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Management Zones in Pastures Based on Soil Apparent Electrical Conductivity and Altitude: NDVI, Soil and Biomass Sampling Validation

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Abstract: The intensification of the Montado mixed ecosystem (agro–silvo–pastoral) is a current endeavor in the context of promoting the sustainability of extensive livestock production in the Mediterranean region. Increased pasture productivity and extensive animal production involves the use of technologies to monitor spatial variability and to implement differentiated management of pasture grazing, fertilization or soil amendment. An intermediate step should lead to the identification and demarcation of areas with similar characteristics (soil and/or crop development), known as homogeneous management zones (HMZ) to implement site-specific management strategies. In this study, soil apparent electrical conductivity (EC_a) and altimetry surveys were carried out in six experimental pasture fields with a non-contact electromagnetic induction sensor (EM38) associated with a Global Navigation Satellite System (GNSS) receiver. These EC_a and topographic maps were used in geostatistical analyses for designing and establishing final classification maps with three HMZ (less, intermediate and more potential). The normalized difference vegetation index (NDVI), obtained from a proximal optical sensor, and soil and biomass sampling were used to validate these HMZ. From a practical perspective, these HMZ are the basis for preparation of fertilizer prescription maps and use of variable rate technology (VRT) in a *Precision Agriculture* project.

Keywords: montado ecosystem; sensors; EM38; active optical sensor; site-specific management

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Citation: Serrano, J.; Shahidian, S.; Paixão, L.; Marques da Silva, J.; Moral, F. Management Zones in Pastures Based on Soil Apparent Electrical Conductivity and Altitude: NDVI, Soil and Biomass Sampling Validation. *Agronomy* **2022**, *12*, 778. https://doi.org/10.3390/agronomy12040778

Academic Editors: Adriana Correa, María Dolores Gómez-López and Jesús Montero Martínez

Received: 14 February 2022
Accepted: 22 March 2022
Published: 23 March 2022

1. Introduction

Over the last decades, the world has witnessed increasing economic and environmental pressures on farmers. The increasing demand for food to feed a growing world population puts an enormous pressure on agricultural production [1]. At the same time, there is a trend for new environmental challenges, thereby increasing the need for environmental conservation practices [1]. The scientific community is responding to these challenges by developing sustainable ways to improve the efficiency of agricultural inputs, in order to maximize production and at the same time minimize environmental impacts [2].

Agro-forestry systems under semi-arid Mediterranean conditions, called Montado in Portugal and Dehesa in Spain, are mixed systems of trees (mainly *Quercus suber* and *Quercus ilex* species) with natural biodiverse pastures (grasses, legumes and other species) and scattered shrubs, and are grazed by animals, which has been proposed as a means for extending the benefits from forest to farmed land [3]. The understory vegetation of shrubs and pastures are the principal source of animal feed in extensive production systems [4]. Soil fertility is the main factor that determines pasture yield and quality [2,5]. Usually, due to intense erosion, the soils of these areas are degraded, shallow, acidic and stony and have low fertility (with low nutrient and organic matter content) while some soil properties exhibit a high spatial variability [2,5]. High spatial variability in soils is due to many physical, biological and chemical processes interacting simultaneously with different intensities [3,6]. Consequently, logical application of fertilizers or soil amendments should be based on an appropriate knowledge of the spatial variability of the main soil properties that can affect pasture yield and quality [7]. Therefore, assessing variability is the first critical step and a necessary condition for implementing strategies for management of this variability in the context of *Precision Agriculture* (PA) [8].

The most suitable and effective management strategy for intensifying and improving the economic feasibility of this silvo–pastoral ecosystem, with an associated increase in pasture productivity and, consequently, in extensive animal production, requires, as intermediate step involving the mapping of the spatial and temporal patterns of the main soil properties and determination of crop response [9], leading to the identification and demarcation of areas with similar characteristics (soil and/or crop development) [10]. These sub-regions of a field with similar soil fertility and production potential [10], with relatively homogeneous combination of yield-limiting factors, soil-landscape attributes [2] known as homogeneous management zones (HMZ) [6,9], can be used as a baseline for most farming decisions [2]. These decisions allow the implementation of site-specific management strategies [11,12], which culminate in the differential application of production factors, namely of fertilizers using variable rate technology (VRT) [9].

