Estimating and mapping pasture soil fertility in a Portuguese montado based on a objective model and geostatistical techniques

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Abstract

Pasture soils can exhibit a high spatial variability which should be characterised to properly manage the yield potential of different within-field areas. Thus, with the aim of proposing an objective methodology to estimate the pasture soil fertility and, later, analyse its spatial pattern, the formulation of the probabilistic Rasch model constitutes a new approach in pasture fields.

In this research, a case study was perfomed to illustrate the proposed method. Consequently, after taking some soil samples (34) and measuring different soil properties (sand, silt, and clay content, organic matter, phosphorus, potassium, moisture content, soil apparent electrical conductivity, elevation, and slope), the use of the Rasch model provides a integrated measure of pasture soil fertility at each sampling location, which can be computed using geostatistical algorithms to map its spatial distribution throughout the field.

After verifying that data fit the model reasonably, the main outputs of the Rasch model were a

ranking of all sampling locations according to the pasture soil fertility and another ranking of the soil properties according to their influence on the soil fertility, being the topographical properties (slope and elevation) the most influential. Later, the ordinary kriging algorithm was utilised to estimate soil fertility throughout the pasture field and the probability kriging algorithm was used to provide information for hazard assessment of pasture soil fertility, being both kriged maps the basis to delineate homogeneos zones. Finally, vegetation indices and pasture yield data at sampling points were employed to check that two zones previously determined were different.

The analysis of zonal differences in pasture systems can lead to an optimal application of inputs and a more cost-effective management, with the associated environmental, economic, and energetic benefits.

Keywords: spatial pattern; Rasch model; kriging; management zones.

1. Introduction

Mediterranean evergreen oak woodlands, called montados in Portugal and dehesas in Spain, have a sparse tree cover, over native grassland (or a dryland grown pasture) that recurrently develops into a shrubland (Paço et al., 2009). In the Iberian Peninsula, they occupy an area of about 2–2.5 million ha (David et al., 2007), mainly located in areas of southern Portugal and Spain with a Mediterranean climate (Paço et al., 2009). These ecosystems, result of a long tradition of land use, are considered a sustainable system adapted to adverse environmental and soil conditions. They are subject to agrosylvopastoral exploitation in a strongly seasonal climate, and the long-term sustainability of these ecosystems may be further threatened by the regional effects of global warming (David et al., 2007), and by the human action (Paço et al., 2009).

Most of these woodlands are anthropogenic ecosystems of high socio-economic and conservation value, and display high biodiversity, however, they have declined sharply due to environmental constraints, forest diseases, inappropriate management, including both intensification and abandonment of agriculture, and socioeconomic issues (Godinho et al., 2016).

Knowledge of on-site and on-time information on soil properties and pasture biomass and its spatial distribution in pastoral ecosystems is needed for site-specific management and can help livestock managers in making critical decisions in terms of planning grazing time, grazing period, grazing interval, stocking rate, and inputs such as fertilizers (Safari et al., 2016; Moeckel et al., 2017). Regardless of the livestock production system, pasture quantity and quality may be limiting at certain times of the year, usually due to climatic influences. To maximise the efficiency of animal production in extensive grazing systems, it is important to know the availability of ground cover and whether livestock can effectively utilise and digest the available forage (Manning et al., 2017).

Traditional soil and crop sampling is based on low sample resolution data collected at typically one composite sample per 1–3 ha (Nawar et al., 2017). Conventional soil and plant sampling techniques are costly, destructive, and time-consuming, thereby limiting the number of measured samples and being impractical for characterising spatial variability in sward characteristics within fields (Safari et al., 2016; Moeckel et al., 2017). With current advancements in information technologies, remote and proximal sensing, and geospatial analyses supported by global positioning systems, it is increasingly possible to identify and analyse the temporal and spatial variability within fields to maximise the yield and protect the environment. New proximal sensors allow the collection of geographically referenced data with high spatial sampling resolution (>1500–2000 readings per ha), enabling the exploration of spatial variability at fine-scale to generate maps representing both spatial and temporal variability (Safari et al., 2016) and delineate accurate management zones (Nawar et al., 2017).

Pastures are highly heterogeneous systems due to variations in sward structure, composition, and phenology, as well as continuous changes caused by different drivers such as environmental factors and grazing. Therefore, the application of sensors in complex grazing systems is difficult and there are some limitations for each specific sensor used for the prediction of sward characteristics (Moeckel et al., 2017). The most common soil and crop attributes produced by proximal sensing are soil apparent electrical conductivity (ECa) and normalised difference vegetation index (NDVI), based on measurements using commercial sensors (Nawar et al., 2017). Optical remote sensing techniques have the potential to detect physiological and biochemical changes in plant ecosystems, and non-invasive detection of changes in photosynthetic energy conversion may be of great potential for managing agricultural production in a future bio-based economy. The content of chlorophyll is a good indicator of plant nutrition, photosynthesis, and growth conditions (Zhang et al., 2017). In this sense, NDVI constitutes a good indicator about photosynthetic activity of forage plants (Manning et al., 2017). Normalised difference red edge (NDRE) is an index that is computed when the red edge band is available in a sensor. It is sensitive not only to chlorophyll content in leaves and variability in leaf area, but also to soil background effects. High values of NDRE represent higher levels of leaf chlorophyll content than lower values. This index can be used to estimate the variability in fertilizer requirements in the soil (e.g., Magney et al., 2017).

Since it is known that soil fertility is the main factor that determine pasture yield and quality, the suitable management of this ecosystem requires the identification of areas with similar permanent characteristics. According to Serrano et al. (2010), the basis for grazing management is the measurement of the spatial variability of pasture soil and vegetation; in turn, the physical and chemical properties of the soil are one of the factors most affecting pasture biomass, so they must be taken into account to delimit homogeneous zones.

