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GIS-Based and Statistical Approaches in Archaeological Predictive Modelling (NE Romania)

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Abstract: Archaeological predictive modelling (APM) is an important method for archaeological research and cultural heritage management. This study tests the viability of a new statistical method for APM. Frequency ratio (FR) is widely used in the field of geosciences but has not been applied in APM. This study tests FR in a catchment from the north-eastern part of Romania to predict the possible location(s) of Eneolithic sites. In order to do that, three factors were used: soils, heat load index and slope position classification. Eighty percent of the sites were used to build the model, while the remaining 20% were used to externally test the model's performance. The final APM was made with the help of GIS software and classified into four susceptibility classes: very high, high, medium and low. The success rate curve and the prediction rate curve reported values of the area under curve (AUC) of 0.72, and 0.75 respectively. The Kvamme's Gain value for the model has a value of 0.56. Therefore, the final APM is reliable, so FR is a viable technique for APM. The final map can be successfully used in archaeological research, cultural heritage management and protection, preventive archaeology and sustainable development.

Keywords: cultural heritage; frequency ratio; AUC; predictive modelling; GIS; Kvamme's Gain; north-eastern Romania

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1. Research Aims

The present work aims to present the results obtained using new statistical method (FR—frequency ratio) for archaeological predictive modelling (APM) in a catchment from north-eastern (NE) Romania. Despite the use of APM globally, only one study was undertaken in Romania, focusing on post-Roman sites [1]. This study aims to fill the gap and to propose and test a new statistical method—frequency ratio applied in APM. This study also aims to prepare the first APM for Eneolithic sites in the NE part of Romania. The final APM will be of great help for cultural heritage management, preventive archaeology, planners, stakeholders, etc. In combination with landslide/gully erosion susceptibility maps, this could represent a powerful tool for cultural heritage mitigation, vulnerability assessment and improving the sustainability of cultural heritage resources.

2. Introduction

The use of GIS and statistical modelling to depict the possible locations of archaeological sites has faced an upward trend over the last decades [2,3]. This has not been matched by an improvement in the statistical methods applied until recently, when a proliferation of different methods can be seen. Currently, APM represents a powerful tool for preventive archaeology [4], cultural heritage management [5,6] and improving national-scale archaeological inventories [7,8]. APMs have been used successfully in different geographical areas of the globe including Africa [9,10], Europe [1,11–13], Asia [14,15] and America [16–18]. Different intuitive (qualitative) and quantitative statistical methods have been used to identify the locations of archaeological settlements. The most commonly used method for building qualitative predictive models is the analytic hierarchy process [9]; the main issues of this method are related to the subjective judgement of the expert(s), and that intuitively finished models can easily be influenced by prior biases in the archaeological record.

Quantitative methods can limit bias, which helps to reduce the effects of this problem and can improve the replicability of the workflow for use in other locations. The most commonly used geospatial formulae for predictive modelling are maximum entropy (MaxEnt) [19], logistic regression [20], evidential reasoning [14], fuzzy logic [21], weight of evidence [22] and multivariate statistics [23].

Statistical modelling of the landscape to find suitable areas for prehistoric settlement choices has been well used by geographers and archaeologists [14,24–26]. This method can effectively be conceptualised as a form of archaeological prospection. The most commonly tested era is the Neolithic, likely due to the pivotal nature of this period, and the fact that landforms were like modern features. Different areas (e.g., Italy [4], Greece [12], Scotland [27]) have distinct landscape features which may have been decisive for prehistoric people when choosing where to place a settlement. For example, in Italy [4], the favoured features were alluvial plains, terraces, caves (lithic industry), and low slope areas, while in Greece [12], the area around Thessaly represented an important connection between the islands of the Aegean Sea with the northern and southern parts of the country, being at the same time characterised by permanent inhabitation. In mainland Scotland [27], on the other hand, the locations of chambered cairns, timber halls and megalithic stone tombs influenced the way Neolithic people chose to place their settlements, as the megalithic stone tombs were perceived as land tenure and symbolize territorial control.

While this method has been widely applied in research archaeology, issues have been reported in CRM use in the Netherlands [28]. These, however, are extremely specific and may stem from the lack of periodisation or landscape specialisation. The lack of widespread use of this model in a European context suggests that testing this methodology using different methods, and for different periods, is extremely important and a desideratum.

