Mapping management zones in a sandy pasture soil using an objective model and multivariate techniques

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Abstract

Soils occupied by dryland pastures usually have low fertility but can exhibit a high spatial variability. Consequently, logical application of fertilisers should be based on an appropriate knowledge of spatial variability of the main soil properties that can affect pasture yield and quality. Delineation of zones with similar soil fertility is necessary to implement site-specific management, reinforcing the interest of methods to identify these homogeneous zones. Thus, the formulation of the objective Rasch model constitutes a new approach in pasture fields.

A case study was performed in a pasture field located in a montado (agrosilvopastoral) ecosystem. Measurements of some soil properties (texture, organic matter, nitrogen, phosphorus, potassium, cation exchange capacity and soil apparent electrical conductivity) at 24 sampling locations were integrated in the Rasch model. A classification of all sampling locations according to pasture soil fertility was established. Moreover, the influence of each soil property on the soil fertility was highlighted, with the clay content the most influential property in this sandy soil. Then, a clustering process was undertaken to delimit the homogeneous zones, considering soil pasture fertility, elevation and slope as the input layers. Three zones were delineated and vegetation indices (normalized difference vegetation index, NDVI, and normalized difference water index, NDWI) and pasture yield data at sampling locations were employed to check their differences. Results showed that vegetation indices were not suitable to detect the spatial variability between zones. However, differences in pasture yield and quality were evident, besides some key soil properties, such as clay content and organic matter.

Keywords: Pasture; Rasch model; Soil fertility; Homogeneous zones.

Introduction

The agrosilvopastoral ecosystem in the southwestern part of the Iberian peninsula, called dehesa in Spain or montado in Portugal, constitutes a unique Mediterranean evergreen oak woodland, where the trees are mainly holm (*Quercus ilex*) and cork (*Quercus suber*). It is an anthropogenic system in which endangered species, such as the Iberian lynx, live and, at the same time, many goods are produced (cork, mushrooms, firewood, etc.). However, the main use is for grazing. The understory vegetation of shrubs and pastures are the principal source of animal feed in extensive production systems. Despite these woodlands being anthropogenic ecosystems of high socio-economic and conservation value, during the last years they have declined mainly due to environmental constraints and inappropriate management (Godinho et al., 2016).

Usually, soils in these areas have low fertility but spatial variability in some soil properties is very important. The degraded, shallow, acidic and stony soils, due to intense erosion and soil transport, have a low nutrients and organic matter content (Serrano et al., 2019). Moreover, the existence of different vegetation types and their annual dynamics introduce more variability, which is even more complicated when grazing animals are incorporated (Schellberg et al., 2008).

Differences in the main soil properties lead to differences in soil fertility and, in turn, this fact determines pasture yield and quality. In consequence, the implementation of strategies for a suitable management of this ecosystem requires the determination of zones with similar permanent soil properties, often referred to as management zones (MZ), which are sub-fields of similar production potential (e.g. Peralta et al., 2015). These MZ are the basis for implementing site-specific management strategies, that will culminate in the application of fertilisers with variable rate technology. However, it is difficult to accurately define MZ in pasture soils because of the complex interactions of all factors that could affect pasture yield and quality. Any approach to delineate MZ must consider the main physical and chemical properties of soil, since these factors affect pasture biomass the most (Serrano et al., 2010) and the spatial variability of biomass productivity is highly related to the spatial patterns of soil nutrients (Stefanski and Simpson, 2010).

The delineation of MZ requires collecting and analysing data throughout the field. Data can be generated from traditional soil sampling of the field and the subsequent laboratory work to obtain the information of the main soil properties. The use of remote or proximal sensing constitutes another source of intensive information of some soil and plant properties. Moreover, topographic attributes and yield data can also be used. However, delineating zones based on soil physical properties most often captures yield variability due to differences in plant available water and, consequently, pasture production potential. The information obtained from different types of data have to allow management decisions to vary in different locations within the field. Several approaches have been proposed to delineate MZ at the field level. One approach is based on obtaining soil information, such as sampling for soil physical and chemical properties, sampling the soil utilising an electrical conductivity sensor or using remotely sensed images for estimating soil properties (e.g., Arshad et al., 2019; Moral and Serrano, 2019, Fortes et al., 2015). Another alternative approach utilises remotely sensed images or yield maps to estimate crop growth variability (e.g., Maestrini and Basso, 2018). The use of both soil landscape and crop information to define MZ has been also reported elsewhere (e.g., Miao et al., 2018).

Most of the studies to evaluate different techniques to delineate MZ have been performed in agricultural fields. Little research has been conducted in pasture systems (Trotter et al., 2014), but the same approaches can be used in pasture soils to define MZ. Some layers of information can be combined using different algorithms, such as a cluster procedure using c-means methods, principal component analysis or the simple use of the coefficient of variation of each data layer (e.g., Xin-Zhong et al. 2009; Morari et al, 2009; Ortega and Santibáñez, 2007). More recently, the use of the Rasch model to consolidate some soil properties and, later, define MZ has been proposed with promising results (Moral et al., 2011; Rebollo et al., 2017), even in pasture soils (Moral et al., 2019). Results from the Rasch model can be more easily understood that those generated by using other approaches. Furthermore, there is no need to define any kind of weight and there are no initial constraints about the variables, that is, original variables can be related or unrelated (Tristán, 2002).

The objectives of this study were to: (1) analyse the suitability of the Rasch model as a measurement tool to determine the pasture soil fertility in sandy soils; and (2) generate MZ using a multivariate algorithm after identifying the spatial distribution of the pasture soil fertility.

Materials and methods

Site description

The experimental field was a farm located about 8 km Southwest of Evora, in Southern Portugal (38º 32.1’ N; 7º 59.8’ W). An overview of the boundary of the site is given in Figure 1. The area of study was approximately 25 ha. This field has been cultivated with permanent pastures for more than 30 years and used for sheep grazing. The tree density is 8-10 trees ha^{-1}, mainly *Quercus ilex ssp. Rotundifolia* Lam.

