

ANALYSIS OF SPATIAL AND TEMPORAL EVOLUTION OF THE NDVI ON VEGETATED AND DEGRADED AREAS IN THE CENTRAL SPANISH PYRENEES

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ABSTRACT:

The temporal evolution of vegetation activity on various land cover classes in the Spanish Pyrenees was analyzed. Two time series of the normalized difference vegetation index (NDVI) were used, corresponding to March (early spring) and August (the end of summer). The series were generated from Landsat TM and Landsat ETM+ images for the period 1984-2007. An increase in the NDVI in March was found for vegetated areas, and the opposite trend was found in both March and August for degraded areas (badlands and erosion risk areas). The rise in minimum temperature during the study period appears to be the most important factor explaining the increased NDVI in the vegetated areas. In degraded areas, no climatic or topographic variable was associated with the negative trend in the NDVI, which may be related to erosion processes taking place in these regions.

1. INTRODUCTION

Maps of active erosion areas and areas at risk of erosion are of great potential use to environmental agencies (governmental and private), as such maps allow erosion prevention efforts to be concentrated in places where the benefit will be greatest. There is no single straightforward method for assessing erosion, as erosion is highly dependent on the spatial scale and the purpose of the assessment (Warren, 2002). Methods for evaluating erosion risk at catchment and regional scales (10-10,000 km²) include the application of erosion models, or qualitative approximations using remote sensing (RS) and geographic information system (GIS) technologies. RS and GIS techniques have been shown to be of potential use in erosion assessment at regional scales, including the identification of eroded surfaces, estimation of factors that control erosion, monitoring the advance of erosion over time, and investigating vegetation characteristics and dynamics (Lambin, 1996).

Various studies have identified changes in vegetation dynamics at continental, regional, and local scales in recent decades. Most changes have been caused by human activity, particularly deforestation and forest fires (Riaño et al., 2007), but land marginalization and rural abandonment have contributed to natural revegetation processes in some regions (Vicente-Serrano et al., 2004). However, numerous reports have found a general increase in vegetation activity in various ecosystems of the world, suggesting that the principal causes of changes in vegetation dynamics are variations in precipitation and/or temperature (Delbart et al., 2008).

Changes in vegetation in the Mediterranean region have followed very different patterns. In general, vegetation growth tends to be favored by increased temperature in areas where water is not a limiting factor (Martínez-Villalta et al., 2008). Studies in the Spanish Pyrenees (Lasanta and Vicente-Serrano, 2007) have investigated spatial and temporal variations in vegetation cover at regional and local scales to i) assess changes in the vegetal cover in the last 50 years; ii) detect trends in the global vegetation biomass; iii) explore changes in leaf activity in forest regions; iv) detect the climate drivers (temperature and precipitation) and spatial patterns of aridity;

and, v) to determine the effects of human land uses. All previous studies have focused on well-vegetated areas, and very few reports have analyzed spatial and temporal variations in vegetation cover on active erosion areas and erosion risk areas, where vegetation is sparse. Badlands are usually defined as intensely dissected natural landscapes where vegetation is scanty or absent. Alatorre and Beguería (2009) identified active erosion and erosion risk areas in a badlands landscape of the Spanish Pyrenees using RS techniques. The presence of bare soil surfaces and the large size of badlands enabled good discrimination using RS data. However, the erosion risk areas surrounding badlands, coinciding with the transition zone from badlands to scrubland or forest, were characterized by poor vegetation cover (10-50%). For this reason, the analysis of vegetation dynamics on active erosion and erosion risk areas is very relevant to the design of measures for the mitigation and remediation of soil erosion and sediment transfer.

The objectives of this study were i) to obtain time series of vegetation activity during two contrasting periods of the growth cycle (early spring and the end of summer) for various land cover classes, including both well-vegetated and degraded areas; ii) to determine the extent by which climate controlled vegetation activity in the various land cover classes, and to define temporal trends; and, iii) to analyze the spatial distribution of trends in vegetation activity on erosion risk areas, as indicators of recovery and degradation, and to quantify the effects of various topographical factors on such trends.

