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Landslide Susceptibility Mapping: A Comparison between Logistic Regression and Multivariate Adaptive Regression Spline Models in the Municipality of Oudka, Northern of Morocco

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Abstract**—**The logistic regression (LR) and multivariate adaptive regression spline (MarSpline) are applied and verified for analysis of landslide susceptibility map in Oudka, Morocco, using geographical information system. From spatial database containing data such as landslide mapping, topography, soil, hydrology and lithology, the eight factors related to landslides such as elevation, slope, aspect, distance to streams, distance to road, distance to faults, lithology map and Normalized Difference Vegetation Index (NDVI) were calculated or extracted. Using these factors, landslide susceptibility indexes were calculated by the two mentioned methods. Before the calculation, this database was divided into two parts, the first for the formation of the model and the second for the validation. The results of the landslide susceptibility analysis were verified using success and prediction rates to evaluate the quality of these probabilistic models. The result of this verification was that the MarSpline model is the best model with a success rate (AUC = 0.963) and a prediction rate (AUC = 0.951) higher than the LR model (success rate AUC = 0.918, rate prediction AUC = 0.901).

Keywords**—**Landslide susceptibility mapping, regression logistic, multivariate adaptive regression spline, Oudka, Taounate, Morocco.

I. INTRODUCTION

THE landslide is the movement of a mass of rock, debris or soil on a slope under the influence of gravity [1], [2]. In recent decades, landslides have received considerable attention as they are the most widespread disaster in the world in terms of loss of life and damage to social economies [3], [4].

In Morocco, areas subject to landslides are mainly the Rif and to a lesser extent the Middle Atlas, due to the existence of the relatively young reliefs which know a very important dynamics compared to the other regions. This dynamic associated with the formation of the Rif chain (Alpine tectonics) is accompanied by instabilities mainly related to tectonic movements. The construction of major infrastructures (roads, highways, etc.) is a triggering factor and favors landslides. The latter causes many economic losses affecting populations, infrastructure and other goods. To solve this, it is necessary to predict which areas are susceptible to landslides. For the landslide susceptibility analysis, LR and MarSpline models were applied and verified for the study area of Oudka, Morocco. Geographic information system (GIS) software ArcGIS package and R studio were used as the basic analysis tools for spatial management, models construction and their validation.

There are many recent studies of landslide hazard evaluation using GIS [5]-[7]. A flow chart outlining the methodology used is shown in Fig. 1. For application and verification of landslide susceptibility models, the study area was randomly divided into two parts, the first for the establishment of the model and the second for its validation. Landslide occurrence areas were detected in the study area by the aerial photography, the data of the geological map and by the data obtained with field surveys using GPS.

Topographic, pedological, hydrological and geological databases were constructed for the analysis. From these databases, eight factors were extracted. Using the detected landslides and calculated or extracted factors, tow landslide analysis methods were applied: LR and MarSpline. For the application of these, the R Studio software has been used. Finally, the analysis results were verified using the relative operating characteristic (ROC) curve including success and prediction rates [8].

II. STUDY AREA

The study area is located in the north of Morocco, in the northwest of Taounate province; it is one of the most exposed areas to landslides in Morocco. The commune of Oudka is situated between the longitudes 4 ° 42'11.40 "W and 4 ° 56'53.70" W and the latitudes 34 ° 42'35.05 "N and 34 ° 42'52.43" N, it covers a surface of 89 km² (Fig. 2). This area is

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a continuation of the Rif Cordillera and is characterized by mountainous terrain with no plains except near the wadi Aoulai along the western boundary of the town.

