyas, E. Huntley, et al. (Eds.), *Climate change and land: An IPCC special report on climate change, desertification, land degradation, sustainable land management, food security, and greenhouse gas fluxes in terrestrial ecosystems* (pp. 249–343). Paris: Intergovernmental Panel on Climate Change.

Nachtergaele F, Petri M. 2013. *Mapping land use systems at global and regional scales for land degradation assessment analysis. Version 1.1*. Rome: FAO. https://www.fao.org/3/i3242e/i3242e.pdf

Orr, B. J., Cowie, A. L., Castillo Sanchez, V. M., Chasek, P., Crossman, N. D., Erlewein, A., Louwagie, G., Maron, M., Metternicht, G. I., Minelli, S., Tengberg, A., Walter, S., & Welton, S. (2017). Land in balance: The scientific conceptual framework for land degradation neutrality. In *Scientific conceptual framework for land degradation neutrality. A report of the science-policy Interface*. Bonn: United Nations Convention to Combat Desertification. https://www.unccd.int/resources/publications/scientific-conceptual-framework-land-degradation-neutrality-report-science

Postel, S. (1999). *Pillar of sand: Can the irrigation miracle last?* W.W. No. New York: W.W. Norton.

Price, J. C. (1993). Estimating leaf area index from satellite data. *IEEE Transactions on Geoscience and Remote Sensing*, *31*, 727–734.

Puigdefabregas, J. (1995). Desertification: Stress beyond resilience, exploring a unifying process structure. *Ambio*, *24*, 311–313.

Rosario, L. P., del Barrio, G., Sanjuán, M. E., Ruiz, A., Martínez-Valderrama, J., & Puigdefabregas, J. (2015). Prioridades de aplicação do Programa de Ação Nacional de Combate à Desertificação com base nas condições do solo. In T. d. Figueiredo, F. Fonseca, & L. Nunes (Eds.), *Proteção do Solo e Combate à Desertificação: oportunidade para as regiões transfronteiriças* (pp. 47–60). Instituto Politécnico de Bragança. http://hdl.handle.net/10198/12212

Ruiz A, Sanjuán ME, del Barrio G, Puigdefabregas J. 2011. r2dRue: 2d rain use Efficience library. R package version 1.04. *R package*. Comprehensive R archive Network. https://cran.r-project.org/package=r2dRue

Sanjuán, M. E., del Barrio, G., Ruiz, A., Rojo, L., Martinez, A., & Puigdefabregas, J. (2014). *Evaluación y seguimiento de la desertificación en España: Mapa de la Condición de la Tierra 2000–2010*. Madrid: Ministerio de Agricultura, Alimentación y Medio Ambiente. https://doi.org/10.20350/digitalCSIC/10575

Siegel, S., & Castellan, N. J. (1988). *Nonparametric statistics for the behavioural sciences*. New York: McGraw-Hill.

Sims, N. C., Newnham, G. J., England, J. R., Guerschman, J., Cox, S. J. D., Roxburgh, S. H., Viscarra-Rossel, R. A., Fritz, S., & Wheeler, I. (2021). *Good practice guidance. SDG indicator 15.3.1*, *Proportion of land that Is degraded over total land area. Version 2.0*. United Nations Convention to Combat Desertification.

Trabucco, A. (2019). *Global aridity and PET database*. CGIAR CSI. https://cgiarcsi.community/data/global-aridity-and-pet-database/

UN General Assembly. 2015. *Transforming our world: The 2030 Agenda for Sustainable Development*. A/RES/70/1. https://www.refworld.org/docid/57b6e3e44.html

UNCOD. (1977). *Desertification, its causes and consequences: Secretariat of the United Nations Conference on Desertification. Nairobi, Kenya, 29 August to 9 September, 1977*. Oxford, UK: Pergamon Press.

Verón, S. R., Paruelo, J. M., & Oesterheld, M. (2006). Assessing desertification. *Journal of Arid Environments*, *66*, 751–763. https://doi.org/10.1016/j.jaridenv.2006.01.021

Wan, X., Chen, X., Huang, Z., & Chen, H. Y. H. (2021). Global soil microbial biomass decreases with aridity and land-use intensification. *Global Ecology and Biogeography*, *30*, 1056–1069. https://doi.org/10.1111/geb.13282

Wang, G., Innes, J. L., Lei, J., Dai, S., & Wu, S. W. (2007). ECOLOGY: China's forestry reforms. *Science*, *318*, 1556–1557. https://doi.org/10.1126/science.1147247

Wessels, K. J. J., Prince, S. D. D., Malherbe, J., Small, J., Frost, P. E. E., & VanZyl, D. (2007). Can human-induced land degradation be distinguished from the effects of rainfall variability? A case study in South Africa. *Journal of Arid Environments*, *68*, 271–297. https://doi.org/10.1016/j.jaridenv.2006.05.015

Xu, D., Li, C., Zhuang, D., & Pan, J. (2011). Assessment of the relative role of climate change and human activities in desertification: A review. *Journal of Geographical Sciences*, *21*, 926–936. https://doi.org/10.1007/s11442-011-0890-1

Zhang, L., Li, X., Yuan, Q., & Liu, Y. (2014). Object-based approach to national land cover mapping using HJ satellite imagery. *Journal of Applied Remote Sensing*, *8*, 1-19. https://doi.org/10.1117/1.JRS.8.083686

Zucca, C., Armas, R., Pace, G., Compagnone, L., del Barrio, G., Sanjuán, M. E., Ruiz, A., Joao Pereira, M., Dinis, J., & Rocha, A. (2012). *DesertWatch extension final report* (p. 48). Rome: Advanced Computer Systems A.C.S. S.p.a. http://due.esrin.esa.int/page_project118.php

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