2. STUDY AREA

The study area, located at 620-2,149 m altitude approximately 23 km north of the Barasona Reservoir (Spanish Pyrenees), is an integrated badlands landscape orientated northwest-southeast and developed on Eocene marls (Fig. 1A and B). A land cover map based on the supervised maximum likelihood method (Alatorre and Beguería, 2009) showed that the study area is occupied by five principal land cover categories: badlands, 19 km² (8.0%); coniferous forest, 65 km² (28.0%); deciduous forest, 21 km² (9.0%); grassland, 32 km²

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(13.0%); and scrubland, 99 km² (42.0%). The spatial distribution of land cover showed that the areas occupied by scrub and the grass border areas could be classified as badlands (Fig. 1C). This spatial distribution suggested that a progressive transition between eroded areas and forest (Fig. 1C). In the same study, a map of the active erosion (badlands) and erosion risk areas was obtained, with the surface areas of these classes comprising 17 km² and 49 km², respectively (Fig. 1D). The surface area of the active erosion region was the same as that obtained from a land cover map generated using the supervised maximum likelihood method. The badlands system comprises a group of typical hillside badlands developed on sandy marls with clay soil, and is strongly eroded over convex hillsides with moderately inclined slopes. Visual comparison of maps showed that the erosion risk areas corresponded principally to the scrubland class (and in some cases the grassland and conifer classes) bordering the badland areas. These areas had spectral characteristics intermediate between badlands and scrubland, indicating either a mixture of classes within a pixel or an intermediate level of degradation (for more details of the study area please see, Alatorre and Beguería, 2009).

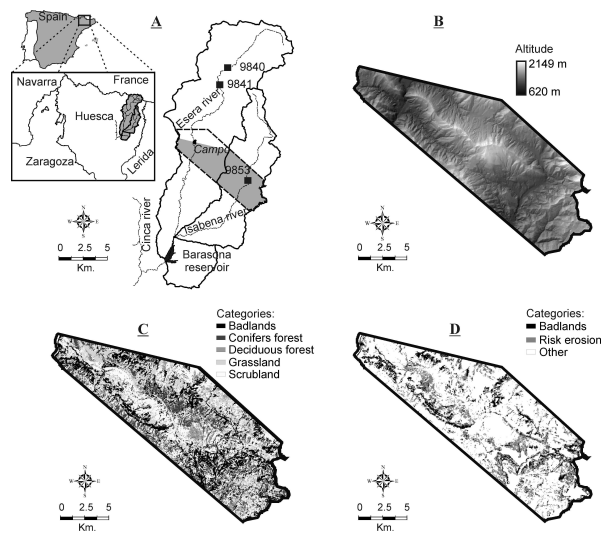


Figure 1. A) Location of the study area: i) subset area indicates the location of badland areas on marls (236 km²); ii) the gray zone indicates the area of the Landsat scene; iii) the black squares indicate the location of meteorological observatories of the National Agency of Meteorology. B) Digital terrain model (DTM). C) Land cover map based on supervised classification using the maximum likelihood method and the maximum probability classification rule (Alatorre and Beguería, 2009). D) Erosion risk maps (Alatorre and Beguería, 2009).

3. DATA AND METHODS

3.1 Data selection and preparation

A database of Landsat TM and Landsat ETM+ images for the period 1984–2007 was used. The database comprised 28 images, 16 of which were from a summer time series and 12 from a spring time series. The two time series were used to identify possible differences in vegetation dynamics as a function of seasonal differences in vegetation activity, and to assess with more robustness any spatial and temporal patterns in vegetation activity. Table 2 shows the dates of the images used in each time series. The database was processed using a procedure that

included calibration and cross calibration of the images (for more details please see, Alatorre and Beguería, 2009). The procedure allowed accurate measurements of physical surface reflectance units to be obtained. The correction applied to the images guaranteed the temporal homogeneity of the dataset, the absence of artificial noise caused by sensor degradation and atmospheric conditions, and spatial comparability among different areas, given the accurate topographic normalization applied. Details of the correction procedure applied to the images, and a complete description of the dataset and its validation have been described by Vicente-Serrano et al. (2008).

