

Comparing land degradation and regeneration trends in China drylands

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Abstract: The aim of this paper is to offer a statistically sound method to make a precise account of the speed of land degradation and regeneration processes. Most common analyses of land degradation focus instead on the extent of degraded areas, rather than on the intensity of degradation processes. The study was implemented for the Potential Extent of Desertification in China (PEDC), composed by arid, semi-arid and dry sub-humid regions and refers to the period 2002 to 2012. The metrics were standard partial regression coefficients from stepwise regressions, fitted using Net Primary Productivity as the dependent variable, and year number and aridity as predictors. The results indicate that: 1) the extension of degrading lands (292,896 km² or 9.12% of PEDC) overcomes the area that is recovering (194,560 km² or 6.06% of PEDC); and 2) the intensity of degrading trends is lower than that of increasing trends in three land cover types (grassland, desert and crops) and in two aridity levels (semi-arid and dry sub-humid). Such outcome might pinpoint restoration policies by the Chinese government, and document a possible case of hysteresis.

Key words: land degradation; potential extent of desertification in China; environmental monitoring; vegetation temporal trends; standard partial regression coefficients

Citation format: Gabriel del B, Gao Z H, Jaime M V, Li X S, Maria E. S, Sun B, Alberto R, Wang B Y and Juan P. 2020. Comparing land degradation and regeneration trends in China drylands. *Journal of Remote Sensing (Chinese)*. 24(S1): 17–24

1 INTRODUCTION

China has many world records. It is the most populous country and the third largest. Its economy is growing at the fastest rate of any major country, which implies to have, at the same time, the world's highest production rate of many commodities (steel, coal ...) and the highest consumption rate of them. These large magnitudes have their environmental counterpart as Wang, (2004) lists: soil erosion area exceeds 3.67 million km² and more than 5 billion ton of soil vanishes due to soil erosion every year. Eight of the 10 top most seriously polluted rivers in the world are in China and among the 432 rivers monitored by Environmental Protection Agency, 80% of them have been polluted.

A paradoxical illustration of both the rich natural resources and simultaneously the extraordinary capacity for consumption of the country is given by the impact of water extractions on one of its most powerful rivers. The number of days without any flow of water on the lower Yellow River (the second largest in China and the sixth in the world) was 230 days in 1997 (Diamond, 2005).

Large-scale transformations seeking the modernization of the country show impressive socioeconomic figures. Some interesting

data retrieved from the China Statistical Yearbook (2016) help understanding the magnitude of the change. For the period, 1978—2015 China experienced a 347% increase in urban population and a shocking 9,168% increase in annual per capita available income of urban households. The pursue of food security doubled the output of major farm outputs and the importation of food increased (for the period 1980 to 2015) from 31.66 to 579.84 USD 100 million.

This explosive growth might be leaving a proportional environmental footprint in China drylands. According to State Forestry Administration (2011), China had a total desertified land area of 2,623,700 square kilometers making up 27.33% of the national territory. To control desertification, the Chinese government implemented some of world's largest ecological restoration projects. The Six Key Forestry Programs (Wang, et al., 2007; Liu, et al., 2014) — which included the Sloping Land Conversion Program (Grain for Green project) and the Three Norths Shelter Forest Program (Green Great Wall) — and the Grassland Ban Policy (DONG, et al., 2007) aim at increasing the vegetation cover by combining prevention and mitigation strategies. This includes prohibiting grazing, planting trees and grasses, and constructing shelter forests to protect farmland against blown sand (Feng, et al., 2015).

Received: XXXX-XX-XX; **Accepted:** XXXX-XX-XX

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The overlapping of friendly-environmental actions and intensive use of natural resources give rise to a mix of land condition trends of challenging forecast. The total desertified area has decreased in many areas, but in others, desertification has continued to expand (*A Bulletin of Status Quo of Desertification and Sandification in China*, 2011). Our aim is to gain insight about contrasting land condition trends through a statistically sound procedure that allows quantifying and comparing the magnitudes of degradation and regeneration processes.

