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LANDSLIDE SUSCEPTIBILITY MAPPING USING GIS-BASED LOGISTIC REGRESSION: THE CITY AL HOCEIMA AND ITS SUBURBS (MOROCCO) CASE STUDY

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Landslide susceptibility mapping using GIS-based logistic regression: The city Al Hoceima and its suburbs (Morocco) case study

Public authorities in the Al Hoceima region have become concerned about landslides given the increasing demand for urban development in the region. Therefore, the identification of landslide susceptibility has become necessary to meet the needs of current and future habitats and to minimize possible landslide disasters. This paper is a demonstration of the application of the logistic regression method to produce the landslide susceptibility map for Al Hoceima. A landslide database with nine predictive factors was constructed by processing cartographic documents, Google Earth images, the restitution plan, the geological map, and the landslide inventory. The obtained susceptibility map shows that 22.1% of the study area is extremely susceptible to landslides, 7.6% of the area is moderately susceptible to landslides and 70.3% of the area is weakly susceptible to landslides. The validation of the map obtained by the logistic regression model used in this analysis gave good results. The superposition of the landslides reserved for validation with the obtained map allows for classifying the majority of the observed landslide pixels into high and very high hazard classes. The results of the ROC curve obtained for the approach used proved that the multivariate approach by logistic regressions is performing better (AUC= 0.894) for the prediction of the landslide hazard in the city of Al Hoceima and its periphery. The map obtained is a major contribution to various urban development plans and is the future orientation of urbanization.

Key words: GIS, logistic regression, landslide susceptibility, region of Al Hoceima, Morocco

INTRODUCTION

Landslides with significant human and material losses threaten the social, economic, and environmental aspects of the region of Al Hoceima. The periphery of the city of Al Hoceima is a densely populated residential area and is mainly composed of mountainous terrain made of marl and shale materials. The region has known a number of landslides and remarkable economic damages in recent years. Population growth and increasing demand for building land on the hill slopes are inevitable. Therefore, identifying areas prone to landslides has become essential for ensuring sustainable development and for minimizing possible landslide disasters. Nowadays, landslide susceptibility mapping uses digital tools to manage spatial data such as GIS and geoinformatics (Sarkar et al. 2008). Thus, in recent years, the use of quantitative methods in combination with GIS has increased enormously and has become more frequent than qualitative methods (Bonham-Carter et al. 1989, Maquaire 2002, van Westen et al. 2003 and Thiery et al. 2004). These methods are based on the analysis of the relationship between factors responsible for the occurrence of landslides and their past and current distribution. They require the collection of a large amount of data to produce reliable results. Quantitative prediction is done for areas where landslides have not yet occurred but exhibit similar environmental conditions to those in the past (geology, geomorphology, climate, human activities' impact, etc.). These methods have been used in recent years by several Moroccan authors. Ezzine et al. (2008) and Master (2011) who applied probabilistic statistical methods to map landslide susceptibility in the Chafechaouen region, using logistic regression and weight of evidence methods. Byou et al. (2021) applied the latter in the city of Al Hoceima and its surroundings in 2021. Both of these methods are commonly used in the context of binary classification problems, especially in the field of risk management (Ezzine et al. 2008). The weight of evidence method is a bivariate approach that allows calculating the weights of continuous or categorical variables in numerical format, which can be used as input for predictive models (e. g., logistic regression, decision tree). Positive values indicate a positive relationship with the target event, while negative values suggest a negative relationship. The logistic regression method is a multivariate statistical approach used for binary classification, estimating the probability that an event will occur based on one or more predictor variables. It can handle both continuous and categorical variables by converting them into numerical representations and simultaneously estimates the model's probabilities and coefficients. This method has been used frequently in recent years by several Moroccan and Algerian authors. El-Fengour et al. (2021) applied this method in the Sahla watershed in Northern Morocco. Mahdadi and Boumezbeur (2020) also applied this method for landslide susceptibility mapping in the Souk Ahras region, Northeastern Algeria.

The objective of this work will be focused on the evaluation of the susceptibility to landslides by the method of logistic regression. The potential of this model derives from its reproducible objective character and from the fact that it quantifies the probability of occurrence of landslides. Thus, this work is structured around two main questions:

– What data are needed for landslide susceptibility mapping using the regression method?

– Is this method more suitable and appropriate for the study area, and does it provide more reliable results?

PRESENTATION OF THE STUDY AREA

Al Hoceima city is located in Northern Morocco on the Mediterranean coast between longitudes 3°54'19" W- 3°59'56" and latitudes 35°15'51" N- 35°12'33" N (Fig. 1). The study covers an area of 34 km² with an altitude varying from 0 to 406 m above sea level. It is a mountainous region, made up of deep valleys, separated by modest reliefs together with steep slopes. These reliefs are marked by limestone ridges reaching 406 m at Jebel Monte Palomas, 300 m at Jebel Malmusi, and by high cliffs often reaching 100 m at the level of the dolomitic plateau "Morro nuevo" and the bay of Al Hoceima.