The delineation of HMZ requires collecting and analyzing data throughout the field, which involves the use of new technologies to monitor spatial variability [13]. Several approaches have been proposed to delineate HMZ at the field level. Data can be generated from a single data layer [2], the traditional soil sampling of the field and the subsequent laboratory work to obtain information on the main soil properties [14]. 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 [14]. New research should make use of current sensor systems, which can gather data at sufficiently high density to characterize small-scale variations now known to be present in the majority of fields [2]. Therefore, HMZ are usually generated from a combination of data layers, including maps of crop yield, topography, soil chemical properties, aerial photographs, soil apparent electrical conductivity (EC_a), or vegetation indices obtained by proximal or remote sensing [2,12].

Several studies have shown the practical interest and the potential of EC_a monitoring for designing and establishing HMZ, implementing smart sampling, and elaborating prescription fertilizer maps [11]. This potential is due to the fact that this parameter integrates the main properties affecting crop productivity [2], namely, texture, soil moisture, organic matter content, and soil cationic exchange capacity [12,15]. Sensors to measure EC_a in the field are of two types: contact, e.g., "Veris 2000 XA" model (Veris Technologies Inc., Salina, KS, USA) or non-contact, e.g., "EM38" (Geonics Ltd., Mississauga, ON, Canada), "GEM-2" (Geophex, Raleigh, NC, USA), or "DUALEM 1 S" (Dualem, Inc., Milton, ON, Canada). These sensors can be carried on mobile platforms mounted on a tractor or on an all-terrain vehicle, allowing quick EC_a surveys and providing large amounts of information on various physical soil properties [8]. On the other hand, the use of vegetation indices obtained by proximal or remote sensing, to delineate HMZ in pastures, has deserved growing interest in the Mediterranean region, in particular, the works of Serrano et al. [3,9,16,17].

In regard to the HMZ validation process, there are many statistical methods to assess the relationship between vegetation indices (or other variables or attributes) and any other parameters [18]. These include a wide spectrum of methods, such as an exploratory analysis of the variables by means of descriptive statistics or a multivariate descriptive analysis to obtain the matrix of Pearson's linear correlation coefficients, or other methods such as a canonical correlation analysis or an analysis of variance (ANOVA), to check whether classes arising from the clustering of indices or other variables provide effective management zones. When the assumptions of an ANOVA cannot be assured, the Kruskal–Wallis test and the Dunn test as a post-hoc analysis can be performed [19]. The use of a simple statistical index, such as the Kappa coefficient [20], to indicate the similarity between the maps generated with a reference map can be a suitable tool [21]. However, in the present study, a global index was defined to facilitate the validation process.

In this study, EC_a and topographic surveys were carried out in six experimental fields with a non-contact electromagnetic induction sensor ("EM38") associated with a GNSS receiver. The objective was to evaluate the soil spatial variability and generate HMZ maps of the soil fertility and, consequently, of the productive potential, the basis for smart sampling and the differential prescription of fertilizers. The normalized difference vegetation index (NDVI), obtained from a proximal optical sensor, and soil and biomass sampling were used to validate these HMZ through a global index.

2. Materials and Methods

Figure 1 shows a schematic representation of the methodology used in this study.

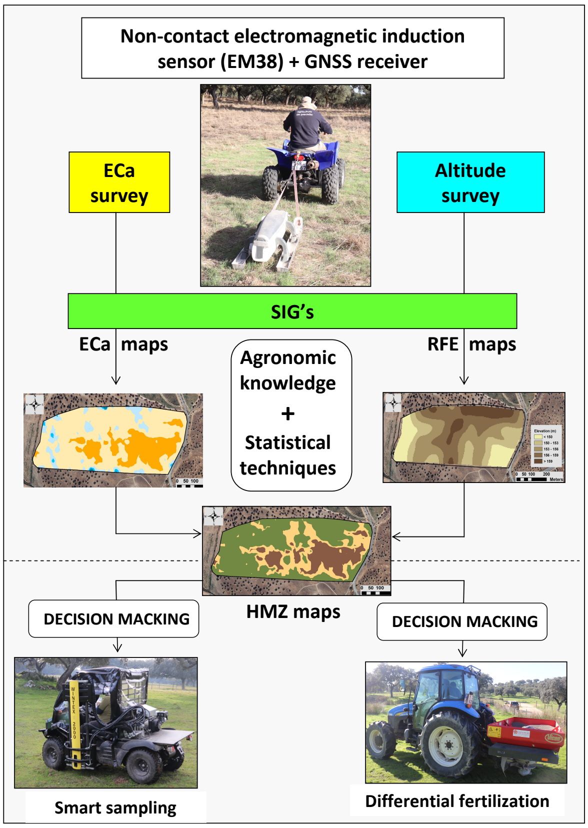

Figure 1. Schematic representation of the experimental approach used in this study.