Time series of the normalized difference vegetation index (NDVI) were obtained from the original Landsat TM and Landsat ETM+ images, for the purpose of monitoring vegetation activity. The NDVI was computed as (Rouse et al., 1974):

$$NDVI = \frac{\rho_{IR} - \rho_R}{\rho_{IR} + \rho_R} \quad (1)$$

where ρ_{IR} is the reflectivity in the near-infrared region of the electromagnetic spectrum and ρ_R is the reflectivity in the red region. Several studies have demonstrated a strong relationship of the NDVI to the fraction of photosynthetically active radiation, the vegetation biomass, the green cover, and the leaf area index. Hence, high NDVI values are indicative of high vegetation activity. A land cover map comprising the major vegetation types in the study area was also used, as well as a map of active erosion areas (badlands) and areas at erosion risk (Alatorre and Beguería, 2009).

March		August	
Acquisition date	Sensor	Acquisition date	Sensor
03/11/1989	TM	08/20/1984	TM
03/30/1990	TM	08/07/1985	TM
03/06/1993	TM	08/13/1987	TM
03/09/1994	TM	08/02/1989	TM
03/28/1995	TM	08/24/1991	TM
03/17/1997	TM	08/10/1992	TM
03/20/1998	TM	08/29/1993	TM
03/23/1999	TM	08/03/1995	TM
03/17/2000	ETM+	08/24/1997	TM
03/10/2003	ETM+	08/14/1999	TM
03/07/2005	TM	08/08/2000	ETM+
03/13/2007	TM	08/26/2001	ETM+
		08/30/2002	ETM+
		08/27/2004	TM
		08/18/2005	TM
		08/01/2006	TM

Table 2. Dates for the Landsat 5 TM and 7 ETM+ images used in the study.

To analyze climate effects on the vegetation activity we used a database consisting of three daily rainfall series from the National Agency of Meteorology, comprising data since January 1984 (Fig. 1A). To guarantee the quality of the dataset the series were checked using a quality control process that identified anomalous records and analyzed the homogeneity of each series (for more details see Vicente-Serrano et al., 2009). Daily temperature data were obtained for the same period from the Serraduy station (Fig. 1A), and these were also checked for possible temporal inhomogeneities. The time series of precipitation totals and maximum/minimum temperature averages were computed from the original daily series by aggregating the original daily values over the period immediately before the images were taken. Thus, climatological series were computed for the following time periods prior to the date of the image: 15 days, 30 days, 3 months (January, February and March for the March images; June, July and August for the August images) and 6 months (October to March, and March to August, respectively). A series of

topographical variables was also analyzed to assess their effects on vegetation activity. This involved use of a digital terrain model (DTM) with a spatial resolution of 20 m to derive the slope gradient (m m^{-1}), as some studies have shown that this can be a major factor explaining rates of vegetation recovery (Pueyo and Beguería 2007). We also derived a model of the incoming solar radiation ($\text{MJ m}^{-2} \text{ day}^{-1}$) to assess topographic control of the energy balance, using an algorithm that includes the effect of terrain complexity (shadowing and reflection) and the daily solar position (Pons and Ninyerola, 2008).

3.2 Statistical analysis

The temporal series of NDVI for each land cover class was checked for temporal trends using the Spearman's correlation test against time. This enabled analysis of the vegetation dynamics in terms of increased (positive correlation) and decreased activity (negative correlation). The significance of the trends was checked using the p value associated with the Spearman's rho statistic.

