

## **Beyond the scale. Building formal approaches for the study of spatial patterns in Galician mounds (NW Iberian Peninsula)**

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### **Abstract**

In Galicia, works that studied the megalithic locational patterns developed only fieldwork-based approaches. As a result, the locational criteria were defined using ideas through a direct analysis at field, and never have been quantified and modelled with GIS methods until nowadays.

In this work, a GIS methodology and a point pattern approach for the study of megalithic locational patterns is carried out. Starting from the definition of locational factors managed by literature, a number of first and second order properties were converted into spatial variables. From this point, specific regularities among the distribution of sites were established, which allows to determine trends in Galician megalithic occupation and open new possibilities of analysis in the study of Galician megalithic landscapes.

### **Keywords**

Megalithism; Galicia; spatial statistics; predictive modelling; point pattern; GRASS GIS; R Statistics

### **1. Introduction: Site location patterning in Galician Megalithic complex**

In Galicia, studies that incorporated a spatial perspective began in 1930s, with the contributions of G. and V. Leisner (Leisner, 1938) who proposed the first map of the distribution of the megalithic phenomenon in the NW of the Iberian Peninsula, identifying areas with high presence of sites as a result of an intensive survey work. Different works have continued this research, with the contributions of A. A. Rodríguez Casal (1990) or the latest one proposed by ourselves (Carrero-Pazos, Rodríguez Casal *in press*).

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The study of the megalithic locational factors certainly had greater attention during the 1980s, with the efforts of authors such as J. M. Bello Diéguez, F. Criado Boado, J. M. Eguileta Franco or J. Vaquero Lastres, which continued the work initiated by previous authors such as Maciñeira or López Cuevillas (Maciñeira, 1943-1944; López Cuevillas, 1959; Bello Diéguez *et al.*, 1984; Criado Boado *et al.*, 1986; 1990; Criado Boado, Vaquero Lastres, 1991; Vaquero Lastres 1989, 1990, 1991-1992, 1993-1994; Eguileta Franco, 1999; Villoch Vázquez, 2000, among others). Their contributions aimed the definition of locational regularities registered during fieldwork. They noticed, for example, that mounds are located at specific altitudes, in relation to the geological substrate or the visibility and intervisibility between sites.

However, following M. Lake and P. Woodman (2003, p. 690), such approaches can be classified as “informal” as they are characterised by the absence of an explicit methodology and the development of a commonsense interpretation, as it mostly happened with visibility studies, centred on viewshed maps determined by eye during the survey works. On the basis of the locational model that can be extracted from all these works, we can summarise the main locational criteria of the Galician Megalithic mounds (**Figure 1**).

[Caption] **Figure 1.** Locational covariates that will be considered in this study (following Carrero Pazos, 2017).

Starting from the rasterization of these variables<sup>1</sup>, we will use site predictive modelling to determine which ones can predict the distribution of monuments, hence supposing that they were relevant in the configuration of the megalithic landscapes. In this work we are not criticising the validity of traditional approaches but discussing them through a quantitative perspective supported by GIS and spatial statistics (Llobera, 2007).

## 2. Study area and Dataset

The study area is located in the south of Galicia, belonging to the region of Vigo and Baixo Miño. These are roughly the limits of the current councils of Soutomaior, Pazos de Borbén, Redondela, Mos, Vigo, O Porriño, Tui, Gondomar and Nigrán (**Figure 2**).

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<sup>1</sup> The research of this paper has been carried out using open source software, specifically GRASS GIS 7.0.2 (GRASS Development Team, 2017), SAGA GIS 6.0.0 (Conrad *et al.*, 2015) and R Statistics 3.2.5 (R Core Team, 2008).

**[Caption] Figure 2.** Study area. Monte Penide and Serra do Galiñeiro.

The megalithic monuments of this zone have been already studied, with the investigations of G. Álvarez Limeses (1935), C. de Mergelina (1936), P. Díaz (1973), J. Filgueira Valverde and A. García Alén (1977), and J. M. Hidalgo Cuñarro and F. J. Costas Goberna (1979). In more recent times, the works of C. Gómez Nistal (2000; Gómez Nistal, Rodríguez Casal 2000) or R. Fábregas Valcarce (2010, orig. 2001) deal with megalithic sites from an overall perspective, but never from a GIS-based methodology. With respect to archaeological data, we are using the archaeological database of the megalithic studies group from the University of Santiago de Compostela (GI-1520), which has 121 sites for that area analysed through fieldwork and “ground-truthing” (LiDAR visualisation techniques) (Carrero-Pazos, 2017).

The limits of the study zone were defined as vectors, based on the different watersheds and sub-watersheds calculated in GRASS GIS 7.0.2 with *r.watershed*. The reason behind this decision is a geographic justification rather than using the current administrative divisions such as counties. In such a way, regions are usually better working areas as they are supported by historical and natural constitutions, although for this concrete case they had to be discarded since it supposed the use of a too big study surface. Therefore, the watershed approach<sup>2</sup> provided a more representative and suitable area for the study of the location of sites and the background.

### **2.1. Geographical and archaeological context**

The study area, located to the South of Vigo, is characterised by a flat surface that belongs to the current councils of Nigrán, Vigo, Mos and Redondela. It is truncated by some elevations such as Outeiro Grande (442 m), Alto do Cepudo (524 m) or As Pereiras (514 m). From a hydrological point of view, the watersheds of Verdugo and Oitavén rivers stand out, as well as the Miñor one that closes to the South the region of Vigo. The Pico San Vicente (432 m), located in Redondela, is the highest point in the North, and has one of the largest concentrations of mounds such as Monte Penide (Chanda Cruz’s group has thirty sites, some of them dolmens, such as the case of A Mamoa do Rei) (**Figure 3**).

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<sup>2</sup> After several tests the chosen size for basins was 62,500 m.

**[Caption] Figure 3.** Geographical context of the area considered.

The main mountain range of the zone is further to the East, Serra do Galiñeiro (Coto de Cales, 742 m). This is an elongated sierra (N-S direction) which truncates the depression of a geological stretch in two sides. In the East, other natural formations can be observed, such as Cavada do Burro's Peak (532 m) or Coto da Eira (881 m), linking with the Meridian Dorsal.

To the South a small plain opens, Mondariz-Balneario, shared by Salvaterra de Miño's council, which is not exempt of elevations, as for instance the cases of Chan da Maceira (367 m), Pena Alta (383 m) or Coto dos Mouchos (757 m), part of Os Montes da Paradanta at the beginning of the aforementioned Dorsal.

## **2.2. Complete Spatial Randomness and Monte Carlo Simulation**

In order to check if the distribution of megalithic sites is uniform and homogeneous throughout the study area, that is to say, if it complies or not with Complete Spatial Randomness (CSR), we can carry out a visual analysis of a distribution map (see figure 3). A first informal glance gives the sense that points are not distributed in a random way, or at least that is not apparent. However, the visual inspection does not allow us to quantify and empirically justify this statement. For this reason, it is necessary to carry out deeper analyses that allow us to know in detail the characteristics and the intensity of point processes, the possible existence of other underlying process that are being masked beyond the general distribution of points (Bevan *et al.*, 2013).

We start from the theoretical study of a random sample and its comparison with the distribution of real data. The first question is the location of the random sample, which should not be located at distances close to the real monuments, in order to obtain greater representativeness of the analysis. Therefore, we have decided to constrain the creation of the random sample to 1 km buffer from the sites, ensuring that the distribution of mounds and random points will never overlap. Subsequently, we observed whether the distribution of both datasets can come from the same population, which would indicate that there are not differences and therefore we could not reject the CSR for the real sample. In this sense, the non-parametric test Kolmogorov-Smirnov (K-S, henceforward) was applied to both samples (the distribution of random points is non-

FINAL VERSION: Carrero-Pazos, M. (2018). Beyond the scale. Building formal approaches for the study of spatial patterns in Galician mounds (NW Iberian Peninsula). *Journal of Archaeological Science: Reports*, 19: 538-551. <https://doi.org/10.1016/j.jasrep.2018.03.026> normal<sup>3</sup>). It provides the probability that both distributions come from the same base population (*p-value* 0.0002468). This means that the location of sites differ from random sample, so we can therefore reject the CSR (**Figure 4: A**). However, there are more robust approaches, such as Monte Carlo Simulation, which allow to use a high number of random locations under CSR conditions. The most utilised tests are Ripley's K Function or its variants *L* Function and *G* Function of the nearest neighbour distance (Bivand *et al.*, 2013). If the distribution of mounds were the result of chance, we might expect that the trend shown in **figure 4 (B, C and D)** for megalithic sites would fall under the random envelope or would be similar to the trend shown by random simulations. Given that this is not the case, we can reject the hypothesis of a random distribution for the megalithic monuments of this area.

