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A predictive model for Palaeolithic sites: A case study of Monforte de Lemos basin, NW Iberian Peninsula

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ABSTRACT

Although a theoretical model for the settlement patterns of Galician Palaeolithic has been proposed in the last decades, it has not been statistically tested. The present paper aims to check whether this previous theoretical model can be verified statistically. For this purpose, a methodology based on the creation of a predictive model has been used in which the main environmental variables were analysed and their suitability for predicting the location of Palaeolithic sites statistically verified. The predictive model shows that the most accurate variables are elevation, slope, cost to potential hydrology, the cost to wetland areas, and visual prominence. The results demonstrated that the theoretical model was fulfilled in some of the variables previously proposed. Thus, we have shown the usefulness of this approach to test hypotheses and the results obtained open new possibilities of analysis in the study of the Palaeolithic sites in NW Iberia.

1. Introduction

The study of settlement patterns provides a large amount of information to understand past societies and it has generated considerable interest in recent years. Currently, some approximations allow us to reconstruct past territories and analyse environmental variables that could be determining the settlement patterns in hunter-gatherer societies during the Palaeolithic period (e.g. Turrero et al., 2013; Burke et al., 2014; 2017; 2021b; García Moreno and Fano Martínez, 2014; Ludwig et al., 2018; Wren and Burke, 2019). This study is based on the reconstruction of past societies based on the analysis of those environmental variables that could determine the choice of places of occupation of hunter-gatherer societies during the Palaeolithic period. For this, there are a series of tools such as Geographic Information Systems (GIS) and spatial statistics, the combination of which facilitates the creation of a predictive model, therefore allowing the analysis and quantification of different variables related to the choice of a specific location by the societies of the past. However, this type of approach based on spatial analysis is practically non-existent in the Northwest of the Iberian Peninsula (de Lombera Hermida et al., 2015; Díaz Rodríguez, 2017; Díaz Rodríguez and Carrero Pazos, 2019; Díaz-Rodríguez et al., 2021; Díaz-Rodríguez and Fábregas-Valcarce, 2022), except for some approximations applied to other chronologies and based on the application of locational patterns, quantitative modelling and predictive modelling (Llobera, 2015; Rodríguez Rellán and Fábregas Valcarce, 2015; Carrero-Pazos, 2018; Rodríguez-Rellán and Fábregas Valcarce, 2019; Carrero-Pazos et al., 2020).

The main objective of this paper is to study the settlement patterns of the Palaeolithic sites from the Monforte de Lemos basin (NW Iberia). We have decided to choose this zone because it is an area that has been intensively studied in the last two decades and it is one of the districts with the highest density of archaeological sites of this chronology in that part of Iberia. As mentioned above, there are some previous approaches based on the application of GIS, but a study based on the application of predictive modelling has never been carried out in this region. We believe that it is a good opportunity to apply this methodology since it

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can provide relevant results. In the present work we hope to be able to identify some of the predictive variables of the occupation of these sites. However, it is very likely that the resulting variables do not match the predictive variables identified in other regions, since each area has its own characteristics shaping the patterns of occupation. In this case we have an inland basin as opposed to a coastal area (García Moreno, 2013; Garate et al., 2020; Parow-Souchon et al., 2021), in a mountainous region (Leloch et al., 2022). Also, other studies carried out on a larger scale

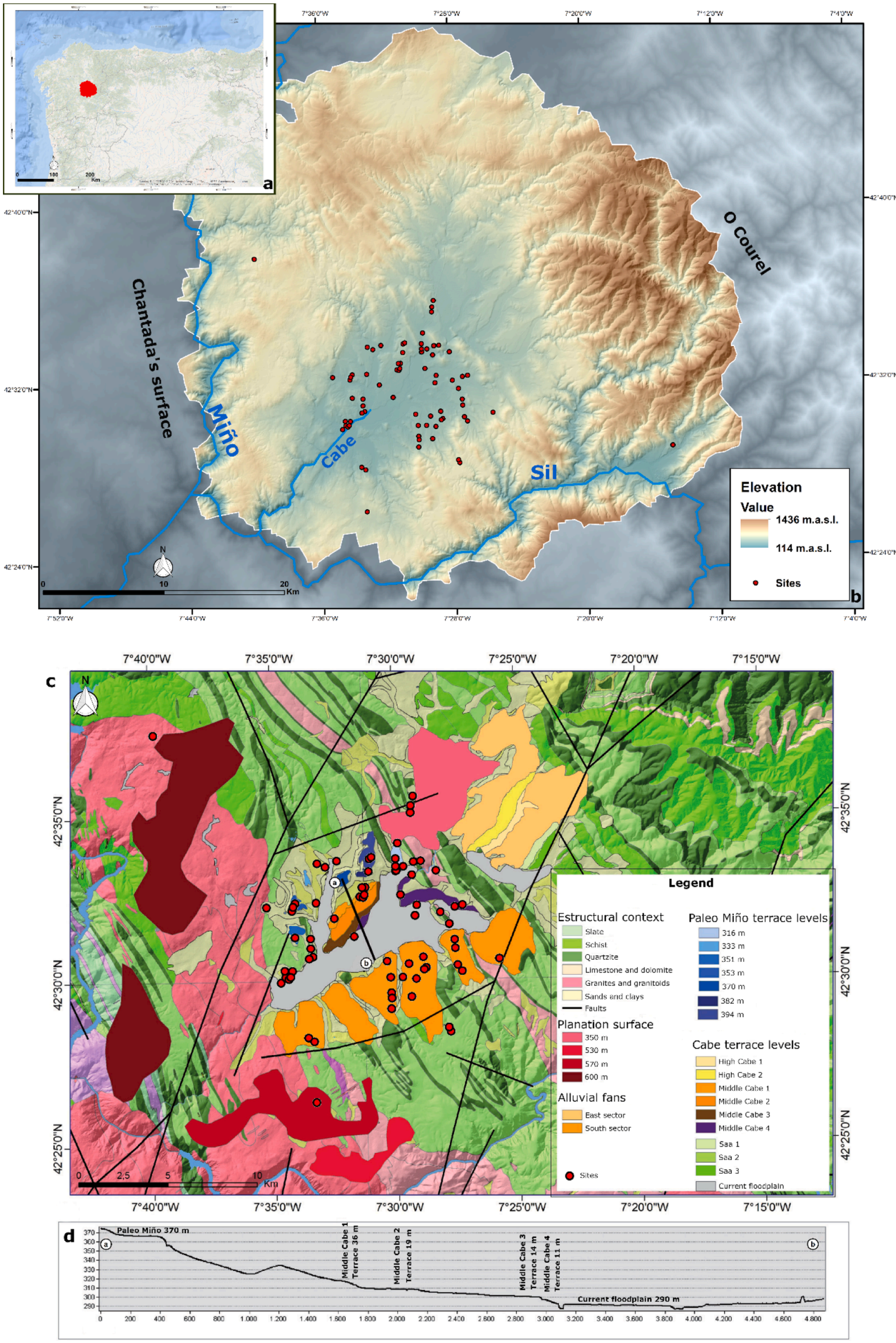

Fig. 1. (a) Location of the region studied (in red). (b) Study area with the archaeological sites (red dots) (c) Geomorphological and geological surface of the study area (modified from de Lombera Hermida et al., 2015). (d) Longitudinal profile of the Monforte de Lemos basin (modified from de Lombera Hermida et al., 2015). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

are bound to yield different results (Burke et al., 2017; 2021a; Wren and Burke, 2019; Jochim, 2022). In other words, in coastal areas the altitude of the archaeological sites will be lower than in the Monforte de Lemos basin; archaeological sites, moreover, will be nearer to the shore and to the hydrological resources (García Moreno, 2010).

In the present study, settlement patterns are analysed based on the creation of a predictive model. That model has been obtained using the different variables that had been previously proposed for the theoretical model established by different researchers. Predictive modelling can be defined as a technique that foresees the location of archaeological sites in a region (Kholer and Parker, 1986). A basic premise of predictive modelling is that human spatial behaviour is to a large extent predictable (Verhagen, 2018). For this reason, we believe that it is possible to identify those environmental variables that could be behind the decision of hunter-gatherer societies when choosing a given location for settlement in that region. We think that some variables, previously established in the theoretical model, would be important when choosing the place of settlement. Identifying these variables allows us to understand the hunter-gatherer ways of interacting with the territory.

2. Regional setting

The study area analysed in this paper is the Monforte de Lemos basin, which is located south of the province of Lugo (Galicia, Spain) in the Northwest of the Iberian Peninsula (Fig. 1a). This area is placed east of the Miño river and north of its main tributary, the Sil river (Fig. 1b) and between two areas with high altitude, how are the Chantada's Surface at the west (600 m.a.s.l.) and O Courel Mountain Range at the east (1600 m.a.s.l.). Another important river course of the basin is the Cabe River, the main fluvial course of the basin. In the Monforte de Lemos basin the transition of endorheic to exoreic drainage and the development of transcontinental drainage to the Atlantic Ocean is similar to the one proposed for the genesis of the Douro and the Tejo/Tajo (Tagus) rivers, involving as main mechanism an overspill induced by a major climatic change of increasing humidity by middle Pliocene (Cunha and Pérez-Alberti, 2022).

The surface of the basin corresponds to the whole of the council of Monforte and to part of those that border it, such as O Saviñao, Pantón, Sober, Pobra do Brollón and Bóveda. The Sil and tributaries mainly run cross the basin area, which mainly consists of Palaeozoic metamorphic rocks with minor granites, that are intensely faulted with WNW-ESE direction. After an episode of neotectonics and a subsequent fluvial reorganization, Pleistocene sediments linked to paleochannels, and alluvial fans covered the margins of silts and tertiary clays in a lake environment. These quaternary deposits, arranged in a sequence of flat surfaces, are identified as fluvial terraces, glacis, and pediments (Ameijenda Iglesias, 2011).

The Monforte de Lemos basin presents certain peculiarities that make it impossible to reconstruct a relative sequence of topographic levels that provides a referential framework for the lithic assemblages located on its surfaces, as has been obtained in some of the main fluvial basins of the Iberian Peninsula (Santonja and Pérez-González, 2000–2001; Cano et al., 1997). One of the problems is the sparse character of the Quaternary fluvial terrace levels (Middle Cabe), that are asymmetrically distributed in the valley, being concentrated in the northern sector (Fig. 1d). Another problem consists of the large extension of pre-Quaternary surfaces that makes it possible for several lithic dispersions ascribed to different technological Modes to be found on the same surface. Finally, there is also an important incidence of the morphogenetic processes in the deposits of the Monforte de Lemos basin (Ameijenda Iglesias et al., 2010).