Although different techniques have been utilised to delineate homogeneous zones (e.g., Shaddad et al., 2016; Fortes et al., 2015) and to combine layers of information (e.g., Moral et al., 2010), they have been applied in agricultural fields. Similar research in pasture systems is scarce (Trotter et al., 2014), despite the same approaches can be useful in pasture soils. Moreover, the use of an objective and probabilistic model, the Rasch model (Rasch, 1980), to integrate data from different soil properties has been successfully applied in agricultural fields (Rebollo et al., 2017; Moral et al., 2011).

The objectives of this study were to: (1) analyse the use of the the Rasch model as a measurement tool to determine the pasture soil fertility, considering and integrating some important soil properties; (2) utilise the Rasch approach to investigate the influence of each soil property on the pasture soil fertility; and (3) generate homogeneous zones using geostatistical algorithms after analysing the spatial distribution of the pasture soil fertility.

2. Materials and methods

2.1. *Site description*

The experimental field was a farm called Silveira (38º 62.2’ N; 7º 94.8’ W), located about 5 km North of Evora, in Southern Portugal. The area of study is 7 ha approximately and an overview of the boundary of the site is given in Figure 1.

The climate of this area is Mediterranean, modified by the interior location and by oceanic influences from the Atlantic. Temperature ranges between 0ºC and more than 40°C, minimum in winter and maximum in summer, respectively. Mean annual precipitation reaches less than 600 mm, but it is characterised by its interannual variability. Precipitation occurs mainly between October and March and is practically nonexistent during the summer. According to the Köppen-Geiger classification, it is a climate type Csa (Peel et al., 2007).

The monthly precipitation and temperature between September 2012 and August 2013 is shown in Figure 2. Accumulated rainfall between March and May was 219 mm, higher than the average expected value, 186 mm. Particularly, March was very rainy, exceeding 3.7 times the expected rainfall (Serrano et al., 2017). The rainfall in these months are important for maintaining the growth of the pasture and lengthening its vegetative cycle, and, in June, the productivity and quality of the pasture is severely affected by the smaller rainfall and higher temperature (Serrano et al., 2017).

The topography is dominated by gentle hills on a slightly sloped area, with elevations between 273 and 282 m, and is crossed by a torrential water line. There are some sparse trees: olive trees, oak trees, ashes, and mulberries. In the substrate 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. Cambisols in undulating or hilly terrain are planted to a variety of annual and perennial crops or are used as grazing land.

2.2. *Soil and pasture sample collection and analysis*

Initially, a regular sampling grid of 34 m was defined in March 2013. Forty-three sampling points (Figure 1) were georeferenced using a real-time kinematic (RTK) GNSS instrument (Trimble RTK/PP-4700 GPS, manufactured by Trimble Navigation Limited, USA).

Soil spatial variability of the experimental field was characterised by 34 samples (Figure 1) collected in April 2013 using a gouge auger and a hammer, in a depth range of 0–0.30 m. The soil was characterised in terms of texture, organic matter (OM) content, phosphorus (P_2O_5), and potassium (K_2O). Each composite sample was the result of five sub-samples taken inside of an imaginary circle with a 3-m radius around each georeferenced point. The soil samples were kept in plastic bags, air-dried, and analysed for particle-size distribution using a sedimentographer (Sedigraph 5100, manufactured by Micrometritics, Norcross, GA 30093-2901, USA), after passing the fine components through a 2 mm sieve. These fine components were also analysed using the following methods (Egner et al., 1960): (i) OM was measured by combustion and CO_2 measurement, using an infrared detection cell; P_2O_5 and K_2O were extracted by the Egner-Riehm method, and (ii) P_2O_5 was measured using colorimetric method, while (iii) K_2O content was measured with a flame photometer.

In April and June 2013, at each sampling point (Figure 1), a pasture sample was taken using a portable electric grass shear at 1-2 cm above ground level. The pasture of each 0.25 m^2 area delimited by a metallic rim were stored in marked plastic bags and weighed to determine the green matter production per hectare (kg ha^{-1}). The samples were placed in an oven at 65ºC for 48 hours to determine the moisture content, which was used to calculate dry matter yield (DM, kg ha^{-1}).

2.3. *Soil apparent electrical conductivity survey*

A Dualem 1S non-contact sensor (Dualem, Inc., Milton, ON, Canada), equipped with a global positioning system (GPS) antenna, was used to measure the soil apparent electrical conductivity (ECa) in all sampling points of the experimental field in April 2013. The sensor, manually transported by an operator 0.20 m above ground surface, measured the ECa from 0-0.30 m and 0-1.30 m soil layers along an imaginary circle with a 3-m radius around each georeferenced sampling point (Figure 1). This work uses the data referent to the soil layer to 0.30 m depth, corresponding to soil sampling depth. The ECa sensor was programmed to register measurements every second. Average ECa at each sampling point was obtained using the values registered from a 2-min sampling measurements.

On the same day, soil samples for soil moisture content (SMC) determination were taken with a gouge auger and a hammer in a depth range of 0-0.30m. To calculate the SMC, these soil samples were weighed, dried at 70°C for 48h, and then weighed again.