Large scale and long-term assessment of degradation and regeneration in drylands can only be achieved by use of Earth Observation data, based on the assumption that a reduction in the measured Net Primary Production at a site can potentially be viewed as land degradation. Based on which, Chinese researchers have carried out degradation assessments of specific ecosystems, such as grasslands (Zhou, et al., 2017) or on a regional scale, e. g. Beijing-Tianjin Dust and Sandstorm Region (Li, et al., 2015).

The analysis presented here is based on 2dRUE results. This is a geomatic tool designed for land condition monitoring and assessment (del Barrio, et al., 2010; Del Barrio, et al., 2016) and was implemented to study China Drylands for the period 2002-2012 (Gao,

et al., 2014, 2016). From these outputs, it is possible to estimate the share of land condition change caused by human activity. Our work presents the balance of decreasing and increasing land condition trends for this territory, both in extent of land and in intensity of these trends.

2 DATA AND METHODS

2.1 China drylands and land-uses

This paper focuses on the Potential Extent of Desertification in China (PEDC) (Fig. 1), composed by arid, semi-arid and dry sub-humid regions identified after the FAO-UNEP aridity index, the ratio of precipitation (P) to potential evapo-transpiration (PET). This was determined by (Sun, et al., 2015) using a high spatial resolution meteorological dataset (1981 - 2010) and by applying the Thornthwaite method to compute PET. PEDC is mainly distributed in north China and host 26.3% of the total population (Li, et al., 2015).