2.1. Characteristics of the Experimental Fields

This work was conducted in six experimental fields ("Azinhal"—"AZI"; "Cubillos"—"CUB"; "Grous"—"GRO"; "Murteiras"—"MUR"; "Padres"—"PAD"; and "Tapada"—"TAP"), five in the Alentejo southern region of Portugal (Beja, Évora and Portalegre districts) and one in Spain, near the Portalegre district (Figure 2). The main characteristics of the experimental fields used in this study are presented in Table 1. These are typical permanent seeded biodiverse dryland pastures that usually grow under a low or moderate density plantation of Holm oak or Cork oak, and are mainly used for grazing by cattle, sheep or pigs on a rotational basis. The soil type is Cambisol with a granite origin [22], characterized by slight or moderate weathering of parent material and by absence of appreciable quantities of illuviated clay, organic matter, aluminum, and/or iron compounds. These acid soils present medium to coarse texture (Table 1; Figure 3), are not very fertile and are mainly used for mixed agro–silvo–pastoral systems [23]. The location of these fields is representative of the temperate climatic conditions of Portugal ("Csa: hot-summer Mediterranean climate" according to the Köppen–Geiger climate classification), with a precipitation gradient: smaller amounts of rainfall in the southern district ("Beja"; mean annual rainfall of 430 mm), intermediate in the central district ("Évora"; mean annual rainfall of 567 mm) and greater in the northern district ("Portalegre"; mean annual rainfall of 950 mm) (source: Portuguese Institute of Sea and Atmosphere).

