Water erosion risk mapping using derived parameters from digital elevation model and remotely sensed data

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Abstract: The aim of this study is to map the areas exposed to water erosion risks in the High Atlas Mountains of Morocco around the Hassan-I dam. The methodology is based on the analysis of the water power index (WPI) as a hydrological parameter, the vegetation cover, and the litho-logical units. The WPI was derived from a Digital Elevation Model (DEM) and the litho-logical units and vegetation cover were derived from Advanced Land Imager sensor on the Earth Observing-1 satellite platform. The image was corrected from radiometric and atmospheric effects, and geometrically rectified using a DEM and grounds control points. These variables were integrated in a Geographical Information Systems environment, and Multi-Criteria Analyses were used to derive the water erosion risks map pointing out the most exposed areas requiring the implementation of suitable conservation measures. The validation of the obtained results shows the simplicity and the potential of this approach for water erosion risks mapping.

Keywords: water erosion risks; GIS; remote sensing; vegetation cover; litho-logical units; hydrological parameter.

1. Introduction

Nowadays, Morocco is experiencing the longest dry episode of its contemporary history characterized by a reduction of precipitation and a rise in temperatures (1). These climate conditions limit the growth of the vegetation cover especially in High Atlas Mountains of Morocco (2). This situation in conjunction with the human activities leads to a degradation of soil by wind and water erosion. Water erosion threatens the whole Moroccan territory and can be considered a major environmental problem in arid and semiarid areas. For instance, in Morocco, annual soil loss exceeds 2000 t/km²/year in the Rif-Mountains regions and varies between 1000 and 2000 t/km²/year in Pre-Rif regions and between 500 and 1000 t/km²/year in mid and High Atlas regions (3). In addition to soil, water erosion degrades water quality and causes silting-up of hydraulic infrastructures (4). In Morocco, the silting-up of dams reduces 50 millions m³/year of the capacity of water stocking, which can be used to irrigate about 5000 ha yearly (3). Therefore, it is necessary to find suitable solutions to conserve natural resources, such as soil and water. For these reasons, different hydrologic models, coupled or not with the models of erosion, were developed. For example, the Universal Soil Loss Equation (USLE) (5) and Revised Universal Soil Loss Equation (RUSLE) (6) were used to quantify soil loss. Furthermore, previous studies have developed methodologies integrating remote sensing and geographical information systems (GIS) techniques to characterize soil erosion in large areas with reasonable costs and accuracy (7–13). Several studies showed that the Digital Elevation Model (DEM) analysis provides satisfactory results in developing erosion surveys as well. In fact, the DEM was used to derive topographic and hydrologic parameters that are responsible for terrain exposure to degradation risks by water erosion. The topographic parameters as plan and profile curvature were used to map the potential areas of denudation, transit, and accumulation of sediments (10, 14), while the hydrologic parameters as the water power index (WPI) were used to measure potential overland flow indicating the possibility of water erosion (10, 11, 15–19). Moreover, various methods for soil degradation characterization were adapted using soil spectral indices derived from remote sensing data (11, 20–25). Other studies also showed that remote sensing gave very good information about eroded areas, such as soils types, litho-logical units, and vegetation cover (10, 26–33). For the quantification of this latter, several vegetation indices were developed in the literature, namely Normalized Difference Vegetation Index (NDVI) (34), Soil Adjusted Vegetation Index (SAVI) (35), Transformed Difference Vegetation Index (TDVI) (36), etc. The aim of this research is to use remote sensing, DEM, GIS, and multi-criteria analyses (MCA) for identifying and
mapping areas exposed to water erosion risks around Hassan-I dam in the High Atlas Mountains of Morocco. The methodological approach integrates parameters derived from the DEM such as WPI and parameters derived from Earth Observing-1 (EO-1) Advanced Land Imager (ALI) data such as vegetation cover and litho-logical units. These data were pre-processed and standardized in GIS environment, and different MCA scenarios were used to map the areas exposed to water erosion risks. Finally, the obtained results were validated according to ground truth information.