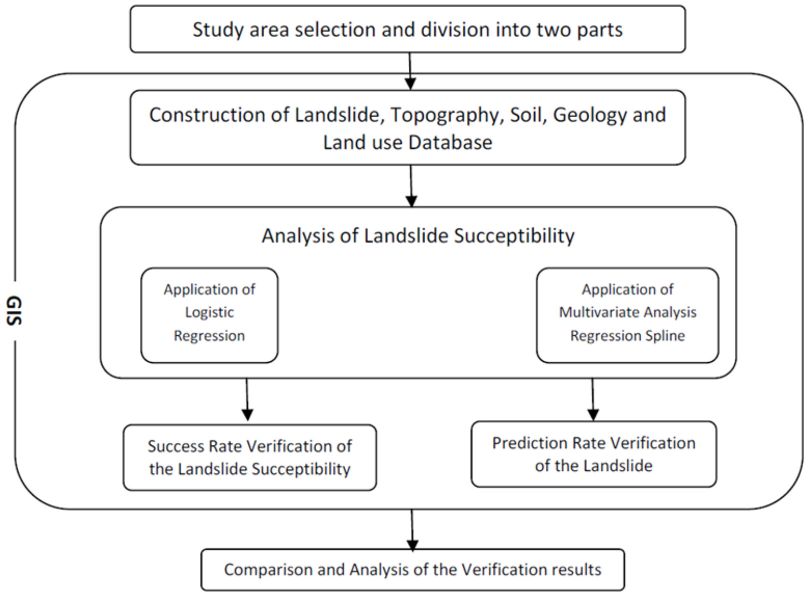


Fig. 1 Flow diagram showing the methodology

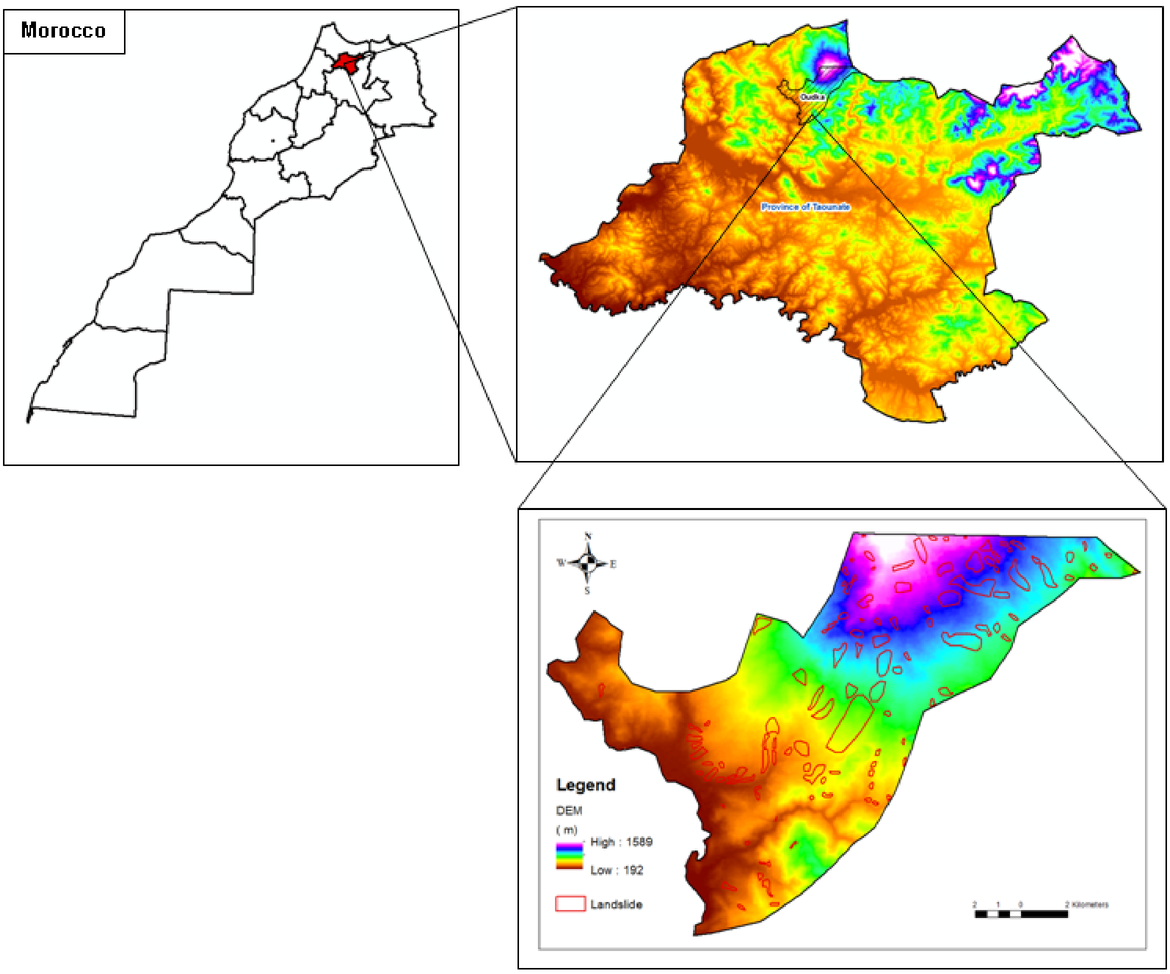


Fig. 2 Geographical location and distribution of landslide in Commune Oudka, Taounate Prefecture, Morocco

Jbel Oudka is considered the most important mountain of the province of Taounate, and its altitude reaches 1600 m. This mountain is characterized by a very important vegetal cover such as the Oudka forest.

In the commune of Oudka, the olive tree occupies the most of the arboreal surface area (92%). It is followed by the cultivation of fig and other crops. Between 1977 and 2018, the Jbel Oudka station recorded an average annual rainfall of 1455 mm [9].

The territory of the commune Oudka is part of the producing area of the Ouergha watershed, it is crossed by several affluents of the oued Aoulai such as oued Elil, oued Elmaleh and oued Assenou.

There are several lacs in this territory and especially in the Oudka forest. The most important of them is Afrat N'joum which is located in the north of the Oudka and which has an area of 13000 m² [9].

The average annual temperature in the region is between 15 and 16 °C. The average maximum temperature of the hottest month is around 34.2 °C, and the average minimum of the coldest month is 0.5 °C. The average extreme thermal amplitude is in the whole pre-rifaine area between 30 ° and 32 °, which corresponds to a semi-continental climate [9].

III. Database Construction

A. Image Data

Image Landsat OLI8 was downloaded from USGS web page and pre-processed by layer stacking of bands 2, 3, 4, 5, 6 and 7. Landsat imagery that was collected along the same satellite path have been mosaicing into a single image. However, atmospheric correction was not necessary for images taken on the same calendar date [9].

B. Landslide Inventory Map

Old landslide data were obtained from: aerial photography, the database of geological maps and field surveys using GPS. Several studies have shown that the best calculation model is one in which the ratio of landslides to non-landslide points is equal to 1 [10].

A total of 105 landslide polygons (Fig. 3) and 43 randomly sampled polygons of the stable surface mapped from different sources were transformed into 8911 cells with a resolution of 30 m for landslide areas and 9005 cells for stable areas (without landslide).

The 8911 cells of the landslide grid and the 9005 cells of the stable zone (without landslide) were randomly divided using the software R into two subsets: half of the cells of the grid were used for the realization of the landslide susceptibility model, while the other half was used for the validation of the model.

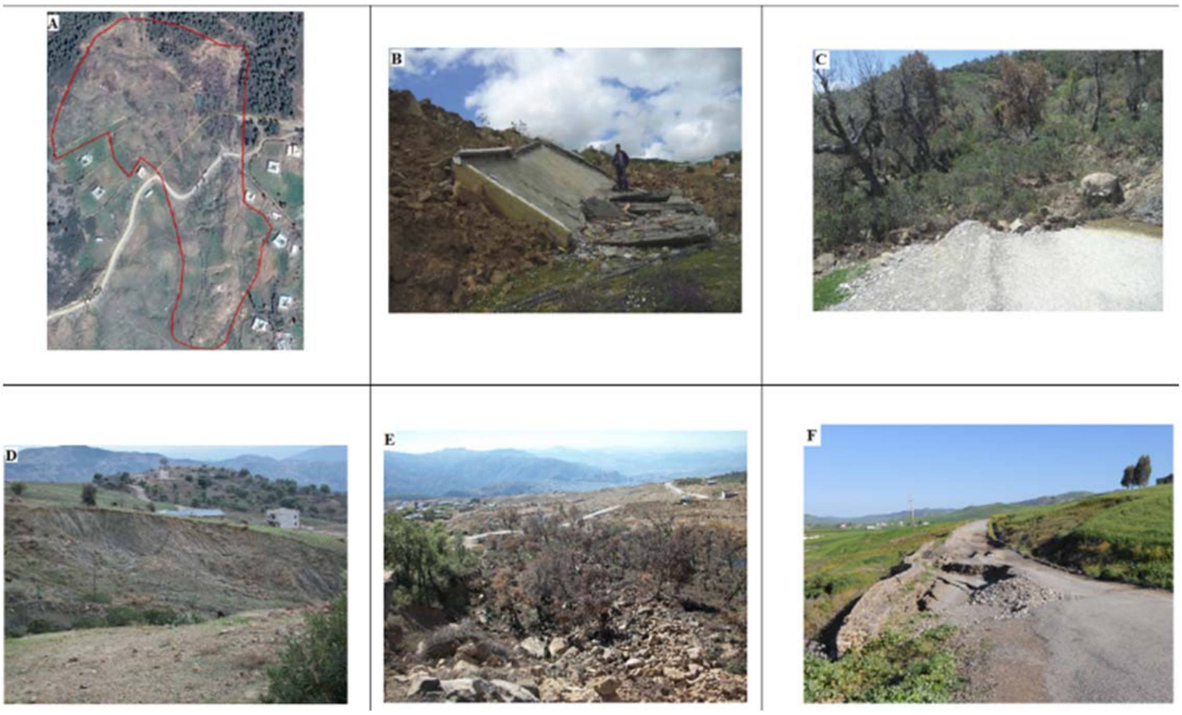


Fig. 3 Overview of the landslides at the level of the oudka commune: (A), (B), (C) landslide of douar Tissoufa; D) landslide at the chaaba located east of douar de tissoufa; (E) slip of mass in limestone mixture into pebbles and marl; (F) landslide at RP 5302

C. Factors

In this study, we divided the conditioning factors into five datasets, including topographic, hydrologic, land use, lithology and human activity datasets. The landslide conditioning factors from these datasets were extracted from different sources and stored in the spatial database with a pixel size of 30 m.