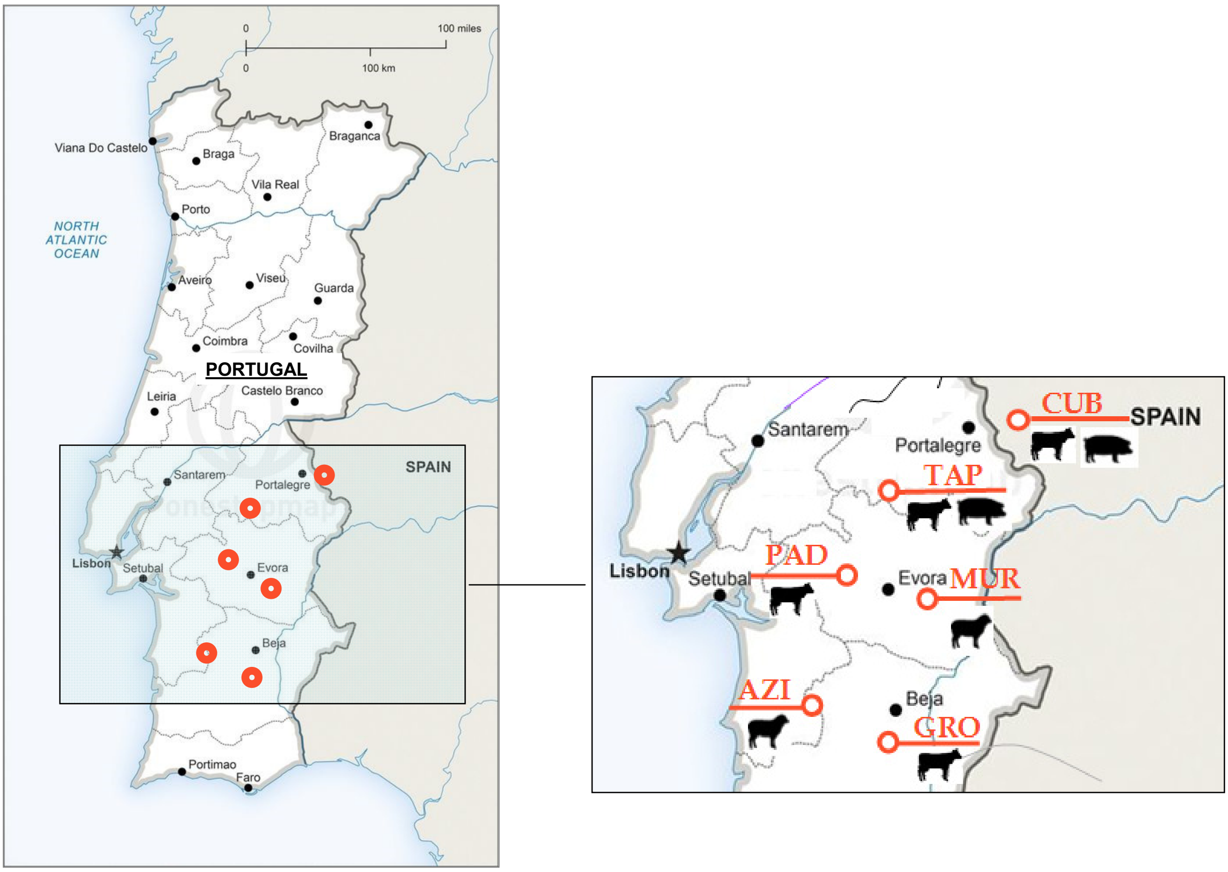

Figure 2. Location of the six experimental fields in the Alentejo, southern Portugal.

Table 1. Main characteristics of the six experimental fields used in this work.

Fiel Code	Coordinates	Area (ha)	Soil Texture *	Pasture Type	Predominant Trees	Animal Species (Type of Grazing)	Annual Rainfall (mm)
"AZI"	38°6.2′ N; 8°26.9′ W	22.3	Sandy loam	Permanent; biodiverse	Holm and Cork oak	Sheep (Rotational grazing)	430
"CUB"	39°10.0′ N; 6°44.6′ W	32.8	Loam	Permanent; biodiverse	Holm and Cork oak	Cattle and Pigs (Rotational grazing)	950
"GRO"	37°52.3′ N; 7°56.7′ W	28.3	Sandy loam	Permanent; biodiverse	Holm oak	Cattle (Rotational grazing)	430
"MUR"	38°23.4′ N; 7°52.5′ W	29.6	Sandy loam	Permanent; biodiverse	Holm oak	Sheep (Permanent grazing)	567
"PAD"	38°36.4′ N; 8°8.7′ W	32.2	Loamy sand	Permanent; biodiverse	Holm oak	Cattle (Permanent grazing)	567
"TAP"	39°9.5′ N; 7°31.9′ W	27.1	Loamy sand	Permanent; biodiverse	Holm and Cork oak	Cattle and Pigs (Rotational grazing)	950

* United States Department of Agriculture, USDA soil taxonomy.

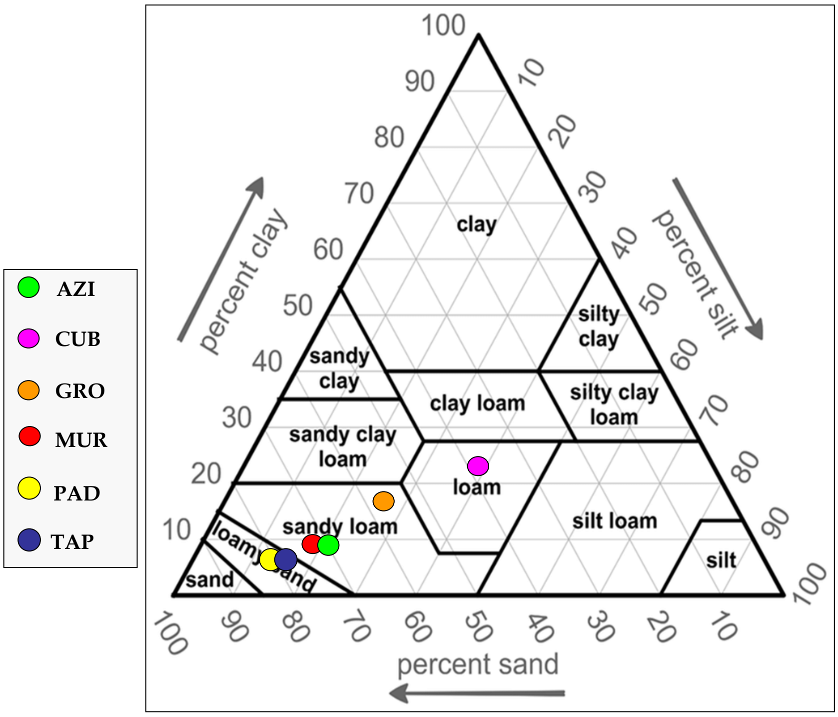

Figure 3. Graphical representation of the soil texture of the six experimental fields used in this study. (United States Department of Agriculture, USDA soil taxonomy).