2.4. *NDVI and NDRE survey*

It was utilised a OptRx active crop sensors (Ag Leader, 2202 South River Side Drive, Ames, IOWA 50010, USA) with its associated power source. The OptRx crop sensors measurements were registered and point positioned by means of a Trimble GNSS GeoExplorer 6000 series, model 88951 with sub-meter precision (Trimble: GmbH, Am Prime Parc 11, 65479 Raunheim, Germany). This sensor simultaneously measures three infrared bands: (i) RED- 670 nm with a range of 20 nm; (ii) Red Edge- 728 nm with a range of 16 nm; and (iii) NIR- 775 nm with basically everything under 750 nm being filtered out. NDVI and NDRE were calculated based on these spectral bands as:

NDVI = (NIR – RED)/(NIR + RED) (1)

NDRE = (NIR – RED EDGE)/(NIR + RED EDGE) (2)

Multispectral information was collected before cutting the pasture in all sampling points (Figure 1), four times during Spring of 2015 (between March and May). The OptRx crop sensor was manually transported by an operator 0.75 m above ground surface (about 0.50 m above the pasture, considering an average pasture height of 0.25 m), along an imaginary circle with a 3-m radius around each geo-referenced point and then stood still at the area within the circle previously defined as being representative of the vegetation. Average NDVI and NDRE of each point were obtained using the values registered from 2-min sampling measurements.

2.5. *The Rasch model*

One of the simplest and powerful Item Response Theory model for measurement is the probabilistic Rasch model. It constitutes the most viable approach for practical testing, as it can be applied in the context in which individual, soil samples in this case, interacts with items, soil properties.

Different data, with different units, can be integrated into a uniform analytical framework. The Rasch model has only one measurement parameter, in a single dimension and scale to measure the classification of both the subjects, soil samples, and the considered items, soil properties. All data are synthesised by means of a commom adimensional referent, defining the construct or latent variable. Thus, 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 (latent variable).

With the aim of achieving an adimensional characterization, the first phase in the formulation of the Rasch model is the categorisation of data, corresponding to the individual soil properties at each location. Particularly, five categories were considered for all soil properties and, in consequence, a measure assigned to class 1 corresponds to the lowest contribution to pasture soil fertility and, on the contrary, the assignment of a measure to class 5 corresponds to the highest contribution to pasture soil fertility. As it was performed in previous studies in agricultural fields (e.g., Moral and Rebollo, 2017), for soil texture properties, the ideal percentage of each texture class was about a third of the total; in consequence, the maximum categorical value, 5, was assigned for an interval around 33% of clay, silt or sand content. For the other soil properties, the highest categorical values correspond to the classes with highest measures. The rest of categories were associated with classes in which their amplitude depends on the maximum and minimum values of each soil property. All data are arranged in a matrix in which each cell, X_{ij}, reflects the category for the soil property i (i varies from 1 to 10) at the sampling location j (j varies from 1 to 34).

One simple assumption of the Rasch model is that some items, soil properties in this case, are more important to subjects, sampling locations in this case, than other items. The sum of item ratings is the starting point for estimating response probabilities and, consequently, a line of measurement is generated with items placed hierarchically according to their importance to subjects. To estimate soil property and sample location positions, this approach was formally implemented in a Rasch model for rating scales (Andrich, 1988).

A stochastic Guttman model is applied to convert scale observations into linear measures with the aim of generating the Rasch measurement. Linear statitics can be applied to these measures and some tests for goodness-of-fit can be used to validate the correct formulation of the Rasch model. In this case study, the Rasch model combines calibrations of some soil properties additively to sampling location measures to define pasture soil fertility probabilities. This stochastic conjoint additivity determines a Guttman scale of probabilities to which the data are fitted (Rasch, 1980).

Chi-square fit statistics, known as Infit and Outfit Mean-Square (Infit and Outfit MNSQ), ratios of observed residual variance to expected residual variance, should be computed to estimate how well each item contributes to the measurement of pasture soil fertility. According to Bond and Fox (2007), items with Infit and Outfit MNSQ values between 0.6 and 1.5 are accepted, taking into account that their expectation is 1.

The Rasch model was formulated with the Winsteps v. 4.0 computer program (Linacre, 2009), allowing to obtain values of the pasture soil fertility for all sample points, incorporating information of the soil properties considered. The different contribution of the 10 soil properties to determine a measure of pasture soil fertility at each sample point was achieved through the stages shown in Figure 3. Consequently, considering the sampling locations (34 in this case study) and choosing the soil properties (10 in this case study) which exert influence on the latent variable, pasture soil fertility, values of all soil properties at each sampling location were computed and, later, this information was processed with the previously mentioned software to obtain the Rasch measures, as well as some fit measures. More information about the mathematical formulation of the Rasch model can be obtained, for instance, in Tristán (2002).

2.6. *Estimates at unsampled locations*

Values of the pasture soil fertility, expressed as the Rasch measure, for all locations in which a soil sample was taken, were obtained with the formulation of the Rasch model, considering information from 10 soil properties. However, since the spatial distribution of the soil fertility has to be determined, it was necessary to estimate the value of this latent variable throughout the field, that is, at other locations where no direct measurements were conducted.

There are many algorithms to interpolate from known data but it is widely recognised the advantages of using geostatistical tecniques (e.g., Webster and Oliver, 2007), as they take into account the spatial variation of the studied variable, pasture soil fertility in this case.

Usually, semivariograms quantify the spatial correlation of the variable, being estimated, for discrete sampling, as:

$$\gamma(h) = \frac{1}{2\,N(h)} \sum_{i=1}^{N(h)} \{Z(x_i) - Z(x_i + h)\}^2 \tag{3}$$

where $\gamma(h)$ is the semivariance value at distance h, $Z(x_i)$ are the sample values at points x_i, with data at x_i and x_i+h, and N(h) is the total number of sample pairs within the distance h.

After computing the experimental semivariogram, that is, some points of a plot are displayed by calculating semivariogram values at different lags, a model (known as theoretical semivariogram) is fitted to the points.