3. Archaeological Background and Study Area

Cucuteni culture is considered to be the last great Eneolithic civilisation of Old Europe. It is part of the Cucuteni–Ariusd–Trypillia Cultural Complex, covering an area of approximately 350,000 km^2, comprising Romania, Ukraine and the Republic of Moldova [29]. The north-eastern part of Romania is well known for its high density of Eneolithic sites; many studies have approached the mobility of Eneolithic settlements and their vulnerability [30] towards natural hazards [31,32] and anthropogenic impact [33]. The discovery of the Cucuteni Culture in the first half of the 19th century marked the beginning of archaeological research in north-eastern Romania. Many archaeological and interdisciplinary studies aimed to better understand how prehistoric people lived [25,34] and moved across the landscape in search of new resources [35–37]. As shown by [38], Romania has an incomplete registry/inventory of archaeological sites. This means that local authorities and cultural heritage planners are incapable of mitigating threats to archaeological sites [39], including looting [40]. The method proposed in this study can be used as a starting point to produce APMs for the entire Moldavian Plain and Plateau and to be used along with the natural hazards susceptibility maps in order to establish the present state of the cultural heritage.

The study area is in the North-eastern part of Romania (Figure 1a), at the contact of Moldavian Plain with Suceava Plateau; it has an area of approximately 340 km^2. In geomorphological literature, the area is known as Dealul Mare–Harlau Coast (Coasta Dealul Mare–Harlau) [41] (Figure 1b). Previous studies have shown the tremendous archaeological potential of this area [25,29–39]. Within this area we created a database of 100 Eneolithic sites, using the online databases of the Institute of Cultural Memory (CIMEC), National Archaeological Registry (RAN) and National Heritage Institute (INP), as well as numerous field trips.