The Spearman's test enables detection of temporal trends in the NDVI series, but does not identify the driving factors involved. To determine the control exerted on vegetation activity by climate, and to isolate climate from other factors, we performed a multivariate regression analysis of the average NDVI values in March and August for the various land cover classes against the climatic variables. As a preliminary step we undertook a correlation analysis to determine the most appropriate time span for the climatologic time series. For both the March and August images we found that the climatological series computed for the 3 months prior to the images had the greatest correlation with the NDVI. Therefore, we used the time series of cumulative precipitation and average maximum/minimum temperature for the 3 months before the acquisition date as covariates in the regression analysis.

As the acquisition date of the images did not coincide among years, which could have affected the NDVI (especially in March, which is very close to the start of the growing period), we also introduced the Julian day of the image as a covariate. To check for temporal trends in the NDVI values that were not explained by variability of the climatic factors and the acquisition date of the images, we also incorporated the year of acquisition of the image as a covariate.

We used a backward stepwise procedure based on the Akaike's information criterion statistic (AIC), as implemented in the function `stepAIC` in the R package for statistical analysis (R Development Core Team, 2008). This function aided identification of the significant explanatory variables for the time evolution of the NDVI for the various land cover classes. The data analysis was based on the goodness of fit and statistical significance of the regressions, the explanatory variables selected, and the beta (standardized) regression coefficients.

To provide a spatially distributed analysis, the multivariate regression analysis was repeated on a pixel-by-pixel basis for the erosion risk areas alone. This enabled mapping of the spatial distribution of NDVI trends not explained by climatologic factors, and thus identification of areas undergoing processes of degradation or recovery. Finally, a correlation analysis was performed on the NDVI trends against various topographical factors (elevation, slope gradient and potential incoming solar radiation), and a bootstrap procedure was used to determine the statistical significance of the correlations. Thus, 1,000 repetitions of the correlation analysis were performed on random samples containing approximately 1% of the pixels

belonging to the erosion risk class, and the resulting significance statistics (p values) were averaged. This enabled avoidance of a sample size effect that would arise if all the pixels of the erosion risk class (approximately 45,000) were introduced together in the analysis, causing the significance test to become over sensitive and thus unreliable.

4. RESULTS AND DISCUSSION

4.1 Temporal variation of the NDVI over all land cover categories, 1974-2007.

The temporal variation of the mean NDVI values in March and August was assessed for each land cover category (Fig. 2, Table 2). In both time series there was a clear difference between the vegetated categories (deciduous and coniferous forests, grassland and scrubland) and degraded areas (badlands and erosion risk areas). The vegetated areas had higher NDVI values, and the greatest average NDVI values occurred in August. The NDVI values in March showed positive temporal trends (i.e., the average NDVI increased with time) for all vegetated classes, particularly for deciduous and coniferous forests where the trends were almost significant at the $\alpha = 0.05$ level. Nevertheless, the increase in the NDVI was not constant, and in some years (e.g., 1997 and 2003) a decrease in the average NDVI was detected relative to the general trend (Fig. 2). The NDVI values in August did not show significant temporal trends for any vegetation class. These results suggest an increase in vegetation activity during the study period, especially in March, when the conditions for growth are best.

The degraded areas (badlands and erosion risk areas) had the lowest average NDVI values, which differed little between March and August because of the very low vegetation cover (Table 2). The NDVI trends were negative in both March and August, and were stronger in the erosion risk areas, for which statistical significance was found in the August time series. This may indicate the presence of a degradation process, such as soil erosion, in these areas.

These results suggest that the occurrence of contrasting temporal trends in the overall area depends on the nature of the land cover, with well-vegetated areas undergoing an increase in vegetation activity and degraded areas suffering a process of further degradation. However, the time variability of the NDVI may also be explained by the evolution of climatic conditions, as discussed below.

4.2 Regression analysis of NDVI versus climatic variables

Regression analysis helped explain the observed NDVI temporal patterns of the various land cover classes. The regression models generally fitted the observed NDVI values well, although for pastures, badlands, and erosion risk areas in March, the model results were slightly below the confidence level (Table 3). A better fit was obtained in March for well-vegetated areas (pine and deciduous forests, and scrubland) than for less vegetated regions (pastures, badlands, and erosion risk areas), as shown by the lower R^2 values. In August the goodness-of-fit was similar for all land use classes (Table 6). In all models one or more climatic variables were identified as significant, indicating that climatic conditions were important in explaining the evolution of vegetation activity.

