**Evolution of vegetation activity on vegetated, eroded, and erosion risk
areas in the central Spanish Pyrenees using multitemporal Landsat
imagery**

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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 and the time variation of the cloud cover during the study period appears to be the most important factors explaining increased NDVI in the vegetated areas. In degraded areas, no climatic or topographic variable was associated with the negative NDVI trend, which may be related to erosion processes taking place in these regions.

Keywords: Landsat, NDVI, Spanish Pyrenees, vegetation activity, erosion risk areas.

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). On a limited spatial scale (less than 100 ha), field surveys can provide an accurate means of analyzing erosion damage. However, approaches that integrate available spatial data need to be applied to focal area selection over larger surfaces. Studies of erosion at spatial scales covering local to regional areas have provided both quantitative (*e.g.*, erosion rates) and qualitative (*e.g.*, erosion risk areas; Vrieling et al., 2006) information.

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 and geographic information system (GIS) technologies. Merritt et al. (2003) provided extensive descriptions of current erosion models. However, in most cases such models have been created for use at small scales, and extrapolation to larger scales (catchment and regional) is very complex and occasionally leads to errors (Kirkby et al., 1996). Remote sensing 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 (Muchoney and Haack, 1994; Lambin, 1996).

Vegetation dynamics play an important role in assessment of environmental processes because of the strong relationships between the biosphere and global parameters including atmospheric CO₂ concentration (Braswell et al., 1997; Zeng et al., 1999), the influence of vegetation on the hydrological cycle at local scales (Beguería et al., 2003; Serrano-Muela et al., 2008), landscape structure and diversity (Kammerbauer and Ardon 1999; Olsson et al., 2000), and erosion and sediment transport (García-Ruiz et al., 1995).

Various studies have identified changes in vegetation dynamics at continental (Slayback et al., 2003; Delbart et al., 2006), regional, and local scales (Andreu et al., 2007; Martínez-Villalta et al., 2008) in recent decades. Most changes have been caused by human activity, particularly deforestation (Achard et al., 2002; DeFries et al., 2002) and forest fires (Giglio et al., 2006; Riaño et al., 2007), but land marginalization and rural abandonment have contributed to natural revegetation processes in some regions (Sluiter and de Jong, 2007). However, numerous reports have found a general increase in vegetation activity in various ecosystems of the world (Myneni et al., 1998; Kawabata et al., 2001; Lucht et al., 2002), suggesting that the principal causes of changes in vegetation dynamics are variations in precipitation and/or temperature (Peñuelas and Filellas, 2001; Nemani et al., 2003; Delbart et al., 2008).

Regional and local factors affecting vegetation dynamics must be considered in addition to the influence of climate. Spatial differences in the rate of vegetation change have been shown to be dependent on topographical conditions (Florinsky and Kuryakova, 1996; Pueyo and Beguería, 2007), soil type (Farrar et al., 1994), human management, land use (Stohlgren et al., 1998), and geomorphological processes including soil erosion.

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 (Andreu et al., 2007; Martínez-Villalta et al., 2008). Declines in forest activity and growth in other regions have been related to recent climatic trends (Maselli, 2004; Sarris et al., 2007). In mountainous areas of the Mediterranean basin the pattern is very complex as a consequence of the diversity of land uses and the interaction of environmental and microclimatic factors (McDonald et al., 2000; Sluiter and De Jong, 2008). Studies in the Spanish Pyrenees (Vicente-Serrano et al., 2004; Vicente-Serrano et al., 2006a, 2006b; 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 (Gallart et al., 2002). Alatorre and Beguería (2009) identified active erosion and erosion risk areas in a badlands landscape of the Spanish Pyrenees using remote sensing techniques. The presence of bare soil surfaces and the large size of badlands enabled good discrimination using remote sensing 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%). Badlands in subhumid mountain areas are subject to greater denudation rates and more active dynamics compared with similar landscapes in arid or semiarid areas (Gallart et al., 2002; Regüés and Gallart, 2004). 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 controls 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 620–1,754 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, 1B). 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 (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 coniferous forest 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 (Alatorre and Beguería, 2009).