2. Methodology

The methodology followed in this research is subdivided into four major stages (Figure 1). Firstly, a DEM with a $30 \times 30$ m pixel size was extracted from the topographic map (1/50,000) to derive the WPI. Secondly, the ALI image was corrected from radiometric and atmospheric effects. In addition, the geometric and topographic corrections were carried out by using a DEM and Grounds Control Points (GCP). In the third step, remote sensed data were used to quantify the vegetation cover by calculating the TDVI and to extract the litho-logical units using supervised classification. Finally, in the fourth stage, all the considered parameters were classified and integrated in a GIS environment, and many MCA were implemented to map the areas exposed to water erosion risks, thus the obtained results were validated against the ground truth.

2.1. The study area

The study area is centered on Hassan-I dam at Azilal province in Morocco covering about $70\,\text{km}^2$. It is located in the High Atlas mountains between the geographical coordinates $31^\circ45'\,\text{N}$–$31^\circ50'\,\text{N}$ and $6^\circ45'\,\text{W}$–$6^\circ51'\,\text{W}$ (Figure 2). The altitude varies between 800 and 1680 m. The shape of the study area molds approximately an elongated depression oriented in an east–west direction. This depression corresponds to the “Guettioua” Synclinal. The centre of the latter is composed by the pelitic-sandstone sediments of the Upper Jurassic (37). The synclinal is surrounded by anticlines composed by Lower Jurassic limestone, which is defined by ridges higher than 1500 m. The slopes are relatively stronger in the south than in the north of the dam. The Hassan-I dam is built on the pelitic and sandstone formation. Furthermore, the study area shows the characteristics of
vulnerable Mediterranean landscapes with respect to the processes of soil impoverishment and environmental degradation (38). The environment is characterized by a semiarid climate with annual average temperature of 20.5 °C and annual average precipitation of 300 mm (39). In addition, the precipitation problem in this region is that the rainfall distribution is irregular. Indeed, the high intensity of rainfall often occurs in few days and in a very short time, especially between December and March. This situation is worsened by the fact that the vegetation cover (olive and almond trees, euphorbia and green oaks) is sparse and scattered. Consequently, the rainfall events strongly affect the amounts of soil loss in Azilal province region in general, and particularly in our study area.

2.2. Image data pre-processing

The image used in this study was acquired by the EO-1 ALI sensor on 1 October 2007. The ALI sensor was launched in November 2000 and it is the first EO-1 sensor to be flown under NASA’s New Millennium Program. It tests the new technology that could improve the thematic mapper and enhanced thematic mapper + sensor series, and ensuring Landsat data continuity (40). The ALI sensor employs a novel wide-angle optics and provides multispectral and panchromatic data with 30 and 10 m spatial resolution, respectively. Table 1 shows the spectral bands of the ALI sensor and their respective wavelengths (40).

The radiometric calibration of the sensor is the operation that leads to establish the relationship between the measured physical amounts at the sensor field of view, the radiation flow reflected by the earth–atmosphere system, and the apparent digital number (DN × (λ)) at the exit of the instrument towards the reception stations (41). It is a critical step that consists of correcting the radiometric sensor drift to extract reliable and precise information from the image (42). The gain and offset published by NASA (40) in 2006 were used to transform the raw data from the DN × (λ) to the apparent radiance at the sensor level (L/λ). As for the atmospheric effects, it is dominated by the absorption caused by the gases (water vapor, carbon dioxide, and ozone) and the diffusion produced by the aerosols and the molecules (43, 44). All the atmospheric parameters that are necessary for the atmospheric correction were calculated by using the Herman radiating transfer model H5S (Simulation of the Satellite Signal in the Solar Spectrum) (45). This model considers the absorption, the diffusion, the terrain elevation, and the sensor altitude. The simulated atmospheric parameters were used to transform the apparent radiance to the reflectance at the ground level, pG(λ).