In some previous studies, a preliminary sequence of different levels of erosion was established that brought together the surfaces of the Monforte basin (Ameijenda Iglesias, 2011). A geomorphological analysis has also been carried out, which has allowed the identification of the different geomorphological units of the basin in greater detail (de Lombera Hermida et al., 2015). These works have allowed us to verify that the opening of the basin brought with it the progressive disarticulation of the existing fluvial network in relation to a post-alpine tectonic reactivation and linked to the existence of tropical climatic conditions. The Miño and Sil rivers were "expelled" to the west (Miño) and south (Sil) progressively fitting into the terrain favoured by antecedent processes (Pérez Alberti et al., 1993). The result of the interaction between tectonic dynamics and the progressive change in fluvial dynamics has resulted in a set of staggered levels in the territory (Fig. 1c). Among them, due to their archaeological importance, we must highlight the levels associated with Paleo Miño, the waters that flowed through where the basin is today during a phase prior to the embedding of the Miño-Sil system, and on the other hand, the Cabe River, that would drain the basin later.

The recent studies had make possible the identification of several evolutionary stages in the basin area (Cunha and Pérez-Alberti, 2022): (1) During the Paleogene and Miocene, endorheic sedimentation occurred. (2) During the latemost Miocene to Zanclean, probably ca. 9.7 to 3.7 Ma, the climax of lithosphere compression created most of the modern relief; sedimentation only occurred locally at piedmonts, as heterometric alluvial fans. (3) The transition of endorheic to exorheic drainage to the Atlantic Ocean could be similar to the one proposed for the genesis of the Douro and the Tejo/Tajo (Tagus) rivers, involving as main mechanism an overspill induced by a major climatic change of increasing humidity by middle Pliocene. 4) Probably during the last 1.8 Ma, the stage of fluvial incision has been responsible for the development of terrace staircases, valley entrenchment and captures.

The relationship of the sites with the different geomorphological surfaces of the basin allows us to observe that a large number of archaeological remains are found mainly on the alluvial fans identified in the south of the basin (n = 19), on Palaeozoic or Tertiary substrata with little development of the Quaternary landfills (n = 34), the fluvial/alluvial surfaces of the Paleo Miño (n = 12), the fluvial formations related to the Middle section of the Cabe River (n = 6) and a few are located in the current alluvial plain (n = 5).

The first Palaeolithic reference to the Monforte basin was a quartzite handaxe found in the middle XX century at Vilaescura (Cano Pan and Vázquez Varela, 1991). The systematic investigation of this area began in 2006 in the frame of two concatenated research projects that were carried out and developed between 2006 and 2010, making possible the location of more than a hundred archaeological sites ascribed to the Palaeolithic and revealing a long human occupation during that period in this region (de Lombera Hermida et al., 2008, 2006; Fábregas Valcarce et al., 2010, 2009, 2008, 2007; Rodríguez Álvarez et al., 2008). Along the survey campaigns, a total of 16 km^2 was reviewed, representing 9.14 % of the total extension of the Monforte de Lemos basin (Fig. 1b), a common coverage when surveying large regions (Díez Martín, 2000). Through Landsat images it has been observed that a dense vegetation cover or forest accounts for 37.23 % of the surface, pasture areas represent 29.4 %, while open land or land dedicated to agriculture accounts for 6.4 % and it is on the latter that the works have focused (Miller et al., 2010). Along with the surveying, archaeological excavations were undertaken at some sites (de Lombera-Hermida et al., 2011; Rodríguez Álvarez et al., 2014).

After the discovery of lithic materials in the area, two research projects were proposed, as mentioned above. During the execution of both projects, some 104 archaeological sites from the Palaeolithic period were discovered.

In the study area, there are few works framed in the Palaeolithic and carried out from spatial analysis and GIS. We can highlight a paper that discusses large-scale territorial mobility and attempts to define the routes of entry to the Northwest of the Iberian Peninsula (de Lombera-Hermida et al., 2011). Other articles analyse isolated variables such as visibility or mobility in the Valverde site, framed in the Upper Palaeolithic (Rodríguez Álvarez et al., 2008; de Lombera Hermida et al., 2012). Another work has been carried out that deals with the analysis of settlement patterns through the study of variables such as visibility, altitude, aspect, slope, proximity to river courses and least-cost paths (de Lombera Hermida et al., 2015). It is a preliminary study based on the descriptive analysis of the mentioned variables, without applying analyses based on spatial statistics that could provide more accurate and precise information. Finally, a study analysing the occupation patterns of Lower Palaeolithic sites in the Monforte de Lemos basin through the application of descriptive statistical methods was carried out (Díaz Rodríguez et al., 2021).

3. Material and methods

3.1. Data acquisition and software

In the present study we made use of the information and data obtained from the two research projects previously mentioned. We have not established a chronological differentiation among the archaeological sites, and we have decided to create a single model that encompasses them all. We lack chronological data since we have a reduced number of sites and that prevents a statistical treatment of a minimum quality. During the execution of these projects and with the objective of identifying and documenting archaeological sites during the survey, the study area was divided into four theoretically defined sectors, considering their geomorphological characteristics: the northern sector (where the main Plio-quaternary formations are concentrated), the eastern and southern sectors (in which the alluvial fans are found) and finally the central sector of the sub-basin. The latter could not be thoroughly surveyed because the present urban nucleus of Monforte de Lemos is located there. The constructions of this nucleus prevented the review of large areas of land likely to contain material remains. But despite this, some finds of lithic material were reported during building works and probably many others have been destroyed in that way (de Lombera Hermida et al., 2015).

The archaeological surveys were carried out in several campaigns from 2006 to 2010. These focused on arable land and land clearance areas where soil visibility was good. These tasks were nearly impossible to undertake in densely vegetated areas that, alas, make up a large part of the basin.

The survey tasks were carried out by groups of between 5 and 9 people who inspected land plots smaller than 1 ha, with surveyors keeping a distance of 3–7 m from each other, walking along transects. In the larger plots, the separation between transects was less than 15 m. The plot was used as a registration unit, identifying in it the number of artefacts. The cadastral registry was used to calculate the extension of the plots and georeferencing them on the surveying maps. The coordinates were taken at the centre point of the dispersions using a Trimble GEO Explorer 2005 (GeoXT) GPS with submeter precision. In addition to the surveys, archaeological excavations were carried out in those places where the density of artefacts could indicate the existence of sites in which the stratigraphic context was preserved (de Lombera Hermida et al., 2015).

The total number of artefacts recovered in the Monforte de Lemos sites amounts to 3522, although a large part of them come from the Valverde excavations (n = 2037, objects recovered in excavation) (Fig. 2a). The distribution of the number of artefacts per site can be observed in the Fig. 2b. There is great homogeneity in terms of the technological and rolling characteristics of the recovered lithic pieces. Although more than 100 sites were located, in this study, we will only use 76. These are those archaeological sites for which we have more accurate information based on the stratigraphic position of the pieces at the time of collection or the bearing level of the lithic industry. In some cases, we decided to exclude some points because these are very close to each other; otherwise, they would cause an overrepresentation within the sample, since there would be two sites in the same cell of the raster map. For these reasons, we have included sites that meet the criteria mentioned above and this includes some isolated findings considered. Based on the morpho-technical analysis of the lithic assemblages, 21 sites were assigned to *Mode 2*, 17 to *Mode 3*, 9 to *Mode 4* and 29 present scarce and non-diagnostic lithic assemblages (defined as indeterminate), many of them correspond to isolated findings (1–4 artefacts) and very dispersed (Fábregas Valcarce et al., 2007, 2008, 2009, 2010, 2011; Rodríguez Álvarez et al., 2008; Rodríguez Álvarez et al., 2014; de Lombera-Hermida et al., 2011; de Lombera Hermida et al., 2012).

The treatment of spatial data has been carried out with different software that allows GIS analysis. The coordinate system used is EPSG: 25,829 (ETRS89 / UTM zone 29 N). GRASS GIS has been used in versions 6.4.3, 7.0.2 and 7.0.4 (Grass Development Team, 2020). Quantum GIS (versions 2.8.1 and 2.10.1) (QGIS.org, 2021) and SAGA GIS (version 2.2.1) (Conrad et al., 2015) have also been used. The latest GIS software used has been ArcGIS 10.3 (USC license) (Esri, 2011). It is the only one that does not share the GNU-GPI license. Finally, to carry out the different analytical approaches, R version 4.0.5 was used, with the R Studio graphical interface (R Core Team, 2021) and the packages required to run the analysis (Table 1).

The Digital Elevation Model (DEM) has been used as a base map to elaborate the different locational variables analysed in this paper. This DEM has been obtained from the National Centre for Geographic Information (CNIG) and has a resolution of 25 m. It is cartography that collects the information obtained from the photogrammetric and LiDAR flights of the National Plan for Aerial Orthophotography (PNOA)

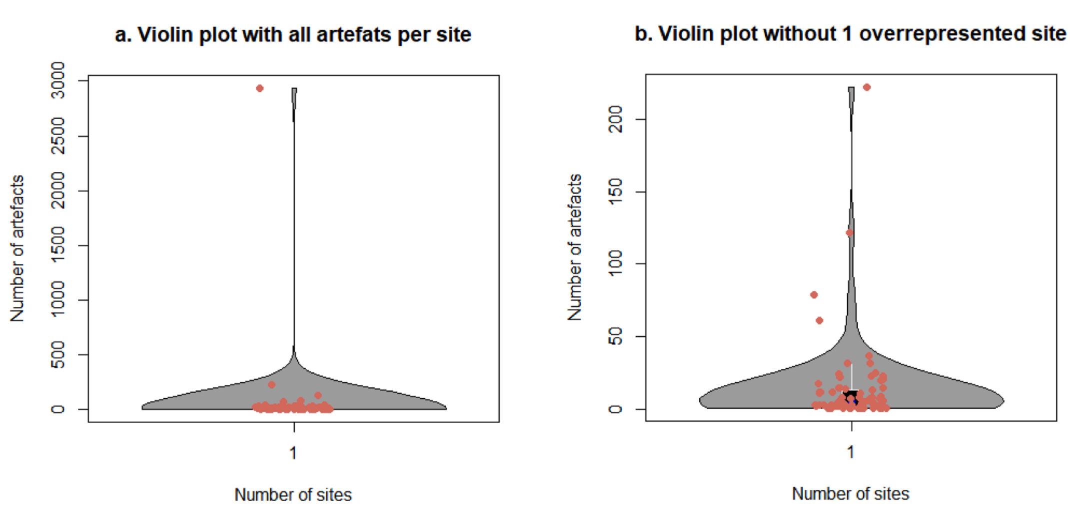

Fig. 2. (a) Violin plot that shows the number of artefacts per site (red dots). (b) Violin plot that shows the number of artefacts per site (red dots) except for Valverde site. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 1
Synthesis of R packages used, authors and application details.