2.2. Soil Apparent Electrical Conductivity (ECa) and Topographic Survey

Soil apparent electrical conductivity (EC_a) surveys were carried out at each experimental field in October 2019. A "EM38" device (Geonics Ltd., Mississauga, ON, Canada) was used in the horizontal dipole orientation with the two receiver coils separated by 0.5 m from the transmitter, providing data from effective depth ranges of 0.75 m and 0.375 m. In this study, only the data referring to the topsoil 0–0.375 m were used. The sensor was mounted on a metal-free sledge and pulled behind an all-terrain vehicle equipped with a GNSS receiver (see Figure 1), which simultaneously provided a topographic survey. The survey was carried out at an average speed of approximately 2.5 m s^{-1} and along parallel lines spaced 10 m, in order to cover the entire field. The EC_a measurements were registered continuously every second, so the spatial resolution was a 2.5 by 10 m grid.

2.3. Soil Sampling and Laboratory Reference Analysis

For characterization of the topsoil (0–0.30 m depth), simultaneously with the EC_a survey (October 2019), eight composite and georeferenced soil samples were collected in each experimental field using a gouge auger and a hammer. Each composite sample was the result of the combination of five sub-samples collected in an area of "10 m × 10 m" (Figure 4). These soil samples were inserted in plastic bags and transported to the "MED—Soil Analysis Laboratory" at University of Évora. The soil samples were weighed, dried at 70 °C for 48 h and then weighed again to establish the soil moisture content (SMC). Dried soil samples were analyzed for particle-size distribution (texture: sand, silt and clay content) using a sedimentographer (Sedigraph 5100, manufactured by Micromeritics, Norcross, GA, USA). The fine soil (fraction with diameter < 2 mm) was characterized in terms of pH, organic matter (OM), phosphorus (P_2O_5) and cationic exchange capacity (CEC). These fine components were analyzed using the following methods [24]: pH in 1:2.5 (soil: water) suspension, using the potentiometric method; OM by combustion and CO_2 measurement, using an infrared detection cell; P_2O_5 was extracted by the Egner–Riehm method and measured using colorimetric method; CEC was measured by the neutral ammonium acetate method.