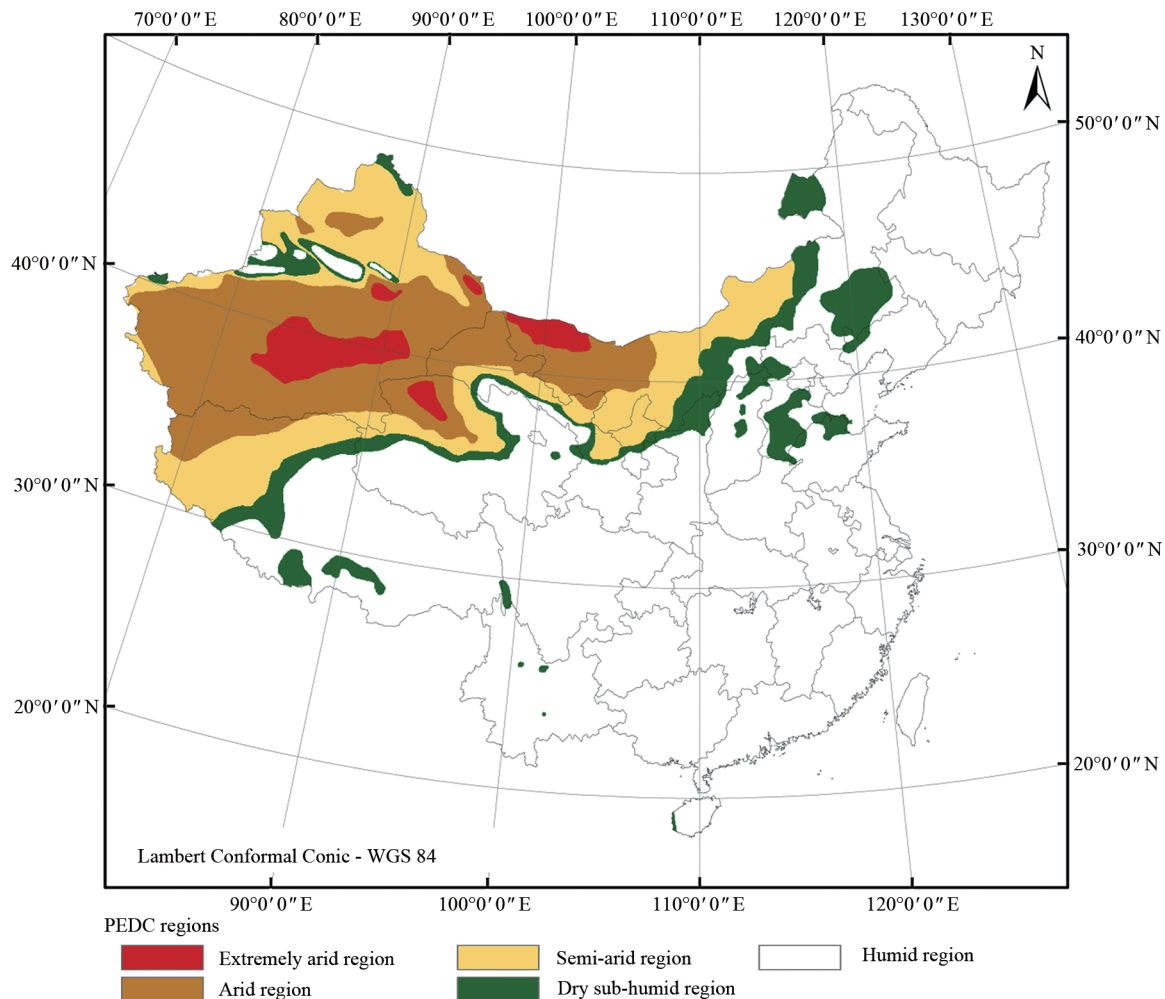


Fig.1 Distribution of aridity regions in China. The Potential Extent of Desertification in China (PEDC) comprehends arid, semi-arid and dry sub-humid aridity levels.

The Land Cover Classification System of the United Nations Food and Agriculture Organization (Di Gregorio and Jansen, 2005) was used as a tool for building the Chinese land cover legend for

the year 2010. The eight categories used in this work (Fig 2.) come from the aggregation of the thirty-eight classes of level II built for China for the year 2010 (Zhang, et al., 2014; Ouyang, et al., 2015).

The main land cover in China Drylands is Grassland (42.5%), followed by Deserts and bare soils (44.4%) and Agriculture

(7.35%). The remnant 6% corresponds to forests, shrublands and other classes.