To integrate the ALI image and all derived variables in GIS environment with auxiliary data, the image was geometrically corrected using a second order polynomial function and 14 GCP extracted from the topographical map at the scale of 1/50,000. The Lambert conformal conic map projection and the Moroccan Datum (Merrich, Zone I) were used. This operation was achieved with a root mean square error (RMSE) equal to ± 7.2 m (0.24 pixel), which is less than the image pixel size and

| Bands | Wavelengths (μm) | Spatial resolution (m) |
|-------|------------------|-----------------------|
| 1*    | 0.480–0.690      | 10                    |
| 2     | 0.433–0.453      | 30                    |
| 3     | 0.45–0.515       | 30                    |
| 4     | 0.525–0.605      | 30                    |
| 5     | 0.630 – 0.69     | 30                    |
| 6     | 0.775 – 0.805    | 30                    |
| 7     | 0.845–0.89       | 30                    |
| 8     | 1.2–1.3          | 30                    |
| 9     | 1.55–1.75        | 30                    |
| 10    | 2.08–2.35        | 30                    |

*Panchromatic band.
fits well with the accuracy of the DEM extracted from 1/50,000 topographical map. The DEM was obtained by the digitization of the curve lines with 20 m interval. Then, these curve lines were interpolated using a Triangular Irregular Network (TIN) method in ArcGIS environment and transformed to a raster format considering 30 × 30 m pixel size output. The accuracy of the DEM was calculated in terms of RMSE between estimated and true altitudes considering 20 verification points (46). The obtained RMSE is equal to ±7.6 m, which is acceptable for a DEM extracted from a topographical map at the scale 1/50,000 (47). Furthermore, it is impossible to eliminate the distortions caused by the topography using only a simple geometric corrections based on a second order polynomial function (48). Consequently, the ALI image was ortho-rectified exploiting the derived DEM (49, 50). This corrected image was used to extract the factors controlling water erosion risks include lithological units and vegetation cover.

2.3. Water power index

In the literature some terrain-based indices and parameters were developed for soil erosion hazard assessment and mapping (15, 51). These indices are based on unit stream power theory (51) that takes into account influence of terrain shape and its geometry as a suited theory to assess erosion risk in complex topographic terrain at watershed/catchment scale. The indices and parameters derived from DEM are slope, aspect, plan, and profile curvatures, capacity of the runoff flow to incise, drainage area, and PWI, which is a hydrologic parameter that measures the erosive power (flow intensity) of the concentrated flow (15). In fact, the WIPI was used in several studies as an indicator of areas susceptible to water erosion (10, 11, 15–19). Other studies were considered this index as one of the main conditioning factors of landside occurrence (18, 52). Furthermore, it was used to analyze the sediment dynamics in mountain basins (53). The later found that the areas where WIPI are low are much more effective to reduce erosion and sediment delivery than areas with high values. According to Moore et al. (15) in 1993, this index is defined by the following equation:

\[
\text{WPI} = \ln[A_s \times \tan(x)]
\]  

(1)

“\(A_s\)” is specific catchment area expressed in m² (watershed area discharging to a specific point or pixel, also called upslope drainage area), “\(\alpha\)” is the slope angle expressed in degree, and “\(\ln\)” is the neperian logarithm.

The determination of specific catchment area was estimated using flow accumulation theme multiple by pixel resolution of DEM (30 m). The flow accumulation, which denotes the accumulated upslope contributing area for a given cell, was calculated by summing the cell area of all upslope cells draining into it. Flow accumulation is calculated by integration of the expression “\(\text{FlowAccumulation(FlowDirection([elevation]))}\)” in “Raster Calculator” tool in the “Spatial Analyst” extension of ArcGIS.

2.4. Litho-logical units

The litho-logical units are indicators of the resistance or the friability of soils materials to water erosion. For mapping the spatial distribution of these units to determine the land fragility to erosion risks, satellite images play an important role (10, 29–31). In this study, the litho-logical units were derived using supervised classification considering all spectral bands of ALI image. The spatial distributions of the most significant classes were localized based on the preexisting maps (geological, topographical, etc.) and using a Global Positioning System (GPS) during the field work. This task allowed us to identify three main thematic classes: sandstones, clay-sandstones, and limestones. The used classification algorithm in this process is based on the Mahalanobis distance, which is a direction-sensitive distance classifier. It is similar to the Maximum Likelihood method but assumes that all class covariances are equal. All pixels are classified to the closest region of interest class unless you specify a distance threshold, in which case, some pixels may be unclassified if they do not meet the threshold (54). The Mahalanobis distance is defined as follows (55):

\[
d^2 = (x - v)^T C^{-1}(x - v)
\]  

(2)

where “\(x\)” is the pixel spectral vector, “\(v\)” is the mean spectral vector of a sample in a multiband image, “\(C\)” is the covariance matrix of the sample, and “\(T\)” denotes the transposition of the matrix.

