L. García Sanjuán
J. Rodríguez López

Predicting the ritual? A suggested solution in archaeological forecasting through qualitative response models[1]

Hamlet *A man may fish with the worm that hath eat of a king, and eat of the fish that hath fed of that worm...*
King *What dost thou mean by this?*
Hamlet *Nothing, but to show you how a king may go a progress through the guts of a beggar.*

1 Introduction

The analysis of mortuary practices is critical in the archaeological interpretation of the structure of social relations of production of prehistoric communities. Patterns of association between the different dimensions of the funerary ritual (grave goods, sex and age categories of the deceased, burial structure and burial position) are one of the pillars of a good part of current interpretation of the evolution of social structures in European Prehistory.

Quantitative methods have largely contributed to the interpretation of the funerary record in terms of social structure; significance tests, cluster analysis and multivariate techniques are commonly used in order to test the existence of different funerary categories and infer their social correlates. This paper intends to discuss further the question of how quantitative techniques can improve the archaeological knowledge of past social structures through the analysis of the funerary record. The *statistical models* discussed here fall into the group of Qualititative Response Models (henceforth called QRMs), which have mainly been studied by biometricians and econometricians but apparently have received little attention from archaeologists. The *archaeological problem* that provides the empirical background for testing the model is the funerary record of the southwestern Iberian Peninsula Bronze Age (*c*. 1700-1100 BC). The development of social complexity in the Early and Middle phases of Bronze Age in SW Iberia remains poorly understood; in this context, it seems clear that, in comparison with recent trends prevailing in the study of the synchronic southeastern (Argaric) Bronze Age, little or no debate has taken place in the past on the theoretical and methodological basis of the empirical evidence.

2 The problem

Common patterns shared by a set of necropoleis located in southern Portugal (Algarve and Alentejo) and western Andalucia, suggest that from *c*. 1700 BC onwards, a transition takes place from a communal-based structure of social relations of production to a ranked social structure where individual roles and leadership are more clearly defined in the mortuary ritual.

On the one hand, in some necropoleis the pre-eminence of specific individuals is underlined by means of the construction of a stone ring and *tumulus* structure around and over the burial. Thus, three basic categories of tombs are visible in the SW Bronze Age in terms of architectural features, namely central burials with a complete stone ring and *tumulus* (type A), peripheral burials with a tangent stone ring and *tumulus* (type B), and peripheral burials with no stone ring and *tumulus* (type C). In necropoleis such as Atalaia (Schubart 1975), Provença (Farinha/Tavares 1974) or Alfarrobeira (Varela 1994) all three types are found, while in the vast majority of necropoleis so far explored, only burials of type C have been identified (Amo 1975; Schubart 1975).

On the other hand, from *c*. 1700 BC on, prestige items such as bronze halberds, swords, daggers and ornaments given as grave goods, as well as engraved stones depicting metal weapons (appearing only in some tombs of southern Portugal), suggest the growing military character of social leadership. The military character of grave goods during this period, however, seems sharply limited if compared to the intensity and extent of weapon-oriented grave goods in other areas of Iberia or Europe. The fact that the amount of metal prestige items found in the funerary contexts of SW Iberia is very low, is perfectly coincident with evidence drawn from settlements suggesting that copper mining and metalworking in the southwest pyritic belt was rather limited between *c*. 1700 and 1100 BC (see for example Blanco/Rothemberg 1981; Hurtado/García 1994; Monge Soares *et al*. 1994)

Therefore, if compared with the Middle and Late Copper Ages, the initial stages of the Bronze Age in SW Iberia seem to involve an increase in internal ranking, different evidence suggests, however, that this increase in social inequality should not be regarded as a transition to a stratified model of society.[2] First, the statistical distribution of prestige items across the burial categories does not assume a stratified pattern; second, unlike in Argaric societies, infant burials are not provided with prestige items, which suggests that social roles are still acquired and not ascribed by birth (García 1992, 1994); third, the fact that many tombs with engraved *stelae* depicting weapons were not supplied with *real* weapons suggests that the leadership is more founded on an ideological than on a material basis — weapons as symbols rather than as a means of coercion supporting a stratified pattern of access to subsistence resources (Barceló 1991).

Hence, if the presence or absence of metal prestige items (weapons and ornaments) in burials is a key indicator in the inference of social status in archaeology, the obvious relevant question arising would be the following: to what extent would it be possible to *predict* the presence or absence of metal items in the tombs *in terms of probability*, having previously achieved some prior knowledge about the trends underlying a given set of data? In other words, under what conditions (i.e. patterns of association between variables) is the probability higher of a metal artefact being found in a specific empirical context?

A previous general approach based on quantitative methods conventionally used in archaeology (Aldenderfer 1987; Carr 1989; Shennan 1988) suggested the existence of some interesting patterns affecting metal artefacts distribution within the funerary record of the SW Iberian Bronze Age.[3] After a cluster analysis based on the Group Average method, three categories (rich, semi-rich and poor necropoleis) were delimited according to the mean values observed for the frequency of different artefact types — not only bronze items — in necropoleis (fig. 1A). Also, a number of categories was defined on the basis of the mean frequency of a series of architectural attributes (fig. 1B). No classes were defined *within* the necropoleis in terms of artefact distributions, not even where there were different architectural types present (scarcity seems to be shared by almost all members of the communities as far as the funerary ritual was concerned).

The three basic levels of artefactual wealth defined were then used as a basis to test the association between funerary patterns and environmental factors such as soil type or land agricultural capability. A correspondence analysis suggested that a general positive association existed between the potential agricultural capability and the cemeteries where metal artefacts are more frequent (fig. 2). This might suggest that the use of costly metal status symbols depended on the general capacity for surplus production within the community — see two spatial (geographical) views of the bronze items frequencies in figure 3. Yet, a much more interesting — predictive — approach to this problem can be achieved by means of the QRMs described below.