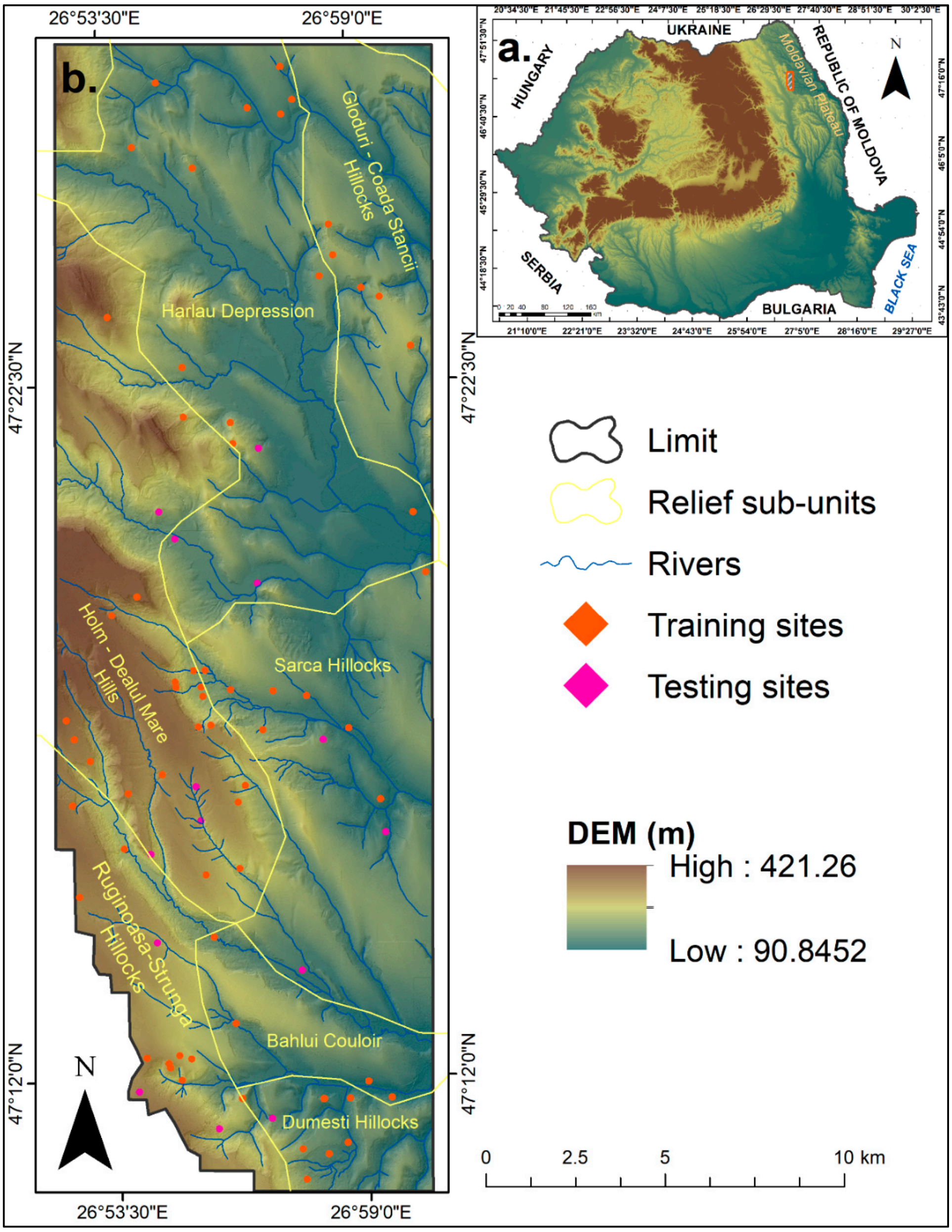

Figure 1. (**a**) Geographical location of the study area in Romania; (**b**) Location of Eneolithic sites, divided into training sites and testing sites.

4. Materials and Methods

Within the study area, there are a total number of 100 Eneolithic sites. Out of these, 80 sites (80%) were randomly selected for model training, while the other 20 sites (20%) were used to test the performance of the model (Figure 1b). This was done to provide an external dataset for testing the model, and due to the small area, number of sites, and the fact that an internal random selection was not to be performed, this high ratio of excluded to included sites was acceptable.

In this study, three factors were used to determine the most likely areas to host Eneolithic sites: soil type, heat load index (HLI) and slope position classification (SPI). Originally, several other possible factors were chosen and tested in combination with each other, including slope, aspect, landforms and distance to rivers; these lowered the predictive strength of the model, and so were abandoned.

Soil types were extracted from The Soil Map of Romania (scale 1:200,000) (Figure 2a); the classification was updated after [42]. The Chernozem soils seem to have been the most important because they are very fertile. As a result of the importance of farming, these areas would have been extremely important. Soil represents a significant factor used in APM [20].

In order to prepare the topographically derived factors for the model (HLI and SPI), a Lidar derived digital elevation model (DEM) with a resolution of 1 × 1 m was used. HLI is a novel method in the geosciences, and this is the first time it is being used in APM; it was calculated with the help of Geomorphometry & Gradient Metrics Toolbox of ArcGIS [43]. By using this factor, we have included slope and aspect as factors, because these are components in the HLI calculation. HLI takes these into consideration by "folding" the aspect so that the highest values are south-west, and the lowest values are north-east [44]. The method also considers the steepness of the slope. In this study, HLI (Figure 2b) was computed and reclassified into five classes 0.097–0.59, 0.59–0.64, 0.64–0.67, 0.67–0.71, 0.71–1.04.

The last factor used to compute the final APM was SPI [44]. This extension computes TPI (Topographic Position Index) grids from elevation grids, providing a simple method to classify the landscape into slope position and landform category using the TPI values [25,45]. SPI was computed with the help of Topography Tools Toolbox of ArcGIS (Figure 2c); prehistoric people's preference for midslope and flat areas is once again highlighted following this classification. Placing the settlements on midslopes was the first criteria, this being enough high to protect them from flooding [25] and other natural hazards of which they were aware [46].

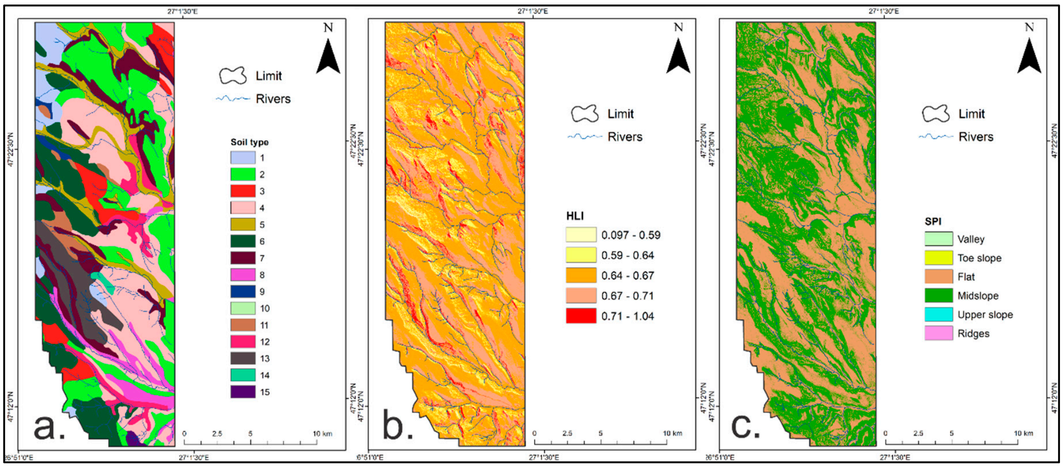

Figure 2. The factors used to compute the archaeological predictive modelling; (**a**) Soil type; (**b**) HLI (Heat Load Index); (**c**) TPI (Topographic Position Index).