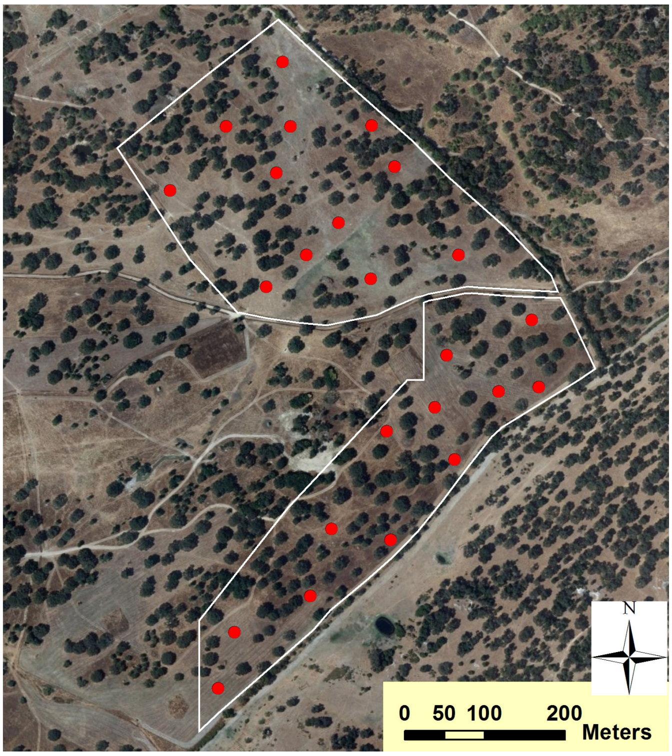

Fig. 1. Study site. Sampling locations are indicated as dots.

The climate of this area is Mediterranean. According to the Köppen-Geiger classification, it is a climate type Csa (Peel et al., 2007). Temperature ranges between 0ºC, minimum in winter, and more than 40°C, maximum in summer. Mean annual precipitation reaches less than 600 mm, mainly between October and March and practically non-existent during the summer, but its inter-annual variability is very high.

The predominant soil is classified as a Cambisol derived from granite (FAO, 2006). Cambisols are characterised by slight or moderate weathering of parent material and by absence of appreciable quantities of illuviated clay, organic matter, aluminium and/or iron compounds. Acid Cambisols are not very fertile and are mainly used for mixed arable farming and as grazing and forest land. The soil in this area is mainly sandy and in this field sand content can reach up to 80%.

Soil sample collection and analysis

Twenty-four sampling locations (Figure 1) were georeferenced with a Trimble 4700 GPS-RTK receiver (Trimble Navigation Limited, Sunnyvale, California, USA), each with an area of 900 m^2 (30 m x 30 m). They were selected from tree-free zones to avoid interference from satellite images. Composite soil samples comprised nine sub-samples, that is, around the main point there were 9-sub-samples for a total of 216 samples. They were collected in November 2017. The soil samples were taken using a gouge auger and a hammer in a depth range of 0–0.30 m, considering the maximum depth of the roots in the pasture, approximately 0.2–0.3 m. The soil samples were kept in plastic bags, air-dried and analysed for their particle-size distributions (using a Sedigraph 5100, Micrometritics, Norcross, GA 30093-2901, USA), after passing the fine components through a 2 mm sieve. Later, the fine components were analysed using standard methods (Egner et al. 1960): pH in a 1:2.5 (soil:water) suspension using the potentiometric method; the total nitrogen (TN) content was determined by the Kjeldahl method; P_2O_5 and K_2O were extracted by the Egner–Riehm method, being measured by the colorimetric method and a flame photometer, respectively; the organic matter (OM) was measured by combustion and CO_2 measurement using an infrared detection cell; and the cation exchange capacicty (CEC) was measured by the neutral ammonium acetate method.

A soil apparent electrical conductivity (ECa) survey was performed in November 2017 using a Veris 2000 XA contact sensor (Veris Technologies, Salina, KS, USA). This sensor is equipped with a global navigation satellite system (GNSS) instrument (Trimble RTK/PP-4700 GPS, Trimble Navigation Limited, Sunnyvale, California, USA) and was pulled by an all-terrain vehicle at an average speed of 2 m s^{-1}, with successive passages across the field. Thus, a set of topsoil georeferenced data, weighted depth readings, from 0 to 0.30 m depths, was generated. The average value of ECa in each sampling location was obtained with the values registered in each square.

Using the aforementioned GNSS instrument, a topographic survey of the area was also performed. The elevation data were sampled in the field with the GNSS assembled on the all-terrain vehicle and the digital elevation model surface was generated with the triangulated irregular network (TIN) interpolation tool from ArcGIS (version 10.3, ESRI Inc, Redlands, California, USA).

Later, this vector information was converted into a grid surface using the Spatial Analyst Tools in ArcGIS.

Pasture sample collection and analysis

At the peak of pasture production, during two days, on 11 and 12 May 2018, a pasture sample was taken at each sampling point using a portable electric grass shear, cutting at 10-20 mm above ground level. Composite pasture samples were collected at nine representative points within each sampling location, each with 0.25 m^2 area. Immediately, each pasture sample was weighed to determine the green matter production (GM, kg ha^{-1}), then dehydrated after being placed in an oven at 65ºC for 72 h to determine the moisture content, which was used to calculate dry matter yield (DM, kg ha^{-1}). The dehydrated samples were also analysed to determine the content of crude protein (CP, %) and neutral detergent fiber (NDF, %), according to standard techniques (AOAC, 2005).

NDVI and NDWI survey

The Copernicus data hub was used to obtain satellite images through the electronic platform "http://agromap.agroinsider360.com" from the "AgroInsider" enterprise (a spin-off from the University of Évora). Consequently, Sentinel-2 band 4 (B4, 10 m spatial resolution, 665 nm), band 8 (B8, 10 m spatial resolution, 842 nm), band 8A (B8A, 20 m spatial resolution, 865 nm), and band 11 (B11, 20 m spatial resolution, 1610 nm), were extracted and atmospherically corrected to compute NDVI and NDWI as:

$$NDVI = (B8 - B4)/(B8 + B4) \tag{1}$$

$$NDWI = (B8A - B11)/(B8A + B11) \tag{2}$$

These Sentinel-2 optical images were obtained for the 24 sampling locations. Images were without clouds and taken in May 2018, the same days when the pasture samples were collected. Multispectral information was collected before cutting the pasture. NDVI of each sampling location resulted from the average of the nine 10 × 10 m pixels that constitute this area and NDWI resulted from reading the 20 × 20 m pixels that contain the centre point of the sampling location.