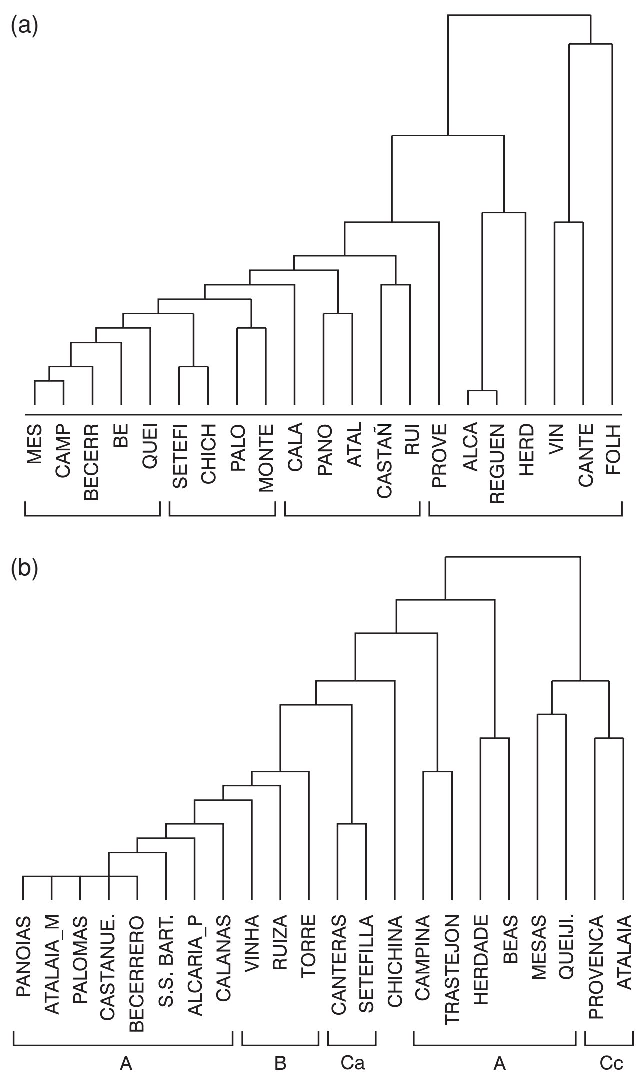

Figure 1. Two cluster analyses for necropoleis from the SW Iberian Bronze Age.

3 The model (the suggested solution)

3.1 Why QRM?

Prior to the development of a rather tedious algebra, a justification should be given about why QRMs have been chosen to examine the archaeological phenomenon described above. This might be achieved by proceeding along two lines of reasoning: one theoretical, since the referents pointed out by the theory must be taken into account; and another technical, since this type of model is regarded here as a potentially valuable tool to be applied in archaeological analysis.

Regarding the theoretical aspect, a brief description of how these models became useful in other Social Sciences can be of help. The use of QRMs was extended in the

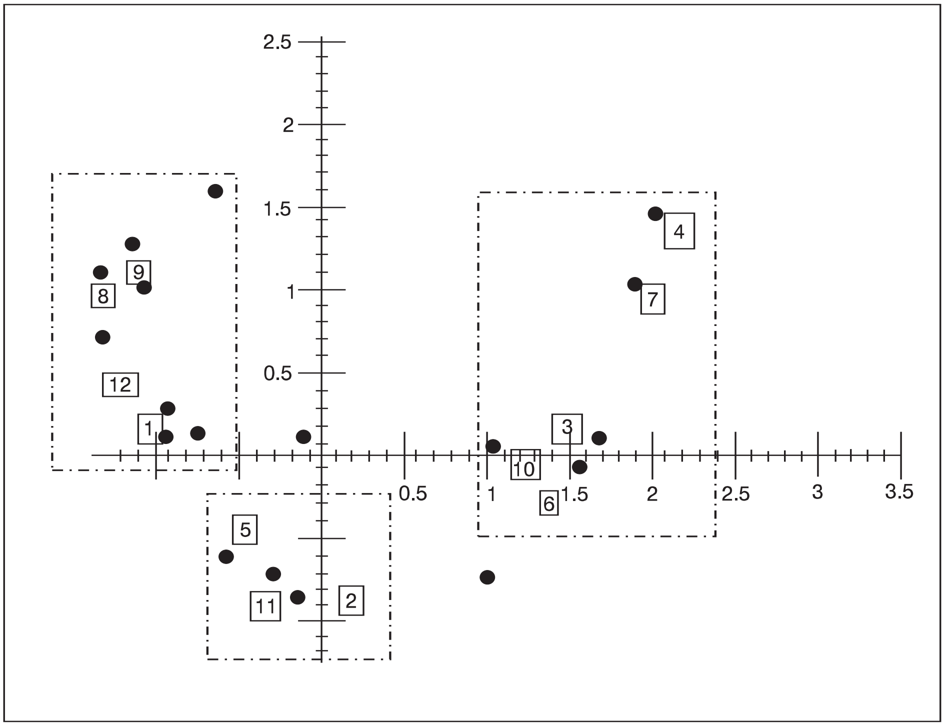

Figure 2. Correspondence analysis for the necropoleis.

sixties by biometricians, who faced the problem of making predictions about some events where the observed values had a discrete form, (i.e., presence/absence of an attribute or, yes = true, no = false). One model, which became very popular in Biology, was that where QRMs were used to predict the effectiveness of an insecticide: a QRM could explain in terms of probabilities whether an insect would remain alive (that is, yes = true = 1), or would die after having been exposed to a given dosage of insecticide (independent/causal variable). Bypassing the evident lethal aspects of the model this example suffices to compare the applicability of these models in Natural and Social Sciences. In an excellent survey, Amemiya (1981) suggested that the QRMs could be used to explain the behaviour of a utility-profit maximizing rational economic agent. For instance, when one has to model the problem faced by a householder of whether to buy or not to buy a car, and to explain this decision with the level of income, taxes, availability of other transport means, … the final choice relies upon a utility maximizing consumer, conditioned by a budgetary and a time restriction. An insect does not enjoy the possibility of choosing to be or not to be. That may be one of the basic differences of the meaning of these models in the Natural and Social Sciences: the nature of the dynamics of the variables involved in a theory.