FR represents a quantitative statistical method used in various branches of geosciences; it offers better prediction and validation results when compared to other statistical methods. For example, it is commonly used in landslide susceptibility mapping [32,46–48], gully erosion susceptibility mapping [49], groundwater assessment and contamination [50,51], flood susceptibility [52], deforestation susceptibility [53], etc. Despite its broad applicability, it has not been used in APM. FR has several advantages over other methods, as it allows all factors to be examined while prioritising those with the greatest applicability. This study tests the view that there is a casual relationship between Eneolithic settlement choice and the features of each location, which can be described through the metrics used in this study. In order to determine the frequency ratio for each class factor, the ratio between Eneolithic sites occurrence and non-occurrence was calculated (Table 1, column 7).

The Eneolithic sites used in this study are representative for Eneolithic culture (chronological framework: ca. 5000–3500 BCE) from the NE part of Romania [54]. Figure 3a shows the site Cucuteni (Cetățuia), the eponymous site of the Cucuteni culture, known as the last great Eneolithic civilisation of Old Europe, part of Cucuteni–Trypillia Cultural Complex [55]. It represents one of the most important archaeological discovery in the 19th century by the German archaeologist H. Schmidt [56]. Figure 3b,c illustrate the sites from Giurgești (Dealul Mănăstirii/Chetrosu) and Costești (Cier/La Școală), respectively. They represent sites iconic for the Cucuteni culture, and each year archaeological investigations take place [57].