The Rasch model

As a measuring tool, the Rasch model is an innovative tool to estimate pasture soil fertility considering that the potential yield of pasture biomass is related to soil fertility. It is a latent variable model with one measurement parameter (Álvarez, 2004), corresponding to a single dimension to measure the ranking of both the subject and items (soil locations and soil properties, respectively, in this case study). Heterogeneous measures of different soil properties can be integrated into an overall variable, facilitating the interpretation of pasture soil fertility.

The Rasch model is often seen as a special case of the item response theory (IRT) models, since the mathematical theory underlying the Rasch model is in some respects the same as IRT (Hambleton et al., 1991). However, there are important differences because, in the IRT paradigm, one model is chosen over another if it accounts better for the data, that is, the data are given and the model is chosen. In contrast, when the Rasch model is employed, the model is given and then the data should fit the model; so misfitting items require diagnosis and may be excluded.

Let n be the different locations in the experimental field where measurements of each soil property, i, were carried out. A latent variable, pasture soil fertility, X_{ni}, is defined in which n refers to the location where the measurement is conducted and i refers to the soil property. In this case study, B_n (n = 1, 2, …, 24) refers to the 24 locations where the measurements of the soil properties were carried out, and d_i (i = 1, 2, 3, 4, ..., 9) refers to the nine soil properties (Clay -1-, Sand -2-, Silt -3-, TN -4-, P_2O_5 -5-, K_2O -6-, OM -7-, CEC -8- and EC -9-). For example, $X_{12,4}$ means the measurement of the property i = 4 (TN) at the location, sample point, n = 12. According to Figure 2, if at a sampling location B_1 all the soil properties did not exert an important influence on pasture soil fertility, then B_1 would be placed to the left of these items d_i (diagram 1). On the contrary, if all the properties are exerting an important influence, then the sampling location B_2 will be located on the right of all d_i (diagram 2). If there are different sampling points, their difference in terms of pasture soil fertility would be given by their relative positions with respect to the number of soil properties which favors fertility. For instance, in the diagram 3, location B_3 surpasses no soil property; location B_4 only surpasses soil property d_9; location B_5 surpasses property d_9 and d_{10}; and location B_6 surpasses all three soil properties, that is, d_9, d_{10} and d_{11}. Consequently, B_3 is the location with least soil fertility, and B_6 has the most. Soil property d_9 does not exert an influence on the location B_3 and influences on the locations B_4, B_5 and B_6. The property d_{10} does not influence on the locations B_3 and B_4, and influences on the locations B_5 and B_6. Finally, property d_{11} does not exert an influence on the locations B_3, B_4 and B_5, and influences on the location B_6. In this example, B_6 is the location where pasture soil fertility is greater since it is influenced by all the soil properties, d_9, d_{10} and d_{11}; B_3 is the location where pasture soil fertility is lower since it is not influenced by any property. On the other hand, d_9 is the soil property which more frequently influences on pasture soil fertility and d_{11} is the soil property which less frequently influences on pasture soil fertility.

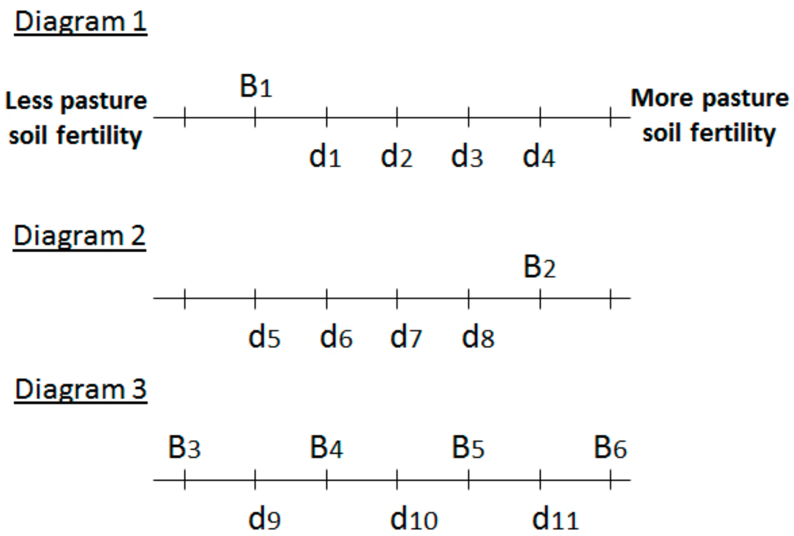

Fig. 2. Representation of the latent variable, pasture soil fertility, as a straight line. Bn is the location n; di is the soil property i. In the diagram 1, the location B_1 is not influenced by any soil property. In the diagram 2, the location B_2 is influenced by all soil properties. Diagram 3 shows a generalization for some locations and soil properties; B_3 is not influenced by any soil property; B_4 is influenced by the soil property d_9; B_5 is influenced by the soil properties d_9 and d_{10}; B6 is influenced by all soil properties, d_9, d_{10} and d_{11}.

The probability that location n has the influence of the soil property corresponding to item i, given the parameters B_n and d_i is:

$$P[X_{ni} = 1; B_n, d_i] = \frac{e^{(B_n - d_i)}}{1 + e^{(B_n - d_i)}} \tag{3}$$

which was obtained by Rasch (1980) in his treatise on latent variables. The parameters B_n and d_i are defined in the same measurement unit of an interval scale and the difference (B_n - d_i) is gauged according to the same measurement unit. The greater is the difference (B_n - d_i), the greater is the probability to be 1. Although expression (3) corresponds to the Rasch dichotomous model, it has been extended to the case of more than two categories, polytomous models (e.g., Ferrari and Salini, 2011).