Amemiya's survey also provides a sample of articles that could surprise a reader not familiar with these issues, since applications are quoted from labour markets, unionized workers, and consumption of non-durables, to criminology, efficiency of educational programs, etc.[4]

Finally, with reference to the technical aspect (*why* and *how* these models could be applied in archaeology) previously mentioned, QRMs provide an elegant tool for solving an elementary problem in archaeological multivariate analysis:

a. It is known that many of the data sets used in archaeological analysis are coded in a discrete form; for instance, if the value of the *aggregate production* cannot be measured through the archaeological record — as Econometrics is supposed to be able to do for modern and present records — the only feasible approach to the construction of a *Bronze Age econometric model* would be a discrete form index (proxy variables) compressing variables referring to different levels of production (for example, metal prestige items).
b. The former aspect would not be a technical-statistical problem at all whenever variables are used as causal regressors in the multivariate analysis. However, if predictions are intended to be over a discrete form

Figure 3A. Surface trend map.

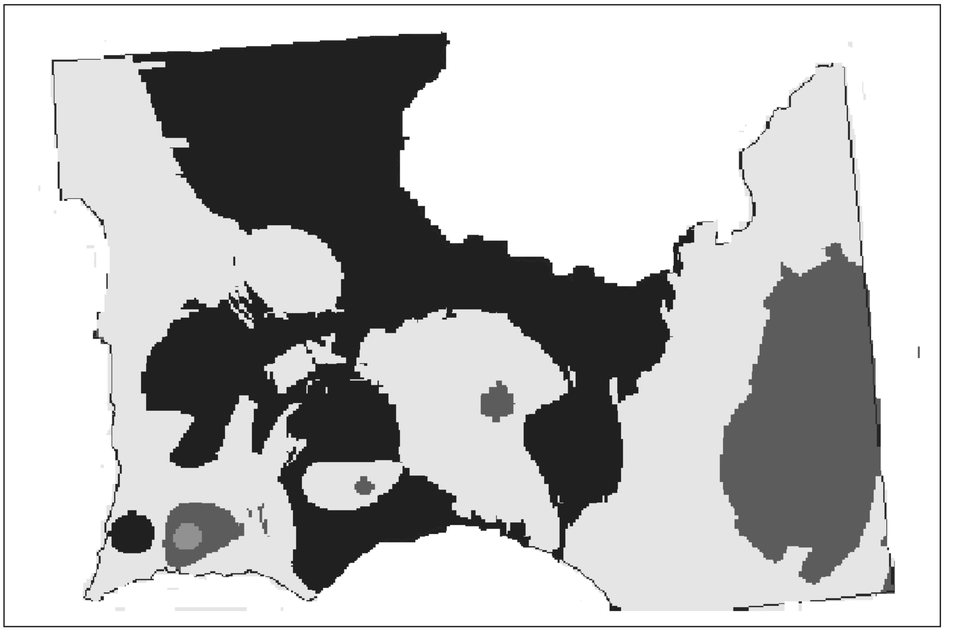

Figure 3B. Interpolation map.

variable, the traditional least square estimation fails to give an answer. For example, a variable reflecting a structure of true or false, (and then, 1 or 0, respectively), cannot be used as dependent variable in a linear model estimated by least squares as will become clear below.

In our opinion, QRMs can easily overcome this problem, improving the efficiency of data analysis and, therefore, hypothesis testing. Thus, an attempt is made to obtain a prediction about a discrete dependent variable (M1-M2) by using a QRM against the dataset mentioned above.

3.2 Mathematical set-up of the model

Let us think of a discrete variable m (say m = *presence of metal elements in a burial*), showing a dichotomous form 0 or 1, ($m \in \{0, 1\}$), that is a boolean structure, this means that m adopts value 0 when a certain property is absent (metal element not found in the archaeological record), and, consequently, value 1 when the property is present. Furthermore, this variable is stochastically distributed according to a discrete Bernouilli model with probability p, that is:

$$m \sim B(p)_{m=0,1} = p^m(1-p)^{1-m} \qquad E(m) = p = P(m=1) \qquad Var(m) = p\,(1-p) \tag{1}$$

where $E(.)$ denotes the expected operator, $P(.)$ stands for probability, and $Var(.)$ is the variance. Since a Bernouilli model is regular, one can use the statistic $\Sigma x_i \,/\, n, (i=1,...,n),$ that is the sample arithmetic mean, as an efficient estimator for p.

Assume now that we have to relate this variable to a set of k independent variables, X. Suppose further that we have been asked whether this variable will adopt value 1 under certain conditions X_i, that is, forecasting whether the property will be present. A first answer could be given using a simple linear (probability) model of the form:

$$m = \alpha + \beta' X + u \qquad E(u) = 0 \Rightarrow E(m) = P(m=1) = \hat{\alpha} + \hat{\beta}' X \tag{2}$$

where u is the error term. Hence, one can use the classical least square method to estimate the set of k+1 unknown parameters involved in the equation (2), and then use the model to set a prediction. Note that now the predicted values of m will not necessarily be 0 or 1, but rather will be in the interval (0, 1). Next, we would interpret these predicted values in terms of probability.