Topographic parameters, such as elevation, slope and aspect, were derived directly from the DEM model. Hydrological data, including distance to streams, were derived indirectly from the DEM. The distance to road parameter reflects the influence of human activities. We used the geological map to represent the lithology and distance to faults. The land use data used in this study are NDVI derived from the Landsat OLI8 image of the study area.

- Elevation: Elevation is a conditioning factor, it is a topographic parameter derived from the Digital Elevation Model (DEM), with resolution of 30 m. In our study area, the values of this factor vary between 192 and 1600 m divided into ten classes: <= 350 m, 350-450 m, 450-550 m, 550-650 m, 650-750 m, 750- 850 m, 850-950 m, 950-1100 m, 1100-1300 m and> 1300 m (Fig. 4 (a)).
- Slope: Slope is one of the key factors for slope stability and is considered to be one of the important factors in landslide susceptibility [11]. This factor has been widely used in the literature [11]-[13]. In this study, the slope map was extracted from the Digital Elevation Model (DEM) and divided into ten classes: <= 5 °, 5 ° - 10 °, 10 ° - 15 °, 15 ° - 20 °, 20 ° - 25 °, 25 ° - 30 °, 30 ° - 35 °, 35 ° - 40 °, 40 ° - 45 ° and > 45 ° (Fig. 4 (b)).
- Aspect: The aspect is considered as one of the main factors of landslide conditioning in landslide susceptibility. It is frequently used in the assessment of landslide susceptibility [11], [12]. For this study, the aspect of the slope was classified into nine classes (Fig. 4 (c)): Flat (-1 °), North (0 ° -22.5 °, 337.5 ° -360 °), Northeast (22.5 ° -67.5 °), East (67.5 ° -112.5 °), Southeast (112.5 ° -157.5 °), South (157.5 ° -202.5 °), Southwest (202.5 ° -247.5 °), West (247.5 ° -292.5 °), and Northwest (292.5 ° -337.5 °).
- Distance to faults: The distance to faults was extracted from the geological map of the study area at a scale of 1: 50,000. It was calculated using ArcGIS software and classified in ten classes (Fig. 4 (d)): <= 150, 150-300 m, 300-450 m, 450-600 m, 600-750 m, 750-900 m, 900-1050 m, 1050-1200 m, 1200-1350 m and> 1350 m.
- Distance to streams: The distance to streams is also a very important factor for landslide susceptibility analysis. In this area, the distance to the rivers was classified into ten classes (Fig. 4 (e)): <50 m, 50-100 m, 100-150 m, 150-200 m, 200-250 m, 250-300 m, 300-350 m, 350-400 m, 400-450 m, and > 450 m.
- Distance to roads: The distance to the road is considered to be one of the factors responsible for the occurrence of landslides and is frequently used for landslide susceptibility analysis [13]-[15]. The distribution of landslides along roads is very common, mainly because the natural state of the slope is damaged during the road construction process. In this study, distance from roads was taken into account to map landslide susceptibility and was classified into ten classes (Fig. 4 (f)): <= 250, 250-500 m, 500-750 m, 750-1000 m, 1000-1250 m, 1250-1500 m, 1500-1750 m, 1750-2000 m, 2000-2250 m and > 2250 m.
- NDVI: NDVI, also called Normalized Difference Vegetation Index, is a measure of surface reflectance and provides a quantitative estimate of vegetation and biomass growth [16], [17].

The NDVI highlights the difference between the visible red band and the near infrared band according to (1):

$$NDVI=(IR-R)/IR+R) \quad (1)$$

where IR is the infrared band of the electromagnetic spectrum and R is the red band of the electromagnetic spectrum.

NDVI values range from -1 to +1, with negative values for areas other than plant covers, such as snow, water, or clouds, where red reflectance is greater than near infrared. For bare soils, the reflectances being about the same order of magnitude in the red and the near infrared, the NDVI has values close to 0. The vegetal formations have values of NDVI positive, generally between 0.1 and 0.7. The highest values correspond to the densest vegetation cover.

For this study, the NDVI value has been reclassified into ten categories (Fig. 4 (g)): <= 0.1, 0.10-0.15, 0.15-0.20, 0.20-0.25, 0.25-0.30, 0.30-0.35, 0.35-0.40, 0.40-0.45, 0.45-0.50 and > 0.50.