[Caption] **Figure 4.** Complete Spatial Randomness Tests. **A:** *Kolmogorov-Smirnov Test*. **B:** *K Function*. **C:** *L Function*. **D:** *G Function*.

### 2.3. Covariables dataset

Once we know that the distribution of mounds differ from randomness, the study of different environmental variables can be carried out, in order to analyse their possible effects on the distribution of sites (first-order effects).

[Caption] **Figure 5.** First-order covariates. **A:** Altitude (m A. S. L.). **B:** Geology. **C:** Slope (%). **D:** Landforms (TPI based classification).

The first variable is the altitude. Sites are normally located on 250-400 m A.S.L, and residual cases are placed at more extreme altitudes. It is interesting to compare the altitude of the monuments with the background elevation pattern, since there seems to be an inclination on choosing locations of 300-400 m A.S.L. (**Figure 5: A**). The geology was also studied, as a result of the reclassification of MAGNA's Official Map (scale 1:50.000), which resulted in the following categories for that area: acidic igneous rocks, metamorphic rocks and intrusive igneous rocks (**Figure 5: B**). A first description allows us to consider trends in the data, such as the acidic igneous rocks represent 56%

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<sup>3</sup> Checked by a Shapiro-Wilk normality test, with a result of  $W = 0.93556$ , *p-value* = 0.0005147.

FINAL VERSION: Carrero-Pazos, M. (2018). Beyond the scale. Building formal approaches for the study of spatial patterns in Galician mounds (NW Iberian Peninsula). *Journal of Archaeological Science: Reports*, 19: 538-551. <https://doi.org/10.1016/j.jasrep.2018.03.026> of the background geology, although most of the sites (65%) are located on areas with metamorphic rocks, a residual percentage in the study area (31%).

The slope was calculated in SAGA GIS 6.0.0 following Zevenbergen and Thorne (1987) method, reclassified by map algebra in GRASS GIS 7.0.2 to follow F.A.O's classification proposed by different archaeological works (Eguileta Franco 1999). More than the 80% of the study area corresponds to 3-5 (6-26%) classes, indicating that the territory is characterised by steep areas with a mild tendency. Areas with extreme slopes are unusual (**Figure 5: C**). In fact, 40% of the sites is located on slopes of class 3 (inclined, 6-13%), followed by an approximate 30% for moderately steep slopes of class 4 (13-25%).

The topographic prominence has been calculated in SAGA GIS 6.0.0 for two radii (local scale, 100 m; large scale, 1000 m), according to the topographic position index module, which compares the elevation of raster cells with the average of the surroundings, previously defined by user through a threshold (Guisan *et al.*, 1999; Weiss 2001; Wilson, Gallant 2000). From here, a landform classification was then modelled, using the TPI based landform classification module in SAGA GIS 6.0.0, with a radius of 200 m. The results, in **figure 5 (D)**, emphasize the location of mounds at open slopes.

The relation of megalithic monuments with areas of movement in landscapes is one of the locational criteria with more tradition of study in Galicia. Starting from F. Maciñeira's contributions during 1940s decade (Maciñeira, 1943-1944), it was established as a proper line of research during nineties -"the geography of movement" (see e. g. Vaquero Lastres 1993-1994; 1995; Villoch Vázquez 1995, among many others).

To study of this factor, the proposals of P. Murrieta-Flores (2012; Murrieta-Flores *et al.* 2014) for the study of South Iberian Megalithism have been followed, similar to the work of M. Llobera (2015) in the Barbanza Peninsula (Galicia), also used by C. Rodríguez Rellán and R. Fábregas Valcarce (2015) for the study of Galician Bronze Age rock art. Other works that carried out transit simulations are the contributions of E. Cerrillo Cuenca (2007), P. Fábrega Álvarez (*et al.* 2011), C. Parcero Oubiña (2013) or A. Bevan and A. Wilson (2013), among many others.

In this work we will use a method that seeks for the creation of a general model of human mobility, starting from the creation of multiple least cost paths that start and stop

FINAL VERSION: Carrero-Pazos, M. (2018). Beyond the scale. Building formal approaches for the study of spatial patterns in Galician mounds (NW Iberian Peninsula). *Journal of Archaeological Science: Reports*, 19: 538-551. <https://doi.org/10.1016/j.jasrep.2018.03.026> at the vector limits of the working area. The aim is to get a density of least cost paths, which implies the calculation of the mobility from one point to the total (*one to many*), but the process is repeated for a high number of points (White, Barber 2012). This method allows to obtain a density of least cost paths, with areas of high density of pathways. The next step was to calculate the cost of passage (in time) to travel from the potential routes to the megalithic sites, allowing us to analyse the relation of movement (and its intensity) between the location of sites and the natural movement across landscape.

In technical terms, GRASS GIS 7.0.2 was the software used for the creation of the density of pathways. The friction surface was created with *r.watershed*, using the topography and the hydrology. The raster map was then reclassified assigning high values to zones that should block the passage such as rivers.

**[Caption] Figure 6.** First-order covariates modelled. **A:** Intensity of potential transit. **B:** Cost of passage from potential routes. **C:** Cost of passage from wetlands. **D:** Visual prominence of landscape.

Subsequently, we created the cost accumulated surface with *r.walk* and, lastly, the least cost vector routes were generated with *r.drain*. The process was then repeated to the whole points taken from the vector area and, using *v.kernel*, we created a kernel density surface of all the pathways. The results show areas with high and low concentration of routes (**Figure 6: A**). The decomposition of the vector limits in separate locations every 500 m resulted in an amount of 458 start and stop points, which produced a total of 209.306 potential routes.

The relation between the natural movement and the megalithic sites was also calculated, through the generation of a cost of passage raster (in seconds) from the routes to the whole of the study area, again with *r.walk* (**Figure 6: B**).

On the other hand, as different authors stated a relation of mounds and watercourses (e. g. Vaquero Lastres 1990), a potential river network was calculated, maintaining in the final raster only the highest values of water accumulation. From this point, a raster of cost of passage (in time) from water zones was generated (**Figure 6: C**).

The visibility is another variable that was inspected in this work. Several approaches have investigated the role of this factor in megalith's location, notably in Spain the

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classical research of L. García Sanjuán (et al. 2006) in South-Iberian megaliths, studying inter-visibility patterns with cumulative viewsheds and significance testing. However, as the study of this factor is certainly a challenge because it should involve the identification of whether it was the view from, the intervisibility between or the view to the monuments which determined their spatial value (De Reu 2012: 227)-, we opted for simplification using the visual prominence of the landscape. The works of M. Llobera (2006; 2007) have defined a methodology to identify areas of the landscape which can be perceived more frequently. The calculation of the total viewshed is defined as “the inherent visibility of all locations in a landscape” (Llobera *et al.* 2010), and is performed by calculating the visibility of each cells in a DEM. The results indicate areas that are visually more prominent in the sense of a greater visual magnitude (Llobera 2003). However, such approaches need high computational efforts. Therefore we decided to make a stratified sampling approach, generating a mesh of regular points over the study area, spaced at 500 m one from the other. The result was a total of 1.967 vision points. Then, for each point, the accumulated visibility with *r.viewshed.cva* in GRASS GIS 7.0.2 was calculated (**Figure 6: D**).