However, this method involves serious limitations since it produces several problems, namely:

1. *A heteroscedasticity problem*, since it can be proved that the error term variance is equal to

   $$Var(u) = p(1-p) = E(m_i)\,[1-E(m_i)] = [\hat{\alpha} + \hat{\beta}'X]\,[1-\hat{\alpha}-\hat{\beta}'X] = Var(m)$$

   and, hence, the ordinary least squares estimators from equation (2) are inefficient. A weighted least square procedure is then needed. Goldberger (1964) proposes to estimate $m=\alpha+\beta' X + u$ by least squares, then compute a weight of the form

   $$\hat{w}_i = \sqrt{\hat{m}_i(1-\hat{m}_i)}$$

   and finally regress $[m_i/w_i]$ on $[x_i/w_i]$. However, as has been noted by other authors such as Maddala (1989), the product $m_i(1-m_i)$ in the root, can be negative, and hence the operativeness of this weighted procedure is invalidated .

2. *Predictions may still fall outside the [0, 1] interval*, and, consequently, the outcome cannot be interpreted in terms of probability:

   $$\hat{m} = \hat{\alpha} + \hat{\beta} = E(m|z = \alpha + \beta' X) = P(m = 1|z = \hat{\alpha} + \hat{\beta}' X)$$

3. *The distribution of the error term is not normal*, (Maddala 198: 16-18), implying that the classical hypothesis tests, where construction relies on the assumption of normality of the error term, are no longer valid, unless we also assume that the explicative variables have a multivariate normal distribution. This suggests that the problem should be modelled using a non linear instead of a linear model.

What is the solution? In the remaining part of this section some basic ideas were borrowed from the literature on QRMs in order to provide an answer. In section IV a case is examined where the dependent variable, m, is a dummy variable taking the value 1 when a metal element has been found inside an individual burial, and 0 otherwise. A set of variables serves to explain the presence/absence of such elements: a discrete index for agricultural capability of the land where the necropolis is located, the volume of the tomb, and some dummy discrete variables (namely, a dummy for ceramic typology, and other dummies indicating the presence/absence of other funerary items near the burial). Thus, prediction about m is interpreted as the propensity of a burial to contain a metal element (hence the *metal detector*). Two models, PROBIT and LOGIT, are an appealing suggestion to the problems not solved by the linear probability model aforementioned. The basic difference between PROBIT and LOGIT relies on the assumption made about the stochastic distribution of the error term u in equation (2) as will be seen below.

Let m^* be some continuous but *latent* variable. We have just said that this variable is to be interpreted as the 'propensity of a burial to be accompanied by a metal item'. But, instead, we observe a discrete dummy variable m according to

$$m = \begin{pmatrix} 1 \text{ if } m^* > \psi \\ 0 \text{ if } m^* < \psi \end{pmatrix}$$

where ψ is a certain threshold, above which one can say that there is a metal element, $m=1$. This concept of a threshold is relevant when interpreting the results as probabilities. Imagine, for instance, that the variable whose realizations we are observing is the score record of a class of students, and we have classified this into two categories: *passed*, whenever the student has been scored *at least with a five over ten*, and *failed* otherwise. In the first case the variable would be valued as 1, and 0 for the second one. In this example the threshold ψ would be equal to 5. Nevertheless, and without loss of generality, let us assume that $\psi = 0$. The model becomes as

$$m^* = \alpha + \beta' X + u$$

And the probability of a metal element is

$$P(m{=}1) = P(m^* > \psi{=}0) = P(\alpha + \beta' X + u > \psi = 0)$$
$$= P\,[u > \psi - (\alpha + \beta' X)] \tag{3}$$
$$= 1 - F\,[(\psi - (\alpha + \beta' X)] = 1 - F\,[-(\alpha + \beta' X)]$$

where $F(.)$ is the cumulative distribution of the error term u.

Once it is assumed that this cumulative distribution is symmetrical, specification (3) becomes clearer since we can write that $F(-Z) = -F(Z)$ and therefore it can be written that $P(m=1) = 1-F(-(\alpha + \beta' X)) = F(\alpha + \beta' X)$. Recall that, through specification (1), the variable m_i , presence of metal elements, follows a Bernouilli model with probability p, $m_i \sim B(p)$. It is important to note that the present model is intended to be based on the fact that the realizations m_i are independent from burial to burial, otherwise the mathematical set up would be much more complicated. Thus, let us assume that the different realizations m_i's are independent of each other. Consequently, the likelihood function can be written as

$$\mathfrak{L} = \prod_{m_i=1} P(m_i{=}1) \prod_{m_i=0} Pm_i{=}0) = \prod_{m_i=1} P(m_i{=}1) \prod_{m_i=0} [1 - P(m_i{=}1)]$$

Finally, the difference between PROBIT and LOGIT models relies upon a different cumulative distribution of the error term u. If the cumulative distribution is normal, taking the form:

$$F(\alpha + \beta X) = P(m{=}1 \,|\, \alpha + \beta X) = \int_{-\infty}^{m^* = \alpha + \beta X} \frac{1}{\sqrt{2\pi}}\, e^{-\frac{u^2}{2}}\, du$$

this is just the PROBIT, or normit, specification. While the LOGIT model is set when the error term distribution follows the next logistic distribution, that is:

$$P(m{=}1 \,|\, \alpha + \beta X) = F(\alpha + \beta X) = \frac{e^{\alpha + \beta X}}{1 + e^{\alpha + \beta X}}$$

Note that both distributions are bounded by 0 and 1. The normal distribution has a variance equal to 1 (see that it has been normalized, so σ^2=1), and the logistic distribution variance is equal to $\pi^2/3 = 3.2898$. Using these properties, one can approximate the estimated regressors of both distributions by multiplying the β's estimates obtained from the PROBIT distribution by $\pi/\sqrt{3} = 1.8138$. Amemiya (1981) proposes to multiply it by 1.6, since he finds that, by trial and error, this value provides a better fit to the data.

