1 Identification of eroded areas using remote sensing in a badlands 2 landscape on marls in the central Spanish Pyrenees

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12 13 Abstract

14 Identification of erosion areas on a regional scale can be very useful for environmental planning, and can
15 help reduce land degradation and sediment yield to streams and reservoirs. Remote sensing techniques were
16 used to determine erosion and erosion risk areas in a badlands landscape in the Ésera River catchment
17 (Spanish Pyrenees). The size, sparse vegetation cover, and high erosion level in the badlands, enabled good
18 visual and digital discrimination relative to other land covers and surfaces. A maximum likelihood
19 supervised method was used to discriminate heavily eroded areas (badlands) from sparse or densely
20 vegetated lands, based on the spectral signature of bare soil on marls. The classification distance was
21 obtained for each pixel and used to determine erosion areas and areas at risk of erosion. Two classification
22 performance statistics (sensitivity and specificity) were used to determine appropriate threshold values.

This showed that most erosion risk areas coincided with low vegetation cover surrounding the badland areas.

Key words: badlands, marls, regolith, classification performance, sensitivity and specificity, supervised classification.

1. Introduction

Maps of active erosion areas and areas at risk of erosion are of great potential use to environmental (governmental and private) agencies, as they allow erosion prevention efforts to be concentrated in those places where the benefit will be highest. There is no single straightforward method for assessing erosion, and erosion evaluation is highly dependent on the spatial scale and the purpose of the assessment (Warren, 2002). For limited spatial scales (<100 ha), field surveys can provide an accurate means of analyzing erosion damage (Herweg, 1996). However, for focal area selection over larger areas other approaches that integrate available spatial data need to be applied. Studies on erosion undertaken at spatial scales covering local to regional areas (Vrieling et al., 2006) have provided both quantitative information (e.g., erosion rates) and qualitative information (e.g., erosion risk areas).

Methods for evaluating erosion risk on catchment and regional scales (10 to 10,000 km²) include the application of erosion models or qualitative approximations using remote sensing and geographic information (GIS) technologies. Merrit et al. (2003) have exhaustively described current erosion models. However, model application outside the regions for which it was developed has generally led to error (e.g., Brazier et al., 2000), and in many cases long and complex processes of calibration have been necessary to enable models to be adapted to particular study areas (Jetten et al., 1999, 2003). In many cases erosion models have been created for use at small scales, so their extrapolation to larger scales (catchment or

46 regional) is very complex and sometimes erroneous (Kirkby et al., 1996; Schoorl et al., 2000; Yair and Raz-
47 Yassif, 2004).

48 The use of remote sensing and GIS techniques has been shown to have potential for erosion
49 assessment on regional scales, including identification of eroded surfaces, estimation of factors that control
50 erosion, investigation of soil and vegetation characteristics, and monitoring the advance of erosion over time
51 (Muchoney and Haack, 1994; Lambin, 1996). In most cases remote sensing techniques have been applied
52 simply to identify the characteristics (or the absence) of vegetation cover, largely because of limited
53 visibility of the soil surface in humid and sub-humid environments (Vrieling, 2006).

54 Other studies have demonstrated the potential of remote sensing techniques in determining temporal
55 and spatial erosion patterns, as well as in qualitative estimation of areas of active erosion and erosion risk
56 areas (Pilesjo, 1992; Rode and Frede, 1997; Metternicht and Fermont, 1998; Szabo et al., 1998; Millward
57 and Mersey, 1999; Reusing et al., 2000; Haboudane et al., 2002; Metternicht and Gonzalez, 2005).
58 Calculation of the percentage of bare soil has also been used to estimate erosion risk (e.g., de Jong, 1994;
59 Paringit and Nadaoka, 2003). This type of methodology has improved detection of erosion areas by the use
60 of high resolution spectral images (MERIS, Landsat, and SPOT) in combination with other layers of
61 thematic information including slope, rainfall, and soil type (Mathieu et al., 1997; Haboudane et al., 2002;
62 Singh et al., 2004). For example, Amissah-Arthur et al. (2000) used SPOT data in combination with
63 biophysical (e.g., soil quality) and socioeconomic data (e.g., land use intensity, population density, carrying
64 capacity, and agricultural intensity) to assess land degradation status in the African Sahel.