The soils in the study area are chromic vertisols with an A–B–C profile, an ochric surface horizon, and a C horizon that is typically greater than 1 m in depth. The original parent material is rich in calcium carbonate, which has accumulated in the form of nodules in the B and C horizons. A significant feature is the formation of cracks arising from shrinkage in the dry season, and these enable mixing of the upper horizon. Under natural conditions the soils are well protected by dense vegetation cover, although they are occasionally subject to piping and gully processes. Disturbance of vegetation cover leads to accelerated erosion and exposure of the underlying gray marls, which are highly erodible, and this in turn leads to formation of a badland morphology (Nadal-Romero et al., 2007, 2008).

The climate is defined as mountainous, humid and cold, with influences from the Atlantic Ocean and the Mediterranean Sea (García-Ruiz et al., 1985). The average annual temperature is 11°C and the average annual precipitation is approximately 876 mm. Precipitation is irregular throughout the year, with a maximum in spring between 180 (April) and 160 mm (May), and a minimum in July–August, when precipitation does not exceed 100 mm. Topography and altitude explain the high rainfall and low temperature of the area. Above 1,700 m precipitation in excess of 2,000 mm year⁻¹ is commonly recorded; periods without rain are rare and very short, resulting in correspondingly brief periods of water deficit. A large proportion of precipitation falls as snow, which persists for several months, as the 0°C isotherm is located at 1,650 m a.s.l.

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 1 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, atmospheric correction using a radiative transfer model (6S) that included external atmospheric information, a non-Lambertian topographic correction to avoid errors caused by differences in illumination conditions, and a relative normalization

between dates using an automatic procedure (Du et al., 2002). 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):

$$NDVI = \frac{\rho_{IR} - \rho_R}{\rho_{IR} + \rho_R} \quad \text{Eq. 1}$$

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. The NDVI is a measure of the photosynthetic capacity of the canopy (Ruimy et al., 1994) and the stomatal resistance with respect to water vapor transference (Tucker and Sellers, 1986). However, 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 (e.g. Tucker, 1979; Tucker et al., 1981; Sellers, 1985). 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).

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). Cloud cover data was obtained from the CRU TS3.0 dataset (CRU, 2010). 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 number of topographical variables were 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; Wittenberg et al., 2007). We also derived a model of the potential annual solar radiation ($\text{MJ m}^{-2} \text{ day}^{-1}$) to assess topographic control of the energy balance, using an

algorithm based on the topographical exposure to the solar beams including the effect of terrain complexity (shadowing and reflection) and the daily solar position (Pons and Ninyerola, 2008).

3.2. Role of climatic factors and time trends on the temporal variation of the NDVI

The existence of statistically significant time trends of NDVI has been used to detect processes of vegetation activity increase or decrease. However the vegetation activity (and hence the NDVI) is affected by a number of natural factors, mostly climatic, that also experience time variation. Therefore, when analyzing time series of NDVI it is important to account for the variance explained by those factors, in order to isolate the NDVI trends attributable to vegetation dynamics. Statistical tests based on the dependent variable alone such as the Man-Kendall's trend detection time series of the NDVI alone, such as the Mann-Kendall's trend detection test,, they do not identify the driving factors involved. As a consequence it is difficult to determine the existence of trends apart from those driving factors. Therefore, in order to determine the existence of temporal trends in the time series of mean NDVI values for each land cover class in March and August we performed a multivariate regression analysis against time (the year of acquisition of the images) and a set of climatic and astronomical covariates.

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, average cloud cover and average maximum and minimum

temperature during 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. It must be noted that, by including as covariates some of the natural factors that control vegetation activity (and hence the NDVI), the analysis was able to determine much more precisely the existence of temporal trends in the annual time series of NDVI.

We used a backward stepwise procedure based on the Akaike's information criterion statistic (AIC), as implemented in the function *stepAIC* in the MASS library of the R package for statistical analysis (Venables and Ripley, 2002). This function allowed retaining only the significant explanatory variables for the time evolution of the NDVI for the various land cover classes, and rejecting the variables not contributing to explaining the observed NDVI values. The analysis of the results was based i) on the goodness of fit and statistical significance of the regressions, ii) the explanatory variables selected, and iii) the beta (standardized) regression coefficients to rank the variables according to their relative importance in explaining the NDVI. The existence of temporal trends in the observed NDVI values that could not be attributed to climatic factors or astronomical factors (the Julian date) and could hence be attributed to re-vegetation or degradation processes was checked by the significance (and sign) of the 'year' covariate.