Due to the proposals of the present paper, we will not further discuss the point of how to choose one or the other model, since the exercise we are to develop next does not involve such a problem. As a reference, we will quote the work of Chambers and Cox (1967) where a hypothesis test is proposed for distinguishing the correct model.

4 The test (the metal detector)

4.1 Variables and data

A sample of 144 tombs from 19 SW Iberian Bronze Age necropoleis has been selected for this study (fig. 4A, the original data are available via the CAA World Wide Web server (http://caa.soton.ac.uk/caa/CAA95/Garcia/)).
All tombs that were considered seriously altered by the excavators have been excluded altogether, so that all the information processed in the following analyses has been recorded from unaltered contexts. The total amount of artefacts found in these 144 tombs is: 23 metal artefacts, 74 pots, 5 lithic artefacts and 3 necklace beads (fig. 4B)

The dependent variable (presence/absence of metal artefacts) has been divided into two main groups: ornaments (rings, armrings or diadems) and weapons (halberds, daggers or swords), that is to say highly ideological prestige items (M1), on the one hand, and arrow points and pointed tools, less ideological items (M2), on the other hand.

Four main axes of variability are taken into account as potentially explicative of the presence/absence of metal items (dependent variable), namely size and structure of the burial, category of the deceased, other (non-metal) grave goods and soil attributes. These four axes of variability contain 10 variables that are regarded as independent across the study:

Two variables are regarded as representative of the general size and structure of the burial:

- Volume (VO). Continuous variable measured in cubic metres (length × width × depth)
- Ring/*tumulus* (AT). Discrete binary variable: 1 (presence) 0 (absence)

It is assumed here that both the volume of the funerary chamber and the presence/absence of a ring and tumulus provide an indication of the investment of labour made in the construction of the burial.

Another two variables account for the biological status of the deceased:

- Sex. Discrete binary variable: 1 (male) 0 (female)
- Age. Discrete binary variable: 1 (adult) 0 (infant)

Other grave goods are included in order to examine whether the presence of metal items is dependent or not on the presence of other artefactual categories:

- Pottery class 1 (CE1). Discrete binary variable: 1 (presence) 0 (absence)
- Pottery class 2 (CE2). Discrete binary variable: 1 (presence) 0 (absence)
- Lithic artefacts (LT). Discrete binary variable: 1 (presence) 0 (absence)
- Necklace beads (CU). Discrete binary variable: 1 (presence) 0 (absence)

Figure 4A. 19 SW Iberian Bronze Age necropoleis.

Finally, two variables have been used to examine the relationship between the presence/absence of metal items and environmental factors, under the assumption that the production of an agricultural surplus would stimulate the production and/or consumption of metal prestige items among social elites. The soil attributes were measured according to D. Rosa and J.M. Moreira (1987) for Western Andalucia and by A.M. Soares (1984) for southern Portugal. Land agricultural capability (CA) is a discrete ordinal variable that provides an indication of the potential productivity of the soil in terms of a number of geographic parameters (see D. Rosa and J.M. Moreira (1987) and A.M. Soares (1984) for a description). Four categories are considered: class 0 for no agricultural capability, class 1 for moderate or poor agricultural capability — severe limitations —, class 2 for good agricultural capability — some limitations — and class 4 for excellent agricultural capability — no limitations — (fig. 5A). For some tests however, these four categories have been simplified into two (A for classes 0 and 1 and B for classes 2 and 3) in order to compress the variability as much as possible. The lithology (LI) is coded as discrete nominal variable with four classes: class 1 for shales, graywackes and sandstones, roughly matching the SW pyritic belt, class 2 for sands, rounded pebbles, poorly consolidated sandstones and clays, class 3 for argillaceous marls and class 4 for sandy argilles, sand and conglomerates (fig. 5B).

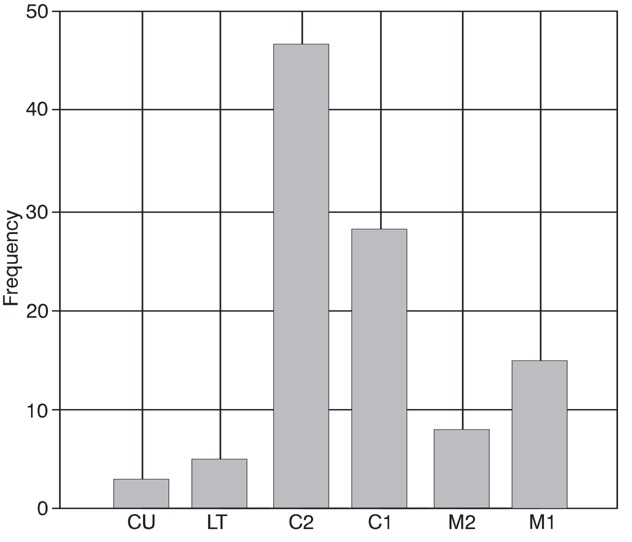

Figure 4B. Different artefact classes for the 19 SW Iberian Bronze Age necropoleis.