Land cover class	March				August			
	NDVI mean	sd	rho	p-value	NDVI mean	sd	Rho	p-value
Deciduous forest	0.63	0.10	0.517	0.0862	0.65	0.11	0.321	0.224
Conifers	0.56	0.12	0.573	0.0538	0.61	0.12	0.168	0.520
Grassland	0.49	0.11	0.336	0.281	0.55	0.15	-0.0265	0.926
Scrubland	0.50	0.11	0.294	0.348	0.52	0.13	-0.0899	0.741
Risk erosion areas	0.48	0.11	-0.196	0.543	0.50	0.14	-0.594	0.0173
Badlands	0.42	0.12	-0.0420	0.904	0.41	0.16	-0.250	0.349

Table 3. NDVI values and temporal NDVI trends (Spearman's rho correlation with time and significance) for each land use category for March and August.

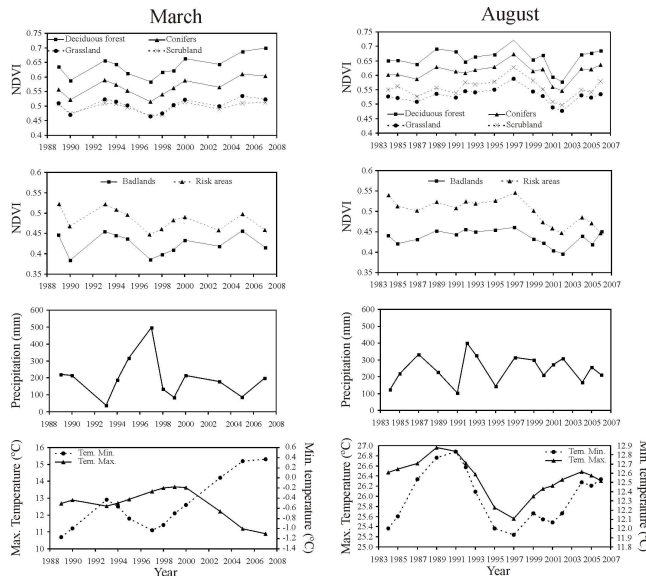


Figure 4. Temporal evolution of the mean NDVI values for March and August between the categories of land cover map and erosion risk areas.

	Pine forest	Deciduous forest	Scrubland	Pastures	Erosion risk	Erosion (badlands)
R ²	0.743	0.779	0.615	0.424	0.467	0.547
p-value	0.002	0.001	0.045	0.084	0.150	0.082
Residual standard error	0.561	0.520	0.728	0.839	0.856	0.789
Beta coefficients:						
Precipitation	-0.317	--	-0.298	--	--	--
T max	--	--	--	--	--	--
T min	0.683	0.678	0.371	1.11	0.701	0.716
Julian day	--	-0.310	-0.326	--	-0.377	-0.457
Time (year)	--	--	--	-0.705	-0.845	-0.719
Temporal trend (change in NDVI):						
per year	--	--	--	0.00216	-0.00433	-0.00326
period 1989-	--	--	--	-4.03%	-7.91%	-6.02%
2007						

Table 5. Regression analysis of NDVI values for March in relation to climatic conditions.

	Pine forest	Deciduous forest	Scrubland	Pastures	Erosion risk	Erosion (badlands)
R ²	0.599	0.591	0.663	0.640	0.681	0.663
p-value	0.028	0.031	0.004	0.005	0.003	0.004
Residual standard error	0.739	0.747	0.649	0.671	0.632	0.649
Beta coefficients:						
Precipitation	-0.325	-0.421	--	--	--	--
T max	-1.59	-1.45	-1.66	-1.62	-1.23	-1.50
T min	1.31	1.34	1.21	1.09	0.806	1.42
Julian day	--	--	--	--	--	--
Time (year)	-0.481	-0.507	-0.688	-0.646	-1.000	-0.789
Temporal trend (change in NDVI):						
per year	--	-0.00247	-0.00241	--	--	-0.00210
period 1984-	0.00197	-5.53%	-5.40%	0.00244	0.00363	-4.72%
2006	-4.43%					

Table 6. Regression analysis of NDVI values for August in relation to climatic conditions.