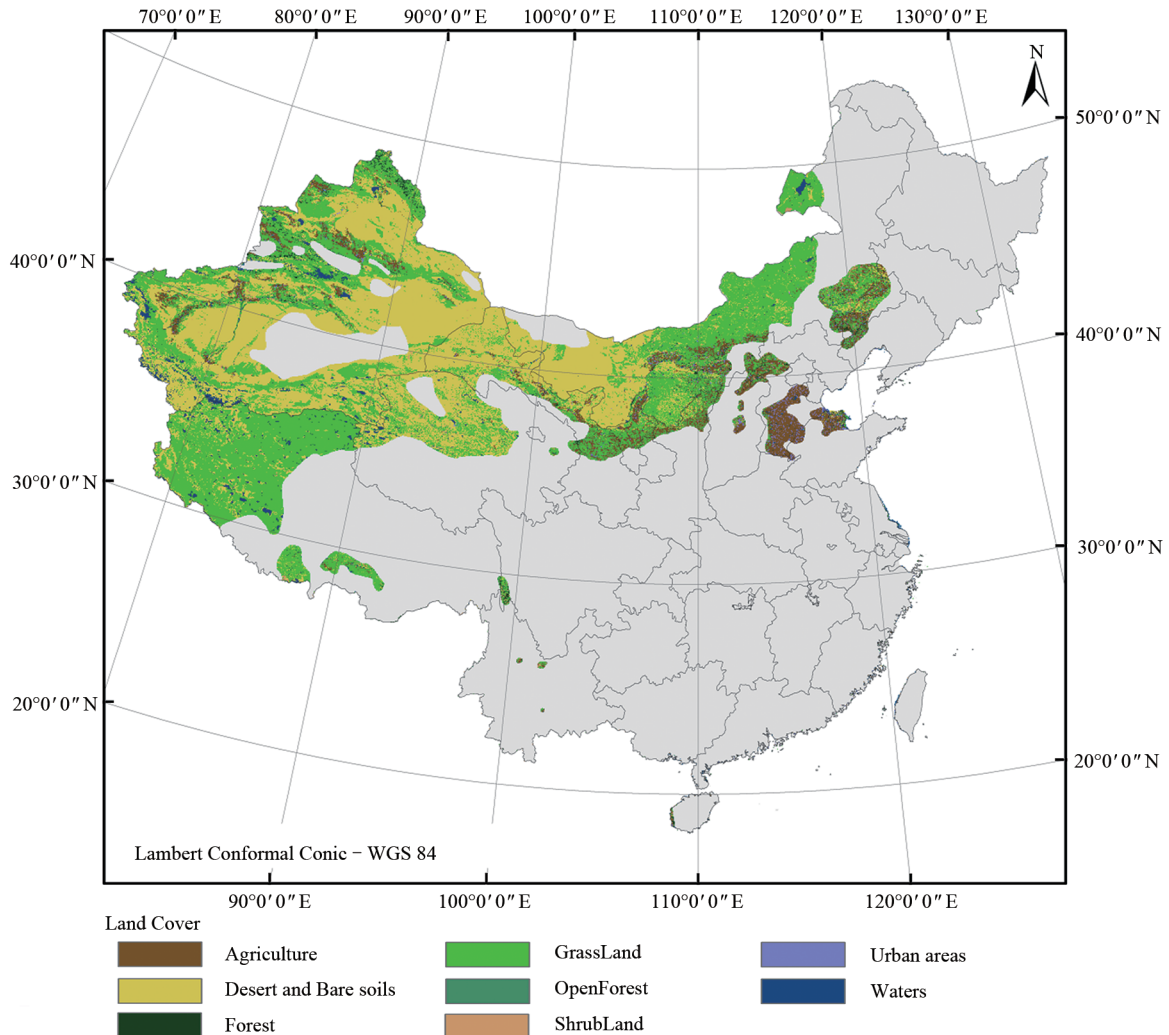


Fig.2 Land cover types distribution in PEDC

2.2 Vegetation and Aridity Index archives

We developed a Net Primary Production (NPP) time-series archive using the CASA algorithm on MERIS satellite data (Sun, Gao and Li, 2014). In parallel, we also assembled a corresponding archive of climate fields from the China Meteorological Forcing Dataset (Chen, et al., 2011). The resulting database, covering the whole China, spanned the period between hydrological years 2002-03 through 2012-13 at a monthly temporal resolution (Gao, et al., 2014, 2016).

Such data were produced with a spatial resolution of 4 km (which results in cells of 16 km²) for a total area of 3,209,440 km². Two aspects supported this choice: the large size of China, and the fact that coarser resolutions have already been used with meaningful results (e.g. GIMMS at 8 km, see for example Tucker, et al. (2005)).

For the purpose of this study it was selected a period of ten years, from April 2002 through March 2012. The aforementioned databases were used to obtain mean annual values of NPP and climate. The latter, consisting of mean maximum, mean, mean minimum temperatures and precipitation, would be then used for com-

puting an aridity measure as a ratio of PET to P following the formula by Hargreaves and Samani (1982).

The input dataset used for this application was NPP, in grams of carbon per square meter per month. This is extremely useful as it outperforms Σ NDVI as an estimate of primary productivity (Wessels, et al., 2007). It also conforms better to the original definition of Rain Use Efficiency (RUE), the ratio between NPP and precipitation (N. Le Houerou and Le Houerou, 1984). However, Σ NPP over a year is only a good estimator of biomass when turnover trends to one, i.e. when most of biomass is renewed yearly. Forests and other woody formations are clearly not in this case, and might result underestimated by this proxy.

2.3 Detection of temporal trends

We applied the 2dRUE monitoring component to determine temporal and aridity trends of vegetation in the PEDC for the period 2002-2012. 2dRUE was described recently in an application to NW Maghreb (Del Barrio, et al., 2016), and its theoretical framework was given in a previous application to Iberia (del Barrio, et al., 2010). As in those cases, the implementation for this study was

done using the r2dRue software library (Ruiz, et al., 2011). Therefore, only a short summary is given below.

2dRUE is a geomatic method that operates on archived time-series of a vegetation index (e.g. NDVI or NPP as in this study) and corresponding climate fields, to produce maps of land condition states and trends. For trends, 2dRUE incorporates a stepwise regression to estimate separately the effects of aridity and time on vegetation. The former can be interpreted as responses of vegetation cover to inter-annual climate variations, while the latter relate to the impact of human activities on land (Evans and Geerken, 2004).