Lastly, previous authors in Galicia suggested a visual relation between mounds and wetlands (Méndez Fernández, 1998; Villoch Vázquez, 2000; Santos Estévez, 2008). As there is not any official cartography that can be used to model the wetlands, we opted for the SAGA GIS’s Wetness Index module. In this analysis, cells represent runoff values, considering that a high humid area is more susceptible to saturate and being converted into a wetland.

### **3. Site predicting modelling and first-order locational patterns**

Once the covariates were defined and quantified, the next step was to carry out the study of the relation between the presence of sites (dependent variable) and the different environmental variables (independent variables). Prior to this, the archaeological sample was divided into two parts: a study sample of 81 cases and a control one with 40 randomly-selected sites, later used to test the validity of the model.

On the other hand, in order to verify the existence of correlations between the covariates –which may evidence collinearity problems-, a Pearson’s correlation test was carried out (**Figure 7**).



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[Caption] **Figure 7.** Pearson correlation test for the covariates, to avoid multicollinearity problems.

The important question here was how to decide which of the correlated variables should be discarded. In order to do that, and with the aim of avoiding over-parametrisation problems, we contrasted Pearson's results with other tests. The comparison of the study sample with a random population could be a possibility, concluding that the distribution of sites should be away from the random one. This is the approach followed by Rodríguez Rellán and Fábregas Valcarce (2015). Thus, two types of statistical approaches were developed in *R Statistics*, which take into account the study of variance. The first one was focused on the application of parametric (T-Student) and non-parametric tests (Mann Whitney Wilcoxon, MWW, henceforward), depending on whether the sample was normal or not, and the second one was the application of a univariate linear regression. This way we were able to observe, for the first case, which variables showed a similar trend to a random population and, for the second one, which variables individually predicted the presence of sites. This allowed us to debug the predictive model, obviating the variables that did not correctly predict the distribution of sites. Previous research has used one random sample (see e. g. Rodríguez Rellán, Fábregas Valcarce 2015) but here we opted for a Monte Carlo Simulation approach, which allows the comparison of the observed data and 999 random samples with the same number of cases (**Table 1**). The results of the univariate logistic regression indicate the covariates that correctly predict the presence of sites (**Table 2**).

[Caption] **Table 1.** Variance analysis between the real sample and a random one.

[Caption] **Table 2.** Results of the univariate logistic regression.

The results of the Pearson's correlation test, jointly with those based on the study of the real and random samples indicate that geology, slope, visual prominence, landforms, wetlands, cost of passage from potential transit routes, topographic prominence index (100 m), must be removed from the model. Those which have been positively selected were included in a generalised regression model (multivariate logistic regression) to

FINAL VERSION: Carrero-Pazos, M. (2018). Beyond the scale. Building formal approaches for the study of spatial patterns in Galician mounds (NW Iberian Peninsula). *Journal of Archaeological Science: Reports*, 19: 538-551. <https://doi.org/10.1016/j.jasrep.2018.03.026> determine their relation with the presence of sites. This is, in fact, the previous step for the creation of the predictive surface.

### 3.1. Generalised regression model (GLM)

Thanks to the use of univariate statistical tests, the relation among all the covariates that accurately predict the distribution of sites was studied. These variables are the altitude, potential transit network, potential hydrologic network, cost of passage from water zones and the topographic prominence index (1000 m).

The multivariate regression model was carried out in *R Statistics*, and the results are shown in **Table 3**. The  $p$  column ( $\Pr(>|z|)$ ) indicates the statistically significant covariates, those which can predict more accurately the presence of monuments and, therefore, we can be expected that influence their distribution. These are the altitude, the geology and the intensity of potential transit through landscape.

**[Caption] Table 3:** Multivariate regression model.

GLM results depend on how the covariates are combined, and it is necessary to test different combinations by eliminating some and adding others, to evaluate the best possible model. This can be implemented in *R Statistics* via stepwise comparison, using the *stepAIC()* function of the MASS package (Venables, Ripley, 2002) which allows the evaluation of the relative merit of different models starting with user's one. The best model will be chosen using the Akaike Information Criterion (AIC), which provides a measure of its relative quality and it is typically used to compare possible models with different combinations of variables (Baddeley *et al.*, 2016, p. 335-336). The lower the AIC, the more accurate the model (**Table 4**).

**[Caption] Table 4:** AIC's best model

The results suggest that the best combination of variables would be a cluster of the potential hydrologic network, the potential transit and the altitude (excluding the topographic prominence index and the cost of passage from water zones).

With these variables, we can now build the predictive surface and a logarithmic probability surface (values form 0 to 1) (**Figure 8**).

**[Caption] Figure 8.** Prediction surface with control sample, and observed values in real data and 999 Monte Carlo simulations.

The validation of the predictive model was done through the control-case method, checking how many sites of the sample that was kept outside the analysis (40) fell in areas with high prediction values. In this case, 34 sites of 40 were located in zones with values greater than 75%, which suggests that the 85% of the control sample is located in areas of high prediction. This gives the conclusion that the model could be used to suggest a precise scheme of the distribution of sites in this study area and, therefore, the variables that were computed by the predictive model (the altitude, the potential hydrologic network and the potential transit) could have played an important role as first-order factors on the distribution of the megalithic mounds. This seems to be justified as well if we compare the distribution of real sample in the prediction surface with 999 Monte Carlo simulations (**see figure 8**). The results clearly suggest that the set of random locations does not share the trend of sites, being their location at the predicted areas, indeed, significant.

#### **4. Approaches to second-order locational patterns**

The observed locational pattern can be the result of the preference for the location of sites in certain areas of landscape or the consequence of attraction or repulsion of sites (second-order dynamics). One of the most frequent approaches to evaluate the second-order properties of a group of points is creating a kernel density surface with several thresholds (Palmisano, 2012) (**Figure 9**).

**[Caption] Figure 9.** Kernel density estimation for different thresholds.

From figure 9, an informal visual estimation of the point pattern can be extracted, pointing out that there is not a unique threshold that can be used to detect the spatial distribution of clusters in this study area, although it is true that all analyses show regularity in the distribution from 1000-1500 m. In this sense, traditionally Clark and Evans' test of nearest neighbour index is used to measure spatial distributions, an analysis which considers distances between points to calculate the average and compare

FINAL VERSION: Carrero-Pazos, M. (2018). Beyond the scale. Building formal approaches for the study of spatial patterns in Galician mounds (NW Iberian Peninsula). *Journal of Archaeological Science: Reports*, 19: 538-551. <https://doi.org/10.1016/j.jasrep.2018.03.026> it with the expected measure for the total area (Baddeley *et al.*, 2016, p. 259). The mean distance between sites in the study area is 235 m, and the distribution of the values is concentrated in less than 500 m, being the range of 0-100 m the one that has the largest number of sites (**Figure 10: A**).

[**Caption**] **Figure 10.** Histogram of nearest neighbor distances (**A**) and Stienen diagram (**B**) of the distributions.

Therefore, most of the sites are located around groups of 100 m radius, so presumably their pattern will be clustered. To quantify this, we can use the Clark and Evans index, which provides a nearest neighbor index closer to 0.23 ( $p < 2.2e-16$ ), showing a statistically significant clustered pattern corroborated under 999 Monte Carlo simulations<sup>4</sup> (Donnelly, 1978). However, from here we cannot carry out any kind of visual analysis, to observe which groups of sites show a clustered pattern and which do not. To do this, a *Stienen* diagram can be used, observing that the majority of cases maintain local distances with radii smaller than 500 m (**Figure 10: B**). Furthermore, clusters of sites can be detected near ridges and the monuments that show low scales of clustering are actually located away from mountains.

These heterogeneous trends suggest that we should use other types of methods which can help on assessing clustering patterns at multiple scales, such as the K functions. In figure 4 (B, C and D) we can observe the analysis of the values for this function (Y axis) and the distance bands between sites (concentric buffers) in the X axis, including the random envelope created by 999 Monte Carlo simulations on which it is assumed that a random Poisson process has been the responsible for generating the point pattern. Values above the random envelope indicate clustering and below, regularity (Baddeley *et al.*, 2016).