To evaluate the classification results, several approaches were used in the literature (54). The quantitative approach based on kappa coefficient is the most popular and it was used in this research (23, 56, 57). This method considers all elements of the confusion matrix (58) which provides the accuracy of all individual classes by referring to the training sites information and it is implemented in the ENVI image processing software (59). At the end of the classification process, the confusion matrix and the kappa coefficient are reported. According to Congalton (56) in 1991 the kappa coefficient is calculated by the following equation.

\[
K = \frac{N \sum_{i=1}^{r} xii - \sum_{i=1}^{r} (x_{ii} \times x_{ii})}{N^2 - \sum_{i=1}^{r} (x_{ii} \times x_{ii})}
\]  

(3)

where “\(r\)” is the number of rows in the matrix, “\(xii\)” is the number of observations in row “\(i\)” and column “\(i\)”, “\(x_{i+}\)” and “\(x+i\)” are the marginal totals of row “\(i\)” and column “\(i\)”, respectively, and “\(N\)” is the total number of observations.
2.5. Vegetation cover

Vegetation cover plays an important role in protecting soil against water erosion risks. In fact, protecting the soil against the action of falling raindrops increases the degree of water infiltration in soil and reduces the speed of the surface runoff. Vegetation cover is one of the most crucial factors in reducing, describing, and accessing soil erosion. For vegetation cover quantification, several vegetation indices were developed according to research needs (60). The most popular and most used index is the NDVI developed by Rouse et al. (34). However, this index shows a high sensitivity to the atmosphere and to the soil background optical properties (61). To minimize these effects, several indices were developed such as TDVI Equation (4) which allows vegetation cover quantification accurately, minimizing atmospheric effects, and soil background optical properties artifacts (36–62). This index was calculated using the red and the NIR bands. Furthermore, for ALI sensor, two spectral bands (6 and 7) cover the NIR region. The band 6 was used to retrieve the TDVI because it is significantly sensitive to the biomass, nevertheless the band 7 it is sensitive to canopy water content (63).

\[
\text{TDVI} = 1.5 \times \frac{\rho_{\text{ALI6}} - \rho_{\text{ALI5}}}{\sqrt{\rho_{\text{ALI6}}^2 + \rho_{\text{ALI5}}^2 + 0.5}}
\]  

2.6. Multi-criteria analysis (MCA)

Often we use GIS for the MCA to localize zones with specific environmental problems and/or to analyze constrained potential risks (64). In the literature, several studies consider MCA for identifying the exposed areas to water erosion risks (11, 65–68). It is an interactive method that gives the user (or the decision-maker) the possibility to select the criteria analysis based on many variables according to the real world. The result can be represented as a thematic map or statistical files (69). One of the most used approaches is to establish a system of performance and of weight by the weighted sum to determine the global performance of the various scenarios. The weights are usually normalized to sum up to 1 (64). For a good weights distribution of criteria, it is interesting to adopt two weighting types: within-criteria and between-criteria (66–69).

Regarding the MCA in this study three steps were considered (Figure 3). In the first step, we classified the obtained variables criterions (WPI, TDVI, and litho-logical units) and we then proceeded by a within-criteria weighting inside each criterion. For example, we classified the vegetation criterion TDVI in three classes: absent (bare soil), medium, and dense cover basing on our field work visit, and we assigned a specific weight level of each class based on their sensitivity to water erosion risks. The scale used for weights assigned is between 0 and 100%. For the WPI and litho-logical unit’s criterions, it is also classified and each class was assigned specific weight levels (Figure 3). In the second step, we proceeded by a between-criteria weighting for all these criteria between them. Each criterion was multiplied by the assigned weight also ranging from 0 to 100% based on their importance in the water erosion processes. Finally, the results of the different MCA were superimposed by addition using the “Raster Calculator” tool in the “Spatial Analyst” extension of ArcGIS to produce thematic maps of different levels of erosion or degradation risks. Several scenarios were considered...
according to different weights for each criterion and the obtained water erosion risks maps were compared with the ground truth.