However, there were differences between March and August, as well as between land cover classes. In March the average minimum temperature was the most important explanatory factor, as evidenced by the fact that this parameter had the

largest (standardized) beta coefficient. The effect of the minimum temperature was positive in all cases, with high minimum temperatures yielding elevated NDVI values. This reflects the importance of relatively warm weather at the end of winter/early spring, at the start of the growing period. The maximum temperature was not a significant explanatory factor for any land use class, and cumulative precipitation was significant in only a few cases (pine forest and scrubland). Counter-intuitively, cumulative precipitation had a negative effect on the NDVI (i.e., greater precipitation resulted in lower NDVI), as shown by the negative signs of the beta coefficients. The time of acquisition of the image (variable = 'day') was significant in March for all land cover classes except for pine forest and pasture, suggesting the relevance of the phenological state of vegetation at this time of the year. In August the average minimum temperature was also significant (positive) for all land cover classes, but the most important explanatory factor was the average maximum temperature. This showed the highest absolute beta coefficient and a negative effect in all cases, meaning that a warm summer resulted in lower NDVI values. Cumulative precipitation was significant only for the pine and deciduous forests, where it also had a negative effect on the NDVI. The time of acquisition of the image had no significant effect for any land cover class.

Having thus explained the climatic and phenological effects on NDVI, we proceeded to identify temporal trends in NDVI values for some land cover classes (Tables 3 and 4). Negative time trends were found only in March, for pastures, badlands and erosion risk areas, representing a decrease in the NDVI of 4-8% in the period 1989-2007. Negative time trends were found in August for all land cover classes, and showed a similar range in the period 1984-2006. The magnitudes of the negative trends were similar for all land cover classes with one exception. Erosion risk areas showed the highest values (around 8%) in both March and August.

The results of regression analysis enabled interpretation of the observed temporal patterns in the NDVI (Fig. 2). The apparent upward trend in the NDVI in well-vegetated areas in March can be explained by a similar trend in the average minimum temperature. A downward trend in the NDVI in erosion risk areas was also evident, but was not clearly related to the temporal evolution of any climatic variable.

These results are in agreement with the evolution observed in the western Spanish Pyrenees. Vicente-Serrano et al. (2004) found a general positive trend in the NDVI for forests and well-developed vegetated areas, which was related to an increase in annual mean temperature, and to patterns of land abandonment and natural revegetation processes. In the present study we also found a positive trend in the NDVI for vegetated areas, and showed that the maximum and minimum temperatures in the 3 months before the Landsat images were taken exerted an opposite influence on the NDVI, and that this effect varied during the year.

The finding that cumulative precipitation had a negative effect on the NDVI was puzzling; a positive effect was expected. This anomaly can be explained by the facts that i) water availability is not a limiting factor for vegetation growth in the study area, which receives an average of around 900 mm year⁻¹, predominantly in winter and spring; and, ii) the amount of precipitation is well-correlated with cloud cover in the region, with rainy periods resulting in reduced incoming solar radiation, which rises on clear days. It is well known that precipitation level ceases to be a limiting factor for vegetation growth in humid regions, where competition for space and solar radiation is more important. Several studies have documented saturation of the NDVI in relation to precipitation in humid

areas (Santos and Negrín, 1997). In such regions the typically nonlinear relationship between precipitation and vegetation activity could explain the absence of a significant positive effect, but not the presence of a negative effect, as found in our study. However, the second explanation (cloud cover) could assist in an explanation of our data. Unfortunately, neither cloud cover nor terrestrial incoming radiation time series was available, so this hypothesis could not be tested.