Both the graph of Ripley's homogeneous K function and its alternative, L function, suggest the existence of a clustered pattern practically in all the distances. However, this analysis does not provide new information that cannot be suggested by an informal study of a distribution map, and the main issue concerning these homogeneous approaches is that they assume that the sample is homogeneous and stationary correlated throughout the study area (Marcon, Pluech, 2003, p. 2), something which is

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<sup>4</sup> R = 0.23455, p-value = 0.002

FINAL VERSION: Carrero-Pazos, M. (2018). Beyond the scale. Building formal approaches for the study of spatial patterns in Galician mounds (NW Iberian Peninsula). *Journal of Archaeological Science: Reports*, 19: 538-551. <https://doi.org/10.1016/j.jasrep.2018.03.026> not true. One possible way to examine this question, suggested by A. Bevan (*et al.*, 2013), might be choosing a smaller working window, thereby eliminating or reducing first-order effects on the point pattern distribution (**Figure 11**).

**[Caption] Figure 11.** Influence of the size of the vector area in the detection of spatial point patterns.

In this case, areas smaller than 400 m A.S.L were eliminated so the study area was considerably reduced. The results can be observed in **figure 11 (B)**, and corroborate that the analytical window influences the characterisation of distributional patterns, since we now have verified clustering in the data up to 2000 m, when the sites continue clustered although it is not really significant, being regular from 5500 m.

To examine whether this observed pattern is the result of the preference for a specific landscape or whether it could be a consequence of attraction or repulsion of the megalithic monuments, the intensity of first-order factors in the calculation of these functions can be considered.

This can be done in *R Statistics* by creating a round of simulations where the observed data is the same but Monte Carlo simulations use the first-order predictive model as the basis for the pattern of the random sample. In addition, we should use the inhomogeneous version of the previous tests, which makes it possible to detect the interaction between sites by eliminating first-order factors, through the creation of an inconstant surface area for the entire study zone (Palmisano, 2012, p. 353).

**[Caption] Figure 12.** Models of nearest neighbour distance and confidence intervals for the study of second-order effects. **A:** Pair correlation function of the observed sites with a 95% envelope conditioned on the first-order covariates model. **B:** Pair correlation function with a 95% envelope from wholly random Poisson process. **C:** Pair correlation function with a 95% envelope also conditioned on both the first-order covariates and a second-order, area-interaction model ( $r = 118$  m). **D:** Pair correlation function with a 95% envelope also conditioned on both the first-order covariates and a second-order, area-interaction model ( $r = 4000$  m).

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The results for the inhomogeneous pair correlation function presented in **figure 12 (A)** show that the trend of real data generally fits with the range of the random envelope, indicating that the point pattern can be explained by first-order dynamics. However, the range of distances lesser than 500 m is still striking because it shows, jointly with the nearest neighbour analysis, that there is an aggregation of sites at local scales that cannot be explained by external factors. This could be explained by the existence of first-order variables which are biasing the distribution of sites at local scales (less than 500 m) but were not included in our model or, on the other hand, by the impact of a second-order property such as a tendency for a pre-existing mound encourage the follow-on construction of further nearby ones. This can be further analysed if we compare, albeit visually, the trend with a purely random distribution (**Figure 12, B**), which suggests that the aggregation of sites at local distances is not the result of chance. Also, since the AIC of the first-order covariates model (3654.161) is lower than the null (random) one (3982.607), we may conclude that the environmental variables are in fact significantly explaining the distribution of sites.

To continue studying the second-order properties, we can build an area-interaction model (Baddeley, Lieshout, 1995), which generates inhibition and clustering patterns with reference to a buffer created for all the points of the distribution. In order to choose the distance of strong interaction between points, the spacing between sites can be observed, although some authors suggest the use of the half the median nearest neighbour distance (Bevan *et al.*, 2013, p. 41), in this case 118 m.

The results of the analysis, presented in **figure 12 (C)**, show that now the real sample falls over the 95% envelope conditioned on both first-order covariates model and a second order, strong area-interaction model ( $r = 118$  m). Therefore, the model now fits the archaeological data. On the other hand, if we use a wider area-interaction radius, for instance, 4000 m (**Figure 12: D**), the real data does not fit the 95% envelope. This suggests that the aggregation of sites at local scales could not have been the result of a weak attraction among sites.

To sum up, the evidence provided indicates the existence of an aggregation process in the distribution of megalithic monuments at local scales; a process that cannot be explained by the first-order covariates model or by chance but by considering a strong interaction between points.

## **5. Conclusions**

The prediction model has suggested the altitude, the potential pathways through landscape and the connection of mounds with areas of accumulated water as the variables that could have conditioned the locational patterns of the megalithic landscape of Monte Penide and Serra do Galiñeiro. This does not mean that other variables - beforehand less significant according to our work- were irrelevant, because the location close to ridges, in addition to open slopes and plains seem to have been relevant locational criteria. Also, the location at topographic prominences may have played an important role, as sites are placed in areas with topographic significance, idea also pointed out by other researchers such as F. Criado Boado (1988). However, the analyses that have been carried out here suggest a location at ridges, areas that by their configuration are relevant in the landscape although to a lesser extent than crests. This fact would be confirmed if we compare the results of the topographic prominence analysis with the absolute visibility of landscape, observing that the mounds tend to be located in areas with wide visibility.

On the other hand, the relation of tombs with water areas is negative, because most of sites are located in areas with low accumulation values, trend which contrasts with the low values of cost of passage (in time) to access to water resources.

The least cost path density, an approximation to potential pathways, seems to be the variable that best predicts the distribution of sites (there could be more variables that have not been taken into account). The results of our study suggest that practically half of the monuments are located in areas where the movement statistically converges, and thanks to a cost-of-passage analysis, we can verify that the whole mounds are located in the proximity of these corridors. Furthermore, there are specific interesting cases, such as the cluster of Chan da Cruz, located at a crossroad of potential routes that run through the territory and descend to the sea, with megalithic mounds that could have acted as landmarks referencing a wide distance displacement.

Therefore, from a general perspective, the analyses carried out here suggest a tendency to locate mounds in prominent areas of the landscape, where the visibility at local scales seem to have played a relevant role within the natural transit of the territory. Perhaps the monumentalisation has to be sought on larger scales, from the landscape itself, and the topographical choice for the megalithic monument may has been more important than

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On the other hand, the clustering processes of megalithic sites are well known in literature, although we now propose that the aggregation starts from a location fixed by environmental variables but also cultural ones, factors that would operate locally. Among them, we can mention the so-called tradition, already defined by R. Bradley (1986, 1987) as the attraction exerted by a monument for the location of later ones, a hypothesis that is widely accepted in literature. The case of Dombate (Bello *et al.*, 2011) or Mámoea da Cruzinha (Silva, 2003) are examples of this process at site scales, with the reuse of previous structures in the construction of new monuments; issues that are supported as well by this work but in macro scale terms, thanks to the study of second-order dynamics. Therefore, GIS and spatial statistics are methods that can provide robust basis for the development of formal approaches on the study of archaeological distributions at macro-spatial scales.

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**Figure 1.** Locational covariates that will be considered in this study (following Carrero Pazos, 2017).

**Figure 2.** The study area. Monte Penide and Serra do Galiñeiro.

**Figure 3.** Geographical context of the area considered.

**Figure 4.** Complete Spatial Randomness Tests. **A:** *Kolmogorov-Smirnov Test*. **B:** *K Function*. **C:** *L Function*. **D:** *G Function*.

**Figure 5.** First-order covariates. **A:** Altitude (m A. S. L.). **B:** Geology. **C:** Slope (%). **D:** Landforms (TPI based classification).

**Figure 6.** First-order covariates modelled. **A:** Intensity of potential transit. **B:** Cost of passage from potential routes. **C:** Cost of passage from wetlands. **D:** Visual prominence of landscape.