3. Results analyses

After generating and correcting the DEM, the WPI equation was implemented in ArcGIS to measure the potential of erosive power of overland flow, which is an indicator of areas susceptible to water erosion. Figure 4 illustrates the spatial distribution of WPI levels. The high classes are located along the valleys where drainage areas are important and over areas with steeper slopes, these areas are characterized by surface flow concentration generating the high levels of erosion risks. Nevertheless, the low classes are encountered in areas where there is a combination of the low slopes and the small areas of drainage where the water erosion risks are low.

The WPI parameter is responsible for terrain exposure to degradation risks by water erosion. In addition to this hydrological factor, the water erosion action also depends on litho-logical characteristics and vegetation coverage. The distribution of the litho-logical formations was derived with Mahalanobis Distance supervised classification method considering all ALI spectral bands. Based on prior visits to the field and according to the previous studies carried out on this area (11–25) the training site for water and three litho-logical units were selected: sandstones, clay-sandstones, and limestones (Figure 5). This classification was achieved with a Kappa coefficient equal to 0.81%, and considered significant. The derived litho-logical unit’s map characterizes the chemical and the physical properties of substrate materials controlling and consolidating the soil erosion.

Furthermore, Figure 6 shows the vegetation cover map include three classes: absent (bare soil), medium,
and dense cover. It shows good candidates for protected zones against water erosion risks.

Finally, in a GIS environment, all the considered variables maps were integrated for MCA to produce thematic maps of different levels of water erosion. At this stage, several scenarios were considered according to different weights for each criterion. Table 2 presents the used weighting distribution for MCA (within-criteria and between-criteria) providing the best erosion risks scenario results. According to this scenario, Figure 7 illustrates the final and optimal map for water erosion risk representing five different classes: high degradation, medium degradation, low degradation, vegetation cover, and dense cover.

Table 2. Weighting distribution used for MCA.

| Criteria         | Classes            | Within-criteria weighting | Between-criteria weighting |
|------------------|--------------------|---------------------------|---------------------------|
| WPI              | Low                | 0/100                     | 30/100                    |
|                  | Moderate           | 30/100                    |                           |
|                  | High               | 70/100                    |                           |
| Vegetation (TDVI)| Dense              | 0/100                     | 30/100                    |
|                  | Medium             | 30/100                    |                           |
|                  | Absent             | 70/100                    |                           |
| Litho-logical units | Clay-sandstones  | 20/100                    | 40/100                    |
|                  | Limestones         | 30/100                    |                           |
|                  | Sandstones         | 50/100                    |                           |

Figure 6. Vegetation classes quantified using TDVI.

Figure 7. Erosion risks map superposed with curve lines.
and water. The analyses of Figure 7 show that the areas with low erosion risk are characterized by the low slopes whose overland flow intensity and energy are low expressed by WPI low values (Figure 4), the litho-logical units are mainly composed with clay-sandstones and limestones (Figure 5), and dense vegetation cover (Figure 6). The areas with medium erosion risk are located in average slopes with intermediate vegetation cover, and the litho-logical units are mainly characterized by clay-sandstones and limestones. On the other hand, the areas with high erosion risk or high degradation are located in the valleys where the overland flow is concentrated generating the important energy of erosion (WPI high values), the vegetation cover is absent, and the dominate litho-logical units are sandstones.