In this case study, measures related to some soil properties taken at different locations should be consolidated into a global variable which highlighted the interpretation of pasture soil fertility. The latent variable, pasture soil fertility, can be regarded as a straight line along which soil properties and sample locations are located. The Rasch model uses a logit scale for B_n and d_i. To explain how this scale works, by taking logarithms of Eq. (3), Eq. (4) can be obtained:

$$\log (P / (1-P)) = B_n - d_i \tag{4}$$

being $P = P[X_{ni} = 1; B_n, d_i]$

The logit of P is log (P / (1-P)). Direct comparisons between different values of B_n and d_i can be made more easily when expressed in logits. An item with lower influence on the pasture soil fertility or a sampling location where soil fertility is higher are associated with larger positive numbers and, on the contrary, an item with higher influence on soil fertility or a sampling location where soil ferility is lower will have larger negative values. Usually, almost all sample locations are expected to have a probability between 0.05 and 0.95 for each soil property to be influential on them; in consequence, according to Eq. (3), B_n - d_i values are between -3 and 3 logits.

The Rasch model is based on the simple idea that some items are more important to subjects than other items. Thus, the Rasch model constructs a line of measurement with the items located hierarchically on this line according to their importance to subjects. The validity of a given test is carried out by assessing whether all items work together to measure a single variable. Chi-square fit statistics, known as Infit and Outfit Mean-Square (Infit and Outfit MNSQ), are computed to determine how well each soil property contributes to pasture soil fertility measurement (i.e., the basic fit statistics is a ratio of observed residual variance to expected residual variance, and is near 1.00 when observed variance is comparable to expected); usually, items should obtain Infit and Outfit MNSQ values between 0.6 and 1.5 (Bond and Fox, 2007) to be accepted, removing those with values beyond these thresholds. In addition, the mean standardised (ZSTD) infit and outfit values, sum of squares standardised residuals given as Z-statistics, are expected to be 0; values for both between -3 and 2 are considered acceptable (Edwards and Alcock 2010).

A key characteristic of the Rasch model is the transformation of raw data to linear units that operationally define a latent variable or theoretical construct, which is the combination of non-categorical measures that are conceptually related to a latent feature. Their unrelated independent units are then categorised with uniform rating scales and transformed to common logit units with Rasch measurements. By describing soil properties in terms of uniform rating categories, independent scale quantities can be expressed as common ratings ranging from low to high. Andrews et al. (2004) considered a similar approach in their soil quality assessment tool, in which some indicators are taken into account and their measurements are transformed using scoring curves.

The probabilistic Rasch model is well known for its effciency and precision of transforming categorical item responses to objective scale measures (Ferrari and Salini, 2011). Initially, the data are arranged in matrix form, where the rows are the soil locations and the columns the soil properties, and each cell reflects the category. In consequence, the soil property measures were coded on a scale between 1 and 5 for each property at each sampling location. As was performed in other similar studies (e.g., Moral and Rebollo, 2017; Moral et al., 2019), the maximum categorical value, 5, was assigned for an interval around 33% of clay, silt, or sand content considering that the ideal percentage of each texture class was about one-third of the total. The other soil properties were coded taking into account that the highest categorical values correspond to the classes with highest measures and the rest of categories were associated with classes in which their amplitude depends on the maximum and minimum values. The use of the proposed categories was checked before processing the categorical matrix in the Rasch model; all categories were utilised for the data.

The Winsteps v. 4.0 computer program (Linacre, 2009) was utilised to implement the Rasch model. The mathematical formulation of this model can be revised, for example, in Tristán (2002), Ferrari and Salini (2011), and Edwards and Alcock (2010). Figure 3 shows the stages to formulate the Rasch model. Taking into account the different contribution of the soil properties, a measure of pasture soil fertility at each sample location was achieved. Consequently, considering the sampling locations and choosing the soil properties which exert influence on the latent variable, pasture soil fertility, values of all soil properties at each sampling location were measured and, later, this information was processed with the previously mentioned software to obtain the Rasch measures, as well as some fit measures.

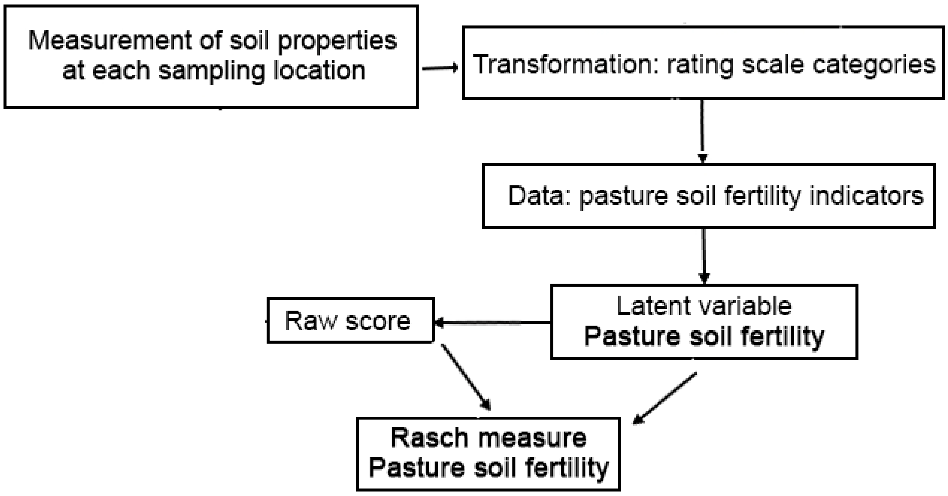

Fig. 3. Schematic diagram of the stages involved in the formulation of the Rasch model.

Mapping of pasture soil fertility and management zones

The formulation of the Rasch model allowed to obtain values of the pasture soil fertility, expressed as the Rasch measure, for all locations in which a soil sample was taken, considering information from six soil properties. Then, estimates of pasture soil fertility at other locations where they are unavailable have to be obtained throughout the field.

Although there are many algorithms to interpolate from known data, radial basis function (RBF) interpolation is a very efficient technique to be used for scattered data (e.g., Kindelan et al., 2016). RBFs constitute a series of exact interpolation techniques, each of them defined by a different function which captures global trends and local variations. A single RBF is any function defined in terms of distance from a point. The family of polyharmonic splines is usually used for interpolation. The completely regularised spline is in this group and was selected in this case study after trying several functions and a validation process (data not shown). More information about the RBFs can be found in Buhmann (2003).