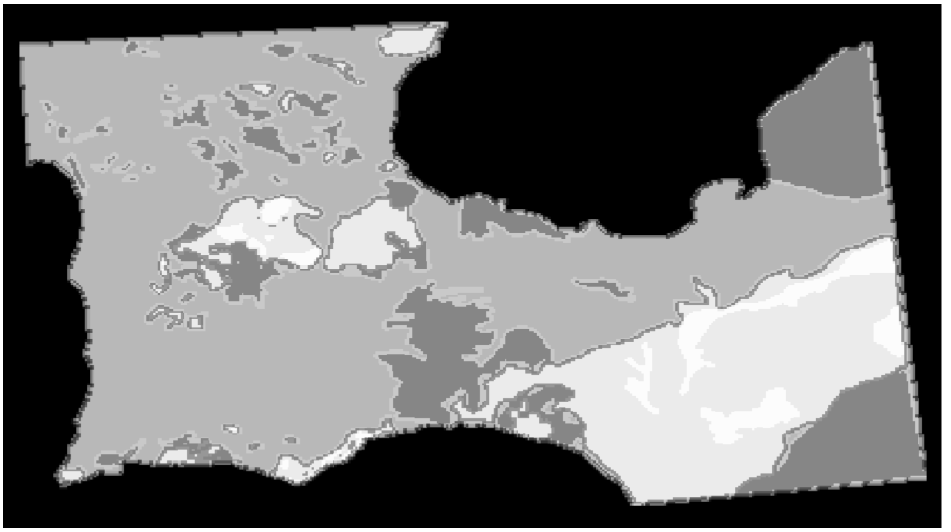

Figure 5A. SW Iberian peninsula land agricultural capability.

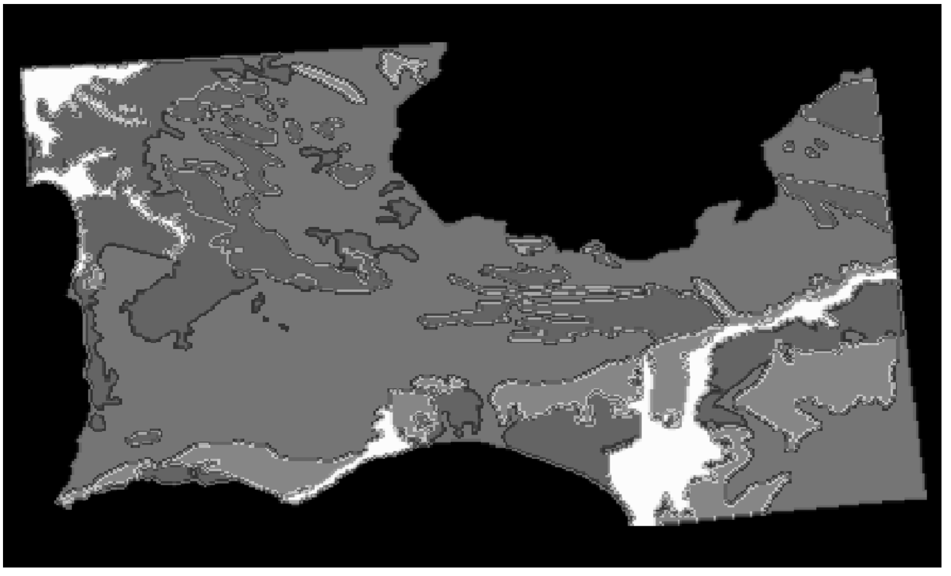

Fig. 5B. SW Iberian peninsula lithology.

4.2 Testing

In this section, a test of the models described above is made against the data described in section 4.1. The ultimate purposes of this test are, firstly, to provide an indication of what variables explain better the presence or absence of metal in the burials (variables M1 and M2), and secondly, to give a numerical prediction of the probability of a metal artefact being found under certain conditions. As already discussed, since the dependent variable is discrete taking only two values, 1 or 0, predictions can only be given, and can only be interpreted, in terms of probabilities. Hence, if the observations are 1 or 0, and if the forecast values for the limited dependent variable falls in the interval (0,1), the traditional measures for the goodness of fit, likewise the R^2, will no longer be useful in explaining the validity of an estimated model. That is the reason why the R^2 will be too low compared with traditionally obtained R^2s for the linear least square regression. Further discussion on the goodness of fit and its alternative measures can be found in Maddala (1983, 1989).

Table 1 expresses the results of a PROBIT regression of M1 over the set of variables (AT, CE1, CE2, LT, CU, AGR). Three estimations have been run in order to set the proper structure of the model, the (***) symbol denoting that the corresponding variable has been deleted for that particular estimation (the removal criterium has been given by the *t-ratio* content together with the coefficient associated with each variable). A first interesting result emerging from these tests is that the most significant variable among the estimations is land agricultural capability (expressed in the dummy variable AGR), which is coincident with the pattern emerging from the correspondence analysis mentioned above. The *sign* of some of the parameters is also of interest: for instance, the parameter associated with CE1, the ceramic category 1, is always negative for both model 1 and 2 (deleted for model 3 due to its low significance level expressed by the t-value). On the contrary, CE2 is always positive and significant, showing a strong positive correlation with the limited dependent variable. This could be interpreted in the sense that ceramic category 2 is associated with a higher social *status*, therefore setting a grave good pattern with metal prestige items. Variables LT and AT do not seem to help much in predicting the ritual in model 1 (t-values around 0) and they have subsequently been removed from models 2 and 3, (both in this first PROBIT and the next, as in the rest of the tables presented below).

Similar results hold for the first LOGIT estimates (table 2). Again, the most significant variable is land agricultural capability, and the same variables are deleted in the three estimated models. The sign of the parameters do not contradict the results of the PROBIT estimation.

One interesting thing to note in both table 1 and table 2 is that variable CU displays a good significance in explaining the presence/absence of metal elements. Nevertheless, when the variables AT and LT have been removed, the t-ratio for CU falls below the acceptable range (1.6 as a rule of thumb). Why? This is a problem of multicollinearity among the variables, since they are probably highly correlated. This is a perverse effect that makes it very difficult to separate the partial effect of each variable from the explained one.

Finally, note that PROBIT and LOGIT estimates can be compared by multiplying the first one by 1.813, (*verbi gratiæ*, the parameter associated with AGR in model 1 PROBIT is 1.331, multiplied by 1.813 gives 2.414, which is very similar to the LOGIT estimate of 2.289).