Package	Author/s	Application Details
dismo	Hijmans et al., (2017)	Methods for species distribution modelling.
geostatsp	Brown, (2015)	Geostatistical Modelling with Likelihood and Bayes.
GGally	Schloerke et al., (2021)	This package is a plotting system based on the grammar of graphics.
ggplot2	Wickham et al., (2020)	Package for creating graphics.
maps	Becker et al., (2021)	Display of maps.
maptools	Bivand et al. (2020a)	Set of tools for manipulating geographic data.
MASS	Ripley et al., (2020)	Functions and datasets to support Venables and Ripley.
patchwork	Pedersen, (2022)	Package for combining multiple plots.
plyr	Wickham, (2020)	Set of tools that solves problems relates with applying or combining data.
raster	Hijmans et al., (2020)	Reading, writing, manipulating, analysing, and modelling of spatial data.
readxl	Wickham et al., (2019a)	Package for read excel files.
rgdal	Bivand et al. (2020b)	Provides bindings to the “GDAL” and “PROJ” library.
rgeos	Bivand et al. (2020c)	Package for topology operations on geometries.
sp	Pebesma et al. (2020)	Classes and methods for spatial data.
spatstat	Baddeley et al. (2020)	Toolbox for analysing Spatial Point Patterns.
tidyverse	Wickham et al. (2019)	Data representations and API design.
vioplot	Adler and Kelly (2022)	This package allows extensive customisation of violin plots.

(https://centrodedescargas.cnig.es/CentroDescargas/index.jsp). Also, the Geologic Map has been used and obtained from the Spanish Government’s online repository (López Olmedo et al., 2022).

3.2. Spatial distribution of sites

The first step in carrying out the spatial analysis of the archaeological sites of the Monforte de Lemos basin consisted of checking whether Complete Spatial Randomness (CSR) exists. For this, a sample of random points was created, with the same number of points as the archaeological sample, with the objective to compare both samples. The next step was to observe whether the distribution of both data sets belongs to the same population or not, which would indicate that there are no differences between the two samples and therefore we could not reject the CSR. For this, we have chosen the variable UTM X, corresponding to the x-coordinate of each point, and we have compared it between both samples. The Shapiro-Wilk test was used to test normality, and the Kolmogorov-Smirnov (K-S) test was used to check if both samples belong to the same population. Similarly, Ripley’s K functions and their L and G variants were used (Bivand et al., 2013). The homogeneous and inhomogeneous K, L and G functions were calculated (Baddeley et al., 2015) using a confidence interval based on Monte Carlo simulations ($n = 99$).

3.3. Definition of covariates

Intending to elaborate the statistical analysis, we have selected some covariates to establish the theoretical model based on previous works carried out in the study area and other similar areas. In the next lines, we will define the covariates used (Table 2 and Fig. 3). The process of obtaining each covariate is explained in greater detail in the SI file.

Altitude (ALT) can be defined as the elevation calculated based on some reference datum. Usually, it is the sea level (if it refers to the

Table 2
Conditioning type, variables, acronym, description and ID number.

Conditioning type	Variables	Acronym	Description	ID Number
Abiotic	Altitude	ALT	Elevation at a given point, in meters, above sea level. It is calculated from a DEM.	v1
Abiotic	Topographic Prominence Index	TPI100	Calculation of the TPI that consists of comparing the elevation of each of the cells of the DEM with the average of the surrounding elevations. Calculated for 100 m radii.	v15
Abiotic	Topographic Prominence Index	TPI500	Calculation of the TPI that consists of comparing the elevation of each of the cells of the DEM with the average of the surrounding elevations. Calculated for 500 m radii.	v16
Abiotic	Topographic Prominence Index	TPI1000	Calculation of the TPI that consists of comparing the elevation of each of the cells of the DEM with the average of the surrounding elevations. Calculated for 1000 m radii.	v17
Abiotic	Slope	SLO	Slope of the ground at a given point. It is calculated from the DEM.	v13
Abiotic	Aspect	ASP	Aspect of the ground at a given point. It is calculated from the DEM.	v12
Abiotic	Cost to potential hydrology	HYDROC	Distance, in time, at a given point to the potential hydrology. It is calculated from the DEM.	v5
Abiotic	Euclidean distance to potential hydrology	HYDROE	Distance, in meters, at a given point to the potential hydrology. It is calculated from the DEM.	v8
Abiotic	Cost to wetland areas	WET	Water accumulation in a conjoin of points. It is measured in displacement cost time. It is calculated from the DEM.	v2
Abiotic	Cost to potential geology	GEOLC	Distance, in time, at a given point to the potential geology. It is calculated from the DEM.	v4
Abiotic	Euclidean distance to potential geology	GEOLE	Distance, in meters, at a given point to the potential geology. It is calculated from the DEM.	v7

(*continued on next page*)

Table 2 (*continued*)

Conditioning type	Variables	Acronym	Description	ID Number
Biotic	Cost to potential goat hunting areas	CPFPCG	Distance, in time, at a given point to the potential goat hunting areas. It is calculated from the DEM, based in slope and CPFPC model.	v3
Other	Visual Prominence	VISPR	Visible number of points, in each cell, from any of the points selected. It is calculated from the DEM.	v14
Other	Cost to Least cost path	LCPC	Potential Least cost paths between given points. It is calculated from the DEM and considering the slope and hydrology.	v6
Other	Index of potential direct insolation	DIRINS	Calculation of potential incoming direct insolation. It is obtained from the DEM.	v10
Other	Index of potential diffuse insolation	DIFINS	Calculation of potential incoming diffuse insolation. It is obtained from the DEM.	v9
Other	Index of potential total insolation	TOTINS	Calculation of potential incoming total insolation. It is obtained from the DEM.	v11
Other	Wind Exposition Index	WIND	Calculation of Wind Exposition Index. It is obtained from the DEM.	v18

absolute altitude) or, for example, the bottom of a valley (if it is relative altitude). This covariate is mentioned in the specific bibliography since it is believed that archaeological sites are located at high points of the landscape (de Lombera Hermida et al., 2015; Fábregas Valcarce et al., 2010; Ramil Rego, 1989/1990, p. 194).

Palaeolithic sites have been considered landmarks in the landscape. We would be facing reference points that would stand out from the surrounding terrain and would be visible or observable from a certain distance (Fábregas Valcarce and de Lombera Hermida, 2010). To model this covariate, the topographic prominence has been calculated, which can be obtained using different methodological approaches. In this case, we use the Topographic Prominence Index (TPI). Following the recommendations of specialized researchers (Nakoinz and Knitter, 2016) and our previous experience (Díaz Rodríguez and Carrero Pazos, 2019), the TPI was calculated for 3 different radii (100, 500 and 1000 m) (TPI100, TPI500 and TPI1000).

The slope (SLO) can be defined as the maximum degree of elevation variation at a given position. It is obtained from the DEM. This is a covariate that has been taken into account in some previous works on the Galician Palaeolithic (de Lombera Hermida et al., 2015, p. 280) or other Iberian regions like the Cantabrian (García Moreno, 2010), Asturian (Fernández Fernández, 2010) and in the Sierra de Atapuerca (Marcos Sáiz, 2006).

Aspect (ASP) has been defined as an important covariate to find the location of archaeological sites (de Lombera Hermida et al., 2015, p. 289). In some studies, it has been described that the majority of sites are oriented toward the second and third quadrants (Ramil Rego and Ramil Soneira, 1996). This covariate has been obtained from the DEM.

The relation between the palaeolithic sites and the river courses has been defended in previous studies (Fábregas Valcarce and de Lombera Hermida, 2010; Ramil Rego, 1989/1990, p. 193; Villar Quinteiro, 1996). The currently hydrological map presents actualisms because of human anthropization and the passage of time in the landscape. To achieve a more approximate image of what existed in the past, we have decided to create our hydrographic network based on the DEM and use a methodology that has been applied in previous works (García García, 2015). The proximity of the sites to the potential hydrology was calculated from all the points of the study area to the close water course. It has been measured in the distance (HYDROE) and displacement cost time (HYDROC).

Although, in previous studies, it has been taken into account the proximity of wetland areas and the visual control over these areas (Criado Boado et al., 1991; López Cordeiro, 2002; 2015; de Lombera Hermida et al., 2015). The wetland areas could be defined as the accumulation of water in a conjoin of points. For this, the SAGA GIS software has been used, and more specifically the Topographic Wetness Index (TWI), which indicates the topographic humidity index in each of the cells of the map used. Once this map was obtained and given that we were interested in those areas in which this humidity index is higher, we proceeded to calculate the quartiles. In this way, we are left with the cells of the map with values above the third quartile. On the other hand, we must bear in mind that the calculation of the TWI is going to attribute a very high value to the cells in which a river coincides, but we are not interested in those cells since they would be falsifying the data. So, we subtracted the hydrological map, previously created, from the TWI polygon map. Thus, we manage to stay with those higher humidity values in which the rivers are not found. Then, we calculated the displacement cost time from every point of the study area to the close wetland areas divided into points (WET).

For the Palaeolithic hunter-gatherers, it was important to have raw materials such as quartzite or quartz in the vicinity. These resources could be obtained from river courses, in the form of pebbles located on river beaches, or collecting raw materials from the veins. We have defined that as potential geology which has been mentioned in previous studies (Ramil Rego, 1989/1990; Villar Quinteiro, 1996; López Cordeiro, 2002; 2015; Fábregas Valcarce and de Lombera Hermida, 2010; de Lombera Hermida et al., 2012). We also considered the potential geology to carry out the analyses. For this purpose, we have used the data obtained from the Mining Geological Institute (IGME). Those areas that could contain raw materials of interest to Palaeolithic hunter-gatherers have been selected and divided into points at established radii. Subsequently, the cost of moving, in time (GEOLC) and distance (GEOLE), from the rest of the cells in the study area to the closest potential geology points has been calculated.

Within the biotic conditioning, we used the variable cost to potential hunting areas. We employed the Central Place Foraging Prey Choice (CPFPC). This model was proposed by M. Cannon (2003) and is based on the theory of foraging. It was used by Marín Arroyo to study the patterns of mobility and control of the territory in eastern Cantabrian. For that purpose, Cannon's model was applied to deer hunting and goats as the most representative species of the Magdalenian diet (Marín Arroyo, 2008; 2009). In the present study, we have used the potential areas of hunting goats and obtained a covariate based on the cost, in time, from any point of the study area to these potential hunting areas (CPFPCG). In order to find these, we have calculated the 1.2-hour isochrones from the sites and we have used the slope map to select, within the isochrones, those cells with slopes greater than 30°.