The extension Geostatistical Analyst of ArcGIS was utilised to perform the interpolation process and a map of estimates was generated with the ArcMap module in ArcGIS to visualise the spatial pattern of the pasture soil fertility in the field. Then, homogeneous zones can be delimited using a classification technique in ArcGIS. However, as topography is an important factor that can affect the potential zones, as was found in another similar study (Moral et al., 2019), it was also considered. In consequence, the final classified map was produced using an unsupervised classification technique on two sets of input data: the pasture soil fertility (as the Rasch measure) and topography (elevation and slope). Unsupervised classification was performed using the ISO Cluster algorithm in ArcGIS. This approach organises the data in the input raster into a user-defined number of groups to produce signatures which are then utilised to classify the data using the Maximum Likelihood Classifier (MLC) function. From a practical perspective, few homogeneous zones should be delineated. Thus, the number of groups was fixed at three in this study.

Finally, the proposed delimitation was evaluated computing the differences on the mean values for the pasture yield variables (GM, DM, CP and NDF) and vegetation indices (NDVI and NDWI) in each zone, using the Kruskal-Wallis nonparametric test and the Dunn test as a post hoc analysis in the IBM SPSS statistical package (version 24, IBM Corp, Armonk, NY, USA). These tests were chosen as the normality in the data cannot be assumed. The Kruskal-Wallis test is a rank-based non-parametric test that can be used to determine if there are statistically significant differences between two or more groups of an independent variable on a continuous or ordinal dependent variable. The Kruskal-Wallis test tells that at least two groups were different but cannot tell which specific groups of the independent variable are statistically significantly different from each other. Consequently, since more than two groups can be defined, determining which of these groups differ from each other were performed by means of the Dunn test as a post hoc non-parametric test.

Results and discussion

Analysis of the Rasch measure: pasture soil fertility

The first output to be analysed after processing the matrix of categorical values by the Winsteps program was the overall information about how the data fit the model as was provided by some statistics. The values of the reliability statistics for the samples and items were 0.55 and 0.32, respectively, much lower than the acceptable limit, 0.70 (Sekaran, 2000). In consequence, it was necessary to revise mainly the items, that is, how soil properties were distributed. When the variable map was visualised (Figure 4), the coincidence of textural variables on the straight line was evident, so two of them were redundant and had to be removed. Furthermore, Infit and Outfit MNSQ values for ECa were higher than 1.5, indicating that it should also be removed. Thus, without ECa, the sand and silt contents, the data were processed again and an improvement of the reliability statistics was apparent. The values for samples and items were close to 0.70. Moreover, the remaining soil properties gave place to acceptable values of the fitting statistics: the Infit and Outfit MNSQ were between 0.6 and 1.5, and the infit and outfit ZSTD between -3 and 2, so each soil property fits the general pattern of the model and contributes to support the underlying latent variable, pasture soil fertility.

Table 1 shows the sum of points of all categories (raw score) for each soil property at each sampling location. The measured values, obtained with the Winsteps programme from the raw scores, are also shown and the sampling locations are displayed in measure order from the site with the highest pasture soil fertility, highest measure, to the location with the lowest pasture soil fertility, lowest measure.

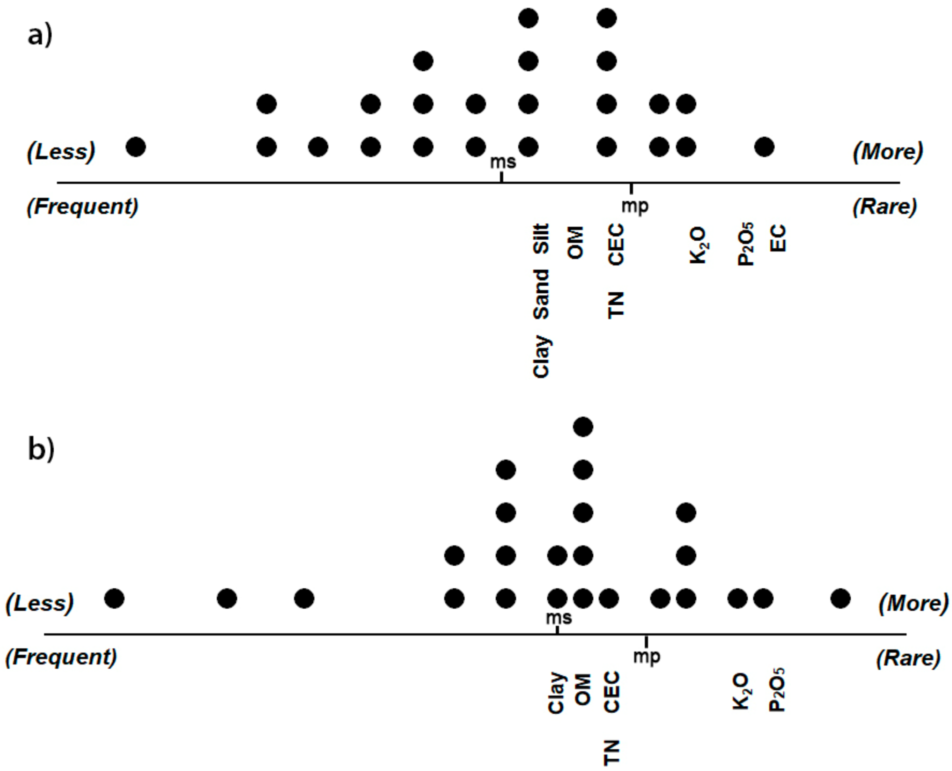

Fig. 4. a) Straight line that represents the latent variable: pasture soil fertility. Distribution of soil samples (points) is above the line: to the right those more fertile; to the left less those less fertile. Soil properties are below the line: to the right less common (rare) properties, with lower influence on pasture soil fertility; to the left more common (frequent) properties, with higher influence on pasture soil fertility; ms and mp are the mean values of the Rasch measure for soil samples and properties, respectively. b) Final latent variable, after removing the soil properties that are redundant or do not fit the model (sand and silt content and EC).