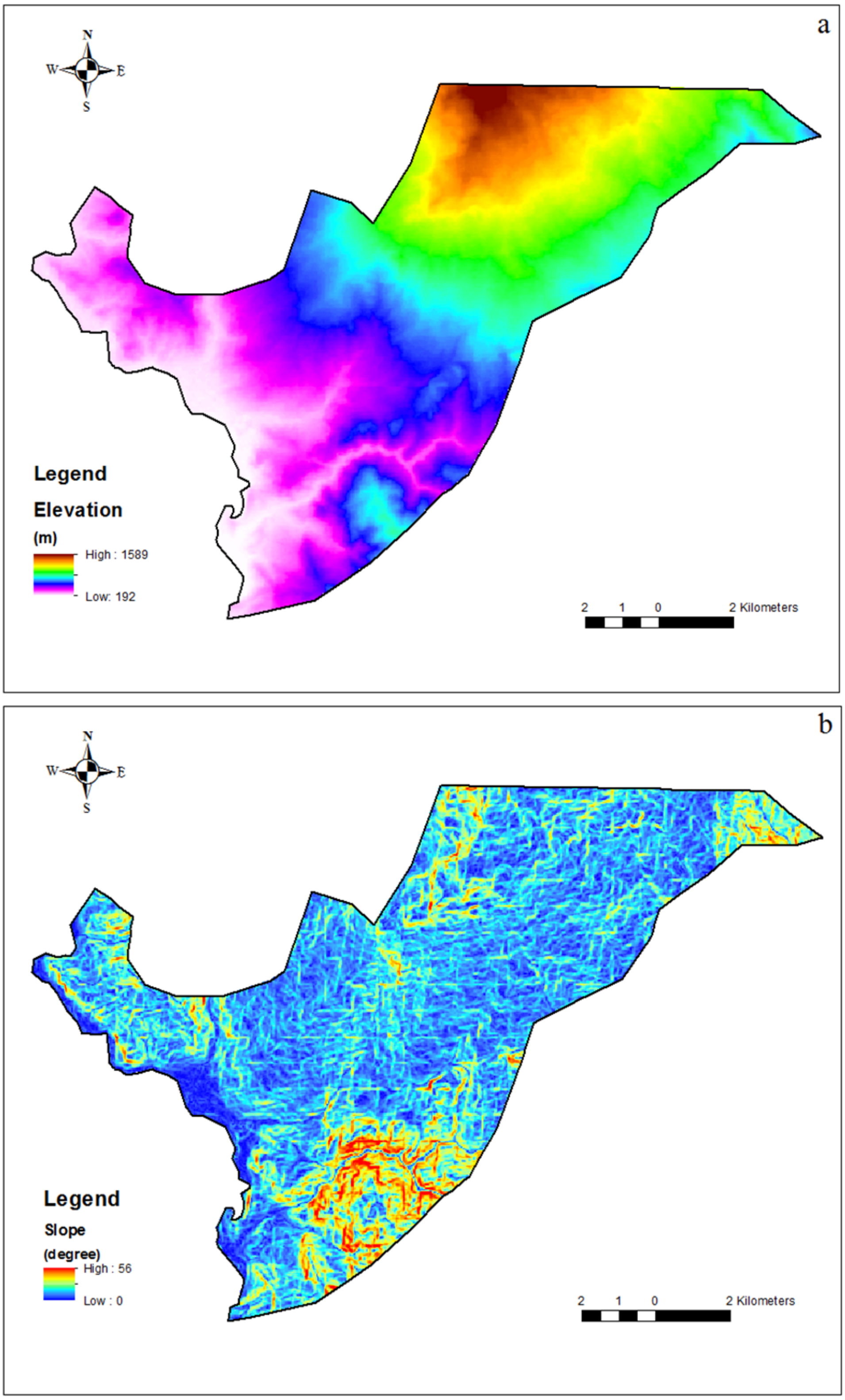
- Lithology: The occurrence of a landslide in the context of geomorphological studies is related to lithology [13], which is considered a very important conditioning factor because each lithological unit has a different influence on the susceptibility to landslides.

In this study, the lithological map of the Oudka was extracted from the Rhafsai geological map at a scale of 1: 50,000. The general lithological setting of our study area is shown in Fig. 4 (h). The resulting map contains categorical data that is transformed into numerical data to lighten the model [10]. We applied, the frequency ratio (FR) that is represented by (2):

$$FR = \frac{Di / Ai}{\sum_{i=1}^{N} Di \Big/ \sum_{i=1}^{N} Ai} \quad (2)$$

where Di is the area of a landslide of the i-th category, Ai is the area of the i-th category for a given parameter, and N is the category number of the parameter.