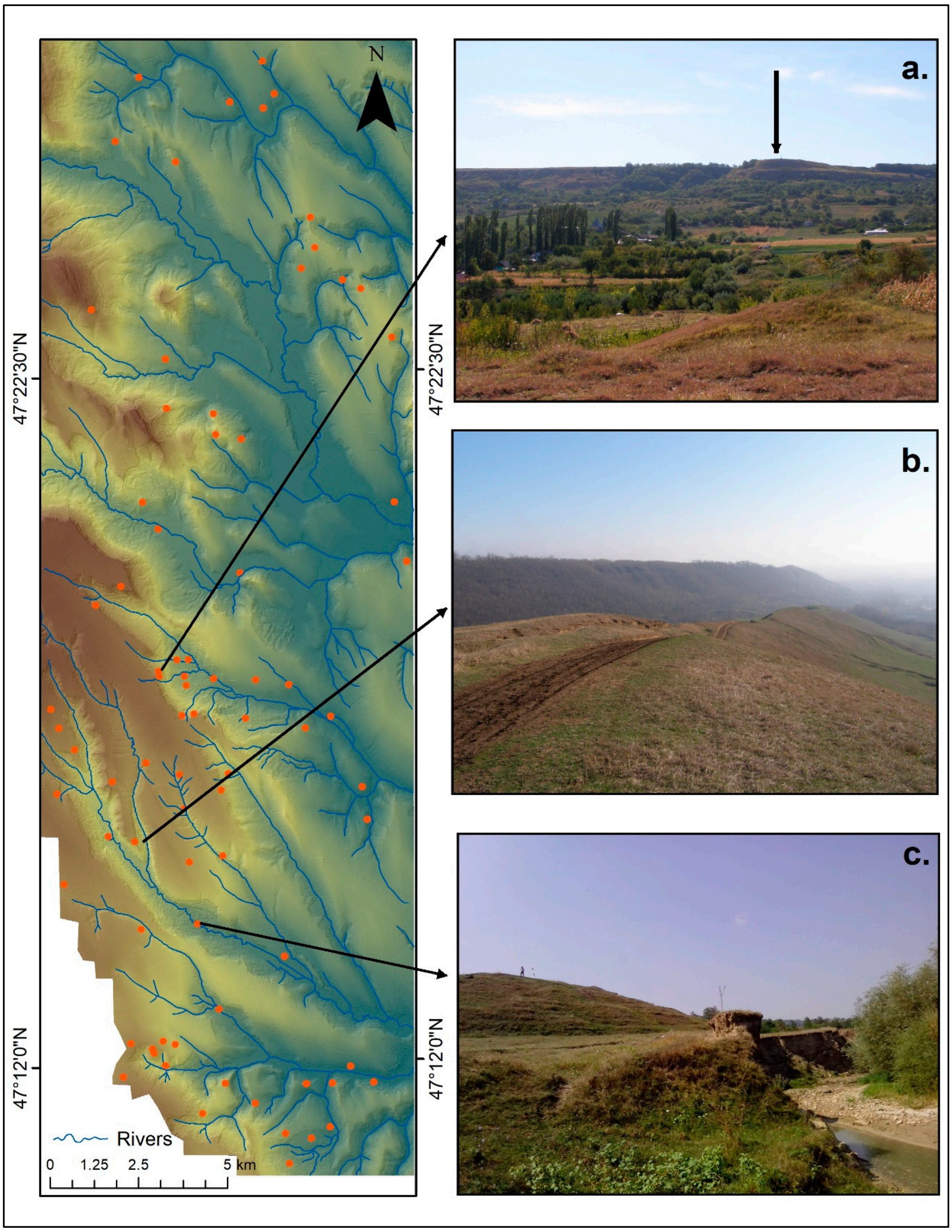

Figure 3. Representative Neolithic sites from the study area; (**a**) Cucuteni (Cetățuia) site, the eponymous site of the Cucuteni culture; (**b**) the site of Giurgești (Dealul Mănăstirii/Chetrosu); (**c**) the site of Costești (Cier/La Școală).

Out of 100 Eneolithic sites within the study area, 13 sites belong to the Precucuteni period (ca. 5000–4600 BCE), 35 sites belong to Cucuteni A period (ca. 4600–4100 BCE), 8 sites are framed to the Cucuteni A-B period (ca. 4100–3850 BCE), 24 sites belong to the Cucuteni B period (ca. 3850–3500 BCE), and 20 sites belong to the same culture, but with an unknown phase (hereafter named Cucuteni unknown) [54–57]. For each site, representing a point, a buffer area of 100 m was made to obtain an average surface of 3 ha for each site, as this is the average surface of a Cucuteni site [29]. This was done to prevent the site from being described as a single point within the GIS, which is a common fiction in geospatial studies [58].

Table 1. Frequency ratio values for the conditioning factors.

Conditioning Factor	Class	No. of Pixels in Domain	Pixels %	Sites Pixels	Sites Pixels %	Frequency Ratio (FR)
Soils (type)	1 Luvisols	14,818,636	4.66	74,529	3.67	0.04
	2 Cambicc Chernozem	60,267,943	18.95	527,989	26.02	0.07
	3 Clay Chernozem	15,907,541	5.00	10,129	0.50	0.01
	4 Chernozem	74,671,552	23.47	371,852	18.33	0.04
	5 Entic Aluviosols	24,407,123	7.67	107,480	5.30	0.04
	6 Phaeozems	40,426,881	12.71	300,325	14.80	0.06
	7 Antrosols	33,237,067	10.45	318,433	15.69	0.08
	8 Gleysols	13,869,069	4.36	2134	0.11	-
	9 Regosols	1,888,710	0.59	-	-	-
	10 Solonetz	115,847	0.04	-	-	-
	11 Rendzina	5,965,903	1.88	81,585	4.02	0.11
	12 Aluviosols	13,567,024	4.27	82,384	4.06	0.05
	13 Stagnosol	16,705,752	5.25	85,916	4.23	0.04
	14 Bare rock	1,158,248	0.36	31,383	1.55	0.22
	15 Phaeozems	1,089,677	0.34	34,935	1.72	0.26
HLI (Heat Load Index)	0.097–0.59	4,898,405	1.54	54,351	2.68	0.28
	0.59–0.64	35,352,785	11.12	252,849	12.46	0.18
	0.64–0.67	154,500,235	48.58	948,083	46.74	0.16
	0.67–0.71	108,268,154	34.04	641,492	31.62	0.15
	0.71–1.04	15,031,047	4.73	131,846	6.50	0.22
SPI (Slope Position Classification)	1 Valley	27,167	0.01	94	0	0.09
	2 Toe slope	162,659	0.05	1290	0.06	0.21
	3 Flat	175,545,165	55.19	1,039,526	51.24	0.15
	4 Midslope	142,172,529	44.70	986,466	48.63	0.18
	5 Upper slope	115,513	0.04	1115	0.05	0.25
	6 Ridges	27,593	0.01	130	0.01	0.12

The weight of each factor was calculated, and by summarising the weights we obtained the APM using the following equation:

$$\mathrm{APM} = \sum \mathrm{FR}_i \tag{1}$$

where FR_i is the FR of each factor type and FR is the area where Eneolithic sites occurred.