Another interesting output of the programme was the relative influence of each soil property on the pasture soil fertility. According to Table 2, the clay content had the highest raw score, which corresponds to the lowest measure. Consequently, the clay content was the most influential property on the soil fertility in this field. OM, CEC and TN were also very influential, which could be expected as they are related to the clay content. In other pasture soils (e.g., Moral et al., 2019) where the sand content is not so high, the influence of texture on soil fertility is not as important as in sandy soils. The clay content determines the fertility level at each location across the field. Water drains quickly through this sandy soil, washing away most of the nutrients and the OM, so only in these locations with higher clay content, moisture content and the nutrient levels are also higher, leading to a higher soil fertility. Some research in agricultural fields with higher clay content showed its important influence on the soil fertility (e.g., Moral and Rebollo, 2017; Rebollo et al., 2017).

Table 1

Results obtained after applying the Rasch model: sum of points of the common scale for all individual soil properties (raw score) and pasture soil fertility (measure). Only some sampling points are shown. In total there are 24 samples.

Sampling location number	Raw score	Measure
23	23	0.79
5	21	0.49
19	20	0.36
8	19	0.22
10	19	0.22
18	19	0.22
…	…	…
20	14	-0.51
13	13	-0.68
24	13	-0.68
11	10	-1.37
2	9	-1.71
4	8	-2.16

Unlike the other soil properties, K_2O and P_2O_5 had the highest measure and the lowest score. This denotes their low influence on the soil variability. Of course, both soil properties are essential for the pasture and, in fact, the low levels of both nutrients make necessary their increase with the aim of contributing to optimise the pasture soil fertility.

Table 2

Item fit statistics. Influence of each soil property on the pasture soil fertility in the experimental field (10 soil properties are considered). Total score, sum of points of the common scale for each soil property considering all samples (24); Measure, position of each soil property along the straight line that represents the latent variable, soil fertility potential; Infit and Outfit MNSQ, mean-square fit statistics to verify if items fit the model; Infit and Outfit ZSTD, standardized fit statistics to verify if items fit the model

Item	Total Score	Measure	Infit MNSQ	Infit ZSTD	Outfit MNSQ	Outfit ZSTD
P_2O_5	52	0.44	1.47	1.81	1.38	1.75
K_2O	55	0.30	1.02	0.32	1.07	0.32
CEC	65	-0.11	0.79	-0.79	0.76	-0.89
TN	66	-0.15	0.61	-2.73	0.65	-2.23
OM	68	-0.23	0.62	-2.02	0.73	-1.75
Clay	69	-0.26	1.39	1.67	1.43	1.69

Figure 4 shows the relative distribution of both sampling locations and soil properties in the same scale according to the pasture soil fertility. As mentioned above, K_2O and P_2O_5 were the properties with the highest measure, and their position is located more to the right in the straight line. The other soil properties are situated to the left, having lowest measures. CEC and TN are almost at the same position on the continuum. Although one of them could be dropped as redundant, they were maintained because they do not alter the fitting to the model. The relationships between the soil properties grouped to the left in the straight line, particularly between the clay content, OM and CEC, can explain this result (Moral et al., 2010).

The sampling locations distributed across the continuum are shown in Figure 4. Thus, a ranking of the sampling locations according to their Rasch measure was obtained. Those samples located to the left in the straight line had very low pasture soil fertility, but those located to the right correspond to sites where soil fertility was higher. Since all samples were georeferenced, those locations in which a higher pasture yield can be expected were visualised (Figure 5). Considering all sampling locations, the highest score was 23, less than the half of the possible maximum score

(60 points) and around 87% of all sampling locations reached less than 20 points. Moreover, the mean Rasch measure for the samples was more to the left that the mean Rasch measure for the soil properties, which indicates the existence of many locations where the soil fertility was not optimum. These are additional evidences about the low overall soil fertility of the experimental field. However, differences between zones are evident and, according to the potential for pasture yield, site-specific management could be conducted. Using the same method, important spatial variability was also found in other agricultural and pasture fields (Moral et al., 2019; Moral and Rebollo, 2017) and MZ were delineated.

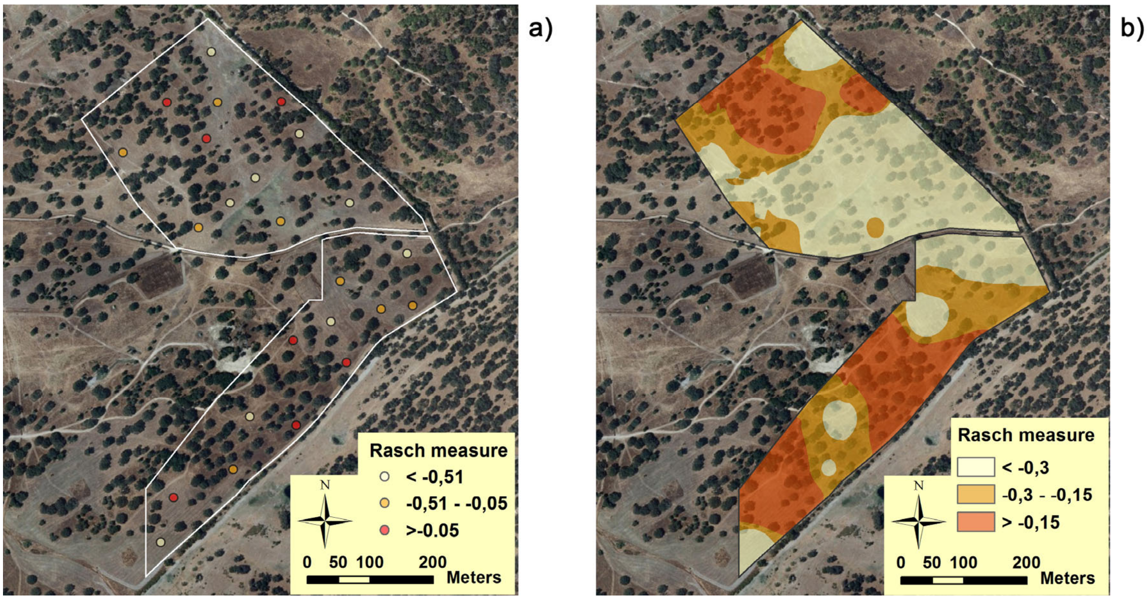

Fig. 5. a) Values of Rasch measures at each sampling location. b) Spatial distribution of the pasture soil fertility, as the Rasch measures. Classification is based on quantiles of the Rasch measures.