We detected trends after fitting, at the pixel level, stepwise regressions of NPP annual averages against year number and annual aridity. Because time and aridity themselves are often correlated, a second predictor was incorporated to the regression model only if it made a significant increment of determination with respect to using the first predictor only. This enabled separating effects of time, which we interpreted as true intrinsic degrading or increasing trends, from effects of inter-annual variations of aridity. We carried out the regressions in standardized form to facilitate future comparisons between predictors, and with other similar studies elsewhere. However, only the temporal trends were used in this study.

The standard partial regression coefficients (SPRC) were the metrics for this study. Their sign indicates whether vegetation cover has increased or decreased over the study period, and their magnitude conveys how many standard deviation units of vegetation are changed per one standard deviation unit of time. Statistical significance was set to $\alpha=0.10$.

We then classified and mapped the resulting SPRC to a map of land condition trends with four categories. These were (i) *Degrading*: significant biomass depletion over time, whatever the response to between-year variation in aridity. (ii) *Fluctuating*: biomass fluctuates between years with aridity, but with no significant variation in the long term. (iii) *Increasing*: significant biomass accumulation over time, whatever the response to between-year variation in aridity. And (iv) *Static*: no response detected over time, neither to changing aridity within the study period.

2.4 Comparison of positive and negative trends: the Mann-Whitney U test

One of the goals of this work is to determine whether NPP change rates are different for increasing and for degrading trends. Whilst available parametric statistic methods (e.g. the ubiquitous *t*-test) may deal with this question and facilitate the extraction of a wealth of quantitative information, they place restrictive conditions on the data (e.g. normality, homoscedasticity) which could not be assumed for this particular problem. For example, increasing and degrading trends are caused by different processes, and may only be assumed to have different variabilities and statistical distributions. Compounding this problem, vegetation density metrics are known to saturate in the higher scale levels (more likely with NDVI than with NPP), which would yield a truncated range of values where both central and dispersion statistics would be unreliable. Instead, we opted for providing a conservative but solid answer to the main question at the beginning of this paragraph, which in turn could guide future deeper studies on quantitative differences in vegetation trends according to concrete working hypotheses.

Assuming that both sets of SPRC may not come from the same continuous distribution, the Mann-Whitney U test for two independent samples, also known as the robust rank-order test (Siegel and Castellan, 1988) was an appropriate choice. Its power approaches

that of the *t*-test with the advantages that: i) as non-parametric, it does not have to meet restrictive data requirements; and ii) being based on ordinal scaling, it increases robustness by releasing accuracy requirements of the original interval scaling of SPRC. The wilcox.test function of the stats R package (R Core Team, 2017) was used in this study.

This two-sample test is used to determine whether the "bulk" of values in one group is lower or higher than the bulk of values in the other group. It works by ranking (in increasing order) the values of the dependent variable (SPRC) irrespective of the grouping, and then comparing the mean ranks of both distributions. The null hypothesis (H_0) states that both samples are stochastically equal.

In our study, H_0 translated to the distributions of SPRC absolute values in the *Increasing* and *Degrading* groups being equivalent. Hence, rejecting it would mean that the rates of environmental degradation and regeneration are different. Statistical significance for this test was set to $\alpha=0.10$.

For implementing the test, we used a stratified-random design to sample approximately 10% of the total PEDC, resulting in 19,183 cells. This ensured a uniform coverage for all the territory, observing the original statistical distribution properties of the variable under study and avoiding spatial autocorrelation between points.

Only significant positive and negative SPRC were used in the Mann-Whitney U test, which finally reduced the size of useful data to 2,896 cells. The study then explored H_0 on this sample considering two factors, land cover types and aridity levels.

3 RESULTS

3.1 Extent and distribution of land condition trends in the PEDC

The land condition trends in Fig. 3 show that 292,896 km² (9.12%) of PEDC have a negative temporal (*degrading*) trend in NPP, which is more than the 194,560 km² (6.06%) that were found to be *increasing*. Areas with negative trends form clusters widely distributed throughout the PEDC, and appear to be more frequent in Eastern Inner Mongolia. However, for most part of the territory under study *Static* is the prevailing class (65.5%), followed by *Fluctuating* (18.5%).

Fig. 4 shows land condition trend distribution within land cover and climatic classes. It is clear that active degradation has its greater extents in Grasslands, Desert and Crop land-covers, while it is well represented across all aridity levels. In all the cases, *degrading* trends prevail over *increasing* ones. The histogram also confirms that most of the data included in the first sampling is under the category *Static* that is not useful for our purpose, as these cells show no response over time or to changes in aridity.