In studies of smaller areas, similar NDVI trends in vegetation evolution have been observed, but human impact has been included among the explanations. The presence of a residual temporal trend in NDVI values following removal of climatic influences is usually considered to constitute evidence that other factors, such as human land use practices, are affecting vegetation activity. In the present study we found significant downward trends in all land cover classes in August. Given the low intensity of land use in the region, attribution of these trends to human causes is difficult. Additionally, positive NDVI trends were found in March, which can be explained by the positive evolution of minimum temperatures. Thus, an early start to the growth period, plus increased vegetation activity during spring and early summer, could cause greater stress on vegetation in August. Following exclusion of climatic effects, downward trends in the NDVI were found in March and August for pastures and badland areas, particularly in erosion risk regions. This could be a sign of degradation in such areas because a decrease in the (already low) vegetation activity in the study area has been correlated with soil erosion processes (Alatorre and Beguería, 2009). In erosion risk areas the relative effect of the temporal trend was greater than the effect of any climatic variable, and consequently this land cover type was the only class exhibiting an overall downward trend in the NDVI. As this land cover class includes very sensitive areas that are at risk of loss of all vegetation cover, thus becoming badlands, we focused further on factors that have contributed to this degradation.

4.3 Spatial distribution of positive and negative NDVI trends in erosion risk areas

The downward trend in NDVI for erosion risk areas in March and August could not be explained by climatic factors, and suggested the involvement of degradation processes including active erosion or lateral expansion of existing badlands. This possibility motivated a detailed assessment of the spatial distribution of NDVI trends in erosion risk areas.

Following removal of climatic influences, the spatial distribution of positive and negative trends in the NDVI of erosion risk areas was similar in March and August, indicating that the process is quite consistent and not merely attributable to seasonal effects (Fig. 7). Negative NDVI trends predominated in both images, indicating the occurrence of degradation processes in these areas. However, there were regions in which positive trends dominated, especially in the March image. The proportion of statistically significant trends increased in August, because of an increase in stress conditions, which predominated in this month.

Mapping of trend values on a pixel-by-pixel basis enabled assessment of the importance of particular topographical conditions on the presence of degradation or recovery processes. In March a positive but not statistically significant ($p = 0.283$) relationship was found between the NDVI trend and elevation (Fig. 8). This may be related to the location of the badland areas; these predominate in the bottom of the Eocene depression, in contrast to forested areas, which are mainly found on slopes. A negative but not significant ($p = 0.364$)

correlation was found between the NDVI trend and the slope gradient, suggesting an association of steeper slopes with more negative trends. This association could be related to the known positive influence of slope gradient on the activity of erosion processes. Similar results were obtained with the August images (Fig. 4), although the relationships with elevation and slope gradient were weaker ($p = 0.447$ and $p = 0.416$, respectively).

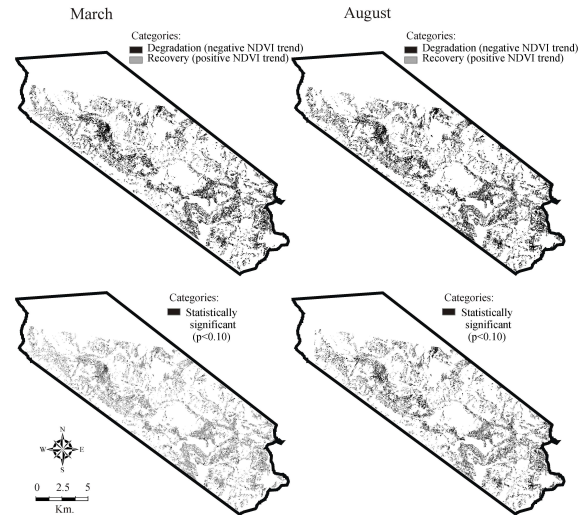


Figure 7. Spatial distribution of the NDVI trends for March and August in erosion risk areas after climatic forcing was accounted for: sign of temporal trend (above) and significance (below).