From the geological point of view the area under study is part of the Bokkoya chain which was shaped by geological layers overlapped by irregular contacts and cut by normal faults. Devonian and Lias limestones; Triassic Dolomites; Eo-Oligocene marls, Silurian shales, and Quaternary dune sands compose the main outcropping materials.

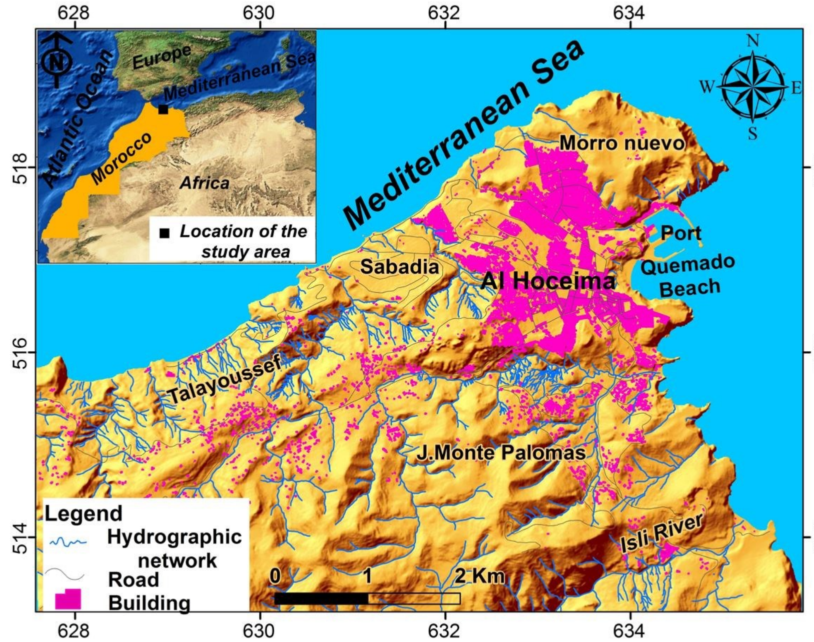

Fig. 1. Situation of the Al Hoceima region

The climate of the area is characterized by being Mediterranean, and semi-arid, marked by temperate winters and hot summers. The average annual rainfall is 325mm; the irregular and extreme rainfall events aggravate the action of the rain on the soil. Most recorded landslides usually coincide with heavy downpours greater than or equal to 60 mm (Margaa and Abdelgader 1998). For example, landslides of big surfaces located in Sidi Mansour, Dhar Masaoud, Inouren, and Port Al Hoceima were triggered following intense and brutal downpours of October 27, 2008, which reached 130mm.

Although precipitation is the most important factor that leads to the appearance of landslides, it is not used in this study since the rain is relatively uniform throughout the study area and also due to the insufficient number of rainfall and rainfall station data (Ayalew and Yamagishi 2005, Regmi et al. 2010 and Yalcin et al. 2011).

METHODOLOGY

Figure 2 shows the methodological approach adopted for the analysis of landslide susceptibility in the city of Al Hoceima and its periphery based on the logistic regression model. This approach includes three steps:

– Acquisition and preparation of data on landslides and the causative factors responsible for their occurrence.

– Landslide susceptibility mapping is based on the logistic regression method.

– Validation of the results obtained.