The fact that all the variables that have been included in these models are of discrete form, could be regarded as a source of criticism from a purely statistical point of view. Due to this limited form, the number of possible outcomes is limited to 2^K, where k is the number of variables included in the regression. Thus, for the first model where k is equal to 6, the number of possible cases that an archaeologist can face is limited to 64 (16 and 4, for models 2 and 3, respectively). This produces the problem that the prediction is again a limited discrete prediction. Furthermore, and due to the multicollinearity problem aforementioned, whenever there is a strong statistical association among the variables included in the model, the number of possible outcomes, is less than could be expected (for instance, at first glance the data matrix indicates a relationship between variables LT and CU).

The next step will be to include the only continuous variable considered in the present paper to predict the presence/absence of metal items, namely, the log of the volume of the tomb. The results for PROBIT and LOGIT are presented in tables 3 and 4. Very similar conclusions are obtained from these new estimations. See, for instance, the low significance level of the coefficient for CU whenever variables AT and LT have been removed. It seems possible to conclude that the set of variables AT, LT, C1 and CU fail to *predict the ritual*, that is to say, fail to *predict the presence of metal prestige items*. In terms of social organisation this is a quite an interesting point, as the presence of funerary monuments (stone rings and *tumuli*) does not correlate with the presence or absence of weapons and ornaments.

Yet, a contradictory result arises since the coefficient for AGR displays the poorest significance level of the set of variables included in the last model (the t-ratio is not significant in any of the three models). In fact, the only significant variable in this case is the grave's volume (VOL). This could be explained both by the fact that VOL is the only continuous variable included in the *metal detector model*, and by a multicollinearity problem involved in the distinct partial correlations between the set of the explanatory variables. The same conclusions apply to the LOGIT estimations.

However, two more sets of partial estimations have been run in order to check the validity of the results described sofar. This has been done by estimating a new model for M1 over CA, (note that the index for land agricultural capability is now measured as an ordinal variable 0-1-2-3, and not as the dummy AGR), and another model for M1 over VOL (tables 5, 6).

The coefficients R^2*s* are just too low to consider any of the models as definite, the main conclusion to be drawn being that the partial t-ratio for variables CA and VOL are sufficiently significant to consider both variables as explicative for M1. Despite this low R^2, a simple forecasting exercise is carried out (as a *metal detector*), to show how this coefficient should be interpreted. To do this, the PROBIT model presented in table 5 has been chosen. Here, the only explicative variable for the presence of metal items is the discrete index for agricultural capability. Table 7 presents the probabilistic computations for the four categories:

The last two columns are very similar except for CA=1 due to the sampling, that is, the models in table 5 have been constructed from a sample of 143, of which 112 correspond to category *CA = 0*, 14 to CA = 1, 7 to CA = 2, and 10 to CA = 3. On the other hand, the limited dependent variable M1 has a value 1, presence, 8 times in the category CA = 0, none for CA = 1, 2 for CA = 2, and finally there are 4 in

Table 1. PROBIT model for M1.

	MODEL 1		MODEL 2		MODEL 3	
	Coefficient	t-Value	Coefficient	t-Value	Coefficient	t-Value
constant	-1.779	-4.942	-1.813	-6.913	-1.844	-7.371
ring/*tumulus*	-0.136	-0.347	***	***	***	***
pottery class 1	-0.195	-0.439	-0.146	-0.334	***	***
pottery class 2	0.710	2.087	0.651	2.002	0.696	2.184
lithic artefacts	-5.892	0.120	***	***	***	***
necklace beads	1.561	1.574	0.447	0.568	***	***
dummy variable	1.331	3.010	1.199	3.254	1.213	3.314

Table 2. LOGIT model for M1.

	MODEL 1		MODEL 2		MODEL 3	
	Coefficient	t-Value	Coefficient	t-Value	Coefficient	t-Value
constant	-3.075	-4.349	-3.185	-5.904	3.243	6.346
ring/*tumulus*	-0.448	-0.558	***	***	***	***
pottery class 1	-0.311	-0.358	-0.215	-0.255	***	***
pottery class 2	1.293	1.957	1.166	1.850	1.243	2.026
lithic artefacts	-13.582	-0.084	***	***	***	***
necklace bead	2.876	1.789	0.746	0.485	***	***
dummy variable	2.289	2.896	2.122	3.213	2.154	3.298

Table 3. PROBIT model for M1.

	MODEL 1		MODEL 2		MODEL 3	
	Coefficient	t-Value	Coefficient	t-Value	Coefficient	t-Value
constant	-0.716	-1.224	-0.724	-1.496	-0.862	-1.929
ring/*tumulus*	-0.188	-0.429	***	***	***	***
volume	0.873	2.588	0.922	2.769	0.864	2.722
pottery class 1	-0.445	-0.792	-0.389	-0.701	***	***
pottery class 2	0.634	1.573	0.561	1.486	0.616	1.674
lithic artefacts	-5.336	-0.106	***	***	***	***
necklace bead	1.816	1.788	0.953	1.154	0.982	1.188
dummy variable	0.571	0.994	0.421	0.850	0.390	0.790

Table 4. LOGIT model for M1.

	MODEL 1		MODEL 2		MODEL 3	
	Coefficient	t-Value	Coefficient	t-Value	Coefficient	t-Value
constant	-1.283	-1.155	-1.290	-1.394	-1.501	-1.777
ring/*tumulus*	-0.491	-0.569	***	***	***	***
volume	1.560	2.473	1.67	2.704	1.591	2.691
pottery class 1	-0.587	-0.578	-0.514	-0.508	***	***
pottery class 2	1.198	1.521	1.011	1.339	1.114	1.524
lithic artefacts	-12.633	-0.075	***	***	***	***
necklace bead	3.372	2.016	1.822	1.246	1.865	1.276
dummy variable	0.913	0.865	0.634	0.686	0.590	0.636

Table 5. PROBIT model and LOGIT model.