3.3. Role of topographical factors on the spatial distribution of the NDVI trends on erosion risk areas

The analysis described in the previous section allowed determining the relevance of climatic factors and the existence of time trends on the observed time variation of the NDVI, *averaged by vegetation class*. However, it did not offer spatial discrimination of the areas undergoing positive or negative trends. As the next step in the analysis we concentrated on the erosion risk areas due to their ecological importance, and we repeated the multivariate analysis described in the previous section in a pixel-by-pixel basis, using the same set of climatic and astronomical (the Julian day) covariates. This enabled mapping of the spatial distribution of NDVI trends not explained by climatologic factors, and thus identification of areas undergoing processes of degradation (negative trend) or recovery (positive trend).

Finally, the Pearson's product-moment correlation test was performed on the NDVI trends as determined pixel-by-pixel against various topographical factors (elevation, slope gradient and potential incoming solar radiation). A bootstrap procedure was used to determine the statistical significance of the correlations: 1000 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 (correlation coefficients and 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. Role of climatic factors on the temporal variation of the NDVI

Preliminary visual inspection of the mean NDVI time series revealed differences between land cover types (Fig. 2). There was a clear difference between the vegetated categories (deciduous and coniferous forests, grassland and scrubland) and degraded areas (badlands and erosion risk areas), both for March and August. The vegetated areas had higher NDVI values, and the greatest average NDVI values occurred in August. In the case of the well vegetated land cover classes, the March NDVI time series seemed to indicate the existence of positive temporal trends (*i.e.*, the average NDVI increased with time), whereas no trends were apparent in the August time series.

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. Negative NDVI trends were apparent to visual inspection in both March and August, being stronger in the erosion risk areas. This may indicate the presence of a degradation process, such as soil erosion, in these areas.

This preliminary result suggested the occurrence of contrasting temporal trends depending 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. Statistical significance of these trends was not checked due to the difficulties involved in trend testing of time series of natural processes when other relevant factors are involved.

Multivariate regression analysis helped explain the observed NDVI temporal patterns of the various land cover classes and determine the existence of temporal trends not explained by the variability of the climatic conditions. The regression models fitted the observed NDVI values very well, and achieved the desired level of significance for all land cover classes (Table 2). A better fit was obtained in March for the well-vegetated classes (coniferous and deciduous forests, scrubland and grassland) than for the less vegetated classes (badlands and erosion risk areas), as shown by the lower R^2 values. Contrary, in August the goodness-of-fit was slightly higher for less vegetated regions (Table 4). In all models one or more climatic variables were identified as significant by the stepwise algorithm, indicating that climatic conditions were important in explaining the degree of vegetation activity.

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 except for the badlands, as evidenced by the fact that it had the largest (standardized) beta coefficients (Table 2). The effect of the minimum temperature was positive in all cases, reflecting the importance of a relatively warm weather at the end of winter/early spring for initiating the plant growing period. This hypothesis is supported also by the fact that coniferous forests showed much lower influence of the minimum temperature than other (deciduous) vegetation classes, as it could be expected from its perennial character. The maximum temperature had a positive effect on the NDVI although lower than that of the minimum temperature, and it was also significant with the exception of the badlands. The cloud cover was also significant for all land cover classes, and its effect on the NDVI was similar to that of the maximum temperature. It had a

negative effect on the NDVI, reflecting the importance of solar radiation in the vegetation activity during this part of the year. The cumulative precipitation, on the contrary, was not significant. The time of acquisition of the image ('Julian day') was significant for all land cover classes except the grassland, demonstrating the relevance of the phenological state of vegetation at this time of the year and the convenience to include this variable in all studies involving the NDVI during critical growth periods. The non-significance in the case of the grasslands can be explained by the fact that the growing period of the grasslands starts much later in the year.