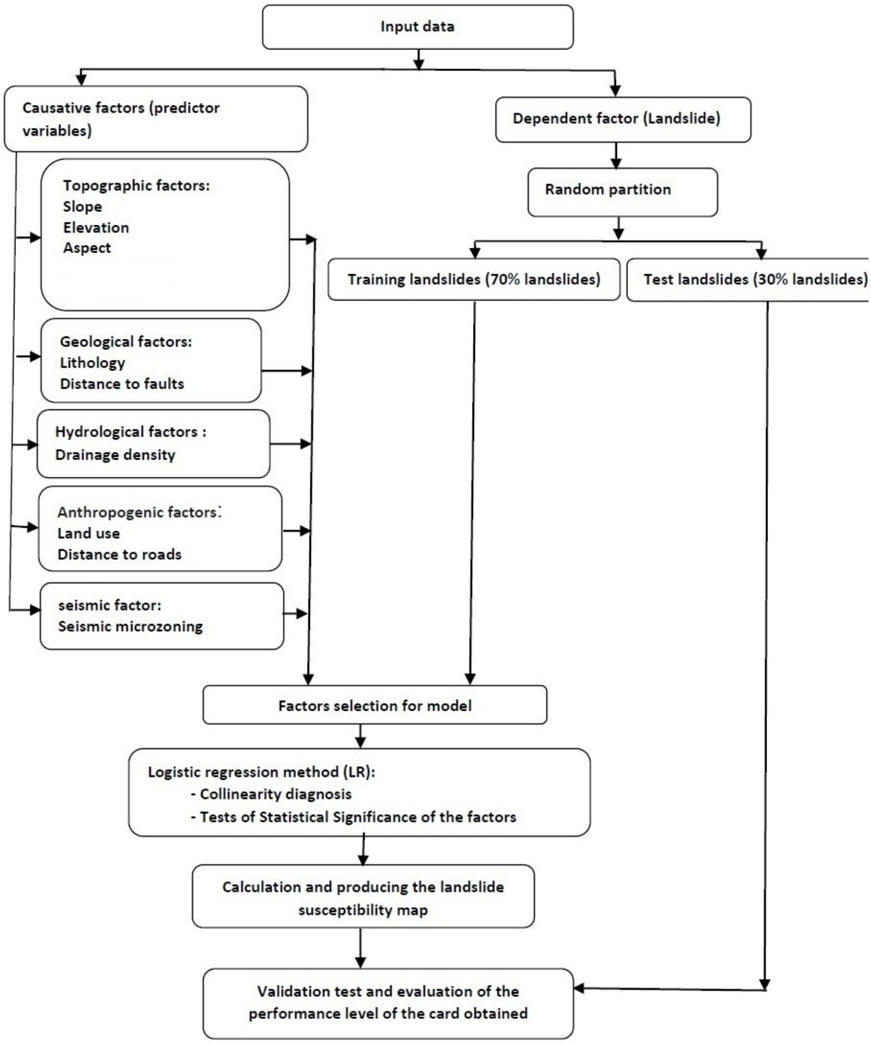

Fig. 2. Flow chart showing the source data and the steps taken to produce the landslide susceptibility map

Data acquisition and pre-processing

For the assessment of the susceptibility to landslides, it is necessary to prepare a database combining the driving factors and the inventoried landslides (Fig. 2). Landslide determinants include four aspects such as geological factors, topographical factors, water factors, and human activity factors. The study selected lithology, distance to faults, seismicity, slope, elevation, slope exposure, drainage density, distance to roads, and land use as landslide factors (Fig. 3). To carry out a detailed geomorphological analysis, a DEM was generated from the restitution plan of the