To assess the accuracy of the derived map, we selected five different areas showing different classes and validated them in reference to the ground truth using GPS for localization and photos for illustration (Figures 8–11). The area 1 in Figure 7 was mapped using MCA as a relatively dense vegetation cover with low degradation classes. Figure 8 illustrates this reality. The area 2 (Figure 7) was considered as mixed three classes with low and medium degradation, and scattered vegetation cover. Figure 9 corroborates these results showing medium and high slopes and, consequently, moderate and high WPI (Figure 4). The area 3 (Figure 7) was mapped as medium soils degradation, and Figure 10 (photo of area 3) represent the truth showing medium soils degradation class with very scattered vegetation cover and some spots with low degra-

Figure 8. Photo of area 1 showing relatively dense vegetation cover class and some low soil degradation spots.

Figure 9. Photo of area 2 illustrating low soils degradation class with scattered vegetation cover and some areas with medium soils degradation.
Figure 10. Photo of area 3 showing medium soils degradation class with very scattered vegetation cover and some pixels with low degradation and others with high degradation.

Figure 11. Photos (a and b) presenting the high soils degradation.
dation and others with high degradation. These observations correlate with the litho-logical units and WPI classes as discussed previously. The area 4 is a small island in the middle of the dam, it shows a low WPI with no vegetation cover (Figure 11(a)), an approximately half clay-sandstone and half sandstone zone (Figure 5), and identified as a mixed area with medium and high degradation. Finally, the area 5 (Figure 7) was identified by MCA as high soil degradation zone. Indeed, this area was localized in the field as shown in Figure 11(b), with clay-sandstones, especially those sandstone classes with very scattered vegetation spots, aggressive slopes, and moderate and high WPI (Figure 4). This validation demonstrates the significant contribution of this simple approach used for water erosion risk mapping.

The analysis of the water erosion risk map (Figure 7) shows that the north flank of the dam where slopes are low to medium is most exposed to the erosion risks because of the excessive exploitation of forest cover and the intensive agricultural practices of the local population. The south flank of the dam where slopes are relatively sharper is less exposed to the erosion risks due to forest preservation and the absence of agricultural practices. We can conclude that the anthropogenic action is the leading cause of soil erosion in this region. Quantitatively, the percentage of the area of each erosion risk class in our study area was estimated (Table 3). About 33, 45% of the study area was covered by moderately erodible soil, while 26, 42 and 19, 26% was covered by highly and low erodible soil, respectively. In fact, these results indicate that soil erosion risks categories are critical from the point of view of soil erosion control.

The results of this research (Figure 7) are in agreement with those of Maimouni et al. (25). The latter use an approach based solely on remote sensing data. In fact, the spectral response variation measured at the satellite sensor is an indicator of environment change. If we consider soil and vegetation, slight changes in color and mineralogy in the first, and variations in the structure and spatial distribution in the second, can constitute indicators of changes and degradation in natural environments. In this perspective, Maimouni et al. (25) analyzed the potential and limits of several spectral indices for mapping land degradation. They found that combination in the Red–Green–Blue (RGB) system of shape index (ALI3–ALI6–ALI10), of coloration index (ALI3–ALI6), and of brightness index (ALI4–ALI5–ALI6) provides very good separating power between the different levels of soil degradation in particular and the different land cover classes in general in a semiarid environment.

The approach adopted in this research did not intended to estimate the amount of soil loss but to provide erosion risk map for the analysis of planning and environmental protection. The map obtained can provide decision-makers with erosion risk areas to develop soil and water conservation plans in general and generate detailed erosion studies for the areas of high erosion risk more specifically.

4. Conclusion

The aim of this study is the identification and mapping of the exposed areas to water erosion risks in the Moroccan High Atlas mountains around the Hassan-I dam using derived parameters from DEM and remotely sensed data. The derived WPI from DEM is a fundamental factor controlling the overland flow speed and its energy, and allows us to determine the spatial distribution of eroding areas on the landscape. Moreover, the litho-logical units and vegetation cover extracted from the ALI image constitute good indicators of different levels of potential erosion. The synergy among these three parameter groups in GIS environment and the MCA were used for water-erosion-risk mapping. The validation of the obtained results to the ground truth shows the simplicity and the efficiency of the proposed methodology for erosion risks and land degradation evaluation and, consequently, to determine the ecosystem fragility. Certainly, such results could be an important tool for politicians, land use managers, and decision-makers especially in the emerging countries.

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