In August (Table 3) the maximum and minimum temperatures were the most important covariates for all land cover classes, with a contrasting effect on the NDVI: while the minimum temperature, as in March, had a positive effect, the maximum temperature had a negative one, reflecting the limiting factor that the summer heat has on the vegetation activity. The cumulative precipitation had smaller effect and only for the coniferous and deciduous forests, and the cloud cover was not significant in any case. Neither was the time of acquisition of the image ('Julian day'), which was expected since summer is not a critical period for vegetation growth in the area.

Having thus accounted for the NDVI variance explained by climatic and astronomical factors, it was possible to assess the existence of trends in the time series of the NDVI (variable Time in Tables 3 and 4). A positive NDVI trend was found in March for the coniferous forests, while negative trends were found for grasslands and erosion risk areas. Negative time trends were found in August for all land cover classes, ranging between 4 and 8% over the period 1984–2006. The strongest trend (around -4% in March and -8% in August) corresponded to the erosion risk areas.

The results of regression analysis enabled re-interpretation of the observed temporal NDVI patterns (Fig. 2). The apparent upward trend in the NDVI in well-vegetated areas in March can be explained very well by a similar trend in the average minimum temperature and cloud cover. Only in the case of the coniferous forests the multivariate regression analysis indicated a positive trend not explained by those variables in March, suggesting an increase of the vegetation activity possibly related to forest growth processes. A downward trend in the NDVI in erosion risk areas was also significant and not related to the temporal evolution of any climatic variable, suggesting a progressive decrease of the vegetation cover that is typical of land degradation processes.

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 (Lasanta et al., 2007; Hill et al., 2008). 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 no significant effect on the NDVI was counter-intuitive, since a positive effect could be 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 (Davenport and Nicholson, 1993; Santos and Negrín, 1997). In such regions the typically nonlinear relationship between precipitation and vegetation activity could explain the absence of a significant effect. In the case of this study, our results showed a clear relationship between the NDVI in March and the average cloud cover over the period immediately before the acquisition of the image, thus confirming the hypothesis that competition for solar radiation is more important than water availability for vegetation growth in the area.

In studies of smaller areas, similar NDVI trends in vegetation evolution have been observed, but human impact has been included among the explanations. Fuller (1998) analyzed 7 years of NDVI composites for Senegal in the interval 1987 to 1993, and observed spatial differences in temporal trends in NDVI depending on agricultural and grassland management practices. Pelkey et al. (2000) indicated that, in Tanzania, the creation of protected natural areas increased vegetation cover growth and biomass relative to areas showing more intensive land use. 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 that 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 grassland 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 (Beguería, 2006; Alatorre and Beguería, 2009). In erosion risk areas the temporal trend was strongest than in any other land cover class, and consequently it 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.

4.2. Role of topographical factors on the spatial distribution of the NDVI trends on 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. 3). 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 March. The proportion of statistically significant trends increased in August, because of an increase in stress conditions that predominate 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 on erosion risk areas. The correlation analysis between the NDVI trends in March and August and several topographical variables revealed very little significance (Figure 4 and Table 4). Only the potential radiation (a function of the exposure of a surface to the solar beams) showed a significant effect on the August NDVI trends. The sign of the correlation between the NDVI trends and the potential radiation was positive, indicating that degradation processes (negative NDVI trends) are more likely 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). This preferential location of the badlands is associated with mechanical weathering processes related to frost and thawing cycles, which are stronger on north-facing slopes (Nadal-Romero et al., 2007).

These results contrast with those of studies that have focused on the topographical control of vegetation recovery in the Spanish Pyrenees, which have shown that shady slopes enjoy a higher recovery rate than do sunny slopes (Lasanta et al., 2000; Vicente-Serrano et al., 2004; Lasanta and Vicente-Serrano, 2006; Pueyo and Beguería, 2007). This has been explained by greater stress on vegetation caused by increased

evapotranspiration rates on sunny slopes. Our results show that the topographic influence on vegetation 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 erosion risk areas). Temporal NDVI trends were identified for each land cover class using multivariate regression analysis, which incorporated the time evolution of climatic (precipitation, cloud cover, and minimum and maximum temperature) and astronomic factors (Julian day of the image).

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 in the time variation of the minimum temperature and the cloud cover. Coniferous and deciduous forests 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.