3.2 Differences between degrading and increasing rates

However, distribution of SPRCs signs just provides partial information about land condition trends. The Mann-Whitney U test adds important information by detecting if one group tends to have higher values than the other group. The statistical significance of the results produces rigorous statements about SPRC's prevalence and allows consolidating conclusions about degradation and regeneration trends. The Mann-Whitney U test helps quantifying the rate of these processes, a key aspect for promoting or consolidating land use policies. For example, where regeneration is taking place at a fast rate, current restoration plans will be underpinned. Slow degradation will require less urgent actions than fast degradation.

Table 1 shows the results of the Mann-Whitney U test for China drylands.

Statistically significant results account for half of the cases. For

these the null hypothesis is rejected and consequently the rate of land degradation and regeneration are different. More specifically, degradation is slower than regeneration in the five significant cases.

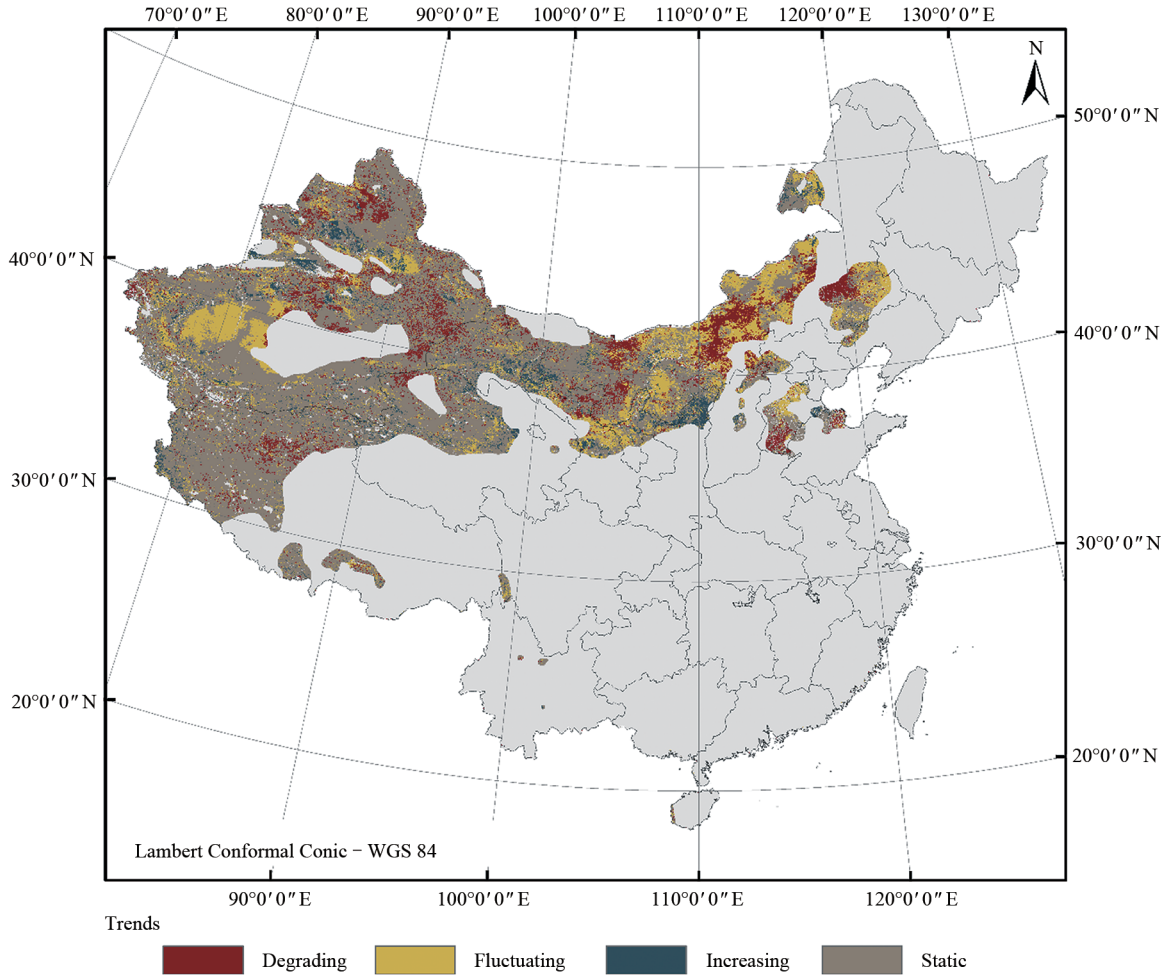


Fig.3 Land condition trends for PEDC after 2dRUE implementation

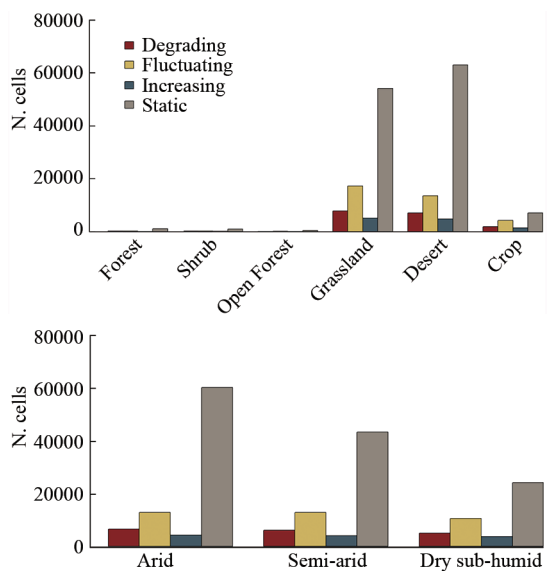


Fig.4 Distribution of vegetation temporal trends by land cover type (above) and aridity levels (below) for PEDC.

Those are three land cover types, including the largest (grassland) and two aridity levels.

The medians of SPRC included in this analysis ranged from -0.620 to -0.680 (*Degrading*) and from 0.676 to 0.703 (*Increasing*) standard deviation units of time to change NPP in one standard deviation unit. In all the cases, including those where no significant differences were found (except the Arid climate class), their absolute value was lower for *Degrading* than for *Increasing* trends, thus supporting the notion that the latter is a faster process.