**Figure 7.** Pearson correlation test, to avoid multicollinearity problems.

**Figure 8.** Prediction surface with control sample, and observed values in real data and 999 Monte Carlo simulations.

**Figure 9.** Kernel density estimation for different thresholds.

**Figure 10.** Histogram of nearest neighbour distances (**A**) and Stienen diagram (**B**) of the distributions.

**Figure 11.** Influence of area size in the detection of spatial point patterns.

**Figure 12.** Models of nearest neighbour distance and confidence intervals for the study of second-order effects. **A:** Pair correlation function of the observed sites with a 95% envelope conditioned on the first-order covariates model. **B:** Pair correlation function with a 95% envelope from wholly random Poisson process. **C:** Pair correlation function with a 95% envelope also conditioned on both the first-order covariates and a second-order, area-interaction model ( $r = 118$  m). **D:** Pair correlation function with a 95% envelope also conditioned on both the first-order covariates and a second-order, area-interaction model ( $r = 4000$  m).

Figure 1

LOCATIONAL ANALYSIS PREDICTIVE MODELING		Variables	Description
First order covariates	<i>Physical and orographic factors</i>	Elevation	25 m. resolution DEM, obtained from LiDAR data.
		Slope	Maximum inclination of elevation at a given point. Derived from DEM.
		Hydrology	Potential hydrologic network.
		Geology	Official MAGNA cartography for geology (IGME).
		Wetlands	Topographic Wetness Index (Boehner et al. 2002).
	<i>Potential factors</i>	Topographic prominence	Defined as a function of height differential between an individual and his/her surroundings as apprehended from the individual's point of view (Llobera, 2001).
		Potential transit	Identification of areas that are statistically more likely to be transited, key points or theoretical nodes in a natural transit network (Rodríguez Rellán, Fábregas Valcarce, 2015).
Visual prominence of landscape		Areas of the landscape that can be perceived more frequently.	
Second order covariates	<i>Cultural factors</i>	Tradition	Evaluation of the spatial dependence between points (attraction or repulsion)