The basis of all geostatistical estimators is the linear regression estimator Z*(x):

$$Z^*(x) - m(x) = \sum_{i=1}^{n} w_i(x) \cdot [Z(x_i) - m(x_i)] \quad (4)$$

where each datum, $Z(x_i)$, has a weight, $w_i(x)$, and m(x) and $m(x_i)$ are the expected values of Z*(x) and $Z(x_i)$ respectively, determining the weights to minimise the estimation variance, Var[Z*(x) – Z(x)], while ensuring the unbiasedness of the estimator, E[Z*(x) – Z(x)] = 0. The weights are generated solving a system of linear equations, with the theoretical semivariogram controling the spatial variability of the variable (e.g., Webster and Oliver, 2007).

The model for the trend, m(x), of the random function, Z(x), differentiates the chosen geostatistical approach. The ordinary kriging algorithm was selected in this study; in consequence, it is assumed that m(x) is unknown but maintains the stationarity within local neighbourhoods. The extension Geostatistical Analyst of ArcGIS (version 10.3, ESRI Inc, Redlands, California, USA) was utilised to perform the geostatistical study and maps of kriged estimates were generated with the ArcMap module of ArcGIS.

2.7. *Delineation of homogeneous zones*

Kriged maps from the estimated values show the spatial pattern of the pasture soil fertility in the field. Later, homogeneous zones can be delimited using a classification technique in ArcGIS. From a practical perspective, few homogeneous zones should be delineated. Thus, two different zones were characterised in the experimental field and the mean value of the pasture soil fertility was considered as the limit value.

With the aim of evaluating the proposed delimitation, the differences on the mean values for DM yield, NDVI, and NDRE in both zones were analysed using a means comparison with t-test for independent samples in the IBM SPSS statistical package (version 24, IBM Corp, Armonk, NY, USA).

3. Results and discussion

3.1. *Data response to the Rasch model*

The matrix of categorical values was processed by the Winsteps program and the output was many results in tables and diagrams. Firstly, the Infit and Outfit statistics were analysed and, according to the Infit and Outfit MNSQ values (Table 1), which are close to one (the expected value), there is an initial evidence of the overall fitting between the data and the model. Furthermore, the mean standardized (ZSTD) Infit and Outfit (the sum of squares standardized residuals given as a Z-statistics) are expected to be 0 (Edwards and Alcock, 2010). Since they are very close to this value for both sampling locations and soil properties (Table 1), the data fit the model better than expected. Additionally, misfits for samples and soil properties are unimportant because the standard deviations of the Infit MNSQ, are lower than 2 (Bode and Wright, 1999), as it is shown in Table 1.

It is also necessary to check how the assigment sale was used. Table 2 shows the parameters that have to be verify (Linacre, 2009): the "Observed Average" and the "Structure Calibration" increase by category value, the Infit and Outfit MNSQ values are between 0.6 and 1.5, and the "Observed Average" values are similar to the "Sample Expected" ones. The probability curves (Figure 4), which represent the likelihood of category selection against the Rasch measure, also confirm the correct selection of five categories because each category value is the most likely at some point on the continuum and there is not category inversions, that is, a higher category is more likely at a higher point than a lower category. For example, if the Rasch measures are -1 and 1, the most likely category assignments are 2 and 4 repectively. There is no a general rule to define the correct number of categories, although five has been successfully utilised in other case studies (e.g., Moral and Rebollo, 2017).

Finally, the last previous analysis consists in examining if each soil property fits the general pattern of the model and contributes to support the underlying latent variable, pasture soil fertility. Acceptable fit of each item implies that the Infit and Outfit MNSQ have to be between 0.6 and 1.5, and the infit and outfit ZSTD between -3 and 2. Table 3 shows how all values are in the intervals, except K_2O. Consequently, all considered soil properties have an important influence and support the latent variable, pasture soil fertility, with the exception of K_2O. This soil property could be removed without affecting the results.

3.2. *Analysis of the Rasch measure: pasture soil fertility*

The sum of points of all categories for each soil property (raw score) and the measure value computed with the Winsteps program are shown in measure order in Table 3, from the higher to the lower measure, that is, from the location with a higher to the lower pasture soil fertility.

The relative influence of each soil property on the pasture soil fertility is also established according to the raw score and, consequently, the measure value. Table 3 shows that the highest raw score, and the lowest measure, corresponds to slope, being the most influential property on the pasture soil fertility in the field. Elevation is the next most influencial. Thus, topographical variables are the most important to explain the soil fertility in this case study, possibly due to the fact that they determine the level of other soil properties, such as the textural components (e.g., Collins and Foster, 2008; Ceddia et al., 2009). Unlike elevation and slope, P2O5 has the lowest raw score and the highest measure, that is, it exerts the lowest influence on the soil fertility in this field. Silt, sand, clay content, and OM have also a low influence on the latent variable. Textural components are not important in this soil to define the most fertile zones since the high sand content determines that the finer soil fractions, particularly clay, are very low to be related to other basic soil properties, from a pasture soil fertility perspective. Previous research in different agricultural fields where clay content is higher has shown its influence on the soil fertility (e.g., Moral and Rebollo, 2017; Rebollo et al., 2017).

The previous information is also displayed in graphic format, visualising both sampling locations and soil properties (in the upper and lower half of the diagram, respectively) in the same scale, classified according to the pasture soil fertility (Figure 5). As it was aforementioned, P_2O_5 is the property with the highest measure, more to the right in the straight line. On the contrary, slope and elevation are situated more to the left, with the lowest measures. As SMC and K_2O are at the same position in the straight line, it could be possible to consider dropping one of them as redundant, and, in this case, K_2O is the property to be removed because, as it was previously indicated, it does not support the latent variable (see Table 4).