4 DISCUSSION

The immediate finding from the results above is that degradation occupies more territory but operates slower than regeneration. The statement seems consistent with the results revealed by the Bulletin of Status Quo of Desertification and Sandification in China (2011), which indicates that desertification keeps falling off by total acreage of but kept expanding in partial locations. Discrepancies may be in land cover consideration, as such results mainly reflect abrupt land cover changes between desertified and non-desertified land, while our study could depict degradation and regeneration even where no land cover change were observed. This should be considered as a new insight beyond the cited Bulletin.

Table 1 Differences in absolute values of standard partial regression coefficients (SPRC) for degrading (*Deg*) and increasing (*Inc*) trends, by land cover and aridity classes within the PEDC area: results of Mann–Whitney U tests. Determination is based on the *U* statistic. Significant cases ($p \leq 0.10$) are marked by ***. Differences are interpreted using Mean ranks, a measure of the mean place in increasing order of a random observation of *Deg* or *Inc* for a given case. Medians of SPRC are provided for reference

	Sample size		Mean rank		<i>U</i> statistic	<i>p</i>	Median	
	<i>Deg</i>	<i>Inc</i>	<i>Deg</i>	<i>Inc</i>			<i>Deg</i>	<i>Inc</i>
Land cover								
Forest	19	6	12.2	15.7	41.0	0.333	-0.641	0.703
Shrub	27	17	20.4	25.8	174.0	0.181	-0.647	0.684
OpenForest	6	10	15.5	4.3	22.0	0.428	-0.620	0.698
Grassland	746	524	571.7	726.4	147835.0	***	-0.626	0.676
Desert	676	454	542.3	600.1	137761.0	***	-0.668	0.684
Crop	165	133	134.3	168.4	8457.5	***	-0.635	0.690
Aridity								
rid	579	414	494.3	500.8	118274.5	0.723	-0.680	0.678
SemiArid	586	388	430.3	573.9	80159.0	***	-0.630	0.686
DrySubHumid	474	342	365.7	467.8	60785.0	***	-0.626	0.677