65 Other methodologies applied to inventories and monitoring of the activity of different erosion
66 processes include band ratios (Pickup and Nelson, 1984; Frazier and Cheng, 1989), vegetation indices
67 (Pickup and Chewings, 1994; Tripathy et al., 1996), combinations of reflective and microwave data
68 (Koopmans and Forero, 1993; Singhroy, 1995; García-Meléndez et al., 1998; Metternicht and Zinck, 1998;

69 Singhroy et al., 1998), and combinations of remote sensing data and other geocoded information (Floras and
70 Sgouras, 1999; Mati et al., 2000; Giannetti et al., 2001; Shrimalil et al., 2001; Zinck et al., 2001; Haboudane
71 et al., 2002; Ma et al., 2003; Symeonakis and Drake, 2004).

72 Various studies in the Spanish Pyrenees have estimated erosion at regional (Beguería, 2005 and
73 2006) and catchment scales (Fargas et al., 1997) using remote sensing and erosion models to i) qualitatively
74 estimate different levels of erosion risk, ii) identify zones with different erosion risk, and, iii) formulate
75 empirical models for predicting erosion risk. These studies have shown that the badland systems on Eocene
76 marls are areas with accelerated erosion processes, and constitute the main sediment sources in the
77 Pyrenees, with very important consequences for the silting of reservoirs (Valero-Garcés et al. 1999).

78 The term badlands is used to describe areas of unconsolidated sediment or poorly consolidated
79 bedrock, with little or no vegetation (Gallart et al., 2002). Such areas are commonly affected by intense soil
80 erosion processes including gulling, rilling, and sheet wash erosion (Nadal-Romero et al., 2008). Badlands
81 develop in a wide range of climatic zones, particularly in semiarid areas, and to a lesser extent in humid and
82 sub-humid regions (Bryan and Yair, 1982; Campbell, 1989; Regüés, 1995; Regüés et al., 1995; Pardini,
83 1996; Torri and Rodolfi, 2000). Badlands are typically associated with accelerated erosion and consequent
84 unstable landscapes (Morgan, 1997), so that their fixation or limitation require considerable effort. In sub-
85 humid regions, the development of badlands is favored by lithological and topographical factors (Morgan,
86 1997; Oostwoud-Wijdenes et al., 2000), and seasonal climatic variability. The latter effect is especially
87 pronounced in areas characterized by strong intra-annual contrasts in temperature and rainfall distribution.
88 For example, freeze–thaw cycles in winter, and wetting–drying in spring–summer, are the main processes
89 involved in regolith weathering, thereby controlling slope development in combination with rainfall-related
90 erosion processes. When these factors are coupled with the presence of rocks that are highly susceptible to

erosion, the resulting geomorphological dynamics are extremely active (Regüés et al., 1995; Nadal-Romero et al., 2007).

The objective of this study was to develop a method for identification and spatial analysis of areas of severe erosion degradation (badlands), and areas of erosion risk associated with low vegetation cover. The study focused on the Eocene marls located in the middle section of the Ésera River basin, in the central Spanish Pyrenees. The method involved the application of remote sensing techniques (supervised classification to discriminate areas with active erosion), implementation of a ROC (receiver operating characteristic) curve to select a classification threshold, and assessment of the level of uncertainty associated with predictions. This approach has been used in other studies because, in regions where the land is naturally covered by vegetation, any lack of vegetation or exposure of earth are clear indicators of active erosion. Thus, the classification used was directed at detection of areas where the substrate was exposed, and spectrally similar areas were regarded as vulnerable to erosion.

2. Study area

The study area is located approximately 23 km north of the Barasona reservoir, in the Spanish Pyrenees, and is an integrated badlands landscape developed on Eocene marls orientated north–southeast (Fig.1) at 620 m to 2149 m (Fig. 2) altitude. The badlands system is conformed by a group of typical hillside badlands developed on sandy marls with clay soil, and is strongly eroded over convex hillsides with a moderately inclined slope. Runoff from this area enters the Viu and Rialvo rivers in the catchment of the Ésera River, and the Viyacarti River in the catchment of the Isábena River.

The soils in the study area are chromic vertisoils with an A-B-C profile, an ochric surface horizon, and a C horizon more than one meter deep. The original parent material is rich in calcium carbonate,

accumulated in the form of nodules in the B and C horizons. A significant feature is the formation of cracks (sometimes more than 1.5 m deep) arising from shrinkage in the dry season, and these enable mixing of the upper horizon.