Delineation of homogeneous zones

The estimates of pasture soil fertility at any unsampled location were conducted using the RBF technique, considering the data from all measures at the sampling locations (Table 2) obtained after the formulation of the Rasch model. As was previously mentioned, the completely regularised spline function was chosen, computing estimated values across the experimental field. Finally, the spatial distribution of pasture soil fertility was visualised (Figure 5). Three zones were delineated according to a classification based on the corresponding quantiles. It is known how the presence of trees tends to improve soil properties, generating areas of higher soil quality where the levels of macro-nutrients and OM are higher (e.g., Serrano et al., 2017). Thus, in this case study, tree density was higher in the most fertile zone, 14,52 trees ha^{-1}, than in the intermediate, 13,72 trees ha^{-1} or less fertile zone, 9,21 trees ha^{-1} (Figure 5).

As was shown in previous studies (e.g., Moral et al., 2019), topographical variables can also be very important to explain the spatial variablity of pasture yield because they determine the level of some soil properties, such as textural components (Ceddia et al., 2009). In consequence, elevation and slope were considered and, from the digital elevation model, the slope map was derived (Figure 6). Then, the pasture soil fertily map and both the elevation and slope maps, were taken as inputs of the clustering analysis. After considering three zones, the MZ map was generated in ArcGIS (Figure 7). It is apparent that pasture soil fertility and MZ maps showed similar patterns due to the fact that there are no excessively steep areas and elevation differences in the field, so they have a limited effect on the definition of different zones. Thus, in this case study, pasture soil fertility map could be considered as the only layer to delineate the MZ. Although the zones are divided into separate parts, most of the areas are concentrated and can be easily treated. The small spots within each zone could be removed from a practical site-specific management perspective.

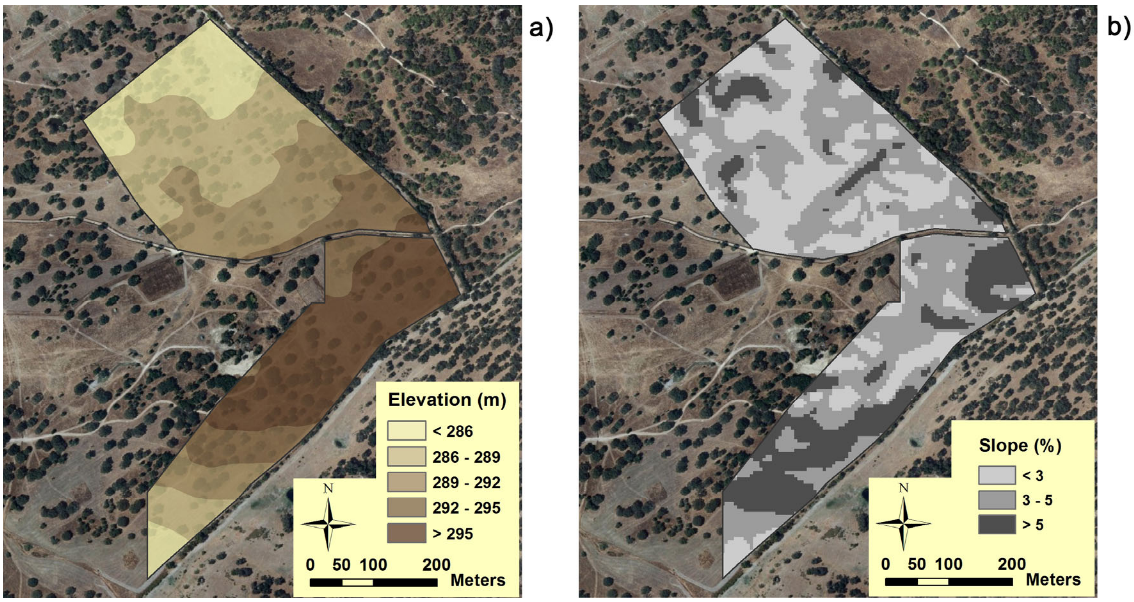

Fig. 6. a) Elevation map. b) Slope map.

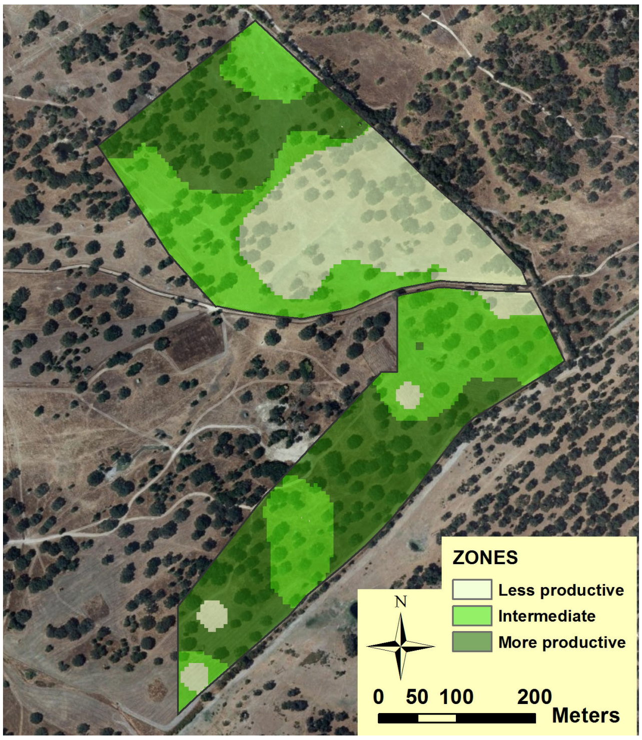

Fig.7. Management zones based on the pasture soil fertility, elevation and slope maps.

The proposed approach to delineate MZ are based on three simple steps: the integration of some soil properties at the sampling locations using the formulation of the Rasch model, the mapping of pasture soil fertility (Rasch measures) and other important variables (mainly related to topography), and, finally, the clustering process of all input surfaces to delineate MZ. One important advantage of the Rasch model is its capacity to generate results without defining weights or other constraints about the variables taken into account. Other approaches are based on analysis where some initial parameters have to be defined and the input layers are weighted (e.g., Mokarram and Hojati, 2017; Chen et al. 2013), which are usually more difficult to properly implement and require more initial information.