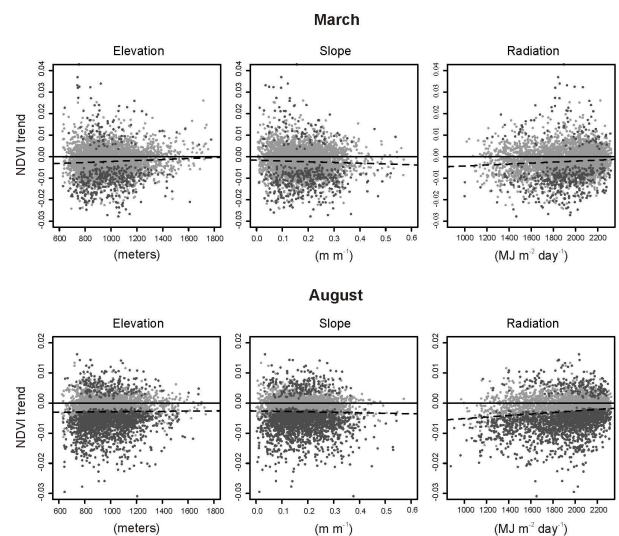


Figure 8. Correlation between the NDVI trends for March and August in the erosion risk areas and topographic variables (after climatic forcing was accounted for). Results are shown for a random sample containing 10% of the original pixels. The black dots indicate pixels with statistically significant trends.

With respect to the potential solar radiation, stronger positive correlations with NDVI trends were found in both the March ($p = 0.133$) and August ($p = 0.0345$) image series, suggesting that degradation processes were preferentially occurring on shady (north-facing) slopes. This is consistent with previous research on the topographical signature of badlands in the Spanish Pyrenees, which has revealed that such regions occur predominantly on shady slopes (Alatorre and Beguería, 2009), and are associated with mechanical weathering processes

related to frost and thawing cycles, which are stronger on north-facing slopes (Nadal-Romero et al., 2007). Our results show that the topographic influences on recovery processes are opposite in well-vegetated areas compared to regions undergoing erosion processes.

5. CONCLUSIONS

We analyzed the temporal evolution of vegetation activity on vegetated and degraded surfaces in a small area of the central Spanish Pyrenees over the period 1984-2007. Two map series of the normalized difference vegetation index (NDVI) were obtained from a series of homogenized Landsat TM and Landsat ETM+ images for the months of March and August. This enabled analysis of the spatial and temporal dynamics of vegetation activity in well-vegetated areas (forests and dense scrubland) and degraded areas affected by erosion processes (badlands and risk erosion areas). Temporal NDVI trends were identified for each land cover class using multivariate regression analysis, which incorporated the time evolution of climatic factors (precipitation, and minimum and maximum temperature). Seasonal differences were expected in the spatial pattern of vegetation activity and vegetation recovery processes, as a consequence of the climatic seasonality of the region and the large differences in water availability between spring and summer (vegetation in the latter season is commonly affected by a high level of water stress). The results obtained could have been affected by the heterogeneity of land use and the nature of land covers selected, because this mountainous area is complex and exhibits great spatial diversity. Nevertheless, at the Landsat image spatial resolution (30 m), both land cover and land use were well-represented in the maps. Assignment to class based on the most representative category, by surface area, in a 30 m pixel size could introduce some errors, but it was necessary to guarantee an effective spatial comparison between the NDVI dataset and categorical information. Moreover, the results were spatially consistent, and clear NDVI patterns that coincided with the spatial distribution of land use and land cover were evident. In summary, this study demonstrated that, in a representative mountainous area of the central Spanish Pyrenees, there has been a significant increase in vegetation activity in the last 24 years, which is largely explained by an increase in the minimum temperature. Conifers and deciduous forest have shown the greatest increase in vegetation activity, whereas the increase in activity of grasslands and scrublands has been moderate. Moreover, in active erosion and erosion risk areas, extreme environmental conditions, which accelerate erosion processes, have restricted vegetation recovery processes over this time period.

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