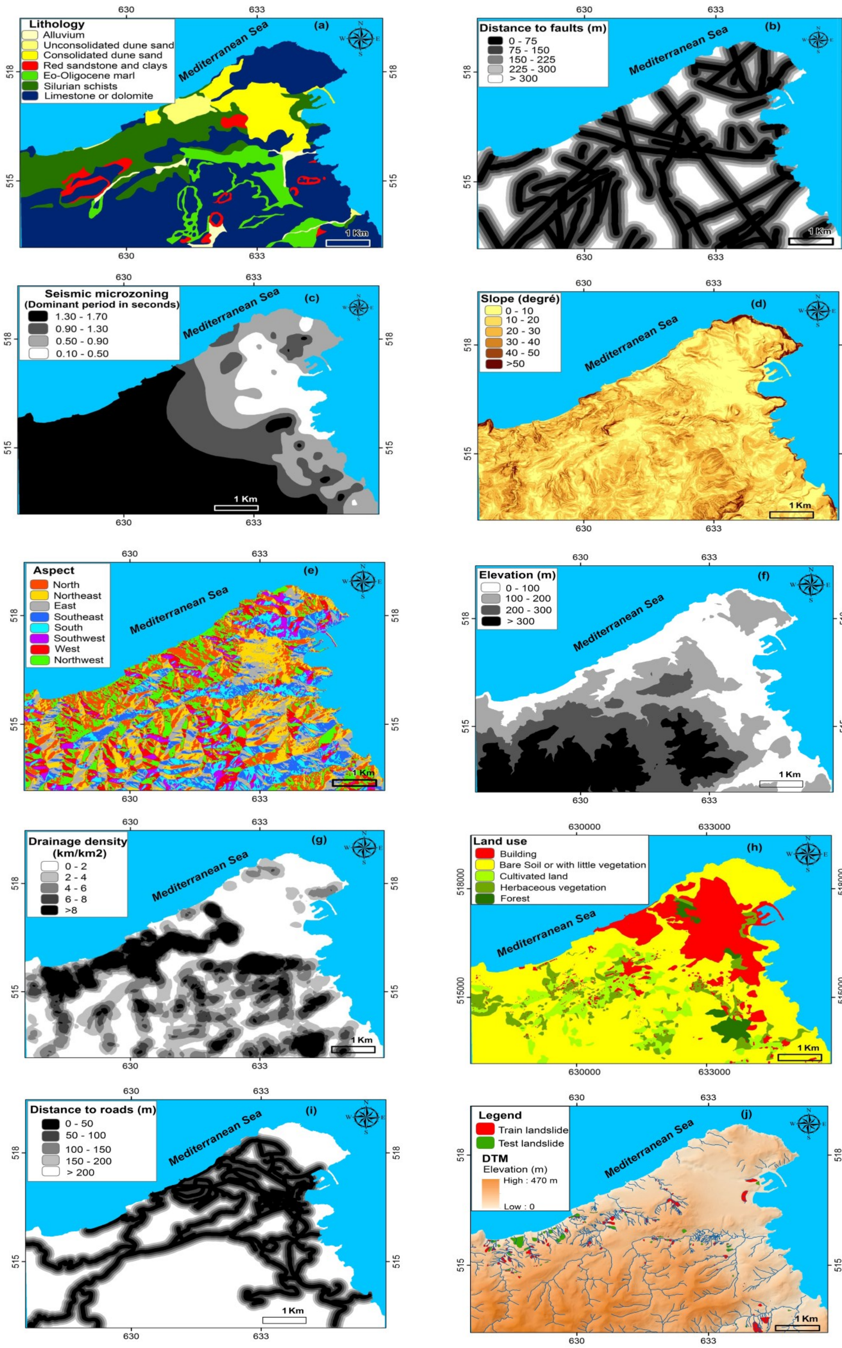

Fig. 3. Determining factors of landslides

a – lithology, b – distance to faults, c – seismic microzoning, d – slope, e – aspect, f – elevation, g – drainage density, h – land use, i – distance to roads. j – landslide inventory map city of Al Hoceima with a scale of 1/2000 (2020 edition, Lambert zone 1 projection) and which is a source of morphological factors such as slope, slope exposure, elevation and drainage densities (El-Fengour et al. 2021). The lithological data was obtained from the geological map of Al Hoceima. Land use mapping was carried out for the whole study area through a visual interpretation of Google Earth images (2022 edition). The landslide inventory was carried out in the field based on geological and geomorphological criteria. Among the 155 landslides inventoried, only 49 landslides occurring in the period 2004 – 2022, detected from the interpretation of Google Earth images, were reserved for the validation phase. Then, all these data are transformed in raster format in 5m cell size and reclassified to be used in the GIS environment to have the same spatial resolutions, projections, etc. The statistical processing of the data was carried out using SPSS 24 software.

Logistic regression

Landslide susceptibility assessment in the city of Al Hoceima and its periphery was carried out by the logistic function. Many studies have used this approach for landslide susceptibility mapping (van Westen 1993, Ohlmacher and Davis 2003, Ayalew and Yamagishi 2005, Lee 2005, Yesilnacar and Topal 2005, van Den Eeckhaut et al. 2006, Mathew et al. 2007, Thiery 2007, Bai et al. 2010, Mărgărint et al. 2011, Mastere 2011, Palm et al. 2011, Wang et al. 2011, Devkota et al. 2013, Ozdemir and Altural 2013 and Pourghasemi et al. 2013). This approach permits the analysis of the different causative factors responsible for landslides. It is based on the assumption that these factors generate a future phenomenon under similar conditions as in the past. This phenomenon is considered a variable to be modeled and the causative factors that govern the triggering conditions are considered predictor variables (Thiery 2007, Ezzine 2008 and Mărgărint et al. 2011). This technique provides weights and coefficients for each predictor variable based on data derived from samples collected in the area of study. These coefficients are used to estimate the probability of occurrence of future landslide events based on the current presence and absence of the phenomena associated with the different predictor variables x_1, x_2, ..., x_n (Lee 2005):

The logistic model is expressed as (Hosmer and Lemeshow 1989, Stafford and Bodson 2006 and Allison 2012):

$$P(Y = 1|x_i) = \hat{p} = \frac{1}{1 + e - \left(\hat{\beta}_0 + \hat{\beta}_1 x_1 + \hat{\beta}_2 x_2 + \cdots + \hat{\beta}_n x_n\right)} \quad 1)$$

The logistic regression equation can be written:

$$Logit(\hat{p}) = ln\left(\frac{\hat{p}}{1 - \hat{p}}\right) = \hat{\beta}_0 + \hat{\beta}_1 x_1 + \hat{\beta}_2 x_2 + \cdots + \hat{\beta}_n x_n \quad 2)$$

where $\hat{p}$ refers to the probability of occurrence of a landslide, $\hat{\beta}_0$ is a constant and $\hat{\beta}_1, \hat{\beta}_2, \ldots, \hat{\beta}_n$ are the regression coefficients of the independent variables used in the logistic model.