The FR method selected soils as being the most important conditioning factor, followed by SPI and HLI. The final susceptibility maps were reclassified into four susceptibility classes low, medium, high and very high. The resulting model must be tested and validated. In addition to the use of the classic procedure to validate the APM [59] (Equation (2)), we used the area under curvature (AUC). Based on the issues identified by [60] which argues the use of topographical features in APM, we chose to address this issue by using in our modelling just three factors.

$$\text{Kvamme's Gain} = 1 - (\text{Area Percentage}/\text{Percentage of Sites}) \tag{2}$$

5. Results and Discussion

The final APM made with the help of the FR method is shown in Figure 4a; the classes of the APM are low probability, medium, high and very high probability. The final raster (1 × 1 m/pixel) was reclassified by using the Natural Breaks (Jenks) method. Calculating the statistics of the APM (Table 2), low probability area covers 0.9% of the total area, while medium, high and very high probability areas cover 17.1%, 46% and 36% of the study area, respectively. High and very high probabilities are related to upper, toe and flat areas, as highlighted by [25]. Medium and low probability areas are mostly associated with very steep slopes, usually affected by geomorphological processes (e.g., landslides). A significant number of sites (33) are located in areas with medium probability, fact that was also highlighted by [25]. It was shown that following the SPI analysis, a significant number of Eneolithic sites were located on middle slopes, as Eneolithic people were aware of the impact of floods [25] and landslides [46]. This is highlighted in this study by the ratio obtained in Table 1 for midslope, with a value of 0.18; higher values have sites located at the toe slope and upper slope with values of 0.21 and 0.25, respectively.

The results of this study complete the conclusions obtained by [25]. Further research is needed in order to frame the Cucuteni unknown sites into one of the four periods (Precucuteni, Cucuteni A, Cucuteni A-B, and Cucuteni B). This represents one of our future goals in our endeavour of fully understand the mobility of Eneolithic populations.

When it comes to the APM validation, reasonably good results were obtained. The success rate (Figure 4b) of the APM produced with FR has been assessed by applying the receiver operating curve (ROC) with the area under curve (AUC), having a value of 0.72. The prediction rate curve has a value of 0.75, which is considered as good. Other studies [61] have reported AUC values of 0.65, therefore our results are pertinent, taking into consideration the resolution of our data used in the study (1 × 1 m/pixel).

A particularly widely applied measure of predictive model quality is Kvamme's Gain, which gives a ratio of the precision of a model against its accuracy [62]. The goal of this is to show that the area described is small enough when compared with its accuracy. The result of this is usually between 1 and −1, with a positive result suggesting that the model works, while a negative result would suggest that the model is predicting areas without features. The Kvamme's Gain in this case is 0.56, which suggests that this has been a success.

$$\text{Gain} = 1 - (36/23) = 1 - 1.56 = 0.56$$

Table 2. Statistical results following the use of frequency modelling (FR) method for archaeological predictive modelling (APM).

Class	Pixel Number	Area (%)	Number of Sites	Sites (%)
Very high	114,551,423	36	23	23
High	146,075,657	46	41	41
Medium	54,695,517	17.1	33	33
Low	2,766,013	0.9	3	3
Total	318,088,610	100	100	100

The method proposed in this study can be useful in making APMs for the whole area of Moldavian Plain; this represents an area with a high density of Eneolithic sites, much of them being still undiscovered and in this way cannot be protected or included in the cultural heritage database. Based on this model, this problem can be solved in an easy and sustainable way. This can be the base for future space-time APMs. Discovering more Eneolithic sites could bring us close to understand their mobility. Using APMs together with natural hazards susceptibility maps will have a significant impact in reducing the effect of hazards on cultural heritage, risk reduction, land use planning, hazard mitigation and for developing sustainable methods and practices for cultural heritage preservation.

The results of this study shows the fact that FR could be successfully used and applied to identify areas likely to host archaeological sites, in this case Eneolithic sites. Following the good validation results, both using ROC and a well-known tool to validate APMs, the Kvamme's Gain, the method proposed can stand alone for future use. Some previous studies reported Gain values of 0.26 [16], 0.70 [15], 0.15 [63] and 0.92 [9], which is placing our method proposed and results obtained as being pertinent. Used in combination with other statistical methods, like AHP [9], fuzzy logic [21] and MaxEnt [19], better predictive models can be produced in the future.