The climate is defined as mountainous, humid, and cold, with influences from the Atlantic Ocean and the Mediterranean Sea (García-Ruíz et al., 1985). The average annual temperature is 11°C, and the average annual precipitation is approximately 876 mm (Fig. 3). Precipitation is irregular throughout the year, with a maximum in spring between 80 and 70 mm (April and May, respectively), and a minimum in July–August when precipitation does not exceed 70 mm.

3. Data and methods

3.1. Data selection and preparation

One limitation of satellite images is that they are affected by radiometric interference including solar rays and the atmospheric conditions. This problem is usually resolved in images of high temporal and spatial resolution (e.g., NOAA-AVHRR) by the creation of multi-temporal compound images and filtration (Gutman et al., 1995). In the case of images with high spatial resolution (such as those of Landsat) and low temporal frequency it is necessary to make more complex corrections.

In this study Landsat data (spatial resolution 30 m) from August 2006 were used because of the lower frequency of cloud cover in this month (Fig. 1A). The image was geometrically corrected using control points and the algorithm developed by Pala and Pons (1996) implemented in the Miramon software, which accounts for topographic distortion by incorporation of a digital terrain model (DTM).

The atmospheric effect on the electromagnetic signal was corrected using the radiative transfer code 6S (Vermote et al., 1997). Illumination conditions were corrected to compensate for differences caused by the irregularity of the terrain. The anisotropic reflectance model was used as this is more robust than Lambert's reflectance model (Riaño et al., 2003). A more detailed description of the process of radiometric and geometric image correction is provided by Vicente-Serrano et al. (2008). Any areas affected by clouds in the corrected images were eliminated through visual recognition.

3.2. Classification procedure

3.2.1. Definition of the thematic categories and training areas

An important objective was to define areas of the Landsat scene representing thematic categories with maximum spectral heterogeneity present in the scene. Although the main objective of the study was identification of active erosion and erosion risk areas, for the classification algorithm it was necessary to establish *a priori* categories that adequately represented the variability of land cover types present in the area. This is because the algorithm of maximum likelihood considers not only the average characteristics of the spectral signature of each category, but also the covariance among categories, allowing for a more precise discrimination.

Aerial orthophotos (SIGPAC, 2003) were used in the establishment of thematic categories in the scene, and also in the selection of training areas for each thematic category. A spectral signature and a matrix of contingency, generated using Erdas 8.7 software, were used to determine the degree of discrimination among categories.

3.2.2. Image classification and validation

Image classification was based on the method of supervised maximum likelihood from the set of thematic categories. The discriminatory capacity of the classification model was determined from a confusion matrix over the training samples. After verifying the adjustment of training samples, a spectral distance map was obtained for the badlands category. This map represents the distance between the spectral signature of each pixel and that of the badland category. From the spectral distance map, maps of active erosion (badlands) and erosion risk areas were prepared by setting a classification threshold. For construction of the ROC curve, and also for validating the final classification, an independent sample of 150 randomly distributed points were visually classified using aerial orthophotos (SIGPAC, 2003).

Determination of the classification threshold for the construction of maps of active erosion and erosion risk areas was based on the ROC curve, a method coming from the signal processing theory and adapted to environmental applications afterwards (Beguería, 2006a). The ROC curve is constructed by calculating, for each classification threshold, the sensitivity and specificity of the resulting classification:

$$sensitivity = \frac{a}{a + c} \quad (1)$$

$$specificity = \frac{b}{b + d}, \quad (2)$$

where a and d , respectively, are the true positives and true negatives, and b and c the false positives and false negatives, respectively (Table 1).