The implementation of the logistic regression model requires preparing a database for each predictor variable. To extract the values of the predictor variables from the raster layers, we generated a binary grid of points. The set of landslide points signifying the presence of landslides is coded as 1. In accordance with the equal proportions of landslide and non-slide grids, the same number of points were randomly sampled from areas outside the landslide areas (Dai and Lee 2002, Yesilnacar and Topal 2005, Bai et al. 2010, Mărgărint et al. 2011 and Wang et al. 2011).

Validation of results

A graphic representation using the ROC curve (receiver operating characteristic) is used for the validation of the results obtained by the model. The ROC curve is a statistical tool that allows the performance of the landslide susceptibility model to be evaluated by comparing the validity of the landslide forecast with other events observed in the field. In this analysis, the construction of the ROC curve is carried out using landslide data reserved for validation (30% of all landslides observed in the field) and which were not taken into consideration in the data used to create the susceptibility map. This mode of representation is based on the threshold values which separate stable and unstable terrain. This curve demonstrates "specificity" on the *x*-axis and "sensitivity" on the *y*-axis. The "sensitivity" or (true positive rate) represents the proportion of pixels affected by landslides correctly classified as unstable. The "specificity" or (1- false positive rate) represents the proportion of pixels not affected by shifts correctly classified as stable (Fressard 2013). The calculation of the sensitivity and specificity associated with the different threshold values is expressed by the following formulae:

$$Sensitivity = \frac{TP}{TP + FN} \qquad 3)$$

$$Specificity = 1 - false\ positive\ rate = 1 - \frac{FP}{FP + TN} \qquad 4)$$

where *TN* is number of pixels correctly classified out of class, *FP* is number of pixels not correctly classified in class, *FN* is number of pixels not correctly classified out of class and *TP* is number of pixels correctly classified in class.

The area under the ROC curve or AUC (Area Under Curve) can be used as a measure to evaluate the discriminative power of the model. The larger the area under the curve, the more the ability of the model to predict the presence and absence of landslides (Dumlao and Victor 2015). AUC is calculated by adding the areas of the polygons between the different thresholds (Beguería 2006):

$$AUC = \sum_{i=1}^{n+1} \frac{\sqrt{(x_i - x_{i+1})^2} * (y_i + y_{i+1}}{2} \qquad 5)$$

where x_i is specificity and y_i is sensitivity at threshold *i*.

Finally, the validation of the results was carried out by comparing the results provided by the LR and a dataset of inventoried landslides (not used in the training phase).

RESULTS AND DISCUSSIONS

Logistic regression modelling is sensitive to multicollinearities between independent variables (Hosmer and Lemeshow 1989 and Dumlao and Victor 2015).

The multicollinearity check shows that there is no multicollinearity between the independent variables. The maximum variance inflation factor and the minimum tolerance index are respectively 1.021 (Vif<2) and 0.528 (Tol>0.2) – Tab. 1.

The logistic regression procedure under SPSS 24 allows for the selection of a varied number of predictors, it also offers a stepwise analysis giving the possibility to select step by step the variables that present the highest degree of representativeness (Mathew et al. 2007). The significance of each of the explanatory variables was tested by the Wald test [(B/standard error)2] and by the corresponding degree of freedom (Palm et al. 2011). Table 1 shows that the level of significance of the different independent variables used in this analysis is lower than 0.05 (p-value < 0.05 – Djeddaoui et al. 2017) except for the variable "distance to roads" which was excluded from the model.

Tab. 1. Coefficients and diagnostic indices for multicollinearity of variables used in the logistic regression equation

Independent variables	Coefficient (B)	Wald	P-value	Exp (B)	Collinearity	Statistics
					Tolerance (Tol)	Variance inflation factor (Vif)
Lithology	0.637	3 635.602	0.000	1.890	0.528	1.892
Slope	0.421	648.704	0.000	1.523	0.838	1.193
Drainage density	0.411	814.267	0.000	1.508	0.534	1.873
Aspect	0.111	151.123	0.000	1.118	0.896	1.116
Land use	0.260	157.234	0.000	1.297	0.799	1.251
Distance to faults	0.199	176.601	0.000	1.220	0.980	1.021
Elevation	0.338	160.530	0.000	1.402	0.584	1.711
Seismic microzoning	-0.073	17.139	0.000	0.930	0.764	1.309
Constant	-9.337	3 920.118	0.000	0.000		

B – regression coefficient of the predictive variable; wald – test de wald; p-value – critical probability; exp (β) – coefficient exponent of the predictive variable; variance inflation factor (Vif)= 1/Tolerance (Tol)

The logistic regression coefficients are $(\hat{\beta}_i)$. The logistic regression coefficients were used to generate the probability (susceptibility) map of landslide occurrence using equations 1 and 2 (Fig. 4).