Other conditioning types have also been considered. One of them is visibility, which has been contemplated to define the occupation of archaeological sites in previous works (López Cordeiro, 2002; 2004; 2015; Rodríguez Álvarez et al., 2008; Fábregas Valcarce and de Lombera Hermida, 2010; de Lombera-Hermida et al. 2011; de Lombera Hermida et al., 2015). In this case, we have used the analysis of visual prominence. This consists of calculating the points visible from each of the

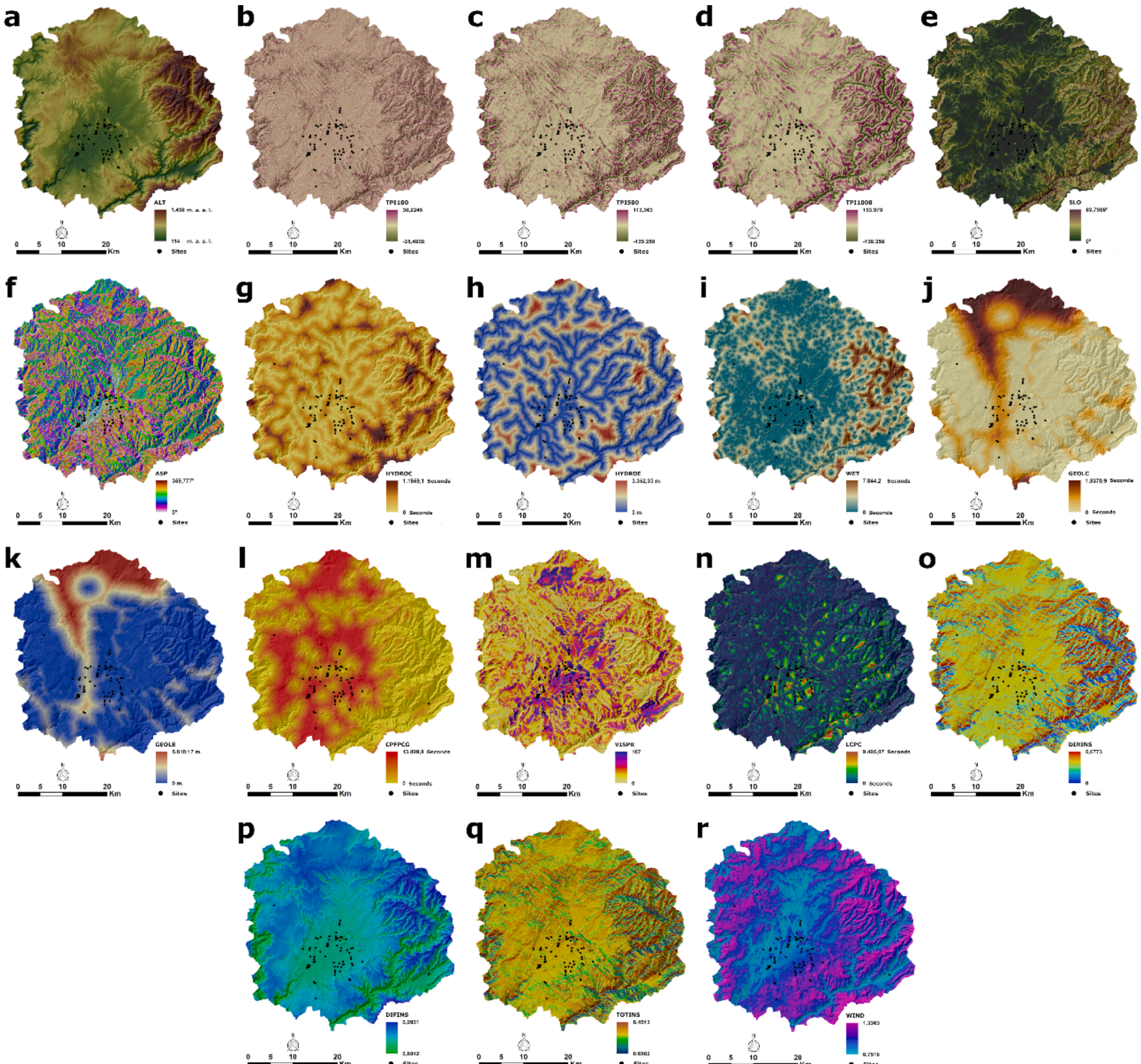

Fig. 3. Covariates analysed in the present study. (a) ALT covariate. (b) TPI100 covariate. (c) TPI500 covariate. (d) TPI1000 covariate. (e) SLO covariate. (f) ASP covariate. (g) HYDROC covariate. (h) HYDROE covariate. (i) WET covariate. (j) GEOLC covariate. (k) GEOLE covariate. (l) CPFPCG covariate. (m) VISPR covariate. (n) LCPC covariate. (o) DIRINS covariate. (p) DIFINS covariate. (q) TOTINS covariate. (r) WIND covariate.

given points. For this, an observer height of 1.75 m has been used. Once the calculation is done, a raster file is obtained where the cells have a value that shows the number of cells visible from each cell (VISPR).

The calculation of potential least cost paths (LCP) will be measured as the relationship that exists between the sites and the movement through the surrounding landscape. We could define it as the transit route generated between two points, depending on various factors and corresponding to the lower cost in energy or time. The natural transit routes or the so-called royal roads were treated in the bibliography. Establishing these routes as one of the variables that mark the pattern of location of the Palaeolithic sites in the Galician region (Ramil Rego and Ramil Soneira, 1996, p. 125; Fábregas Valcarce and de Lombera Hermida, 2010, p. 267; de Lombera Hermida et al., 2015, p. 289; López Cordeiro, 2015, p. 301; Díaz Rodríguez, 2017). This consists of carrying out a calculation of transit routes in a specific area, without considering the archaeological sites. For this, it is necessary to have a starting and arrival point. In response to this, we were inspired by a previous work that used a methodology based on the calculation of optimal routes between all points of the landscape, called FETE (From Everywhere to Everywhere) (White and Barber, 2012). In this work, an analysis was employed that uses all the points of a grid as starting points and at the same time as arrival points, in such a way that the calculation allows representing the territory covering everything and creating the least cost path. However, that requires computer equipment that is powerful enough to run those analyses. Therefore, we have decided to adapt this model following the methodology used in another study (Rodríguez Rellán and Fábregas Valcarce, 2015). It is a simplification that has been previously described in more detail (Díaz Rodríguez, 2017; Díaz-Rodríguez et al., 2021), but briefly, it consists in dividing the border of the study area into points at a certain established radius between them and calculating the LCP between them using a point as a starting point and the rest as stopping points and repeating the analysis with all the points (LCPC).

In some previous studies, it has been mentioned that the archaeological sites of the Galician Palaeolithic could be located on slopes facing west to better take advantage of the calorific value of the sun's rays (Ramil Rego and Ramil Soneira, 1996, p. 125). In addition, it seems logical to think that insolation could have played an important role in the occupation of an archaeological site. However, it has not been openly considered in the bibliography referring to this area, but it has

Table 3
Results for the statistical tests applied.

Shapiro-Wilk Test (sites)		Shapiro-Wilk Test (random sites)		K-S Test (sites vs random sites)	
W	*p-value*	W	*p-value*	D	*p-value*
0.87411	2.188^{e-06}	0.95329	0.007074	0.36807	7.229^{e-05}

been considered in other regions of the Iberian Peninsula. Some studies have analysed its influence when choosing a place of occupation, as occurs in the area of the Asón River Valley, in Cantabria (García Moreno, 2008; 2015). In our study, the insolation has been obtained from SAGA GIS, through the Potential Incoming Solar Radiation module (Conrad et al., 2015) and calculated in three different ways (DIRINS, DIFINS and TOTINS).

The last of the variables used in the analysis is that of the prevailing winds (WIND). Shelter from prevailing winds may be another variable to take into consideration when hunter-gatherer societies choose their places of occupation (Villar Quinteiro, 1996; García Moreno, 2010; de Lombera Hermida et al., 2015, p. 290). As to quantify this variable, it has been obtained the wind exposition index through the Wind Effect Index from the SAGA GIS module (Böhner and Antonić, 2009; Conrad et al., 2015).

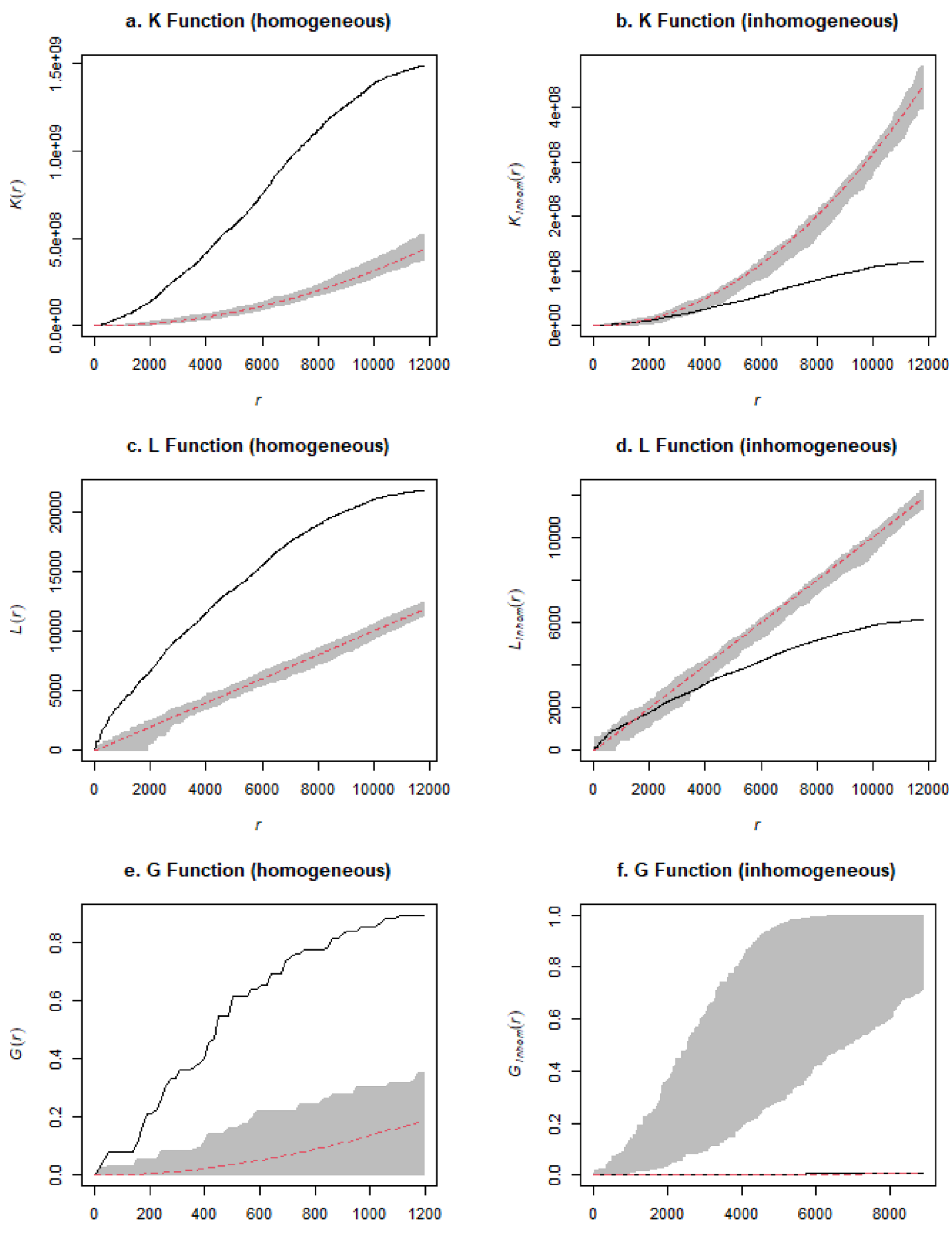

Fig. 4. K, L and G Functions (a-f).