Figure 5 shows how some soil samples are aggregated and most of them have very low score, indicating a low pasture soil fertility. A ranking of the sampling locations according to their Rasch measure was obtained, indicating where the most fertile places for pasture are located and, consequently, those which got lower measure, less fertile, are also determined. Only 5 samples reached half of the maximum score (50 points), that is, around 15% of all sample locations. Additionally, the mean Rasch measure for samples is more to the left than the mean Rasch measure for soil properties, indicating that pasture soil fertility is not optimum at many locations. Although globally this field is not very fertile, there are differences between zones and site-specific management could be performed according to particular soil conditions related to potential for pasture yield. Therefore, the most suitable conditions of pasture soil fertility can be expected in areas where soil samples have achieved higher measure. Similar spatial differences have been highlighted in agricultural fields (e.g., Moral and Rebollo, 2017) in which the more suitable zones for crops were selected using the same approach.

Another evidence of the good agreement between the data and the model is the fact that there are few misfits (soil samples which do not follow the general pattern of the model). Table 4 shows the soil samples that displayed misfit at least in one soil property. Seven samples displayed misfits and only one (sample 11, Table 4) had two misfits, for K_2O and P_2O_5, with positive residuals in both cases, that is, the score for this sample related to these soil properties is higher than expected. Other samples have misfists only for K_2O, but two of them (samples 8 and 20, Table 4) with positive residuals and another one (sample 31, Table 4) with negative residual (the score for this sample related to this soil properties is lower than expected). There are two soil samples (samples 5 and 27, Table 4 in which misfits for P_2O_5 are evident, with positive residuals. Finally, sample 32 (Table 4) has a negative residual in elevation. The main deficiencies of any soil location, which could affect pasture soil fertility, can be analysed by the misfit study and this information can be visualised in a geographical information system. If it is convenient, any work to amend both soil properties could be performed in these particular zones.

3.3. *Spatial analysis and mapping of pasture soil fertility*

The initial exploratory analysis of the Rasch measures at sampling locations revealed the similarity of the mean (-1.61) and median (-1.73). Moreover, the coefficient of skewness and kurtosis are 0.92 and 3.62, respectively, suggesting that data fit a normal distribution. The coefficient of variatios is 45.68%; in consequence, it is expected a high spatial variability of the pasture soil fertility in the experimental field.

An omnidirectional experimental variogram was computed and a spherical theoretical variogram (range = 71.35 m; sill = 0.59; nugget effect = 0.03) was fitted to its points. The ratio of nugget to sill is 5.09%, indicating the existence of a strong spatial dependence since it is lower than 25% (Cambardella et al., 1994).

The ordinary kriging algorithm was chosen to estimate at unsampled locations. Thus, the spatial distribution of pasture soil fertility in the experimental field can be visualised. Figure 6 shows two zones which were delineated from the mean value of the pasture soil fertility (Rasch measure), -1.61. They can be regarded as the lower and higher soil fertility areas in the experimental field. The reliability of the kriged map was assessed by means of a cross-validation process, estimating the variability of the predictions from the true values. Some prediction error statistics (Webster and Oliver, 2007) were used as diagnostics: the root mean square error was 0.66, the mean standard error was 0.69, the mean standardized error was -0.02, and the the root mean squared standardized error was 0.96. Since all these statistics are very low and the root mean square error is close to the mean standard error, the kriged map is appropriate. Moreover, the assessment of uncertainty was completed with some additional information: since the mean standard error is close to the root mean squared prediction error and the root mean squared standardized error is close to one, the variability in predictions is correctly assessed.

It is also possible to use the probability kriging algorithm to generate a map in which two zones are determined. Thus, considering the mean value (-1.61), the probability map of pasture soil fertility higher than this value is delineated. In this map, probabilities provide a measurement of confidence for hazard assessment of pasture soil fertility. Figure 6 shows the map with zones above and below 0.75 as the probability value threshold, that is, more and less fertile zones, respectively.

NDVI and NDRE data at sampling locations (Figure 6) were utilised to analyse differences between the two zones. When the zone with higher pasture soil fertility was considered, the mean NDVI and NDRE were 0.55 and 0.20, respectively. These values in the zone with lower pasture soil fertility were 0.52, for NDVI, and 0.18, for NDRE, that is, 5.4% and 10% lower, respectively. Although differences between both zones are moderate, they are sufficient to manage them according to the expected pasture yield. Particularly, this is important in fields like the one considered in the present case study, where in general soil properties have inappropriate levels to reach an optimum soil fertility but zonal differences are apparent. This fact was highlighted after comparing the pasture yield in both zones. The mean DM yield in the zone with higher pasture soil fertility was 1641.83 kg ha^{-1} and in the zone with lower soil fertility was 1370.42 kg ha^{-1}, that is, around 16.5% lower. Additional means comparison with t-test showed that mean values for DM yield, NDVI, and NDRE in both zones were statistically significant under a confidence level of 99%.

Table 5 shows the mean values of the soil properties in both zones of the field. Significant differences were also obtained, with better levels of all soil properties in the zone where the pasture soil fertility is higher. This is in accordance with the NDVI and NDRE values measured and, accordingly, with the DM yield differences.

4. Conclusions

The formulation of a probabilistic and objective model (the Rasch model) to estimate a measure of pasture soil fertility, integrating different soil variables (texture, SMC, OM, phosphorus, potassium, ECa, elevation, and slope), has been successful. Data reasonably fit the model and, in general, the considered soil properties have an important influence on the latent variable, pasture soil fertility.

A classification of all soil samples according to their soil fertility level was obtained and, moreover, it was analysed the influence of the soil variables on the pasture soil fertility in the experimental field, obtaining how topographical variables, elevation and slope, are the most determining in this particular field.

The use of geostatistical algorithms to interpolate at unsampled locations can provide an accurate representation of the spatial distribution of the pasture soil fertility, which can be utilised to delineate homogeneous zones in the field. This is very important in pasture fields like the one considered in the present case study, where pasture soil fertility has a general low level but zonal differences are apparent.