The different lithological components of the Oudka commune with their frequency ratio values can be found in Table I.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Elevation
(m)
High : 1589
Low: 192
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Slope
(degree)
High : 56
Low : 0
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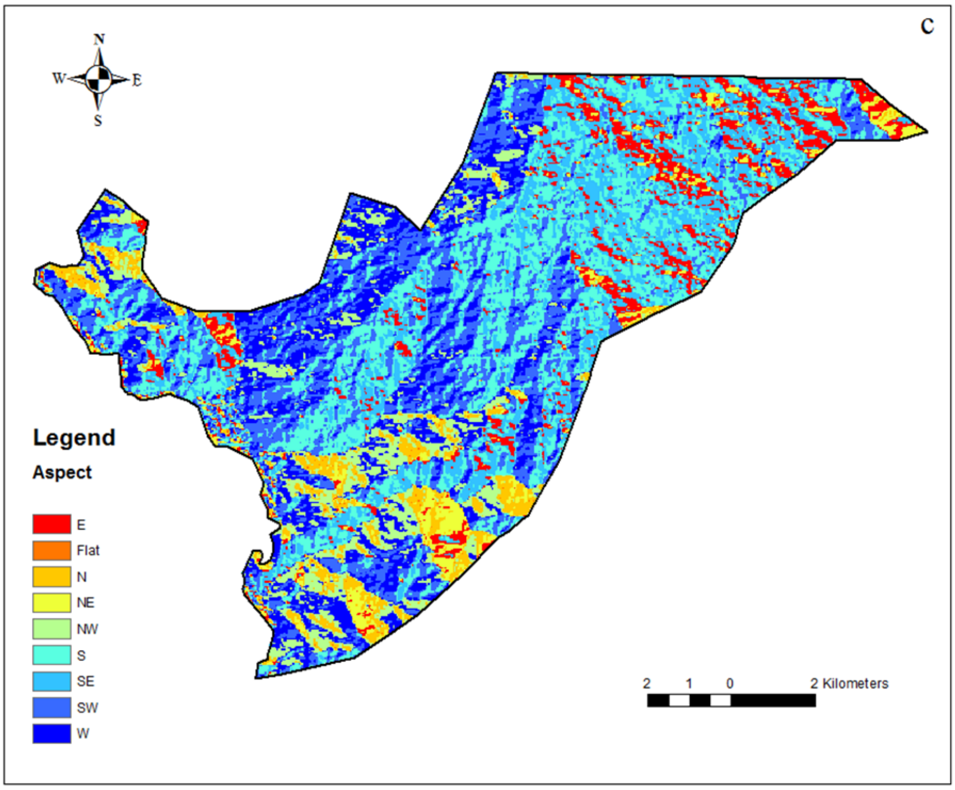
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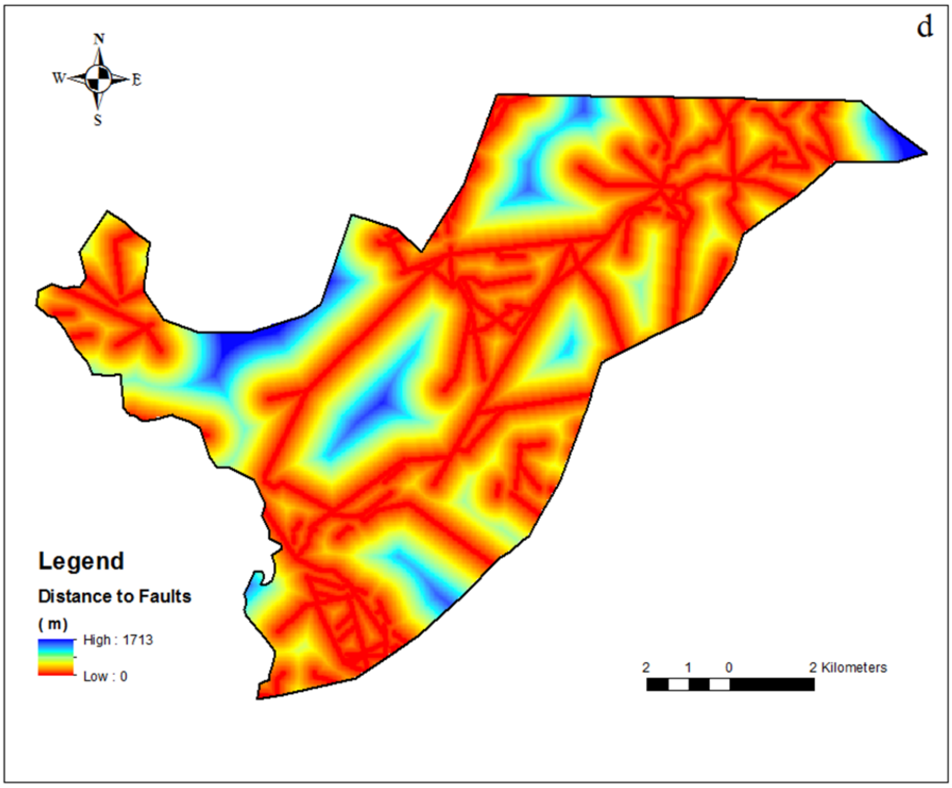
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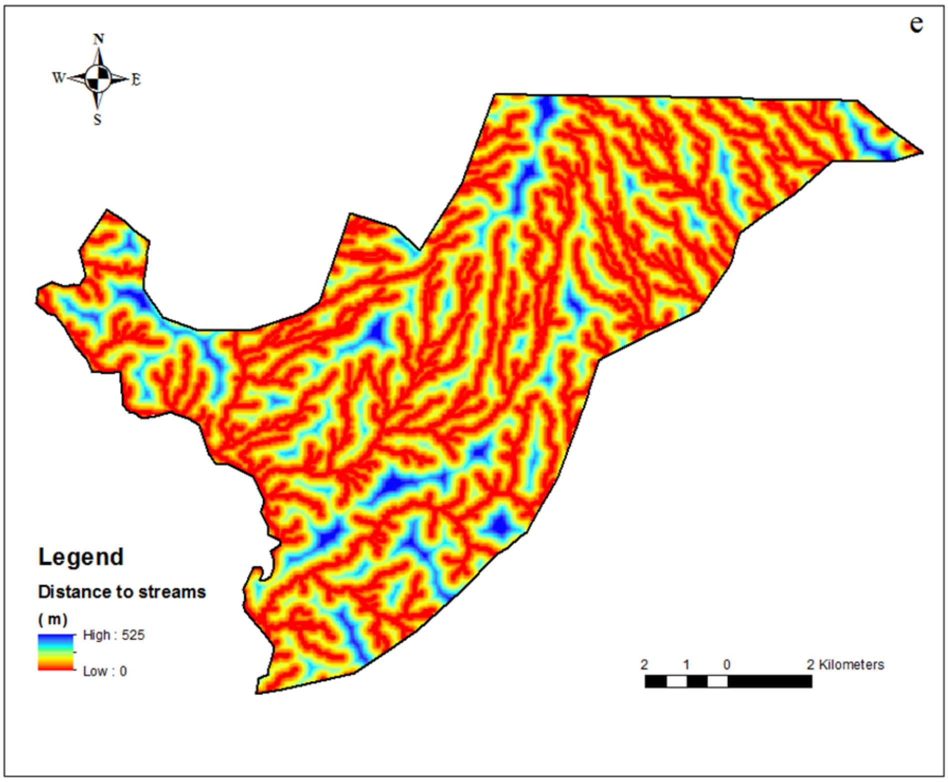
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Distance to streams
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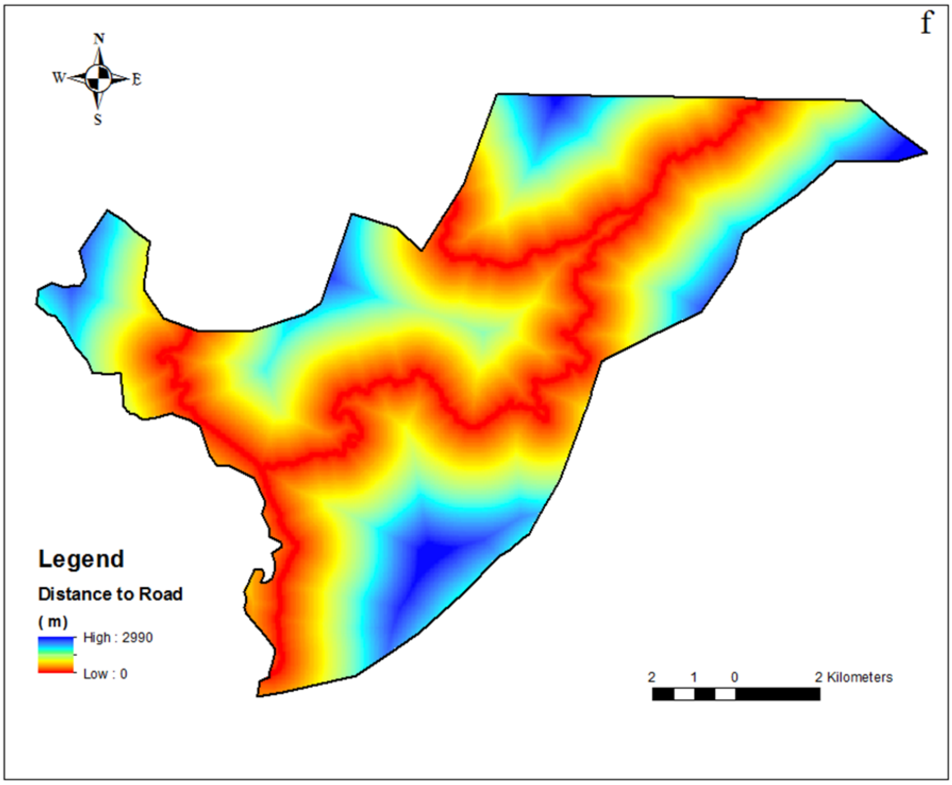
2 1 0 2 Kilometers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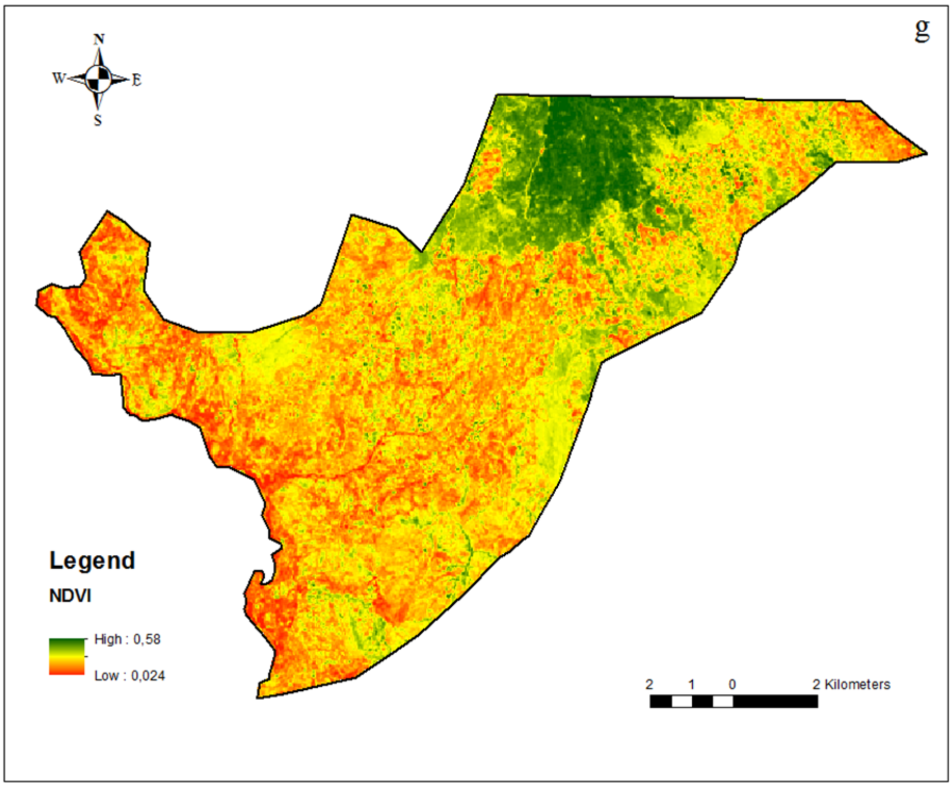
Distance to Road
(m)
High : 2990
Low : 0
2 1 0 2 Kilometers