	Probit model		Logit model	
	Coefficient	t-Value	Coefficient	t-Value
constant	-1.5306	-8.616	-2.7062	-7.288
Land agricultural capability	0.3909	2.867	0.72841	3.012
R^2 =		0.0777		

Table 6. PROBIT model and LOGIT model.

	Probit model		Logit model	
	Coefficient	t-Value	Coefficient	t-Value
constant	-0.3555	-1.171	-0.5810	-1.148
volume	0.9921	3.586	1.8357	3.676
R^2 =		0.1320		

the category CA = 3. Thus, there are a total of 14 cases where M1 has taken value 1. The sample used to construct these models has been drawn from a bigger sample of 374, and the selection criteria were to choose those tombs where we could know, at least, the volume, the presence/absence of the ceramic typology, and, of course, those which had not been expoliated. 24 tombs of the 374 were of type CA = 1, and 5 of them contained a metal item. Note that none of these 5 have been included in the reduced sample of 143. However, let us have a look at what is going to happen when we remove the observations for CA = 1, and we estimate a PROBIT model:

$$\begin{aligned} M1^* = \; & -1.4623 + 0.41287\text{CA} \\ & (-8.248) \quad (3.057) \end{aligned}$$

The normal probability values in table 8 have approached the observed values of the last column in table 7. Thus, this estimated probability can be considered as the marginal propensity of a determinate area to contain burials with metal elements. But, what about a prediction for CA = 1? It is easy to see that the latent variable adopts a value of M1* = -1.4623 + 0.41287 = -1.04943, and the table for the cumulative normal distribution indicates that this happens with a probability of 0.1492 (= *P(M1=1 conditioned to CA = 1))*. Therefore, if 24 tombs out of 374 fall in the category of *CA = 1*, the metal detector predicts the existence of about 4 metal items (that is, $0.1492 \times 24 = 3.58 \simeq 4$), the real number of observations being 5. The proximity between the predicted and the observed values is therefore clear (the metal detector works!).

Of course, this is only a simple example where there is only one explicative discrete variable, showing only four possible states, and, hence, implying that, again, the predictions of a discrete binomial variable are discrete as well as the observations.

Finally, note that our insistence on the significate of the R^2 coefficient stems from the fact that it cannot be interpreted in the same sense as in the traditional least square regression, since the meaning and source of the residuals are quite different. Some authors refer to this as the *R^2 syndrome*.

5 Conclusions

From a methodological point of view, an attempt has been made in this paper to increase the predictive capacity of archaeological reasoning through econometric experience. A case study has been chosen where some previous indications existed about the pattern of association and dependence among the relevant variables (*i.e.* that previous knowledge has served as a basis for hypothesis testing). This predictive view has been constructed on discrete variables with only two states {0,1}. Furthermore, the PROBIT and LOGIT models have allowed us to construct an innovative (predictive) view of the pattern of relationships among the variables in terms of the t-statistic (*i.e.* estimated value divided by the standard error).

On an empirical level, the presence of bronze prestige items in Bronze Age tombs is closely related to the variables VO, CE2 and CA, that is to say, to the size of the burial chamber, a set of carinated pots and the general agricultural potential of the soil where the community was settled. Alternatively, the presence of bronze items is not dependent on the variables AT, CE1, LT, CU and LI, that is to say, presence of ring/tumulus structures, a set of non-carinated pots, lithic artefacts, necklace beads and lithology class of the soil (associated with availability of mineral resources). For the sake of simplicity, and in order to keep the lenght of this article within reasonable limits, only those tests considered more relevant have been included and discussed.

Table 7. Probabilistic computations for four categories.

	m*= α + β CA	Normal Probability	Observed %
Land agricultural capability = 0	-1.5306	0.0629	0.0714
Land agricultural capability = 1	-1.1396	0.1272	0
Land agricultural capability = 2	-0.7486	0.2271	0.2857
Land agricultural capability = 3	-0.3576	0.3603	0.4

Table 8. Probabilistic computations for three categories.

	m*= α + β CA	Normal Probability
Land agricultural capability = 0	-1.4623	0.0718
Land agricultural capability = 2	-0.6366	0.2622
Land agricultural capability = 3	-0.2237	0.4115

Remark

The data in this paper were processed with the MV-ARCH (Wright 1989), Idrisi (Eastman 1990) and LIMDEP (Greene 1990) systems.

notes

1 For the original data, please refer to the CAA World Wide Web server on http://caa.soton.ac.uk/caa/CAA95/Garcia/.

2 Recent literature on the European Bronze Age displays rather diverse and contradictory applications of terms such as *stratified society*, *class society* and *state*. The term *stratified society* is used here in opposition to *ranked society,* according to the definition given by M. Fried (1967). However, and unlike Fried, we conceptualise the *stratified society* as an equivalent to *class society* and therefore to the *state* itself (Hindess/Hirst 1975).

3 Study carried out within a wider dataset of 31 necropoleis and 321 tombs (Garcia 1992) from which the sample used in this paper has been drawn.

4 It could be objected that the above mentioned survey is rather old, and that recent developments in econometrics have followed different trends. But we still are in favour of QRM since many of the areas mentioned by Amemiya in 1981 are receiving nowadays important contributions. See also Nelson (1987) for an introductory treatment on QRMs.

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L. García Sanjuán
Department of Prehistory and Archaeology
University of Sevilla
María de Padilla s/n. 41004
Sevilla
Spain
e-mail: lgarcia@sevax1.cica.es

J. Rodríguez López
Department of Economics and History of Economic Institutions, University of Huelva
Plaza de la Merced s/n. 21002
Huelva
Spain