The sensitivity of the model is the proportion of positive pixels correctly predicted, or the probability that a pixel belonging to a particular category is correctly predicted. The specificity of the model is the proportion of negative pixels correctly predicted, or the probability that a pixel not belonging to a particular category is correctly predicted. Thus, models with high sensitivity are characterized by ability to correctly

predict positive pixels or pixels belonging to the category of interest, whereas models with high specificity are those able to correctly predict negative pixels or pixels not belonging to the category of interest. High sensitivity is usually associated with poor specificity, evident as an overestimate of the areas belonging to the category of interest. An optimum model would be one with a highest possible value of both sensitivity and specificity. The sensitivity and specificity statistics provide information on the degree of uncertainty in the classification. Specifically, the values (1-sensitivity) and (1-specificity) represent the probabilities of committing an error of omission (type II error, or false negative) and an error of commission (type I error, or false positive), respectively (Table 1). Other common statistics of the classification model, such as overall reliability, are biased estimates that depend on the proportion of pixels actually belonging to each category, and therefore should not be used for comparison between different case studies (Beguería, 2006b). The overall reliability is defined by equation 3:

$$reliability = \frac{a + d}{a + b + c + d} \quad (3)$$

The ROC curve method allows the degree of uncertainty associated with a specific classification threshold to be determined. For identification of active erosion areas (badlands) a classification threshold was fixed to be equal to the spectral distance for which the sensitivity of the model was 0.9, corresponding to a 10% probability of an error of omission. For identification of erosion risk areas a classification threshold was fixed that was equal to the spectral distance for which the sensitivity and specificity were approximately equal.

3.3. Topographic characterization of the badlands and erosion risk areas

The topographic characteristics of the areas classified as badlands and erosion risk areas were analyzed, as were the slope and aspect (derived from the DTM), and the variance of these properties between the two categories and the whole study area, were derived.

4. Results and Discussion

4.1. Selection of categories and training areas

The definition of thematic categories and selection of training areas were based on visual analysis of aerial orthophotos (SIGPAC, 2003). The thematic variability of the study area comprised five categories: erosion active areas (badlands), scrubland, grassland, conifers, and deciduous forest. The training areas were used to obtain spectral signatures for each thematic category (Fig. 4). The badlands were characterized by high brightness values for all bands, and had greater spectral variability.

Discrimination among the different spectral signatures was good with the exception of band 5 (SWIR), where the values for average reflectivity of badlands, scrubland, and grassland were very similar. Because of the response of Landsat band 5 to variation in soil moisture and vegetation biomass (Chuvieco, 1996), it is likely that in August 2006 the badlands and scrubland, and to a smaller degree the grassland, had similar moisture conditions. In the badland areas of the sub-humid climate zone, the lack or sparseness of vegetation is because of difficulties in vegetation colonization of the very unstable hillsides, which occurs because of the dynamic geomorphology of the area during most of the year (Solé et al., 1997). In the central Pyrenees the distribution of scrub is very diffuse, as a consequence of spatial differences in the rates of vegetation succession over recent decades (Vicente-Serrano, 2006). Colonization of bare soil areas is slower, resulting in scrub areas with low vegetation cover (Pueyo and Beguería, 2007). Vegetation cover has

been stable in the central Pyrenees between 1990 and 2000, with only 0.9% of the area in the process of scrub colonization.

The contingency matrix obtained for the sampling areas, using the maximum likelihood classification algorithm, showed that all categories had a 90% success value (Table 2). In the case of the badlands there was a confusion level of 1% in the scrubland category, confirming the uncertainty associated with transition areas.

4.2. Thematic classification

A land cover map was obtained from the classification algorithm (Fig. 5), and validation using the independent random sample showed a global reliability of 81.83%. The grassland category was the worst discriminated, with an omission error of 14.04% (sensitivity = 0.860 and specificity = 0.742) (Table 3), whereas deciduous forest was the best discriminated, with a commission error of only 6.25%. The classification model had a probability of omission error of 12.90% with respect to the badlands category (sensitivity = 0.871), but classification of the badlands involved some scrub areas that were incorrectly classified, resulting in a commission error of 22.86% (specificity = 0.771).

The area occupied by each category was: badlands 19 km², coniferous forest 65 km², deciduous forest 21 km², grassland 32 km², and scrubland 99 km². It was also evident that the areas occupied by scrub and grass bordered areas classified as badlands (Fig. 6). This spatial distribution suggests that there is a progressive transition between eroded areas and forest.