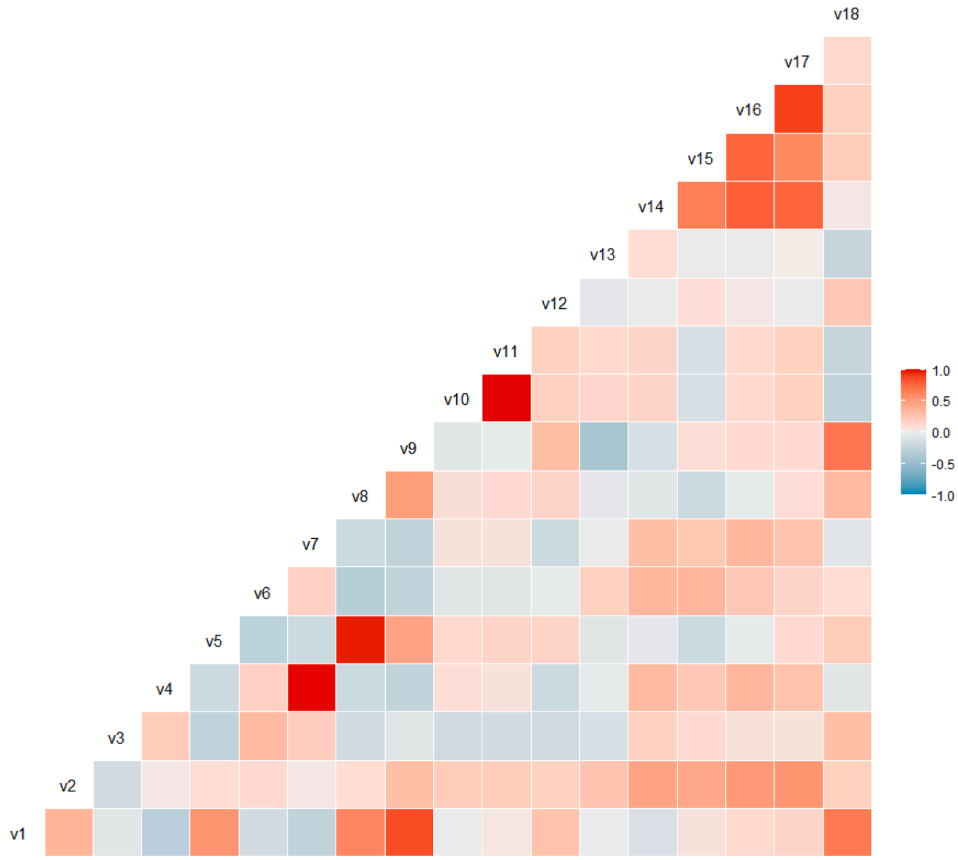

Fig. 5. Pearson's correlation test for the different covariates analysed.

Table 4
Multivariate regression model results.

Coefficients	Estimate	Std. Error	Z value	Pr (>|z|)	
(Intercept)	7.2294176	2.6165387	2.763	0.00573	**
ALT	−0.0167014	0.0073815	−2.263	0.02366	*
SLO	−0.3456405	0.1244542	−2.777	0.00548	**
VISPR	0.0458370	0.0204803	2.238	0.02521	*
WET	−0.0017355	0.0011814	−1.469	0.14183	
HYDROC	0.0007585	0.0004113	1.844	0.06514	.
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 '' 1					

3.4. Predictive model

The predictive model can be considered one of the first tools in the GIS applications to archaeology (Church et al., 2000; Vermeulen, 2001). It is a method that allows the prediction of the value or the probability of presence of a dependent covariate in a place using one or more independent covariates. Predictive models are defined as tools to project known patterns or relationships into unknown times or places (Warren and Asch, 2000). Also, can be defined as a technique that tries to predict the location of archaeological sites or materials in a region (Kholer and Parker, 1986). The use of GIS in archaeology arose in North America due to the need to manage large extensions of land, difficult to manage with conventional survey methods. The objective was to catalogue, inventory and protect the largest possible number of sites. Faced with this dichotomy, predictive models were developed that would allow delimiting the areas that were more likely to contain archaeological sites.

The first applications of the predictive model were based on the intersection of environmental and, to a lesser extent, cultural variables that were measured in a Boolean way, considering the absence or presence of certain conditions that favoured human occupation in a specific place. That is if in a specific place human habitation could not exceed 800 m of altitude, this duality was established, distinguishing those sites with lower altitudes as suitable (a value of 1 was given) and those with higher altitudes as unsuitable (a value of 0 was given).

The passage of time and the evolution of GIS allowed to carry out predictive models more complex, treating the study variables quantitatively, in such a way that they could be given more importance to some over others. This is based on the weighted value method. In this way, it seeks to predict the location of archaeological sites, and if the patterns of occupation of the human societies of the past responded to a series of conditions. In which some had greater importance than others in response to the different circumstances affecting those societies.

Predictive models can be divided into three categories (Nakoinz and Knitter, 2016). First are the point density approximations, which do not consider the localization preference of sites (Ben-Said, 2021; Bevan, 2020; Bevan et al., 2013; Bivand et al., 2013). Second are inductive approximations, which are based on known points that have locational characteristics that can be extrapolated to the whole population (Carrer, 2013; Deeben et al., 1997; Verhagen and Whitley, 2012). Finally we find deductive approaches, which seek to answer the question of why sites are in certain places (Kamermans and Rensink, 1999; Kvamme, 2005; Verhagen, 2007).

Based on Conolly and Lake (2006), we can establish that to carry out a model prediction, a series of phases must be followed. First of all, it is necessary to collect the data, the following is the statistical analysis of these data, later the application of the model and finally its validation is carried out (Duncan and Beckman, 2000, p. 36; Warren and Asch, 2000, p. 13).

In addition, it is based on the premise that it is possible to differentiate between areas of the landscape with evidence of occupation (sites) and landscape areas without such evidence (non-sites) in the function of one or more landscape attributes. In the first phase, the location of the sites and "non-sites" through an arbitrary sampling program. Regardless

Table 5
Result of Pearson's correlation analysis.

	v1	v2	v3	v4	v5	v6	v7	v8	v9
v1	1.00000000	0.35667635	−0.08357172	−0.28339367	0.54714328	−0.15925967	−0.26518694	0.61769529	0.86176382
v2	0.356676347	1.00000000	−0.16481891	0.02943039	0.10461158	0.11178294	0.03151997	0.09750010	0.29435648
v3	−0.083571723	−0.16481891	1.00000000	0.20694941	−0.26028585	0.31158221	0.19941915	−0.17000958	−0.07917093
v4	−0.283393666	0.02943039	0.20694941	1.00000000	−0.19947868	0.16664158	0.99385695	−0.19259836	−0.25044668
v5	0.547143284	0.10461158	−0.26028585	−0.19947868	1.00000000	−0.27402528	−0.20076738	0.96186192	0.45396958
v6	−0.159259671	0.11178294	0.31158221	0.16664158	−0.27402528	1.00000000	0.16706366	−0.30574482	−0.24922514
v7	−0.265186938	0.03151997	0.19941915	0.99385695	−0.20076738	0.16706366	1.00000000	−0.18934388	−0.24586908
v8	0.617695291	0.09750010	−0.17000958	−0.19259836	0.96186192	−0.30574482	−0.18934388	1.00000000	0.49252864
v9	0.861763823	0.29435648	−0.07917093	−0.25044668	0.45396958	−0.24922514	−0.24586908	0.49252864	1.00000000
v10	−0.001182526	0.20318306	−0.16646437	0.08748130	0.12586380	−0.06197167	0.07189207	0.08319093	−0.06354271
v11	0.037685743	0.21265617	−0.16523256	0.07491593	0.14865235	−0.06874893	0.05999455	0.10759489	−0.02521872
v12	0.272538906	0.17073204	−0.17574213	−0.18906411	0.14140918	−0.02571088	−0.19697658	0.14829719	0.29269640
v13	−0.005418655	0.26452627	−0.12710314	−0.03053605	−0.07222588	0.19078521	−0.01776864	−0.04101609	−0.41293738
v14	−0.102990013	0.45706674	0.18183008	0.31091594	−0.05276793	0.34181459	0.30502394	−0.07698603	−0.11712191
v15	0.060261887	0.43508317	0.11544349	0.23797655	−0.17975567	0.34227219	0.24584415	−0.20583225	0.08898387
v16	0.130278882	0.52366338	0.07807601	0.33944224	−0.03236342	0.24325614	0.33744628	−0.03989121	0.10846128
v17	0.154691765	0.53228780	0.05719123	0.26712282	0.10944885	0.14483218	0.26040509	0.09212769	0.10982423
v18	0.674642514	0.18941960	0.29408736	−0.07928285	0.20639941	0.10541525	−0.05346513	0.30995669	0.68629862

of that, they are usually divided into a training sample with which the model is created and a test sample to check its accuracy. This is known as split sampling and usually set the split at 50–50 % or 60–40 %. In the present study the split sampling was based on a random selection criterion. In this same phase, primary data is used to arise from the combination of various maps of elevation, hydrology, geology, etc.

The second phase consists of identifying the attributes of the landscape that discriminate places with and without significant sites. For this, the variables are statistically tested previously chosen. Univariate analysis of each of the attributes is performed, starting from the null hypothesis, according to which their values in places with or without sites come from the same population. Once the most suitable attributes have been identified, it is about creating the predictive model, for which logistic regression analysis is usually applied.

The third phase seeks to calculate, cell by cell, the value of the presence of sites using map algebra. In the last phase, the accuracy of the model is examined using the test sample that had been set aside during the model creation process. It is about establishing how many observed sites of the test sample fall within the area where, according to the prediction, there are sites. This calculates the predicted percentage.

However, it is necessary to allow for a series of considerations, since the models tend to be more accurate at low probabilities and less accurate at high probabilities (Conolly and Lake, 2006). In addition, it is usual for the probability of the appearance of sites to be so low that all observed fall in the area where the prediction indicates its presence, although there are also usually many "non-sites" that fall into that category on the same area, which exemplifies that the model has accuracy in predicting the absence of archaeological sites.

In any case, our main objective for the application of the predictive model is not to find new sites but to establish the variables that allow us to predict the distribution of these sites correctly and to indicate those variables that could play a fundamental role in the location of archaeological sites attributable to the Palaeolithic period in the landscape.

4. Results

4.1. Complete spatial Randomness

To analyse the Complete Spatial Randomness (CSR), firstly we checked if the archaeological distribution of sites displays normality. To check this, we have chosen UTM X as the variable to compare both data samples. We used the Shapiro-Wilk test. This test indicates that the sites do not present normality because the p-value is less than 0.05 (W = 0.88135, p-value = $3.557e^{-06}$) (Table 3). Besides, when we compare the archaeological sample with a random sample created, we observe that the H_1 is performed and both samples belong to different populations through the K-S Test (D = 0.36807, p-value = $7.229e^{-05}$). As we can see in the K, L and G homogenous functions graphs (Fig. 4), the black line is not close to the confidence interval and that means that we can reject H_0 and accept H_1 because the CSR is not fulfilled. Also, if we observe the inhomogeneous K and L functions, we can see that the clustering of sites occurs up to 2 km.