Figure 2

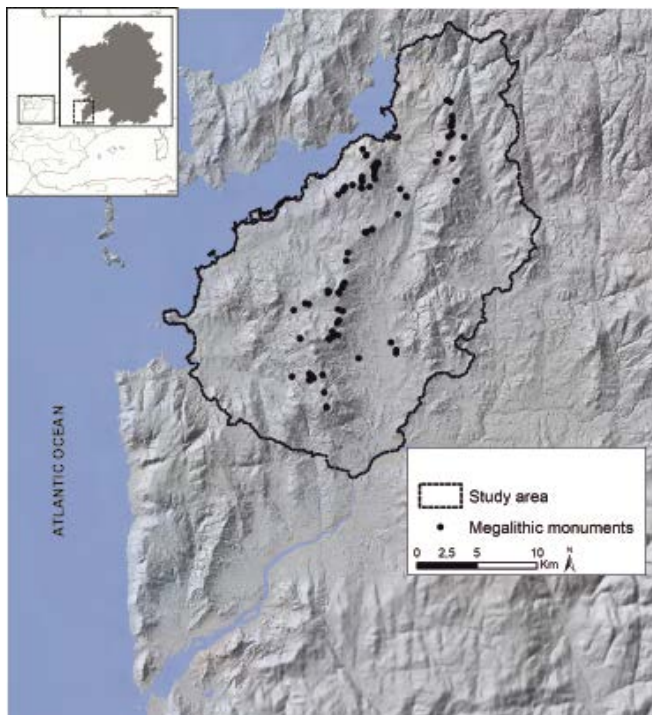




Figure 3

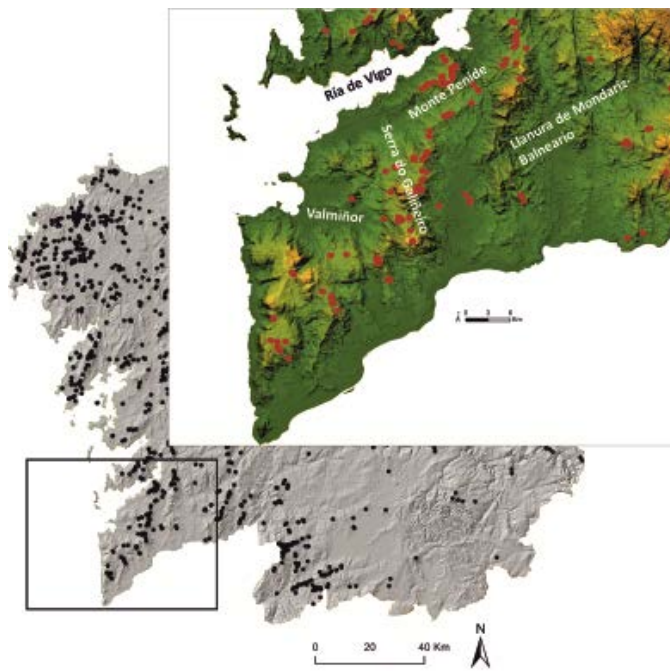


Figure 4

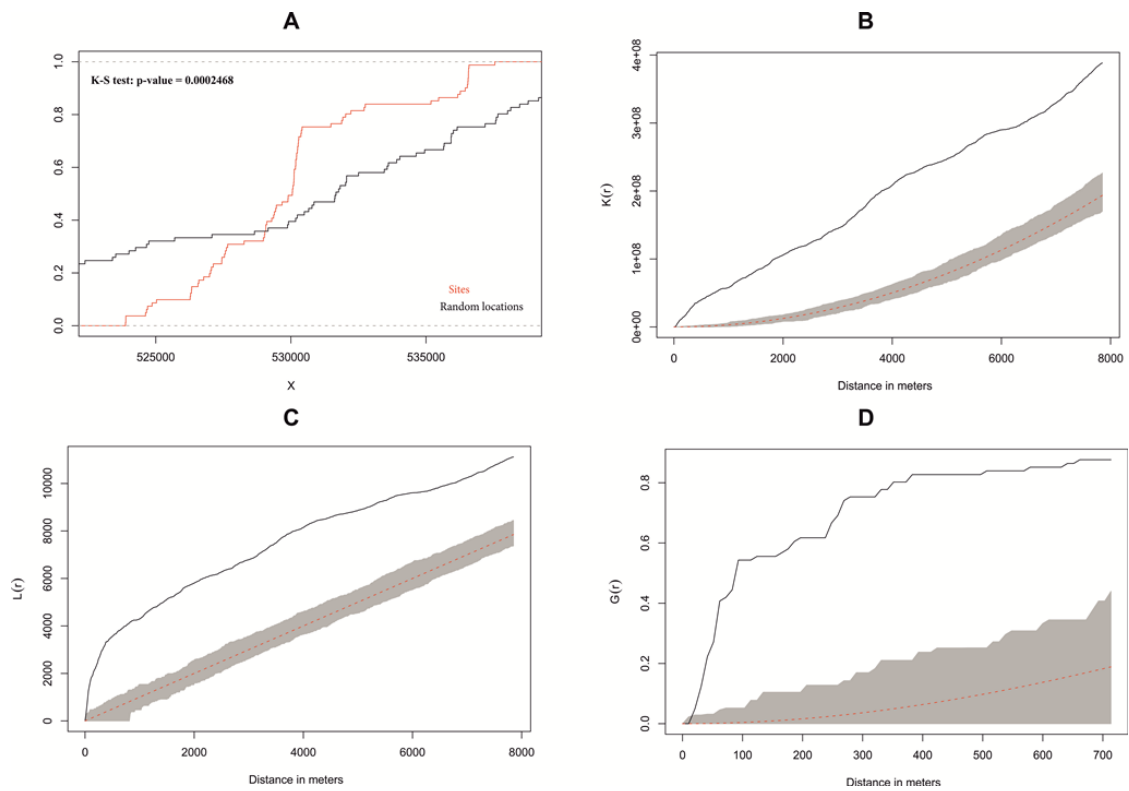


Figure 5

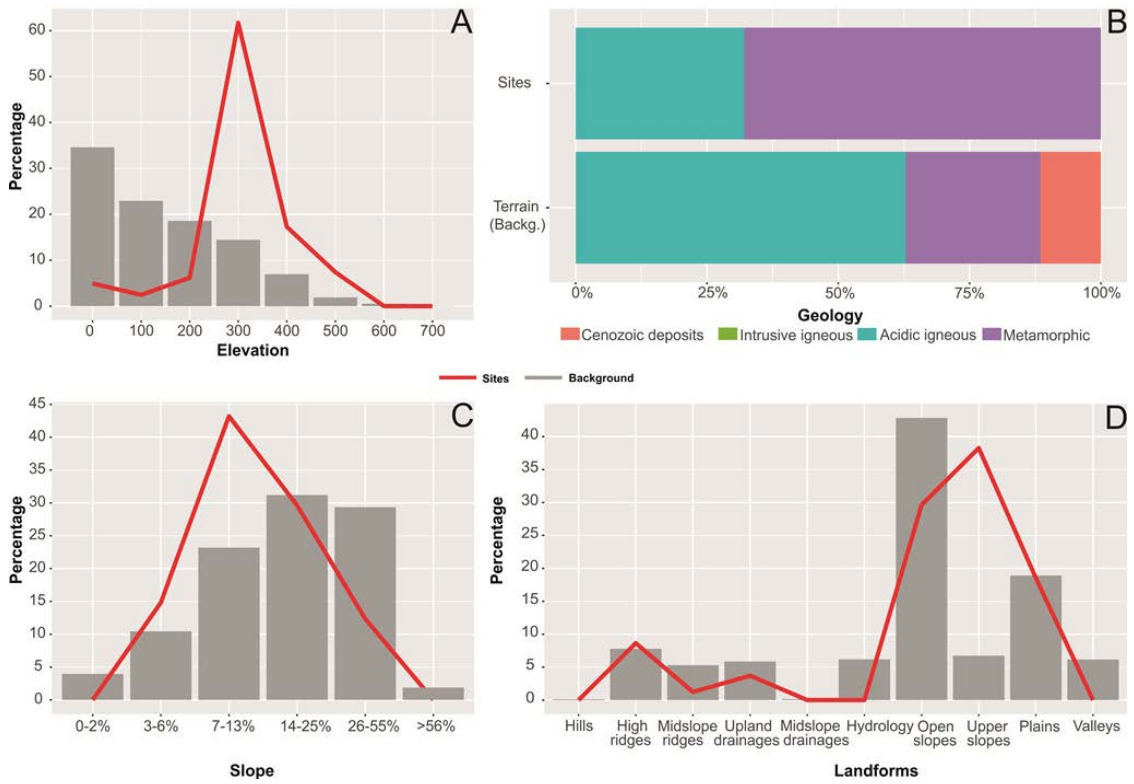


Figure 6

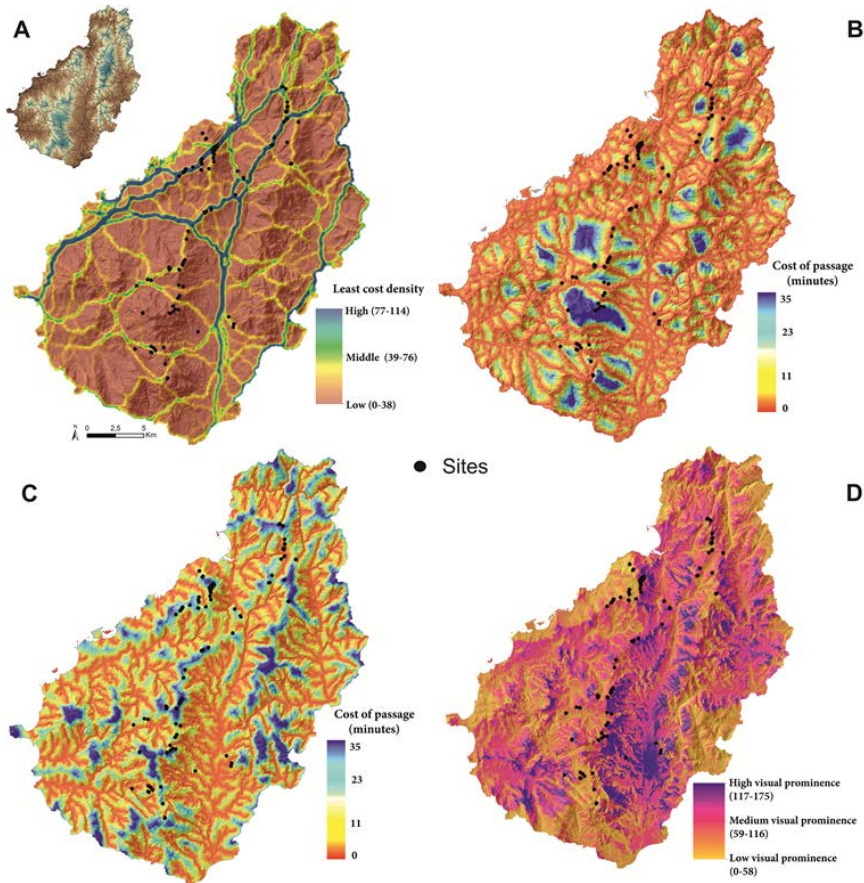


Figure 7

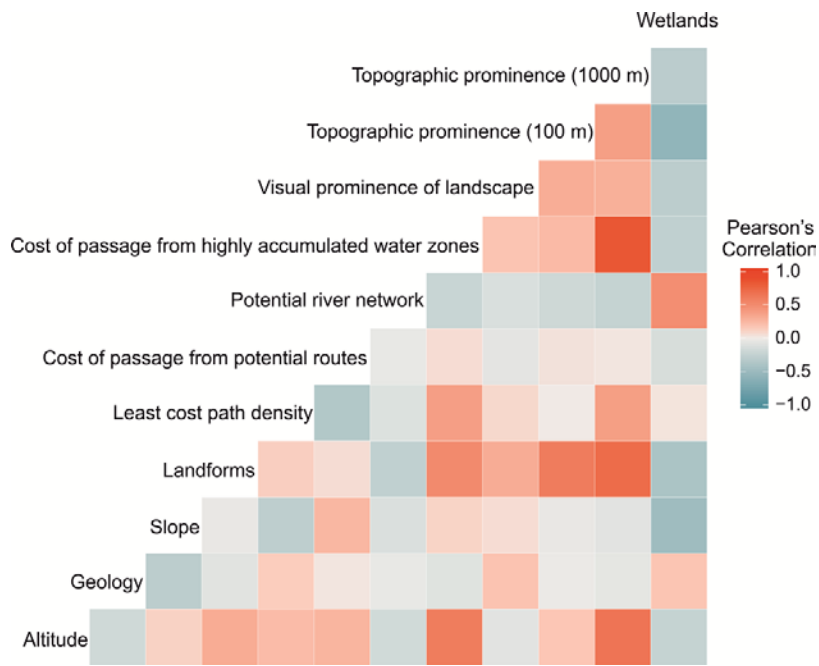


Figure 8

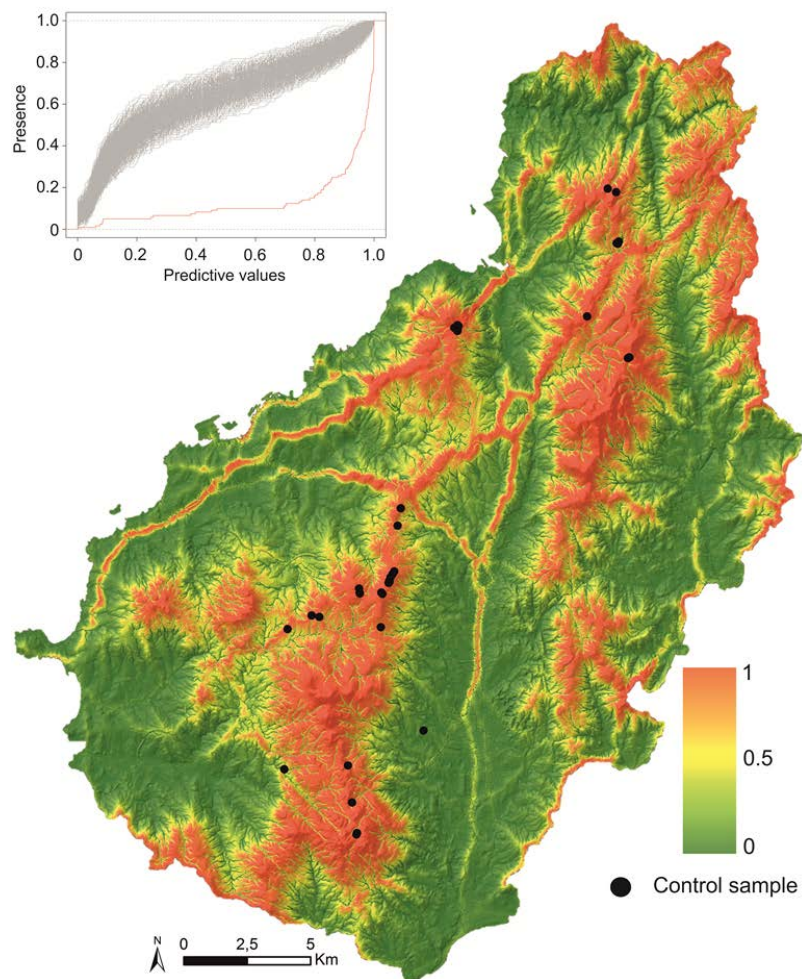


Figure 9

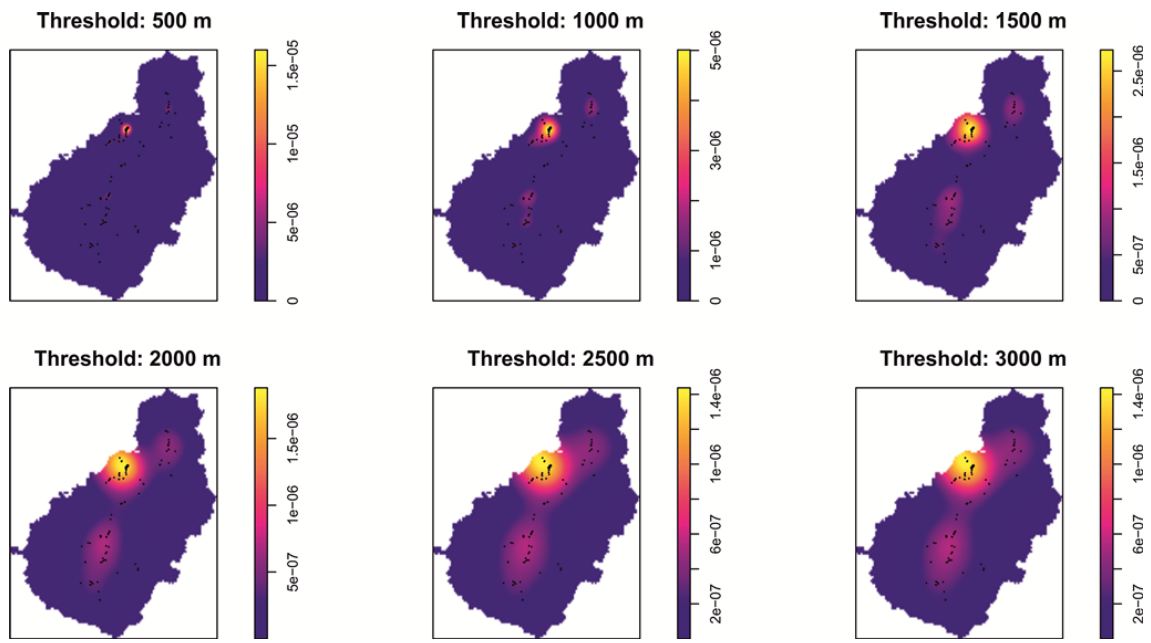


Figure 10

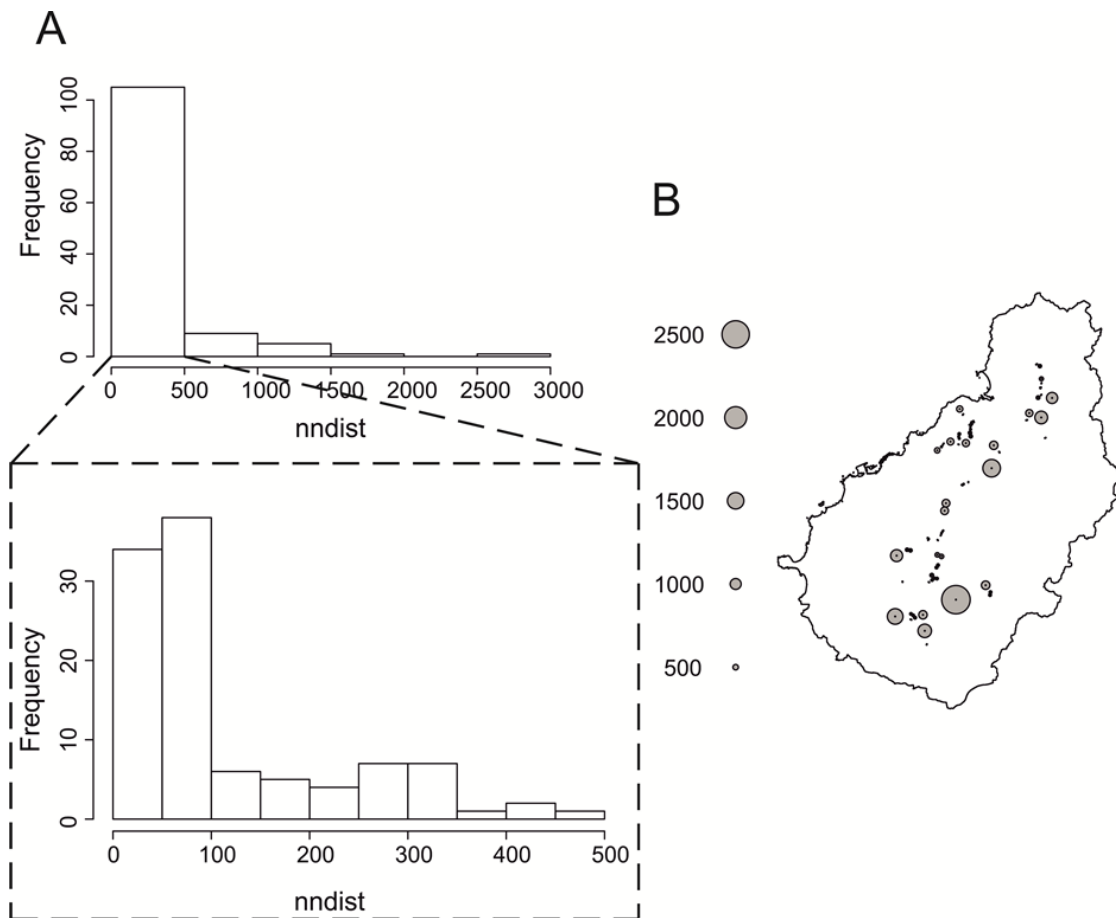


Figure 11

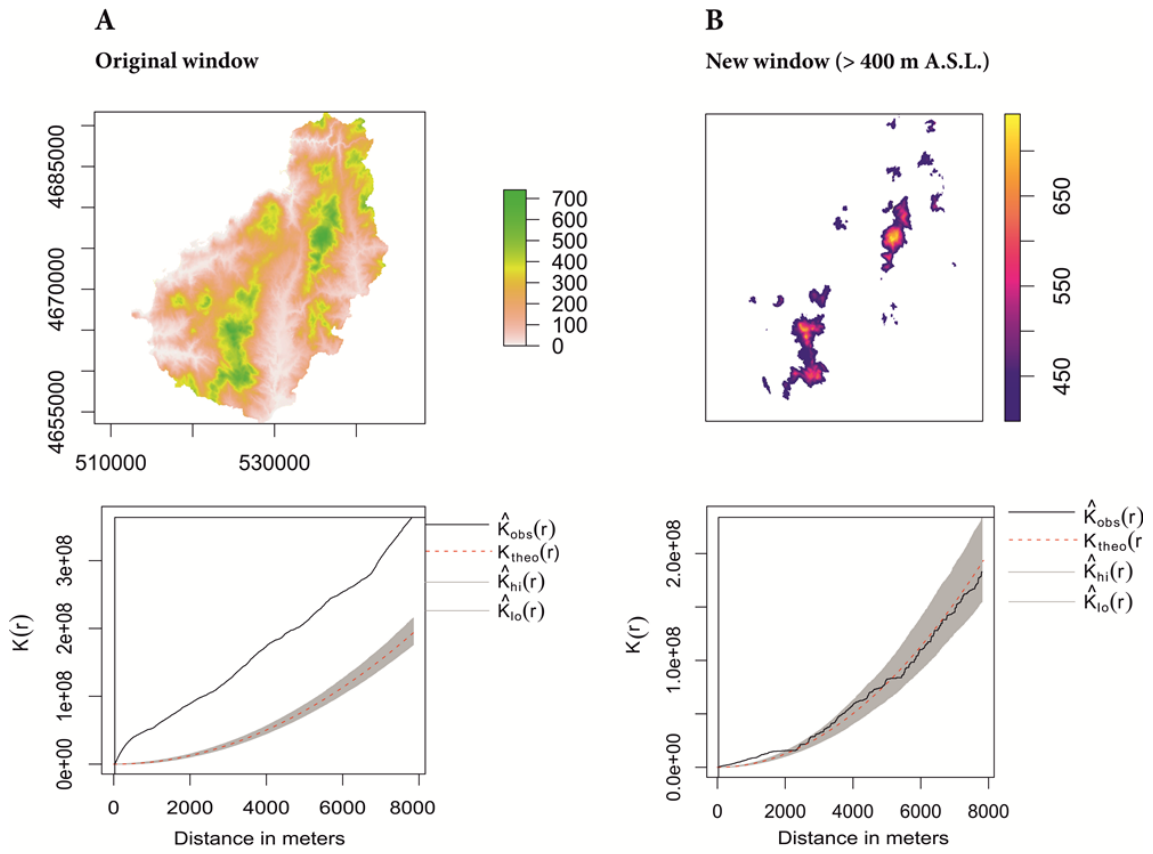
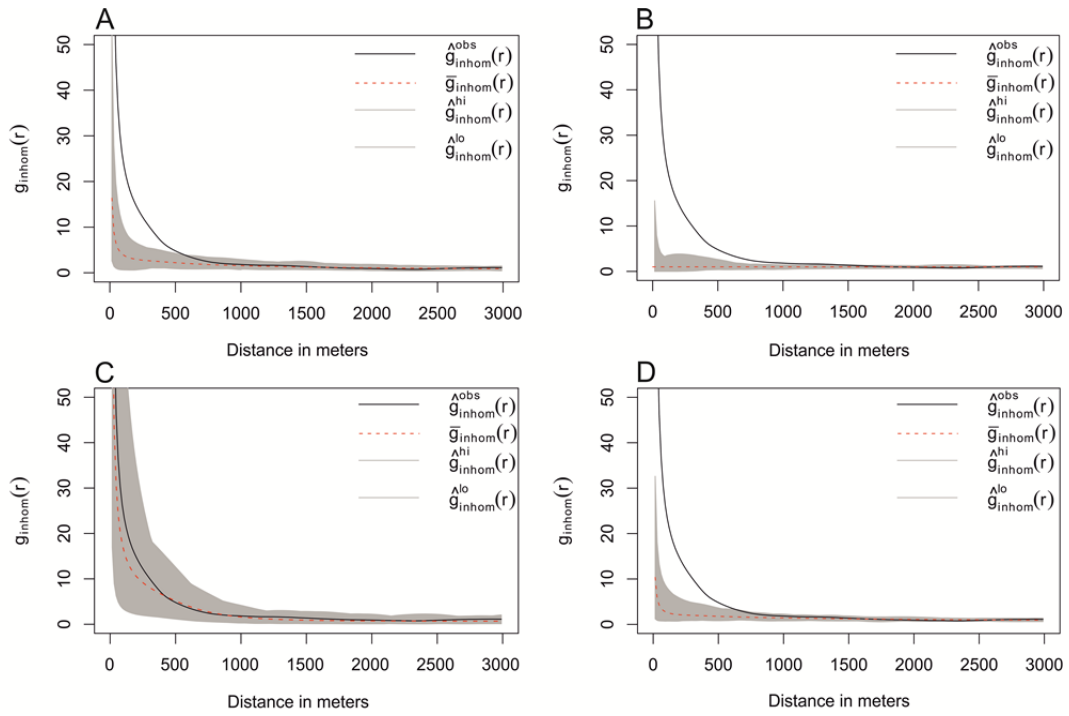


Figure 12



**Table 1.** Variance analysis between the real sample and a random one.

**Table 2.** Results of the univariate logistic regression.

**Table 3.** Multivariate regression model.

**Table 4.** AIC's best model.

<b>Dependent variable: Presence of sites</b>	<b>Shapiro-Wilk Normality test</b>	<b>Distribution type</b>	<b>Test</b>	<b>Result</b>
<b>Covariates</b>				<b>p-value</b>
Altitude	3.497e-07	Not normal	MWW	1.063e-15