Acknowledgments

This research was supported by the projects CGL2006-11619/HID, CGL2008-00831/BTE and CGL2008-01189/BTE (Spanish Commission of Science and Technology and FEDER), ACQWA (FP7-ENV-2007-1- 212250; VII Framework Program of the European Commission), ‘Las sequías climáticas en la cuenca del Ebro y su respuesta hidrológica’ (‘Obra Social La Caixa’ and the Aragón Government), and ‘Programa de grupos de investigación consolidados’ (Aragón Government). The first author was supported by a scholarship from The National Council for Science and Technology of Mexico (CONACYT).

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Table 1. Dates for the Landsat 5 TM and 7 ETM+ images used in the study.

March		August	
<i>Acquisition date</i>	<i>Sensor</i>	<i>Acquisition date</i>	<i>Sensor</i>
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. Multivariate regression analysis of average March NDVI values. Variables excluded by the stepwise procedure are marked with ‘—’.

	Coniferous forest	Deciduous forest	Scrubland	Grassland	Erosion risk areas	Badlands
R ²	0.972	0.987	0.928	0.908	0.843	0.653
p-value	<0.001*	<0.001*	<0.001*	<0.005*	0.021*	<0.010*
Residual standard error	0.008	0.004	0.008	0.007	0.013	0.016
Beta coefficients:						
Precipitation	--	--	--	0.293	--	--
Cloud cover	-0.565	-0.598	-0.722	-0.933	-0.741	-0.499
T max	0.180	0.538	0.545	0.912	0.647	--
T min	0.681	1.29	1.15	1.94	1.13	--
Julian day	-0.236	-0.157	-0.209	--	-0.300	-0.581
Time (year)	0.368	--	--	-0.429	-0.481	--
Temporal trend (change in NDVI):						
per year	+0.00233	--	--	-0.00132	-0.00199	--
period 1989-2007	+4.05%	--	--	-2.03%	-3.94%	--

* significant at confidence level $\alpha = 0.05$

Table 3. Multivariate regression analysis of average August NDVI values. The covariates excluded by the stepwise procedure are marked with ‘—’.

	Coniferous forest	Deciduous forest	Scrubland	Grassland	Erosion risk areas	Badlands
R ²	0.591	0.599	0.663	0.640	0.681	0.663
p-value	0.031*	0.028*	<0.005*	<0.006*	<0.003*	<0.004*
Residual standard error	0.026	0.022	0.016	0.021	0.016	0.012
Beta coefficients:						
Precipitation	-0.421	-0.325	--	--	--	--
Cloud cover	--	--	--	--	--	--
T max	-1.45	-1.59	-1.66	-1.61	-1.23	-1.50
T min	1.34	1.31	1.21	1.09	0.801	1.42
Julian day	--	--	--	--	--	--
Time (year)	-0.507	-0.481	-0.688	-0.646	-1.00	-0.789
Temporal trend (change in NDVI):						
per year	-0.00247	-0.00197	-0.00241	-0.00278	-0.00363	-0.00210
period 1984-2006	-4.43%	-5.53%	-5.40%	-5.46%	-8.02%	-4.72%

* significant at confidence level $\alpha = 0.05$

Table 4. Correlation between the NDVI trend and topographical characteristics, erosion risk areas.

	March NDVI		August NDVI	
	cor. coef.	<i>p</i> -value	cor. coef.	<i>p</i> -value
Elevation	0.0680	0.255	0.0104	0.454
Slope gradient	-0.0463	0.371	-0.0259	0.424
Potential radiation	0.0945	0.146	0.142	0.0388*

* significant at confidence level $\alpha = 0.05$

Figure captions

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: Eriste Central (9840, 1100 m a.s.l), Sesue Central (9841, 930 m a.s.l), and Serraduy (9853, 775 m a.s.l). 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).

Figure 2. Temporal evolution of the mean NDVI values for March and August between the categories of land cover map and erosion risk areas.

Figure 3. 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 4. 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.

March

August

March

Categories:

- Degradation (negative NDVI trend)
- Recovery (positive NDVI trend)

August

Categories:

- Degradation (negative NDVI trend)
- Recovery (positive NDVI trend)

Categories:

- Statistically significant ($p < 0.05$)

Categories:

- Statistically significant ($p < 0.05$)

0 2.5 5
Km.