Although initially the combination of the Rasch model and geostatistical techniques had been proposed in agricultural fields as a tool to developing an objective strategy to define management zones, it can also be used in pasture systems to analyse zonal differences. Thus, application of inputs can be optimised and a more cost-effective field management, with the associated environmental, economic, and energetic benefits, can be achieved.

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FIGURE CAPTIONS

Fig. 1. Study site. Sampling locations are indicated as black squares and locations in which soil samples were taken are indicated as black dots.

Fig. 2. Monthly rainfall and monthly mean temperature between September 2012 and August 2013.

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

Fig. 4. Probability curves for the five categories considered in the case study.

Fig. 5. 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.

Fig.6. a) Homogeneous zones map based on the kriged map of pasture soil fertility. Both zones are delineated considering the mean Rasch measure (-1.61) as the limit value. Dark zone is the more fertile and light zone is the less fertile. b) Homogeneous zones map based on the probability map of pasture soil fertility higher than -1.61. Dark zone could be considered as very fertile (probability to exceed -1.61 is higher than 0.75).

In both maps, black dots are the locations in which soil samples were taken and black squares are the locations in which pasture samples were taken and NDVI and NDRE were measured.

TABLES

Table 1

Overall model fit information; summary of all 34 soil samples and all 10 soil properties. Total Score, sum of points of the common scale considering all soil properties; Measure, logit position of the soil properties 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

	Total Score	Measure	Infit MNSQ		Outfit MNSQ	
Mean	20	-1.61	0.95	0.1	0.95	0.1
Standard Deviation	4	0.74	0.36	0.7	0.49	0.7
Maximum	33	0.52	1.82	1.5	2.88	2.1
Minimum	15	-2.79	0.39	-1.4	0.39	-1.2
Summary soil samples						
Mean	215.5	0.00	0.99	-0.2	0.99	-0.1
Standard Deviation	33.2	0.61	0.23	1.5	0.25	1.6
Maximum	262.0	0.96	1.36	2.0	1.40	2.2
Minimum	164.0	-0.85	0.56	-3.3	0.56	-3.2
Summary soil properties						

Table 2

Response scale use. Observed Count, number of times the category was selected considering all samples and soil properties; Observed Average, mean value of logit positions modelled in the category; Sample Expected, optimum values of the average logit positions for the data; Infit and Outfit MNSQ, mean-square fit statistics to verify if items fit the model; Structure Calibration, logit calibrated difficulty of the step representing the transition points between one category and the next

Category	Observed Count	Observed Average	Sample Expected	Infit MNSQ	Outfit MNSQ	Structure Calibration
1	153	-2.66	-2.68	1.00	1.01	None
2	99	-1.72	-1.63	0.96	1.02	-1.70
3	42	-0.42	-0.59	0.93	0.77	-0.27
4	27	0.72	0.63	1.03	1.04	0.46
5	19	1.54	1.68	0.95	0.92	1.52

Table 3

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 (34); 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	38	2.44	1.01	0.2	1.10	0.4
Silt	44	1.37	0.73	-0.7	0.73	-0.6
Sand	49	0.86	0.59	-1.5	0.68	-1.0
OM	51	0.69	0.67	-1.2	0.64	-1.3
Clay	59	0.15	0.63	-1.5	0.68	-1.3
SMC	65	-0.18	0.82	-0.7	0.77	-0.9
K_2O	66	-0.23	1.71	2.5	1.68	2.3
ECa	70	-0.43	1.54	2.0	1.52	1.9
Elevation	95	-1.42	0.81	-0.8	0.86	-0.6
Slope	143	-3.25	0.80	-0.8	0.87	-0.4
Mean	68	0.00	0.93	-0.3	0.95	-0.1
S.D.	29.3	1.48	0.37	1.3	0.35	1.2

Table 4

Misfits for those soil samples in which they have been computed. The score indicates the points for each soil property. Positive and negative misfits are indicated by the sign

	K_2O	P_2O_5	Elevation	Sample
Score:	3	2		11
Misfit:	2	4		
Score:	3			8
Misfit:	3			
Score:	4			20
Misfit:	2			
Score:	1			31
Misfit:	-2			
Score:		2		5
Misfit:		2		
Score:		2		27
Misfit:		2		
Score:			3	32
Misfit:			-2	

Table 5

Mean values of each soil property for samples in the less productive zone (Zone_less) and the most productive zone (Zone_more) according to the delineation of the homogeneous zones. Differences are significant for a 99% confidence level

	Sand (%)	Clay (%)	Silt (%)	OM (%)	EC (mS/m)	SMC (%)	K_2O (mg kg^{-1})	P_2O_5 (mg kg-^{1})	Elevation (m)	Slope (%)
Zone_less	70.06	16.01	13.91	1.29	2.96	10.20	88.54	18.18	275.85	1.67
Zone_more	64.38	19.55	16.09	1.68	8.42	16.07	98.17	24.67	274.98	1.28