4.3. Maps of Badlands and erosion risk areas

248 Once the image classification procedure had been validated, identification of badlands and risk
249 erosion areas was performed by using only the spectral distance map generated in the initial classification,
250 showing the badlands category (Fig. 7). The map of spectral distance is an intermediate requirement in the
251 process of supervised classification, and is used to assign each pixel to the category of greatest similarity
252 (smaller spectral distance). However, as the main focus of this study was on a single category, a more
253 precise result was obtained using the map of spectral distance in conjunction with a user-determined
254 classification threshold. The spectral distance as determined by the maximum likelihood method has the
255 advantage of not using the linear or euclidean distance between the centers of the spectral signatures, but to
256 be based on the variance/covariance matrix among all spectral signatures, thus resulting in a much more
257 precise distance statistic.

258 The ROC curve for the badlands had a medium-to-high discrimination capacity (Fig. 8). The ROC
259 curve shows the values of sensitivity and specificity associated with different possible values for the
260 classification threshold. Determination of the classification threshold requires a compromise between
261 sensitivity and specificity, as it is impossible to maximize both at the same time. Thus, a high sensitive
262 classification threshold (i.e., one yielding a very low omission error) will be associated with moderate
263 specificity values, and results in an overestimate of the area belonging to the badlands category. The
264 opposite result would be obtained by setting a high specific threshold.

265 We selected a model with a high specificity (0.900) to minimize commission errors (false positives).
266 This is a common approach in statistical analysis, equivalent to selection of a confidence level of $\alpha = 0.1$.
267 For the spatial delimitation of erosion risk areas a classification threshold value was chosen that resulted in
268 approximately equal values for sensitivity and specificity (0.750 and 0.710, respectively).

269 The application of both classification thresholds to the map of spectral distance for the badlands
270 category allowed producing maps for the active erosion and risk erosion areas (Fig. 9), with surface areas of

these categories of 17 km² and 49 km², respectively. The surface area of active erosion for the badlands category was the same as that from the land cover map generated previously. Visual comparison of the maps showed that the erosion risk areas corresponded to the scrubland category (and in some cases the grassland and conifer categories) bordering the badlands areas. These areas had spectral characteristics intermediate between badlands and scrubland, indicating either a mixture of the categories within the pixel or an intermediate level of degradation. Both possibilities are consistent with classification of the above categories as erosion risk areas.

The DTM morphological analysis showed a predominance of north (33%) and south (45%) orientations over the study area (Fig. 10A). The badland areas occurred predominantly on hillsides oriented to the north (44%), whereas the erosion risk areas had a distribution similar to the total study area (Fig. 10, C and B). The markedly different distribution of badlands relative to other categories in the study area suggests that different erosion processes are active in opposing hillside orientations. The aspect angle is a determining factor in the dynamics, intensity, and effectiveness of weathering processes in badland areas developing in mountainous sub-humid regions (Nadal-Romero et al., 2007). This is a consequence of regolith weathering dynamics arising from climatic factors (particularly freeze–thaw processes involving cryoclastism, cryosuction, and ice growth) on north-orientated hillsides, whereas on south-orientated hillsides the most effective weathering process is thermoclastism, which is related to high daily temperature variations (Nadal-Romero et al., 2006). Confirmation of this effect would suggest that areas at risk with a north orientation should be a focus for erosion risk mitigation efforts.

The frequency distribution of the slope in each category was also analyzed (Fig. 11), but there were no significant differences among the badlands, erosion risk areas, and the total study area.

5. Conclusions

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295 This study has demonstrated the utility of remote sensing and GIS techniques in basic and applied
296 geomorphological research, both at watershed and regional scales (study areas between 10 and 10,000 km²).
297 The use of a supervised classification method using the maximum likelihood algorithm on a set of *a priori*
298 categories enabled reliable mapping of areas with active erosion and vegetation. Selection of training areas
299 using aerial orthophotos (SIGPAC, 2003) enabled identification of areas in each of the designated
300 categories, based on maximum variability among spectral signatures. The use of an independent set of
301 randomly selected pixels allowed for validating the classification model, which was very good (82% overall
302 accuracy).

303 The use of an ROC curve to assess uncertainty in the classification model (based on the magnitude
304 of omission and commission errors) allowed classification thresholds for the active erosion and erosion risk
305 areas to be determined. It was found that 7% of the surface area was affected by active erosion processes
306 that resulted in a morphology typical of badlands, and 21% of the surface area was classified as at risk of
307 erosion. This suggests that there was a high degree of uncertainty in the spectral signatures of pixels
308 separating badlands from other areas. These are erosion risk areas, either through intensification of erosion
309 processes or because of head erosion in headwaters in the adjacent badlands. The erosion risk areas
310 bordering the badlands coincided with transition zones from badlands to forest, where the soil was poorly
311 covered by vegetation (10–50% cover). These are marginal areas with slopes greater than 15%, where the
312 establishment of vegetation is very difficult.