Our mixed results are in line with Li, et al. (2015) who report that China Drylands have already become unsustainable. The reasons of this trend rely in a complex matrix of land use changes that

Specifically, urban area increased by 68.57% from 1990 to 2005, reaching 13.57 thousand km² (Liu, et al., 2014) and is likely to increase by more than 25% between 2005 and 2030 (Huang, et al., 2014). Cropland decreased in the south (due to built-up land expansion) and increased in the north (comparative advantages, the introduction of cold-tolerant rice varieties and irrigation facilities, converted large areas of dry lands to paddy rice lands), with the total area remaining essentially unchanged.

Fast rates of increasing trends are usually associated with land use transformation. The effect of water in barren lands gives as a result landscape greening. These anomalies are well documented in several cases around the world (del Barrio, et al., 2010; Hill, et al., 2010; Zucca, et al., 2012; Del Barrio, et al., 2016). In the case of China the use of aquifers to transform desert land into crops implies groundwater depletion at a rate of 8.3 ± 1.1 km³/yr (Feng, et al., 2013) placing the country in the first positions of the world ranking of ground water depletion (Dalin, et al., 2017). Hence, the massive extraction of water from aquifers is greening the landscape and declining water table in much of northwest China (Danfeng, Dawson and Baoguo, 2006; Zhang, et al., 2014).

In parallel, the impact of ecological conservation programs has resulted on a significant increase of forest areas and has inhibited part of the degradation of natural grassland. Whilst NPP of semi-arid grasslands in North China has been reported to decrease from 341.30 Tg C to 305.54 Tg C (Tian and Qiao, 2014), our results are consistent with an incipient reversion of grassland degradation after extensive conservation initiatives by the Chinese government.

These results may also help to document a possible case of hysteresis. This pattern arises when forward and backward switches occur at different critical conditions (Scheffer, et al., 2001). Consequently, degradation and restoration could elapse between alternative stable states. The existence of different rates of change for degradation and restoration suggests alternative paths between these states, a hallmark of hysteresis.

Indeed, we may be comparing different sections of the curves,

has been analyzed with detail by Liu, et al. (2014). They highlight that land-use intensification in China continued to increase during the two recent decades.

and rates discrepancies can be attributed to changes in the slopes. For supporting hysteresis, further work should be done on explicit land degradation and regeneration curves. For doing that, more data are needed to fit proper curves that would depict the shape of the processes.

5 CONCLUSIONS

This study aimed at obtaining quantitative results on land degradation and regeneration rates in the PEDC, by applying a stepwise regression to estimate separately the effects of aridity and time on vegetation. Both the basic method and the input data were already consolidated in the literature, and the main aspect here was the statistical comparison of intensities between degradation and greening-up processes.

Active degradation trends were found in 292,896 km² (9.12% of PEDC), whilst greening-up trends were detected in 194,560 km² (6.06%). However, the latter trends were found to be significantly faster in three land cover types (grassland, desert and croplands), and

Two aridity levels (semi-arid and dry sub-humid). The emerging fact that active degradation occupies more extent, but regeneration is a faster process was consistent with published accounts.

This study does not enter to explain the underlying patterns of those findings, because of the size and complexity of the study area (whole PEDC). Rather, it provides with an opportunity for subsequent detailed studies dealing with concrete land degradation / greening-up syndromes in areas that should be now easier to stratify.

In the opposite end of spatial scale, we believe this study provides with a basis for an estimate of Indicator 15.3.1 (Proportion of land that is degraded over the total land area) of the Sustainable Development Goals initiative. That indicator is innovative because it accounts for both states and trends of land degradation, for which our approach provides with concrete results.

Finally, an extension of the analysis presented here to other re-

gions of the world is feasible, as SPRC are surrogates of 2dRUE tool. This is a low-cost methodology that uses open-access data and cover large areas. It has been already implemented in Iberia, the Maghreb, Sahel, north-eastern Brazil, and Mozambique. Additionally, it has been officially adopted by Portugal (Rosario, et al., 2015) and Spain (Sanjuan, et al., 2014) to report regularly to the UNCCD Strategic Objective 2 about progress indicators dealing with ecosystem condition.

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