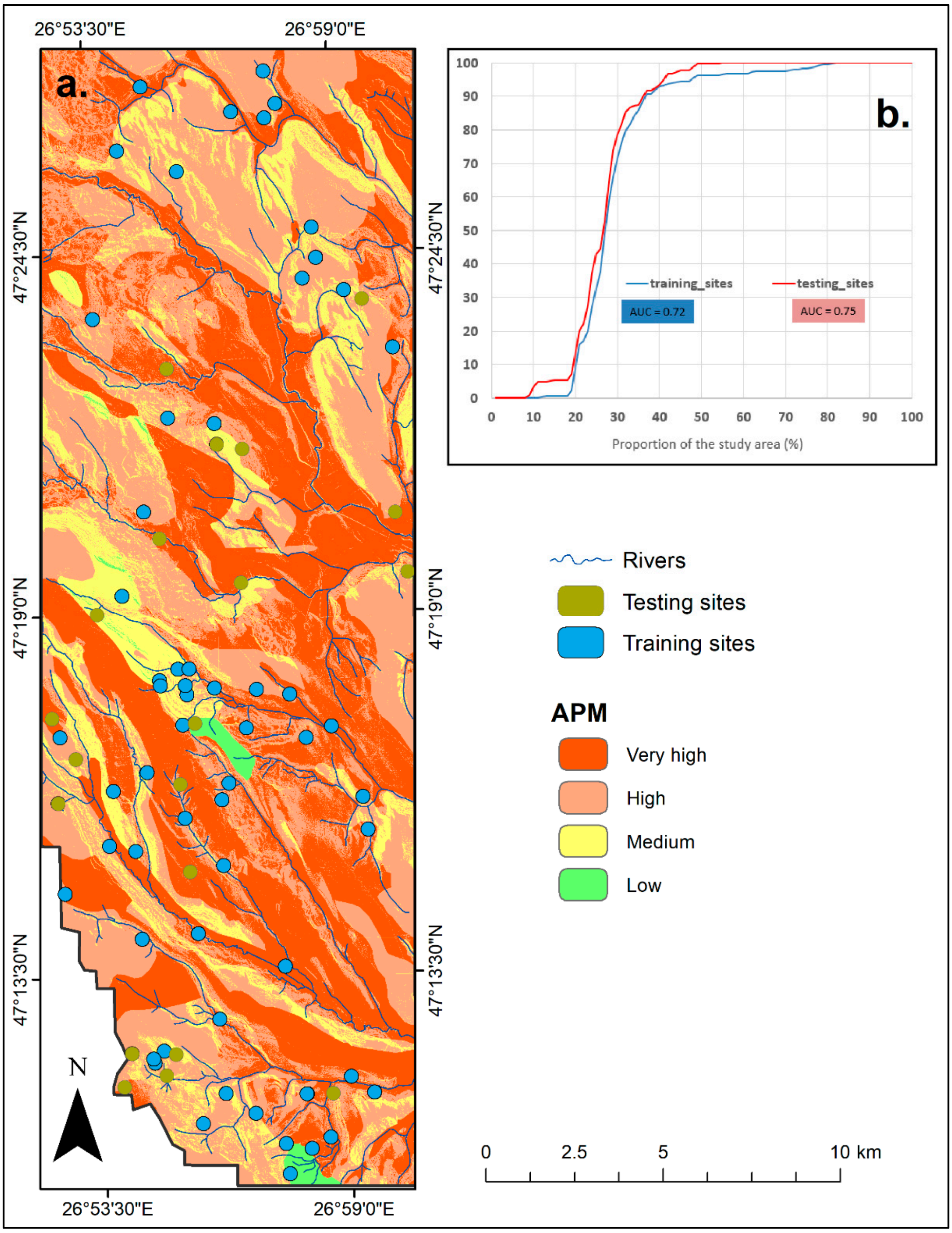

Figure 4. (**a**) The final APM generated with the help of FR; (**b**) Success and prediction rate curves with associated area under curve (AUC) values.

Another significant use of the APM is in the preparation of future infrastructure projects (building roads and motorways). As highlighted by [39], the road network in this area has increased significantly from 0.67 km/km^2 in 1894 to 2.64 km/km^2 in 2012. The future A8 motorway [64], which is projected to intersect the southern part of the study area, will be one of the biggest infrastructure projects from the north-eastern part of the country (Figure 5). Currently, the projected path of the motorway does not intersect any known Eneolithic sites; however, it overlaps with areas identified as having a high and very probability of "hosting" archaeological sites.