With the aim of verifying whether the MZ were significantly different, NDVI and NDWI data at each sampling location were utilised. The median values of both vegetation indices in each zone were very similar, as the Kruskal-Wallis non-parametric test and the Dunn test as a post hoc analysis showed (Table 3). Therefore, the spatial variability detected by optical sensors at vegetation level is not related to the spatial pattern of soil fertility. The use of vegetation indices is suitable to monitor pasture development status, that is pasture vegetative vigour: NDVI and NDWI reflect chlorophyll content and water content, respectively.

Table 3

Median values of the vegetation indices and pasture variables in each management zone (the less productive zone is Zone_less, the intermediate productive zone is Zone_medium, and the most productive zone is Zone_more). Within each column, different letters indicate significant differences ($P < 0.05$) according to the Dunn test.

	NDVI	NDWI	Green matter (kg ha^{-1})	Dry matter (kg ha^{-1})	Crude protein (%)	Neutral detergent fiber (%)
Zone_less	0.62 a	0.31 a	24677 a	3800 a	12.68 a	50.80 a
Zone_medium	0.65 a	0.33 a	25228 b	4114 b	11.46 b	50.23 a
Zone_more	0.64 a	0.33 a	25752 b	3962 b	11.95 b	53.23 b

When the pasture variables were analysed, differences in yield and quality were apparent, but only between the zones with higher and intermediate pasture soil fertility and the zone with lower soil fertility (Table 3). However, the proposed zoning was able to explain variations in some key soil properties which are related to soil fertility, such as clay content, OM or CEC (Table 4). In contrast with other similar studies (e.g., Moral et al., 2019) in which the sand content in the soil was not so high, the low values of ECa in the three MZ, around 2 mS m^{-1} (Table 4), made useless its consideration. Peralta and Costa (2013) suggested that the application of ECa for site-specific management might not be feasible due to its inconsistent relationship with other soil properties, as occurred in this study, besides the low values throughout the field. The low levels of some other important soil properties, such as P_2O_5 or TN, which are the main limitations of this soil, made that their differences between MZ were insignificant (Table 4). However, the low values of P_2O_5 in the most productive MZ reflected the higher extractions in these areas, highlighting the need to take into account the spatial variability in the field.

Table 4

Median values of soil properties in each management zone (the less productive zone is Zone_less, the intermediate productive zone is Zone_medium, and the most productive zone is Zone_more). Within each column, different letters indicate significant differences (P < 0.05) according to the Dunn test.

	Clay content (%)	TN (g kg^{-1})	P_2O_5 (mg kg^{-1})	K_2O (mg kg^{-1})	OM (%)	CEC (cmol kg^{-1})	ECa (mS m^{-1})
Zone_less	9.56 a	0.09 a	40.78 a	93.55 a	1.51 a	10.74 a	2.06 a
Zone_medium	10.47 b	0.07 a	26.28 b	77.43 b	1.24 b	8.49 b	2.52 a
Zone_more	11.26 c	0.10 a	28.96 b	109.02 c	1.65 c	12.84 c	2.34 a

Conclusions

The usual practice in pasture systems is to apply the same rate of fertiliser over the whole field, leading to incorrect applications of fertiliser at different places in the field and, in turn, involving economic, environmental and energy drawbacks. Site-specific management is a rational way to improve the fertiliser use efficiency by adjusting the fertiliser rates to the soil and pasture variability.

The delineation of MZ in pasture fields is the first stage to implement a site-specific management. Soil information is essential to calculate the requeriments throughout the field and, in this sense, the formulation of the Rasch model is an interesting tool to estimate a measure of pasture soil fertility, integrating different soil variables (in this study, clay content, OM, P_2O_5, K_2O, TN and CEC). Data reasonably fit the model and the considered soil properties have an important influence on the latent variable, pasture soil fertility. However, in sandy soils, clay content is the key soil property to determine soil fertility at any location, probably due to the close relationship between this textural class and other important soil properties, such as OM or CEC.

Besides soil pasture fertility, as the Rasch measure, topography has also to be considered because it could alter the level of the soil properties. However, due to the characteristics of the experimental field, after the clustering process considering both topography (elevation and slope) and soil pasture fertility, the spatial pattern of the MZ was similar to the distribution of the soil pasture fertility, that is, the influence of topography was not important.

The proposed approach constitutes an objective and logical technique to map soil spatial variability, making it possible to generate high spatial resolution maps, necessary for implementing site-specific soil management. Thus, variable-rate applications of inputs can be performed, and fertilisation can be decreased in less fertile and less productive areas; consequently, the application of chemical substances can be minimised with the aim of obtaining more cost-effective field management, besides environmental and energy benefits.

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FIGURE CAPTIONS

Fig. 1. Study site. Sampling locations are indicated as dots.

Fig. 2. Representation of the latent variable, pasture soil fertility, as a straight line. Bn is the location n; di is the soil property i. In the diagram 1, the location B_1 is not influenced by any soil property. In the diagram 2, the location B_2 is influenced by all soil properties. Diagram 3 shows a generalization for some locations and soil properties; B_3 is not influenced by any soil property; B_4 is influenced by the soil property d_9; B_5 is influenced by the soil properties d_9 and d_{10}; B6 is influenced by all soil properties, d_9, d_{10} and d_{11}.

Fig. 3. Schematic diagram of the stages involved in the formulation of the Rasch model.

Fig. 4. a) Straight line that represents the latent variable: pasture soil fertility. Distribution of soil samples (points) is above the line: to the right those more fertile; to the left less those less fertile. Soil properties are below the line: to the right less common (rare) properties, with lower influence on pasture soil fertility; to the left more common (frequent) properties, with higher influence on pasture soil fertility; ms and mp are the mean values of the Rasch measure for soil samples and properties, respectively. b) Final latent variable, after removing the soil properties that are redundant or do not fit the model (sand and silt content and EC).

Fig. 5. a) Values of Rasch measures at each sampling location. b) Spatial distribution of the pasture soil fertility, as the Rasch measures. Classification is based on quantiles of the Rasch measures.

Fig. 6. a) Elevation map. b) Slope map.

Fig.7. Management zones based on the pasture soil fertility, elevation and slope maps.