4.2. Predictive intensity surface

Once checked the CSR, we proceeded to carry out a predictive model to evaluate which of the covariates would be capable of predicting the location of the archaeological sites of the Monforte de Lemos basin. In this work, we will base ourselves on the Generalized Linear Models (GLM). The results of this model depend largely on the measure of the combination of covariates between them. That is, depending on the variables that we introduce in the model the predictive results can vary. For this reason, the choice of these is important, since introducing variables that are correlated can cause errors or result in an unreliable model.

To check if there was a correlation between the variables, we have been used Pearson's correlation test (Fig. 5) which allowed us to identify those that were like each other. In this way, we decided to use 18 variables that, once verified, with Pearson's correlation, their number were reduced. We realized that some of them were collinear (Table 5). In this way, we have decided to eliminate DIRINS because it has a high correlation index with TOTINS (0.99895788). In the same way, DIFINS has also been eliminated, but because it has a strong correlation with ALT (0.861763823). Another one that has been eliminated has been TPI1000, whose correlation is evident with TPI500 (0.897952424) and in turn, TPI500 has a strong correlation with TPI100 (0.775616991), so we have decided to remove both TPI1000 and TPI500 and keep only with TPI100 based in the results of this variable on another study (Díaz Rodríguez and Carrero Pazos, 2019). Another variable suppressed has been GEOLE, due to the high level of correlation that has with GEOLC (0.99385695). Lastly, we have also decided to remove HYDROE due to its strong relationship with HYDROC (0.96186192). If we stop to analyse the variables related to hydrology and geology, in one we have considered the Euclidean distance and in another the displacement cost, but both start from the same principle, so, logically, that there exists this strong correlation between them. As seems to happen with those based on insolation and topographic prominence.

After Pearson's correlation results (Fig. 5 and Table 5), we reduced

v9	v10	v11	v12	v13	v14	v15	v16	v17	v18
0.86176382	−0.001182526	0.03768574	0.27253891	−0.005418655	−0.10299001	0.060261887	0.130278882	0.15469177	0.67464251
0.29435648	0.203183058	0.21265617	0.17073204	0.264526268	0.45706674	0.435083167	0.523663376	0.15469177	0.67464251
−0.07917093	−0.166464365	−0.16523256	−0.17574213	−0.127103143	0.18183008	0.115443493	0.078076013	0.05719123	0.29408736
−0.25044668	0.087481299	0.07491593	−0.18906411	−0.030536055	0.31091594	0.237976545	0.339442243	0.26712282	−0.07928285
0.45396958	0.125863805	0.14865235	0.14140918	−0.072225879	−0.05276793	−0.179755668	−0.032363424	0.10944885	0.20639941
−0.24922514	−0.061971673	−0.06874893	−0.02571088	0.190785207	0.34181459	0.342272194	0.243256138	0.14483218	0.10541525
−0.24586908	0.071892069	0.05999455	−0.19697658	−0.017768644	0.30502394	0.245844151	0.337446280	0.26040509	−0.05346513
0.49252864	0.083190925	0.10759489	0.14829719	−0.041016093	−0.07698603	−0.205832252	−0.039891211	0.09212769	0.30995669
1.00000000	−0.063542708	−0.02521872	0.29269640	−0.412937384	−0.11712191	0.088983868	0.108461275	0.10982423	0.68629862
−0.06354271	1.000000000	0.99895788	0.17676705	0.136164217	0.14817340	−0.131546127	0.123754508	0.18661709	−0.26524359
−0.02521872	0.998957885	1.00000000	0.18935697	0.123520728	0.14420152	−0.125987555	0.128422159	0.19022280	−0.23607266
0.29269640	0.176767054	0.18935697	1.00000000	−0.040791264	−0.01421752	0.087201274	0.029890183	−0.01880984	0.23118242
−0.41293738	0.136164217	0.12352073	−0.04079126	1.000000000	0.10481389	0.003463091	0.008060367	0.01750512	−0.22540834
−0.11712191	0.148173405	0.14420152	−0.01421752	0.104813887	1.00000000	0.656898449	0.780065896	0.76426279	0.03326149
0.08898387	−0.131546127	−0.12598755	0.08720127	0.003463091	0.65689845	1.000000000	0.775616991	0.60635886	0.20381251
0.10846128	0.123754508	0.12842216	0.02989018	0.008060367	0.78006590	0.775616991	1.000000000	0.89795242	0.18468664
0.10982423	0.186617090	0.19022280	−0.01880984	0.017505124	0.76426279	0.606358855	0.897952424	1.00000000	0.13039354
0.68629862	−0.265243588	−0.23607266	0.23118242	−0.225408337	0.03326149	0.203812511	0.184686636	0.13039354	1.00000000

the number of covariates to 12 and discarded 6. The 12 selected are the ones we have used to carry out the GLM: ALT, SLO, TOTINS, ASP, VISPR, TPI100, WET, LCPC, WIND, CPFPCG, HYDROC and GEOLC. To run this process we have used R and the function stepAIC() from the MASS package (Ripley et al., 2020), which evaluates the relative merits of different models starting with the one we have proposed. The best model will be chosen using the Akaike Information Criteria (AIC), which allows us to provide a measure of their relative quality and is used to make comparisons between possible models with different combinations of covariates (Baddeley et al., 2015, pp. 335–336). The smaller the AIC value, the more accurate the model will be.

The stepAIC() function tells us which is the best combination of covariates to include in our predictive model. This does not mean that the discarded covariates are not important in the settlement pattern, but these are excluded because the function does not consider them statistically relevant in combination with the rest. As can be seen in Table 4, these covariates are ALT, SLO, VISPR, WET and HYDROC. The p column (Pr(> |z|)) indicates the statistically significant covariates, those which can predict more accurately the presence of sites. So, we have 5 covariates that, combined with the rest, better predict the distribution of the archaeological sites, while the other 7 (TOTINS, ASP, TPI100, LCPC, WIND, CPFPCG and GEOLC) remain discarded. Considering the predictor variables obtained from the Multivariate regression model the results indicate that the hydrology covariates present a lower predictive value. Therefore, these will be weighted with a lower value when creating the predictive archaeological surface. With the covariates that best predict, the predictive surface was created using the algebra of maps in R. The predictive value of each cell was computed, using the equation, logit(p) = α + β1x1 + β2x2 +…+βnxn, where α is the intercept (the predicted value of the dependent variable when all independent variables are 0), β the coefficients and χ the covariates. This gives us an algorithm of the probability of the presence of sites divided by the probability of the absence of sites. Later, to calculate the relative probability of the existence of sites in a particular location, the following applies equation: $p_i\frac{exp^{/()}vi}{1+exp^{/()}vi}$.

First, a raster map is created with the predictive values of each covariate, adding the estimated value of the intercept to the multiplication of the variables and its estimated value. The map of predictivity archaeological surface is created following the results obtained from the Multivariate regression model (Table 4) and with the next formula = (exp(Predictive_Surface))/(1+(exp(Predictive_Surface))) and from the function logodds <- 7.2294176+(ALT* −0.0167014)+(SLO* −0.3456405)+(VISPR* 0.0458370)+(WET* −0.0017355)+(HYDROC* 0.0007585). With this procedure a relative probability surface is obtained. The last step is to convert that map into a log-likelihood surface with values between 0 and 1 (Fig. 6).

To validate the reliability of the predictive model, before starting to calculate the predictive model we decided to divide the total sample (whose number amounts to 76) of sites into two samples. In this way, on the one hand, we have a training sample (composed of 46 archaeological sites), with which the GLM analyses have been carried out, and another control sample (composed of 30 archaeological sites) that was kept out of the calculation process. The objective of this division is to check how many of the sites, from the control sample, are in areas with high archaeological potential. In this case, 23 sites are above 75 % of the predictive threshold (76.7 % of them), while 2 are located above 50 % (6.6 %) and 5 below 50 % (16.7 %). If we establish that from the value of 0.5 the prediction is effective, we have that 25 of 30 sites are in high prediction zones (83.33 %) (Fig. 6).

These results indicate that the model could be used to suggest a precise distribution scheme for the sites of the Monforte de Lemos Basin. Therefore, the variables verified by the predictive model could have first-order effects on the location of the Palaeolithic sites. This analysis shows that the set of random samples does not seem to share the trend of the sites, their location being predictive and consequently significant from the set of variables: ALT (altitude), SLO (slope), WET (cost to areas of wetland), VISPR (visual prominence) and HYDROC (cost to potential hydrology).

4.3. Evaluation of predictive covariates

Once the predictive model has been carried out, we will proceed to the analysis of the covariates that predict the location of the archaeological sites. Two approaches were used for this, the first of which is based on the analysis of the intensity relationship between the dependent variable (presence of sites) and the different predictor covariates (Fig. 7). The second approach is based on the analysis of each variable from the comparison between the percentage of cells (bars) and sites (line) (Fig. 8). Both approaches were carried out in R Statistics (R Core Team, 2021) using the *rhohat* function from the *spatstat* package for the first one (Baddeley et al., 2015, p. 218) and the *ggplot2* package for the second (Wickham et al., 2020).

After these analyses, we have been able to verify that most of the archaeological sites are found at altitudes between 300 and 400 m.a.s.l. Considering the comparison graph between the percentage of cells and sites, we observe that it is a percentage higher than 80 % when what we might expect taking into account the percentage of terrain, should be a distribution between 300 and 700 m.a.s.l. (Fig. 8a). The *rhohat* function allows estimating the correlation between the intensity of points