Geology	0.09813	Normal	T-Student	0.03998
Slope	7.539e-09	Not normal	MWW	0.4849
Landforms	0.0003048	Not normal	MWW	0.5105
Least cost path density	1.376e-15	Not normal	MWW	4.205e-07
Cost of passage from potential routes	< 2.2e-16	Not normal	MWW	0.03717
Potential river network	< 2.2e-16	Not normal	MWW	0.5039
Cost of passage from highly accumulated water zones	1.743e-05	Not normal	MWW	4.67e-08
Visual prominence of landscape	2.087e-06	Not normal	MWW	0.9186
Topographic prominence (100 m)	0.01229	Not normal	MWW	0.0857
Topographic prominence (1000 m)	0.1225	Normal	T-Student	1.099e-06
Wetlands	4.366e-10	Not normal	MWW	0.5978

<b>Dependent variable: presence of sites</b>		
<b>Covariable</b>	<b>p value</b>	<b>Description</b>
Altitude	0	Good predictor
Geology	0.06099946	Bad predictor
Slope	0.2713321	Bad predictor
Landforms	0.01019788	Good predictor
Least cost path density	3.597377e-10	Good predictor
Cost of passage from potential routes	0.6242061	Bad predictor
Potential river network	0.00111871	Good predictor
Cost of passage from highly accumulated water zones	6.873698e-08	Good predictor
Visual prominence of landscape	0.6101202	Bad predictor
Topographic prominence (100 m)	0.1604479	Bad predictor
Topographic prominence (1000 m)	2.16697e-10	Good predictor
Wetlands	0.06970302	Bad predictor



<b>Coefficients</b>	<b>Estimate</b>	<b>Std.Error</b>	<b>Z value</b>	<b>Pr(&gt; z )</b>	
<b>(Intercept)</b>	-3.4201714	0.6468606	-5.287	1.24e-07	***
<b>Altitude</b>	0.0137736	0.0023533	5.853	4.83e-09	***
<b>Least cost path density</b>	0.0657404	0.0172721	3.806	0.000141	***
<b>Potential river network</b>	-0.0450663	0.0214592	-2.100	0.035721	*
<b>Cost of passage from water zones</b>	-0.0017089	0.0009755	-1.752	0.079794	.
<b>Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1</b>					
Eliminated covariates: Topographic prominence index (1000 m)					

<b>stepAIC Function</b>			
	Df	Deviance	AIC
<b>&lt;none&gt;</b>		107.79	117.79
<b>Potential river network</b>	1	114.56	122.56
<b>Least cost path density</b>	1	137.62	145.62
<b>Altitude</b>	1	167.59	175.59