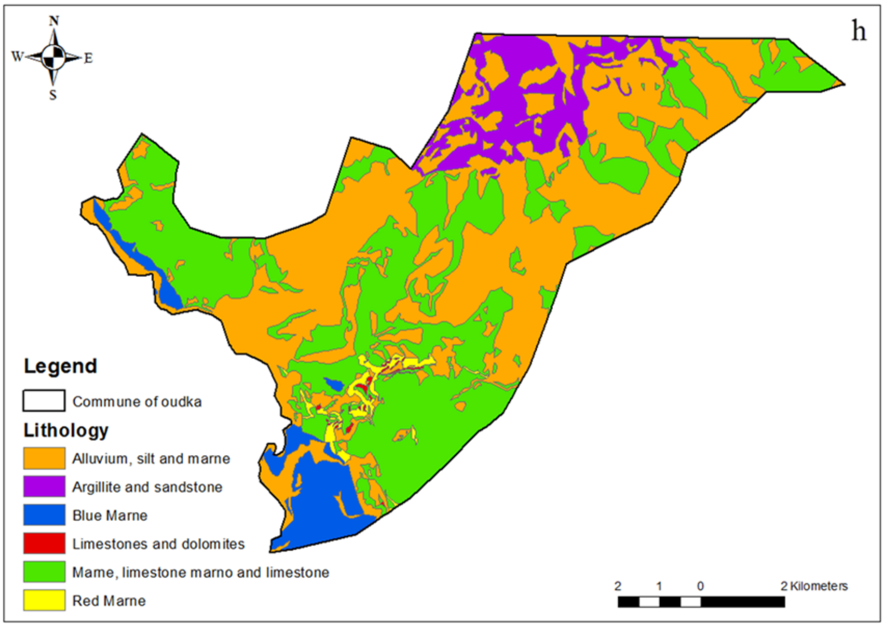


Fig. 4 Maps of some landslide conditioning factors: (a) elevation; (b) slope angle; (c) aspect; (d) distance to faults; (e) distance to streams; (f) distance to road; (g) NDVI; (h) Lithology

TABLE I
FREQUENCY RATIO VALUES OF THE DIFFERENT LITHOLOGICAL COMPONENTS OF THE OUDKA

Factor	class	Type	Study area (points)	Percent of class %	Landslide points	% area cover by landslide in each class	Landslide frequency %
Lithology	A	Alluvium, silt and marne	47968	48.780	7012	78.689	1.613
	B	Blue Marne	5154	5.241	80	0.898	0.171
	C	Argillite and sandstone	8000	8.135	1	0.011	0.001
	D	Marne, limestone marno and limestone	35663	36.267	1816	20.379	0.562
	E	Limestones and dolomites	255	0.259	1	0.011	0.043
	F	Red Marne	1295	1.317	1	0.011	0.009

IV. Landslide Susceptibility Mapping

A. LR Model

The LR model is a mathematical method to establish the relationship between independent factors and landslides [10], [18], [19]. It is useful for predicting the presence or absence of a characteristic or outcome based on values of a set of predictor variables. Past studies compared LR to support vector machines, classification trees and likelihood ratios and found that LR was more accurate [19]-[21], [4]. Therefore, a common logistic-regression model has been used for landslide susceptibility mapping. The predicted values range from 0 to 1 and can be defined by (3):

$$P(Y = 1/X) = \frac{1}{1 + e^{-C(X)}} \tag{3}$$

when: $C(X) = b_0 + b_1X_1 + b_2X_2 + \dots + b_nX_n$ where P is the probability of landslide occurrence (landslide susceptibility index), C(X) is the linear logistic model, b0 is the intercept of the model, n is the number of landslide-conditioning factors, bi is the weight of each factor, and xi is the landslide conditioning factor.

B. MarSpline Model

In 1991, Friedman [22] proposed a MarSpline method that is a nonlinear, non-parametric regression method. This regression method allows the resolution of several relationships that are difficult to solve by other conventional regression methods. The model is automatically determined by the data through a forward/backward iterative approach [23]. The MARSpline model can be defined as a sum of basis functions (4):

$$F(x) = a_0 + \sum_{i=1}^{n} a_i f_i(x) \tag{4}$$

where fi (x) is a basis function, n is the number of basis functions in the model, and f0(x) is the constant basis function, the coefficient of which is a0. All of the coefficients are calculated using ordinary least squares (OLS). The basis functions are represented by (5):

$$f_i(x) = \prod_{j=1}^{di} \left[S_{ij} (X_{v(i,j)} - t_{ji} \right] \tag{5}$$

where di is the number of variables (interaction order) in the ith basis function Sji, Xv(j,i) is the vth variable,1 ≤ v(j,i) ≤ d, and tji is the knot location for each of the corresponding variables. MarSpline estimates the function through a set of adaptive piecewise linear regressions called the 'basis functions'. The implementation of MarSpline is carried out with R studio software.