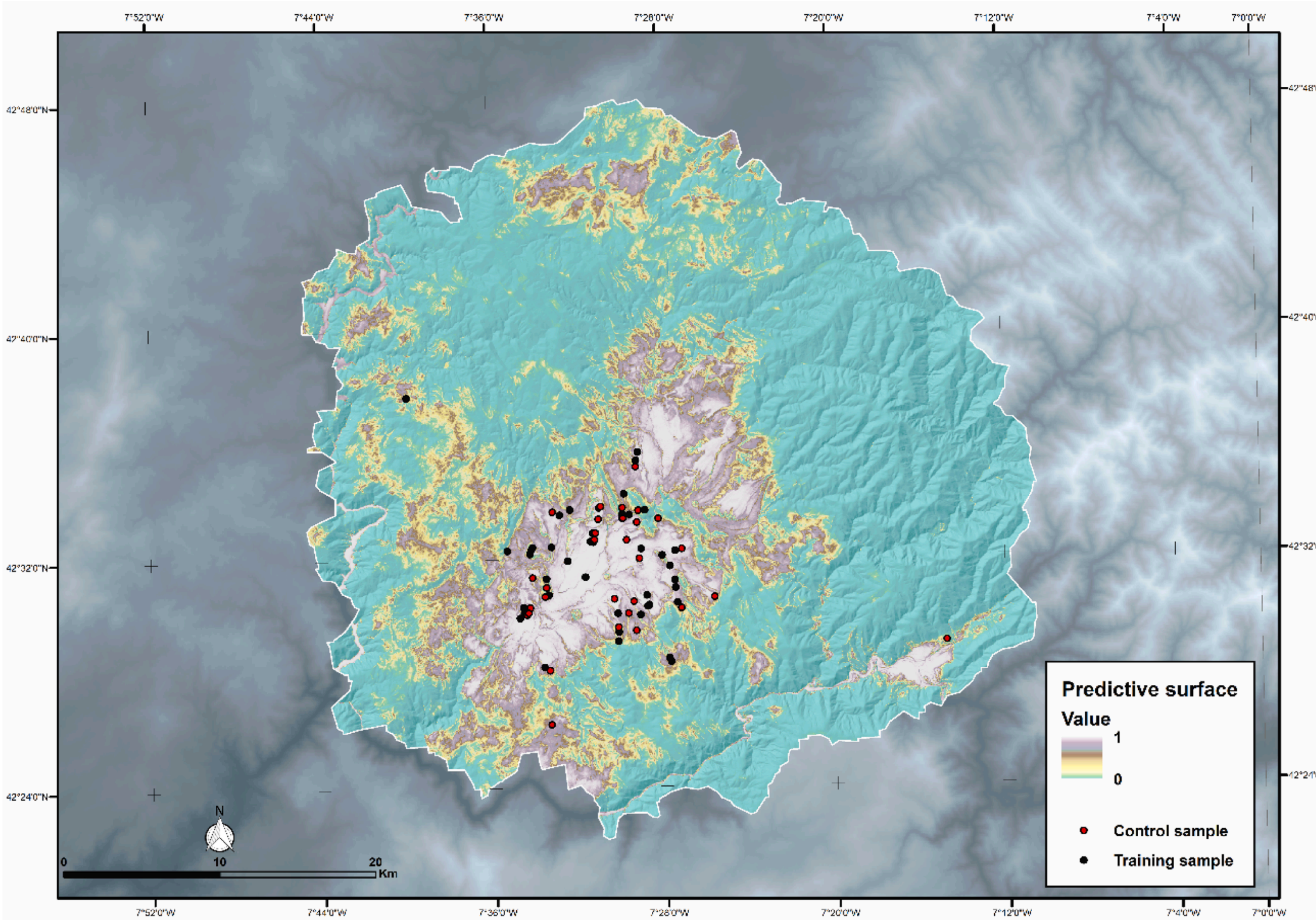

Fig. 6. Predictive surface with the control sample (red dots) and the training sample (black dots). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

(archaeological sites) and a given variable. The results of the *rhohat* function corroborate that the archaeological sites are grouped between 300 and 400 m. a. s. l., which differs from what is expected under random conditions (Fig. 7a).

The grouping of archaeological sites according to slope occurs between the 0-5° (Fig. 7b). In this case, the trend corresponds to the percentage of terrain, since most of the cells, about 30 %, are in the 0-5° range and 80 % of the archaeological sites occur precisely there (Fig. 8b). Most of the archaeological sites are in areas with values less than 5°, which may be because a large part of the analysed area lacks steep slopes and is rather flat since we are basically in a basin area.

The distribution of sites, according to the hydrological covariates, seems to follow a random distribution in both cases. Most of the archaeological sites are grouped between 0 and 3000 s from the potential hydrology (Fig. 7c), and more than 30 % are between 1000 and 2000 s (Fig. 8c). In the case of the variable related to the cost to wetland potential areas since the grouping of sites is concentrated in the first 2000 s (Fig. 7d) and the percentage of sites located in that range is more than 75 % (Fig. 8d). This distribution of sites also matches the highest percentage of cells in the raster map.

Finally, regarding visual prominence, archaeological sites are clustered in values of 0–50 visible cells (Fig. 7e). There is a higher percentage of sites in values located in the range that goes from 20 to 60 (Fig. 8e). This differs from what is expected in random conditions, since the largest number of cells, 50 % of them, is concentrated in the range between 0 and 20 visible cells.

5. Discussion

In this work, we characterize the covariates that best predict the occupation pattern of the Palaeolithic archaeological sites of the Monforte de Lemos basin from the application of a predictive model. The results presented here show that the main predictor variables are elevation, slope, cost to potential hydrology, the cost to wetland areas, and visual prominence. Studies based on descriptive statistical analyses had previously been carried out (de Lombera Hermida et al., 2015; Díaz Rodríguez et al., 2021; Díaz Rodríguez, 2017; Díaz-Rodríguez et al., 2021), but this is the first time that a study of this type, based on the creation of a predictive model, has been applied to the analysis of the distribution of sites framed chronologically in the Palaeolithic of the Northwest Iberia.

However, it must be considered that the predictive model has limitations. In other words, the result obtained may vary depending on the variables used during the application of the multivariate regression. That is why the prior choice of these variables, and the application of the correlation analysis are important. In the present study, an attempt has been made to test a theoretical model previously defined by various researchers. We have been able to confirm the importance of some of the variables that had been mentioned in the literature to define the settlement pattern, as occurs with the 5 variables mentioned previously. Although some variables have been discarded by the multivariate regression model, they must also be considered. Others seemed to be relevant in the location of archaeological sites and finally have not been, such as the Topographical Prominence (López Cordeiro, 2002, p. 71; Fábregas Valcarce and de Lombera Hermida, 2010, p. 267) or the LCP

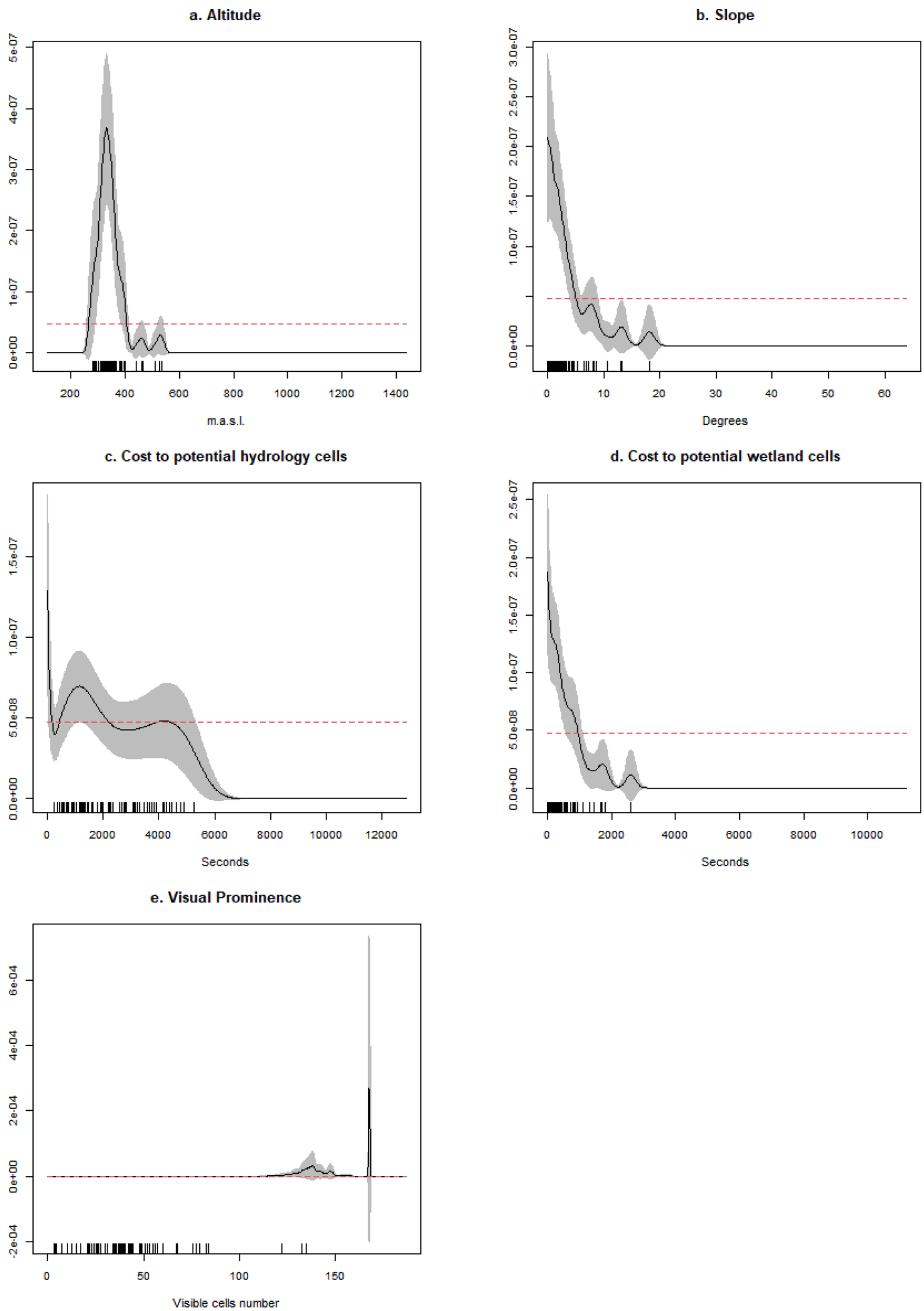

Fig. 7. (a) Palaeolithic site intensity as a function of altitude (solid lines show function estimate while grey shading is pointwise 95% confidence envelope). (b) Palaeolithic site intensity as a function of slope. (c) Palaeolithic site intensity as a function of cost to potential hydrology cells. (d) Palaeolithic site intensity as a function of cost to potential wetland cells. (e) Palaeolithic site intensity as a function of visual prominence.

(Ramil Rego and Ramil Soneira, 1996, p. 125; López Cordeiro, 2015, p. 301). In addition, there are other variables proposed in the theoretical model that could not be incorporated due to the limitations of their modelling and incorporation into the multivariate analysis, such as visibility (de Lombera Hermida et al., 2015; Ramil Rego, 1989/1990). Also, we have verified that some variables have had to be rejected when calculating the predictive model because they presented too many similarities between them. The analyses based on the Euclidean distance and the cost of displacement in time are notable since they present statistical similarities that prevent us from comparing both variables. Besides, those based on the different types of insolation and the topographic prominence at different radii.