The interpretation of the association between predictor variables and landslide occurrence based on $\exp(\hat{\beta}_i)$ (shows that geological conditions: lithology and faults can have a positive influence on landslide initiation). For example, as the results show, landslides are concentrated in lithology dominated by marl, or shale, and also by the proximity of faults. In addition, the hydrographic network and the steep slopes constitute a remarkable effect on the occurrence of these phenomena. They are followed by the moderate influence of other factors: such as anthropic action and slope exposure which have a medium effect on the occurrence of these events.

The susceptibility or probability of a landslide occurrence is calculated for all pixels of the study area; where 0 corresponds to no susceptibility while 1 corresponds to total susceptibility. The classification of the landslide hazard is based on natural ruptures of probability or abrupt changes in probability values. Therefore, four probability classes were obtained: null/low (0 – 0.150), medium (0.151 – 0.421), high (0.422 – 0.685), very high (0.686 – 0.976), and from these classes, the landslide hazard zoning was carried out in Al Hoceima city and its periphery (Fig. 4). According to this classification, about 22.14% of the area is classified as a high and extremely high susceptibility zone. The moderate susceptibility zone covers 7.60% of the total area and 70.26% of the total area is included in the low susceptibility zone (Tab. 2).

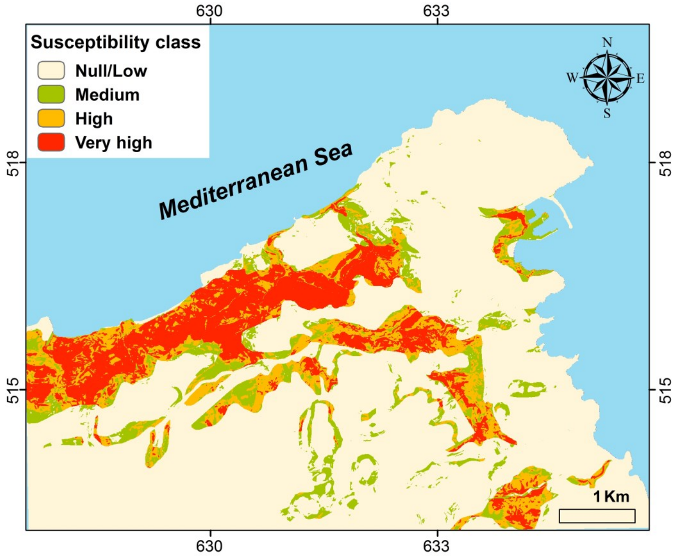

Fig. 4. Landslide susceptibility map of studied area

The results of the landslide susceptibility analysis were checked with the help of the location of the inventoried landslides which is not introduced in the susceptibility analysis. The accuracy of the results was assessed by calculating the ROC curve (receiver operating characteristic) and the percentage of landslides observed in the different susceptibility classes. The area under the ROC curve is a useful indicator to test the quality of the probabilistic model by describing its ability to predict the presence or absence of a landslide event. The value of AUC is between 0.5 and 1. If the value of AUC is close to 1, it means that the model is very accurate, while values close to 0.5 indicate model inaccuracy.

In this study, the AUC value reached 89.4% (Fig 5), implying a strong correlation between the predictive variables and observed landslides in the field. These variables enable the development of a high-performing model for predicting areas prone to landslides. In Table 2, 93.08% of observed landslides are concentrated in only 22.14% of the total area with high and very high susceptibility.

This vulnerability is due to the combination of a set of factors favoring the appearance of landslide phenomena. The study area is a mountainous region belonging to the Bokkoya range receiving violent precipitation due to N or NE disturbances caused by polar discharges. These weather conditions can indeed increase the risk of landslides. The irregular and intense nature of precipitation in autumn and at the end of summer aggravates the situation and often causes landslide phenomena, especially in the northern and eastern slopes of the city, which reflects the positive effects of the lithology, slope, aspect, and elevation on the occurrence of landslides, as indicated by the β coefficients (Tab. 1). Vulnerable areas are dominated by weathered shales and marls. They also increase as we approach fault lines. For example, numerous recent landslides have been detected in Sidi Mansour and east of Sabadia where the Ajdir fault intersects with other faults.