FIGURES

Fig. 1

Fig. 2

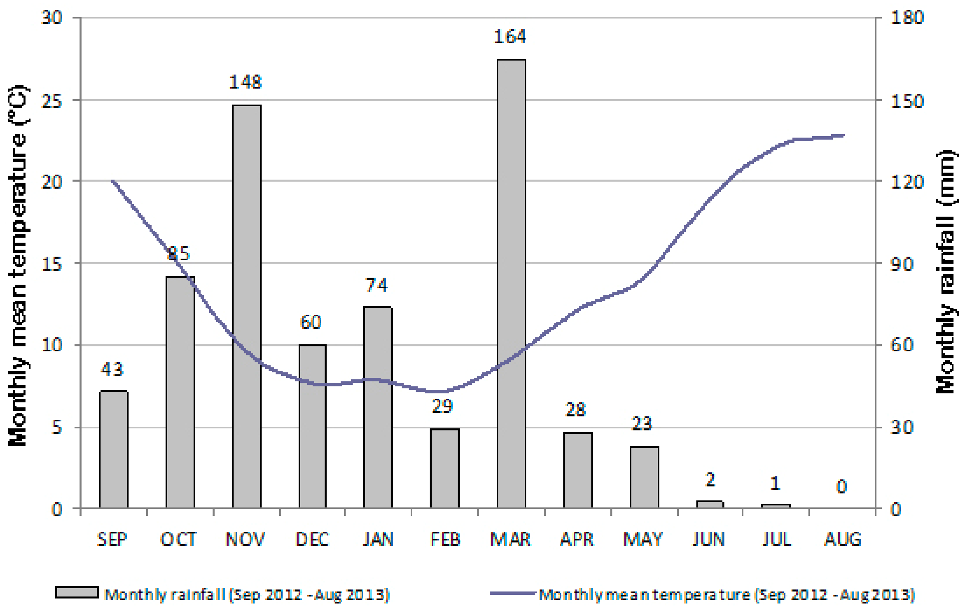


Fig. 3

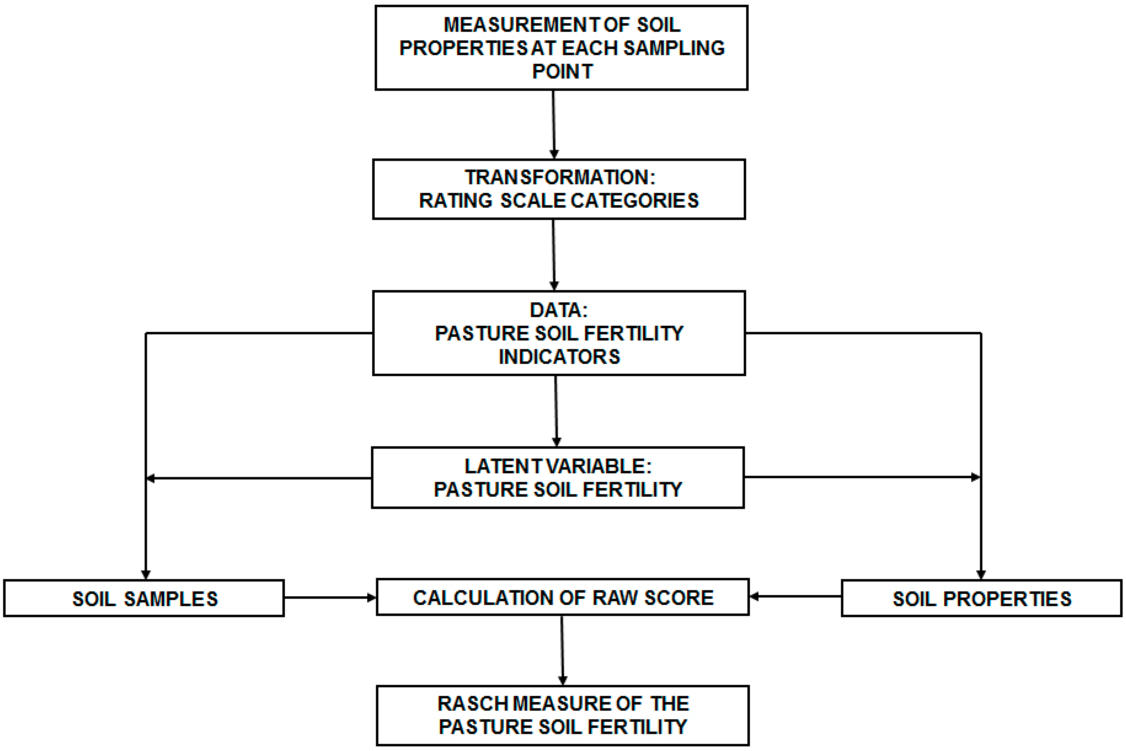
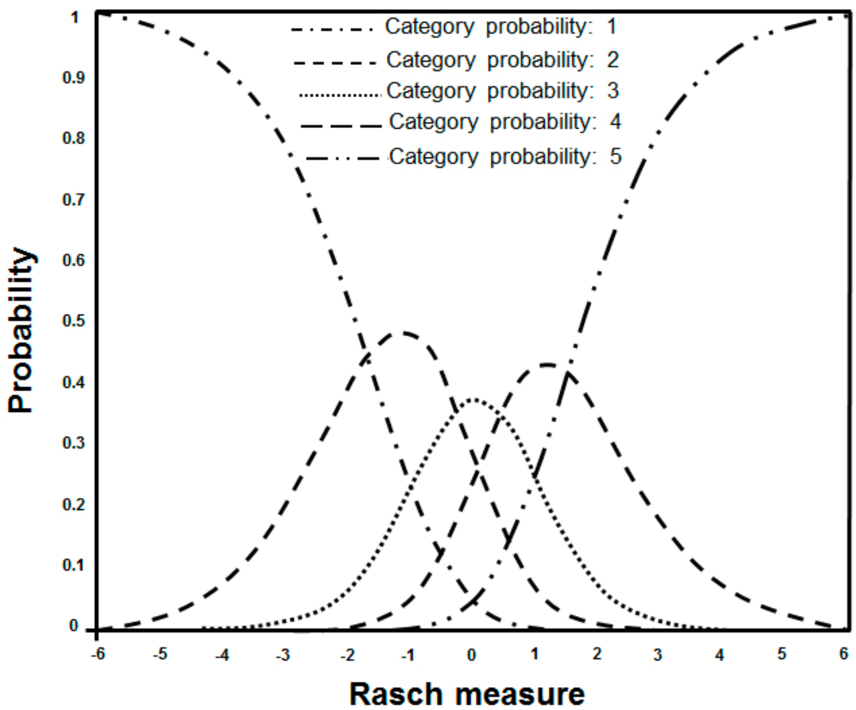