C. Results of Landslide Susceptibility Models

The database containing a dependent variable (landslide) and the eight independent variables (Altitude, Slope, Aspect, distance to faults, distance to streams, distance to the road, NDVI, Lithology) were randomly divided into two parts the first to create models and the second for the validation using the R software.

In the case of the LR model, the multicollinearity should be checked. To quantify multicollinearity, there are several methods such as: Pearson's correlation coefficients [24], variance decomposition proportions [25], conditional index [26], Variance Inflation (VIF) and Tolerances [27], [28].

In our case, the variance inflation factor (VIF) was used. The resulting values of VIF, as shown in the following table (Table II), are all less than 4, indicating that there is no colinearity problem to explore. In cases where landslide factors had a VIF value greater than 4, these factors will not be applied to the LR model.

To evaluate the effectiveness of the training datasets, the Hosmer and Lemeshow test was used and gave in the LR model being statistically significant and predictive.

The relationship between conditioning factors and landslides based on LR is illustrated in Table III.

TABLE II
Multicollinearity Diagnosis Indexes for Independent Variables

Factors	VIF
Elevation	2.0219
Slope	1.1242
Dist_fault	1.1312
Dist_streams	1.0983
Dist_road	1.1296
Aspect	1.1667
Geology	1.1745
NDVI	1.8110

TABLE III
Coefficients of the LR Model

Parameters	LR model coefficients
Elevation	0.003
Slope	0.004
Distance to fault	- 0.002
Distance to streams	- 0.005
Distance to road	0.0002
Aspect	0.005
Geology	3
NDVI	- 2.314
Constant	- 6.002

From Table III, the Distance to Fault, Distance to Streams and NDVI are negatively related to landslide susceptibility, i.e. when the values of these factors increase, the susceptibility of landslides decreases.

The landslide susceptibility map has been realized (Fig. 5), based on the weights indicated in Table III. The area of susceptibility is very high, and it is the area where there is a high probability (P > 0.8) to have a landslide.

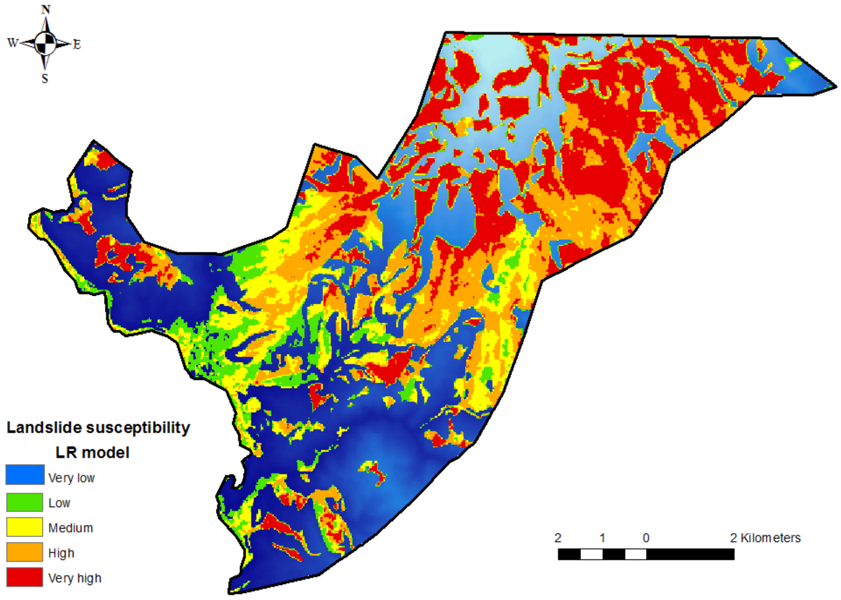


Fig. 5 Landslide susceptibility map produced from LR model

For the MarSpline model, the implementation was performed with the R software based on the training database and the fourteen basic functions (Table IV).

TABLE IV
COEFFICIENTS AND BASIS FUNCTIONS OF THE MARSPLINE MODEL

	Marspline model basis functions	Marspline model coefficients
BF1	max(0,Elevation-265)	-0.213647
BF2	max(0,373-Elevation)	-0.204117
BF3	max(0,Elevation-373)	0.213144
BF4	max(0,Elevation-801)	0.007225
BF5	max(0,429.534637-Dist_fault)	0.002557
BF6	max(0,295.465729-Dist_streams)	0.004196
BF7	max(0,Dist_streams-295.465729)	-0.028934
BF8	max(0,582.494629-Dist_road)	-0.003606
BF9	max(0,Dist_road-582.494629)	-0.001306
BF10	max(0,1.607985-Geology)	-13.387262
BF11	max(0,0.192658-NDVI)	-30.793324
BF12	max(0,NDVI-0.192658)	4.826796
BF13	max(0,NDVI-0.25172)	-47.973135
BF14	max(0,NDVI-0.312795)	47.533463
	Constant	24.812086

From the coefficients and the basis functions of the MarSpline model shown in Table IV, where the probability of presence of landslide Y takes the form (6):

$$Y = 24.812 - (0.214 * BF1)-(0.204*BF2)+(0.213*BF3)+(0.007*BF4)+(0.003*BF5)+ (0.004*BF6) - (0.029 * BF7) - (0.004*BF8) - (0.001*BF9) - (13.387 * BF10) - (30.793*BF11) + (4.827*BF12) - (47.973*BF13) + (47.533*BF14) \tag{6}$$

The landslide susceptibility map was realized (Fig. 6). The area of very high susceptibility it is the area where there is a high probability (P > 0.8) to have a landslide.

V. VALIDATION AND COMPARISON

The landslide susceptibility maps resulting from the application of the different statistical models (LR and Marspline) were divided into five classes. The accuracy of these landslide susceptibility maps was evaluated by calculating the ROC and the percentage of landslide points observed in various susceptibility categories [19].

The Area Under the ROC Curve (AUC) represents the quality of the probabilistic model (its ability to predict the occurrence or not of an event) [29].

The ideal model shows a curve that has the largest AUC, AUC ranges between 0.5 and 1. If the value of AUC is close to 0.5, it indicates inaccuracy [30].

An ROC curve of 1 indicates a perfect prediction. In this study, all landslide susceptibility models were validated using success rate and prediction rate methods.

The success rate results were obtained by comparing landslide susceptibility maps with landslides in the training data set, while the prediction rate results for the susceptibility models were evaluated using the validation dataset independent of that used in the landslide model construction process and using the R software.

The ROC curves of this study are illustrated in Fig. 7.