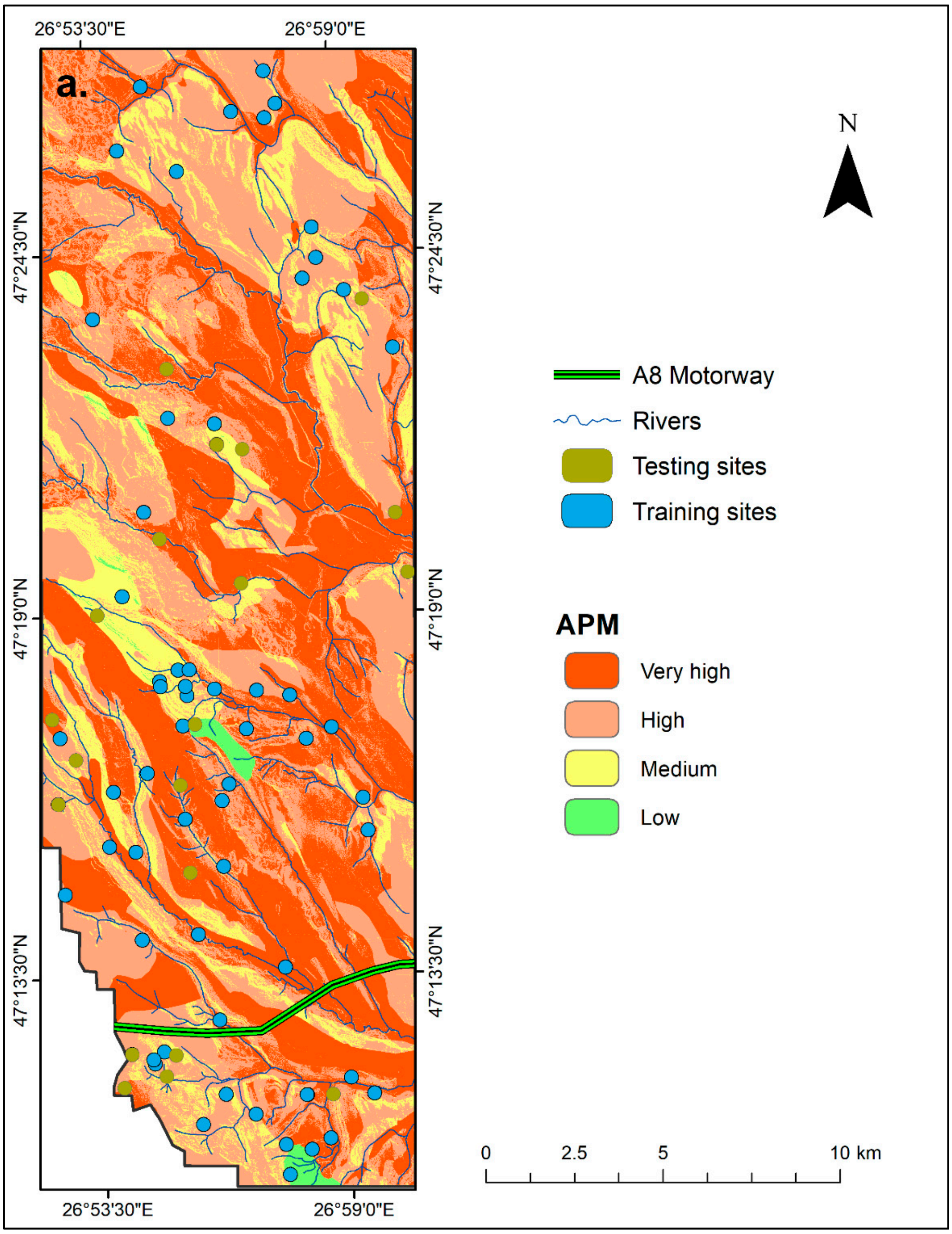

Figure 5. The A8 Motorway overlapping the APM.

6. Conclusions

Over recent years, APM has become a powerful tool in searching new locations of archaeological interest. There are very few studies (only one) employing statistical modelling of archaeological site locations in Romania. This study aims to fill that gap and to propose a new method—FR to APM. To do this, a set of three factors were used, i.e., soils, HLI and SPI. The statistical modelling procedure involved the selection of 80% of the sites to build the model and 20% of the sites were used to test the model's performance. The final APM was divided into four probability classes: low, medium, high and very high. With a success rate of 72%, a prediction rate of 75% and a value of 0.56 for Kvamme's Gain, FR proves to be a reliable method in determining areas with a high archaeological potential. Final maps can be used in preventive archaeology in studies that deal with the degradation of archaeological sites from natural hazards, cultural heritage management, understanding prehistoric people mobility and behaviour and finding sustainable development measures for cultural heritage.

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