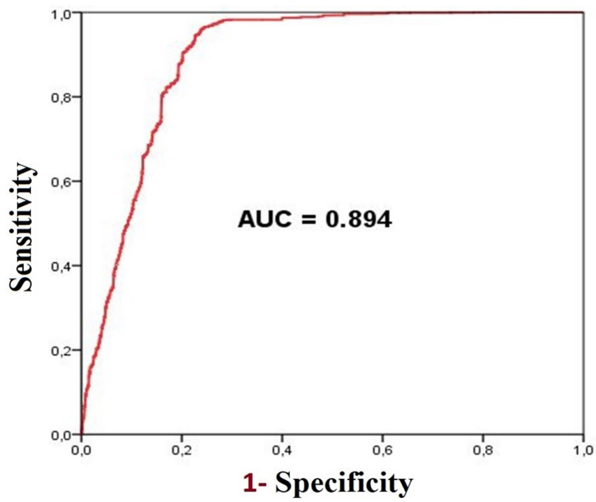

Fig. 5. ROC curve of the susceptibility map produced in this study

In addition, a significant area of high sensitivity to landslides was observed along the maritime coast mainly in the northwest part of Talayoussef. These are areas of ancient landslides constituting folded schists of the Silurian age. These zones are often reactivated by the reduction of their main body due to wave of the sea and erosion, which favours the propagation of sliding upstream, in the form of retrogressive sliding.

Tab. 2. Characteristics of the four classes of landslide susceptibility

Susceptibility class	Probability	Share from the total study area (%)	Landslide surface inventoried (%)
Null/Low	0 – 0.150	70.26	1.52
Medium	0.151 – 0.421	7.60	5.40
High	0.422 – 0.685	9.34	27.98
Very high	0.686 – 0.976	12.80	65.10

Similar results were obtained using the bivariate approach based on Bayes' theorem "weight of evidence" (Byou et al. 2021). They demonstrate that the factors used in this analysis influence the genesis of landslides. The combination of topographic, hydrological, geological, seismic, and land-use factors contributes to improving the predictive power of the model and achieving high prediction accuracy (AUC = 89.8%). The final map shows a good agreement between the obtained susceptibility map and existing data on landslide locations. The susceptibility classes limit the areas of maximum susceptibility to those of the ancient Boujibar and Talayoussef landslides, where there is a conjunction of factors responsible for the occurrence of this phenomenon.

CONCLUSION

Most of the factors selected in this analysis exhibit a strong correlation with the occurrence of landslides. The coefficients of the model indicate that geological conditions, such as lithology and faults, can have a positive influence on landslide triggering. For instance, the results show that landslides are concentrated in lithologies dominated by marls, schists, argillites, and red sandstones, as well as in proximity to faults. Additionally, the hydrographic network and steep slopes significantly affect the occurrence of these phenomena. They are followed by other factors, such as slope exposure, land use, distance to faults, and elevation, which have a moderate effect on landslide occurrence.

Based on our findings, the logistic regression method has proven to be efficient and suitable for landslide prediction in the city of Al Hoceima (AUC = 89.4%), similar to the "weight of evidence" approach (AUC = 89.9%). Furthermore, the high to very high susceptibility zones generated by both methods encompass the highest percentage of all the landslides recorded in the study area (over 90% of the inventoried landslides). Therefore, we can conclude that these results are compatible with the existing terrain conditions. The accuracy and predictive capacity of the susceptibility map obtained through the logistic regression method could provide valuable data for urban planning and infrastructure construction in the future or in other areas with similar conditions.

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Taoufik B y o u

MAPOVANIE NÁCHYLNOSTI NA ZOSUV PÔDY POMOCOU LOGISTICKEJ REGRESIE ZALOŽENEJ NA GIS: PRÍPADOVÁ ŠTÚDIA MESTA AL HOCEIMA A JEHO PREDMESTÍ (MAROKO)

Zosuvy pôdy sú považované za jedno z najnebezpečnejších prírodných rizík, ku ktorým môže dôjsť náhle a môžu mať za následok straty na ľudských životoch a značné materiálne škody. Mesto Al Hoceima a jeho predmestia je regiónom, v ktorom sa často vyskytujú zosuvy pôdy. Zrážkové udalosti, ku ktorým došlo v posledných desaťročiach, poukázali na zraniteľnosť celého regiónu z hľadiska výskytu zosuvov pôdy. Táto zraniteľnosť sa neustále zvyšuje v dôsledku zväčšujúcej sa hustoty zástavby. Väčšina obyvateľov si svoje domy postavila v oblastiach nevhodných na výstavbu, napríklad v blízkosti vodných tokov alebo na nestabilnom teréne. Poukazuje to na potrebu mapovania náchylnosti na zosuv pôdy v skúmanej oblasti s cieľom usmernia rozvoja miest v budúcnosti.