The AUC values obtained from the susceptibility maps show that the MarSpline model gave the highest success rate (AUC = 0.963) and the best prediction rates (AUC = 0.951) compared to the LR model (success rate AUC = 0.918 and prediction rate AUC = 0.901). These results indicate that the MarSpline model is the best model for determining landslide susceptibility in the study area.

The landslide susceptibility maps were verified by landslides covering 4463 pixels of the municipality Oudka. These landslides were not used in the construction of the models. The landslide susceptibility maps of the two models were divided into five categories (Fig. 8): Very low (0 < LSI ≤ 0.2), Low (0.2 < LSI ≤ 0.4), medium (0.4 < LSI ≤ 0.6), high (0.6 < LSI ≤ 0.8) and very high (LSI > 0,8).

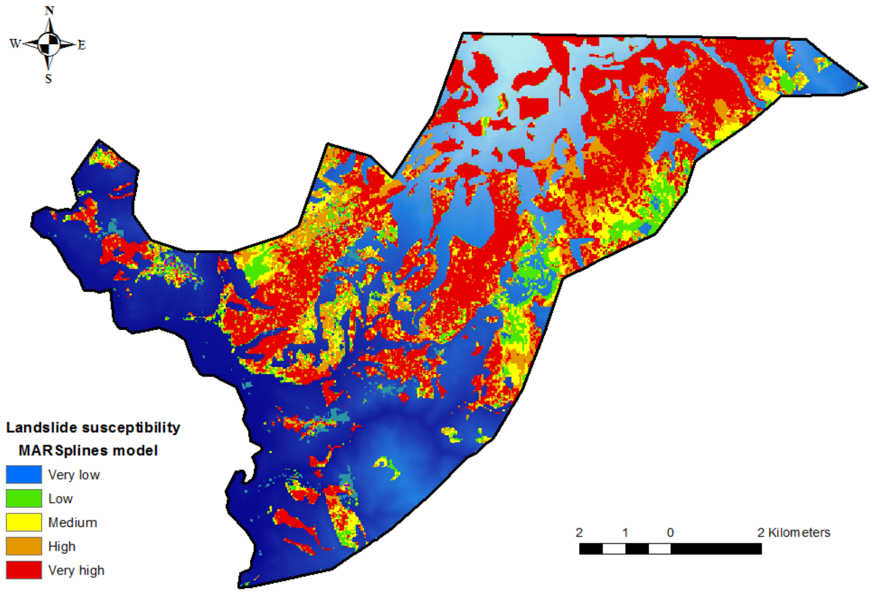


Fig. 6 Landslide susceptibility map produced from Marspline model

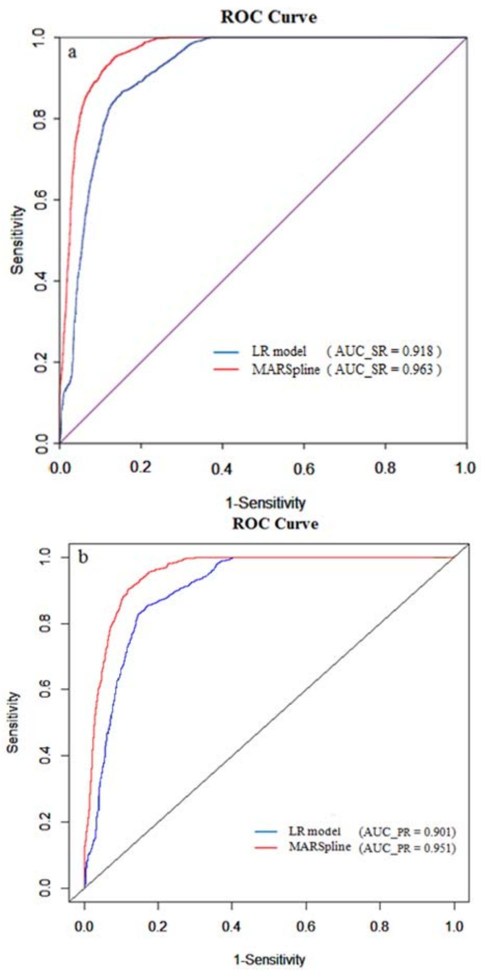


Fig. 7 ROC curve evaluation of the LR and MarSpline models: (a) success rate curves and (b) prediction rate curves

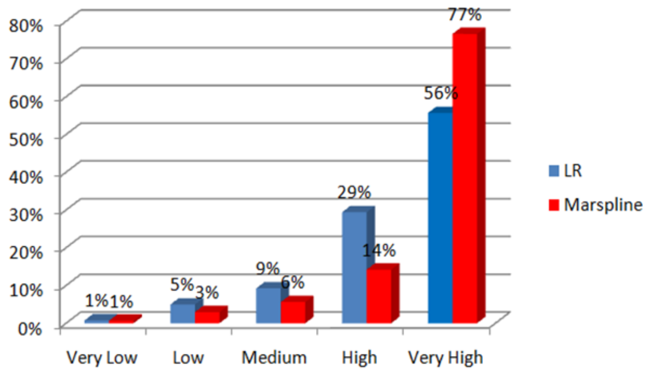


Fig. 8 Percentages of test landslide points falling into different susceptibility categories using LR and MarSpline

The superposition between the verification landslides (4463 pixels) and the landslide susceptibility maps resulting the LR and MarSpline models, allowed us to determine the percentages of test landslide points falling into different susceptibility categories (Fig. 8).

In the very low susceptibility class, we found just 1% of the observed landslides for the LR and MarSpline methods.

In the very high susceptibility class, we found 56% and 77% of landslides observed for the LR and MarSpline methods, respectively. However, in the high and very high susceptibility classes, we found 85% and 91% of the landslide observed in these classes for the LR and Marspline methods, respectively.

By comparing the results of the LR and Marspline analysis, we determined that the MarSpline method was better than the LR method.

The MarSpline method is the best approach for the assessment of landslide susceptibility for the Oudka commune.

VI. Discussion and Conclusions

Different researchers have proposed various methodologies for the landslide susceptibility mapping.

The demolition of five constructions by the landslide of Tissoufa, northern Oudka, caused by the heavy rainfall of 2013 has highlighted the need for the establishment of landslides susceptibility map in the municipality of Oudka.

In this study, LR and MarSpline methods were applied to landslide susceptibility mapping for the municipality of Oudka, north of morocco. The study included three main stages such as landslide inventory, analysis and evaluation of the susceptibility map.

The accuracy of the landslide susceptibility maps was evaluated by the calculation of the ROC. The results show that the MarSpline model gave a success rate (AUC = 0.963) and a prediction rate (AUC = 0.951) higher than the LR model.

The calculation of the percentages of test landslide points using LR and MarSpline showed that the results obtained for the two high and very high susceptibility classes are 85% and 91% respectively for the LR and MarSpline methods.

These results show that the best method that can be used is MarSpline.

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