If we look at the predictive variables and what their importance and their choice may imply for a hunter-gatherer society, we can see that the

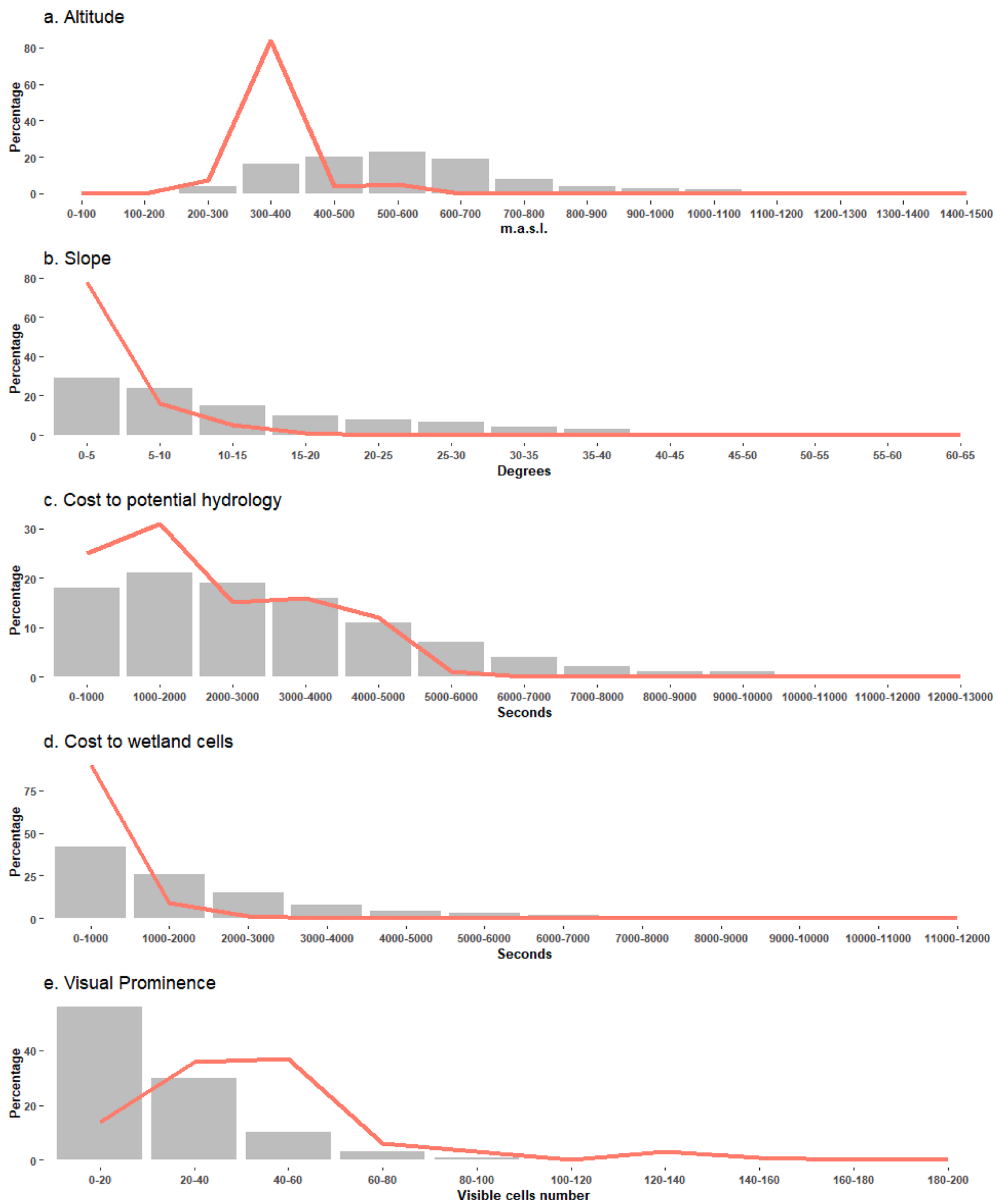

Fig. 8. (a) Altitudinal distribution of sites (red line) compared to that of the terrain cells in the study area (grey bars). (b) Slope distribution of sites compared to that of the terrain cells in the study area. (c) Cost to potential hydrology distribution of sites compared to that of the terrain cells in the study area. (d) Cost to wetland cells distribution of sites compared to that of the terrain cells in the study area. (e) Visual prominence distribution of sites compared to that of the terrain cells in the study area. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

sites are located in areas with low altitudes, since the occupation from a certain altitude would be limited by the most rigorous moments of the last glaciation and that would be linked to glacial or periglacial deposits (Viana-Soto and Pérez-Alberti, 2019). For this reason, it would be difficult to identify archaeological sites of this chronology in high locations, because it would be very difficult to inhabit those places. As for the slope, the sites are on low slopes, which may be because it is a fundamentally flat area. It is a basin that has large flat surfaces and better conditions for its occupation. Regarding potential hydrology and wetland areas, climatic fluctuations must be taken into account, since during the more temperate and humid periods it is very likely that the immediate streams had more stable flows, as has been reported in some previous paleoclimatic approaches (Rey-Rodríguez et al., 2016). However, it is logical to think that the archaeological sites should be in the vicinity of areas with abundant water, where they can be supplied with this resource and that at the same time would act as areas of attraction for animals that would go to these areas and that could be hunted by these individuals. The most difficult variable to interpret from an archaeological point of view is visual prominence. Given the results obtained, which show that most of the sites are in areas with low levels of visual prominence, we can understand that these are little exposed areas. These are zones sheltered and little visually exposed. The orographic configuration of the area, considering that it is a basin, helps the existence of these visually sheltered places.

We must not confuse visual prominence with visibility. Above all, due to the type of calculation that we have used to obtain this variable. As indicated in the procedure carried out for its calculation (SI) and following the recommendation of other authors (Conolly and Lake, 2006), we have inverted the positions of the observer and the observed cells. For this reason, what this variable shows us is a map with the number of cells visible from each cell. Therefore, we must interpret that the archaeological sites are found in those less exposed areas visually speaking. This is logical as it is a depression, since a large part of its extension is made up of low areas. On the other hand, in a previous work we have evaluated the visibility from the archaeological sites to the rest of the study area (de Lombera Hermida et al., 2015). This has allowed us to verify that the visibility is very wide, unlike what happens in other mountainous areas of the NW Iberian (Díaz Rodríguez, 2020). This result is compatible with what usually occurs in this chronology in different regions (García-Moreno, 2013).

The results obtained in this work follow the line begun in previous studies with similar results in the study area (de Lombera Hermida et al., 2015). But unlike previous works, which were based on a descriptive statistical analysis of the settlement pattern, it has been possible to statistically assess the importance of the locational variables previously proposed in the theoretical model. The geomorphological characteristics of the Monforte de Lemos basin contrast with the results obtained in other mountain regions of the NW Iberia, such as the Northern mountain ranges or the mountain range of O Bocelo. In the mountain areas there exist different geomorphological characteristics to wich hunter-gatherers had to adapt themselves. This is reflected in that the predictor variables of the mountain areas differ, in some cases, with those of the Monforte de Lemos basin. Altitude acts as a predictor variable in all areas, but nevertheless the sites of Monforte are located at low altitudes and slopes, while in the mountainous areas, the archaeological sites are located at medium–high altitudes and the slope is not a variable that predicts the location of these sites. But it does highlight the cost to potential hydrology and orientation (in the mountain range of O Bocelo) and the cost to potential humidity, potential geology and insolation (Northern mountain ranges) (Díaz Rodríguez, 2020).

In the case of other areas of Western Iberia that have been studied for the Middle Palaeolithic, the location of archaeological sites at low elevations and shorter distances from the riverbanks has been verified, which apparently influences the availability and exploitation of lithic raw materials (Cascalheira et al., 2022). In another area close to our study region, Eastern Cantabria, it was documented that the sites occupied from the Upper-Final Magdalenian were located either on predominantly flat terrain, or in rocky areas, while in earlier times there seemed to be a tendency to inhabit places that combined both types of terrain in their vicinity (García Moreno, 2010). In the Sierra de Atapuerca, a pattern has been identified for Mousterian sites, based on proximity to hydrological elements, biotic resources and wide visual control (Marcos Sáiz, 2006).

We have not been able to establish distinctions in the pattern of occupation in terms of the chronology of the sites or their functionality. Either because we do not have sufficient chronological data, or because the number of archaeological sites is small and does not allow us to compare them with each other maintaining a guarantee of basic statistical representativeness. The division into a training sample and another control sample would leave us with a few sites that are too small to apply this methodology with guarantees and to create three different models for the Lower Palaeolithic, the Middle Palaeolithic, and the Upper Palaeolithic. It would be interesting to carry out this approximation in the future to identify if there are different patterns of occupation over time.

Cultural and/or social criteria (second-order effects) have not been addressed in the present work. The study of first-order effects has been prioritized to analyse the general trends in the location of Palaeolithic sites in the landscape. Second-order effects of a point pattern describe the relative intensity of points influenced by the spatial configuration of other points and whose set of points depends on the location of other points (Nakoinz and Knitter, 2016). These characteristics or factors have been interpreted as cultural or social variables that arise from the dispersion of points in the study area (Bevan et al., 2013). The analysis of the spatial relationship between the archaeological sites themselves remains for later approaches.

6. Conclusions

Summing up, we have demonstrated the usefulness of the predictive model as an analytical method for the study of Palaeolithic settlement patterns in the Monforte de Lemos basin. Also, this type of approximation allowed us to test the previous theoretical model and evaluate their suitability from a statistical standpoint. A total of 5 variables of the 18 used have turned out to be suitable for predicting the location of the analysed archaeological sites. Therefore, the effectiveness of the theoretical model that had been proposed over the last decades in the case of some of these variables has been verified. Perhaps we should look for ways to analyse some of the variables that could not be modelled or analysed using the methodology proposed in this study. This is the case, for example, of the visual control of certain areas of the territory or the study of second-order effects, in which the grouping or repulsion that some sites exert on others would be studied. But to get there, the chronology of the archaeological sites should be defined and due to the nature of the findings, it is currently not possible to obtain that information.

Looking into the future, it would be interesting to know if the same occupation pattern is fulfilled in other nearby areas or whether there are regional differences depending on the study area or the chronology of the Palaeolithic sites. One might think it is not the same whether these societies lived in a mountainous area or in a plain. The characteristics of these two scenarios are different and adaptation to the environment would have a greater weight than a previously defined idea of the ideal place to live. If they did not have a choice, at a certain time of the year, the place of occupation chosen by these communities would be the most appropriate considering the possibilities offered by the territory in which they were located. For this reason, it is important to carry out studies on a regional scale, because it deals with the analysis of societies with great mobility, exploiting the surrounding territory. Therefore, it would not make much sense to try to find a global pattern from the study of very large areas. The logical thing leads us to think that there would be a strong regionalization conditioned by natural limiting agents that prevented expanding mobility at certain times of the year, such as large rivers or mountain ranges. For this reason, we believe that these societies were confined to a naturally delimited space and had to look for the most appropriate places to live within the possibilities offered by each territory.

CRediT authorship contribution statement

Mikel Díaz-Rodríguez: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Writing – review & editing, Visualization. **Ramón Fábregas-Valcarce:** Investigation, Writing – review & editing, Project administration, Funding acquisition. **Augusto Pérez-Alberti:** Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data used in this paper and the code executed in R are available at https://github.com/mikeldiazrodriguez/patterns_monforte and archived on zenodo (http://doi.org/10.5281/zenodo.7808861).

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The data used in this paper and the code executed in R are available at https://github.com/mikeldiazrodriguez/patterns_monforte and archived on zenodo (https://doi.org/10.5281/zenodo.7808861).

Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jasrep.2023.104012.

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