Tvorbe máp náchylnosti na zosuvy sa v posledných rokoch dostáva čoraz väčšej podpory zo strany výskumných inštitúcií. Dôvodom môže byť na jednej strane záujem o ochranu životného prostredia a na druhej strane rozvoj a rozšírenie počítačových techník, ktoré umožňujú ukladanie, transformáciu, spracovanie a analýzu veľkého množstva údajov. Metódy náchylnosti na zosuvy sú založené na analýze vzťahu medzi kontrolnými faktormi zodpovednými za vznik tohto javu a ich minulým a súčasným rozložením. Odporúčané štatistické metódy sú dvojrozmerné, napríklad Bayesove metódy (teória dôkazov), alebo viacrozmerné, konkrétne viacnásobná regresia, logistická regresia, diskriminačná analýza atď.

Tieto metódy si vyžadujú zber veľkého množstva údajov, aby sa dosiahli spoľahlivé výsledky. Kvantitatívne predpovede sa robia pre oblasti, v ktorých sa zosuvy ešte nevyskytli, ale majú podobné podmienky prostredia (geologické, geomorfologické, klimatické, vplyv ľudskej činnosti atď.). Výber metódy závisí od rozsahu skúmanej oblasti, vedeckých poznatkov a praktických skúseností výskumníka. V prípade mapovania veľkého rozsahu (malá plocha) sa odporúča použiť štatistické a deterministické prístupy. Táto situácia nás motivovala použiť viacrozmerný pravdepodobnostný model vo veľkej mierke založený na logistickej regresii na štúdium nebezpečenstva zosuvov v meste Al Hoceima a jeho okolí. Ďalšou motiváciou bola dostupnosť súboru údajov s vhodným rozsahom pre použitý prístup.

Údaje použité v tejto analýze možno rozdeliť do šiestich kategórií: geologické faktory (litologická fácia, zlomy), seizmické faktory (seizmická mikrozonácia), geomorfologické faktory (nadmorská výška, sklon svahu, expozícia svahu a zakrivenie povrchu), hydrologické faktory (hustota odtoku), klimatické faktory (zrážky) a antropogénne faktory (využitie zeme a vzdialenosť od ciest). Digitálny model terénu (DTM) bol vytvorený z vrstevníc mesta Al Hoceima v mierke 1/2000 (1-metrový interval vrstevníc) s rozlíšením 5 m × 5 m. Používa sa na mapovanie geomorfologických faktorov: nadmorskej výšky, sklonu svahu a expozície svahu. Mapovanie využitia zeme sa vykonalo pre celú skúmanú oblasť na základe vizuálnej interpretácie snímok Google Earth (z roku 2022). Hustota hydrografickej siete bola odvodená na základe tokov zakreslených na reštitučnom pláne. Geologické faktory boli získané z geologickej mapy Al Hoceima v mierke 1 : 50 000 (vydanie z roku 1984). Pri posúdení seizmického faktora sme vychádzali zo seizmickej mapy mikrozonácie mesta Al Hoceima v mierke 1 : 40 000 (vydanie z roku 2004). Hoci sa faktor zrážok považuje za relatívne rovnomerný vzhľadom na prítomnosť jedinej stanice pokrývajúcej celé územie mesta Al Hoceima, tento faktor nebol do analýzy zahrnutý. Zosuvy pôdy boli inventarizované a zmapované pre celé mesto Al Hoceima a jeho okrajové časti. Tieto udalosti sú znázornené polygónmi na základe inventarizácie zosuvov a interpretácie satelitných snímok Google Earth. Následne boli všetky tematické vrstvy integrované do geografického informačného systému (GIS) pomocou softvéru ArcGIS 10.4 a prevedené do rastrového formátu. Odporúčaná veľkosť pixelov pre všetky mapy príčinných faktorov použité v tejto analýze bola stanovená na 5 × 5.

Táto metóda nám umožnila preskúmať dôležitosť faktorov zodpovedných za vznik zosuvov a získať kombináciu príčinných faktorov, ktorá by mohla byť dostatočná na vytvorenie vysoko výkonného modelu z hľadiska predpovedania oblastí, v ktorých je pravdepodobný výskyt zosuvov. Analýza presnosti modelu sa vykonáva pomocou krivky ROC (Receiver Operating Characteristic, t. j. operačná charakteristika prijímača), pričom sa porovnáva inventarizačná mapa so získanou mapou náchylnosti.

Výsledky krivky ROC ukazujú, že porovnanie mapy náchylnosti na zosuvy s inventarizačnou mapou predstavuje značnú predpovednú schopnosť (AUC=0,894, Area under the ROC Curve, t. j oblasť pod ROC krivkou). Viac ako dve tretiny inventarizovaných zosuvov sa nachádza v rámci tried vysokej a veľmi vysokej náchylnosti. Získané výsledky ukazujú, že model sledovaný v tejto štúdii funguje uspokojivo a môže byť nástrojom na hodnotenie rizika zosuvov v oblastiach vystavených tomuto javu.

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