313 Finally, DTM was found to be a useful primary tool for morphological exploration of active erosion
314 areas and erosion risk areas. In the study area, asymmetry in the development of badland areas was deduced
315 from the orientation, with more development of badlands on shady hillsides because of weathering. In
316 contrast, hillside slope did not appear to have a significant effect on badlands formation in the study area.

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 496 *International Journal of Applied Earth Observation and Geoinformation*, 3: 43–53.

497 Table 1. Confusion matrix: Y_1 , belonging to class Y ; Y_0 , not belonging to class Y . Values a and d are the true
 498 positives and true negatives, respectively, and b and c are the false positives (type I error) and false
 499 negatives (type II error), respectively.

		Observed	
		Y_1	Y_0
Predicted	Y_1	a	b
	Y_0	c	d

500

501 Table 2. Contingence matrix of the classification applied to the training sample (proportion and total number
 502 of pixels).

	Observed categories	Badlands	Conifers forest	Deciduous forest	Grassland	Scrubland	Total (pixels)
Predicted categories	Badlands	0.99	0	0	0	0.01	832
	Conifers forest	0	0.94	0.01	0	0	1098
	Deciduous forest	0	0.04	0.95	0	0.02	308
	Grassland	0	0	0	0.99	0	300
	Scrubland	0.01	0.02	0.04	0.01	0.97	1151
Total (pixels)		835	1164	247	298	1145	3689

503

504 Table 3. Confusion matrix among categories (proportion and total number of pixels).

		Observed categories	Badlands	Conifers forest	Deciduous forest	Grassland	Scrubland	Total (pixels)	Commission error (%)	Specificity
Predicted categories	Badlands		0.87	0.00	0.00	0.02	0.05	70	22.86	0.771
	Conifers forest		0.00	0.75	0.05	0.00	0.00	16	25.00	0.750
	Deciduous forest		0.00	0.25	0.82	0.00	0.00	64	6.25	0.938
	Grassland		0.03	0.00	0.00	0.86	0.11	132	25.76	0.742
	Scrubland		0.10	0.00	0.12	0.12	0.84	264	10.98	0.890
								Total	18.17	0.818
		Total (pixels)	62	16	73	114	281	546	Total	
		Omission error (%)	12.90	25.00	17.81	14.04	16.37		17.22	
		Sensitivity	0.871	0.750	0.822	0.860	0.836		0.823	

505

506 **Figure captions**

507 Figure 1. Location of the study area: A, area of the Landsat scene; B, location of badland areas on marls
508 (236 km²).

509 Figure 2. Digital terrain model (DTM) of the study area.

510 Figure 3. Thornthwaite diagram in Campo, Huesca: T, monthly average temperature (°C); P, monthly
511 average precipitation (mm); ET, potential evapotranspiration (mm); WS, hydric balance (mm; P-ET).

512 Figure 4. Spectral signature for each of the thematic categories. The vertical bars indicate the standard
513 deviation with respect to the average reflectivity.

514 Figure 5. Land cover map based on supervised classification using the maximum likelihood method.

515 Figure 6. Detail of the transition areas between badlands and forest (conifers and deciduous forest).

516 Figure 7. Spectral distance map (UD: digital units) of the badlands category in relation to other categories.

517 Figure 8. ROC curve for classification of the active erosion areas (badlands). The central segmented line
518 represents a model without predictive capacity. Therefore, the further the ROC curve is from the central line
519 the greater is the discriminatory capacity of the model. U1 and U2 indicate the classification thresholds
520 selected for assessment of active erosion and erosion risk areas, respectively.

521 Figure 9. Active erosion (badlands) and erosion risk maps, obtained from the spectral distance map and the
522 classification threshold.

523 Figure 10. Percentage distribution of hillside aspect: A, total area; B, badland areas; C, erosion risk areas.

524 Figure 11. Frequency histogram of hillside slope: A, total area; B, badland areas; C, risk erosion areas.

Fig. 1

Fig. 2

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Fig. 7

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