MEASUREMENT OF SOIL PROPERTIES AT EACH SAMPLING POINT
TRANSFORMATION: RATING SCALE CATEGORIES
DATA: PASTURE SOIL FERTILITY INDICATORS
LATENT VARIABLE: PASTURE SOIL FERTILITY
SOIL SAMPLES
CALCULATION OF RAW SCORE
SOIL PROPERTIES
RASCH MEASURE OF THE PASTURE SOIL FERTILITY

Fig. 4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Category probability: 2
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Category probability: 4
Category probability: 5
Probability
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0.9
0.8
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-3
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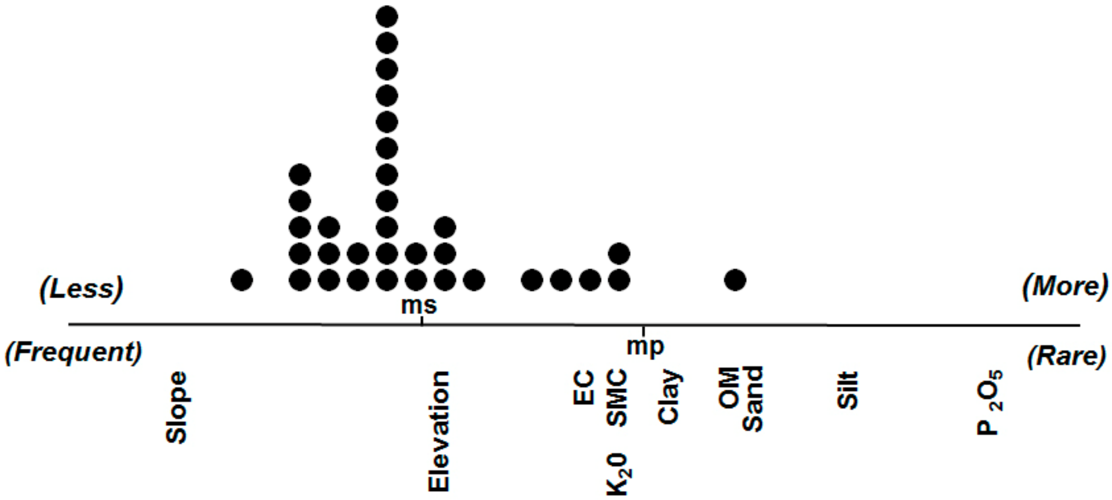
Rasch measure

Fig. 5


(Less)
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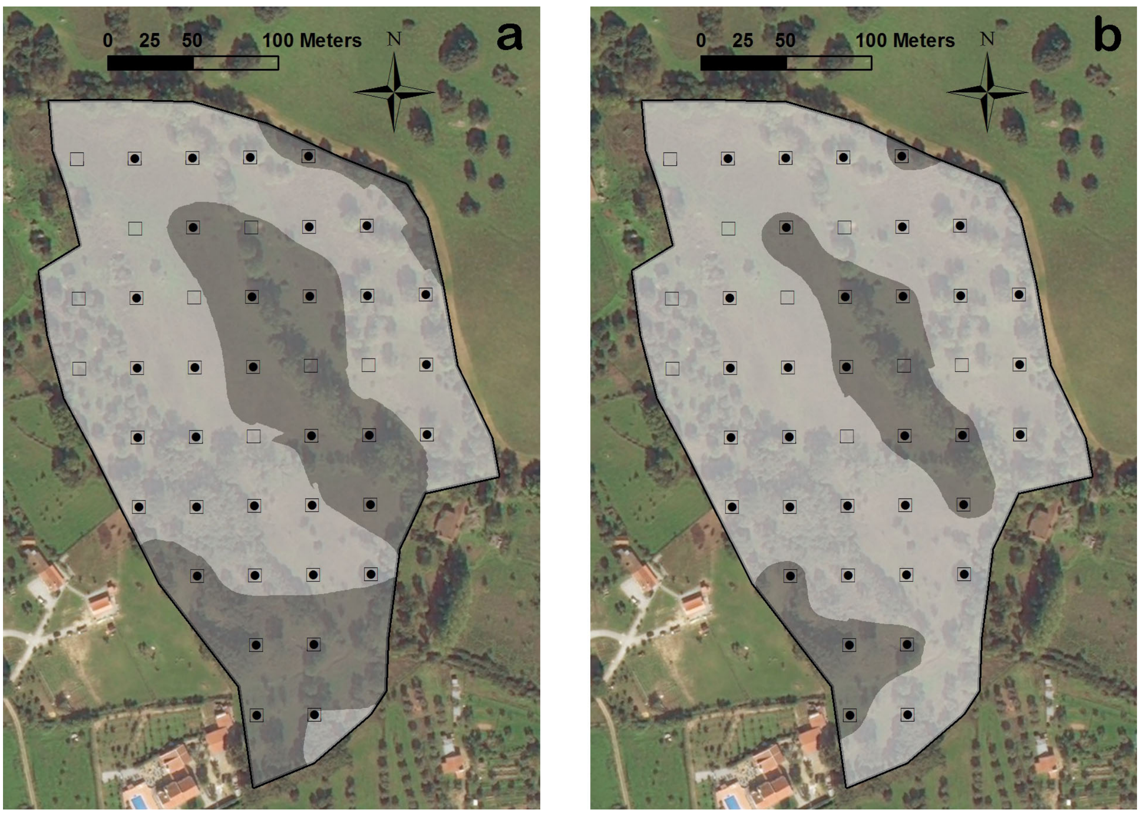
P_2O_5

Fig. 6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