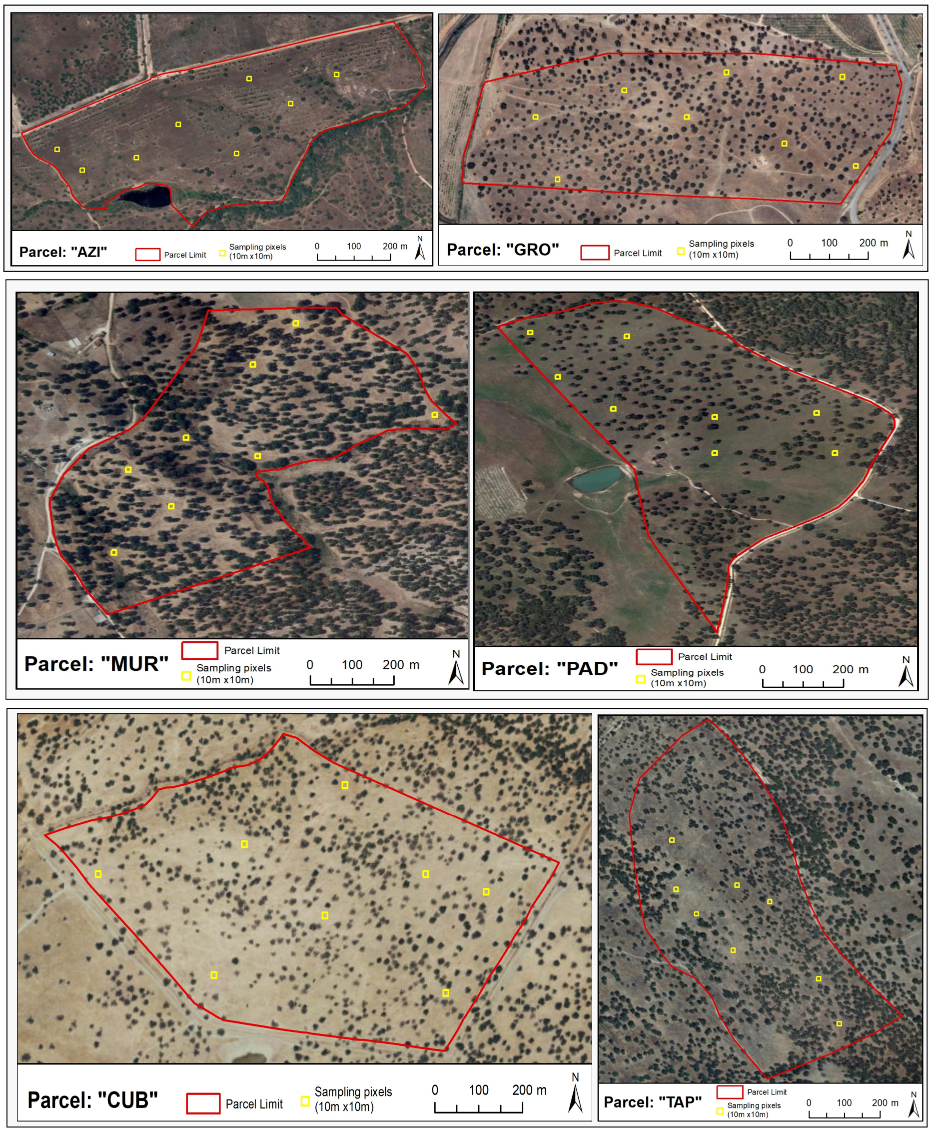

Figure 4. Eight "10 m × 10 m" sampling areas georeferenced in each of the six experimental fields.

2.4. Normalized Difference Vegetation Index (NDVI) Measurements with Proximal Optical Sensor

Proximal optical sensor (AOS, OptRx, Ag Leader, Ames, Iowa, USA) measurements in each experimental field were carried out at the same eight georeferenced areas as the soil sampling (10 m × 10 m; Figure 4). This process was performed at four different times through the growth cycle, i.e., between January and June 2020 (Table 2). However, in "Cubillos" ("CUB") experimental field (Located in Spain), due to road traffic restrictions imposed as a result of the COVID-19 pandemic, it was not possible to carry out two of the pasture collections (dates 3 and 4). The optical sensor (equipped with a small portable battery as the power source) was placed 0.5 m above the pasture and provided simultaneous measurement of three visible and infrared bands. With two of these spectral bands, red (670 nm) and near infrared (NIR, 775 nm), NDVI was calculated [16]. The AOS operator walked each sampling area for a five-minute period, which allowed the collection of approximately 300 NDVI records.

Table 2. Dates of pasture and NDVI sampling in each of experimental fields used in this work.

Year 2020	"AZI"	"CUB"	"GRO"	"MUR"	"PAD"	"TAP"
Date 1	21/01	29/01	21/01	22/01	20/01	22/01
Date 2	02/03	10/03	02/03	09/03	09/03	10/03
Date 3	21/04	*	21/04	20/04	20/04	24/04
Date 4	28/05	*	28/05	29/05	29/05	01/06

* Dates not sampled at the experimental farm located in Spain due to road travel restrictions imposed as a result of the COVID-19 pandemic.

2.5. Pasture Biomass Sampling and Normalized Difference Vegetation Index (NDVI) Measurements

Pasture sampling in each experimental field was carried out at the same eight georeferenced areas as the soil sampling and proximal optical sensor measurements (10 m × 10 m; Figure 4). In each of these areas, composite pasture samples were obtained by collecting five subsamples with electric shears at 1 to 2 cm above ground in a 0.5 m × 0.5 m area (defined with a metal quadrat). The sampling process was performed at four different times through the growth cycle, i.e., between January and June 2020 (Table 2), except in "Cubillos" ("CUB"), due to the above mentioned restrictions. Pasture samples were inserted into numbered plastic bags and transported to the MED—Animal Nutrition and Metabolism Laboratory at the University of Évora. Once in the laboratory, the pasture samples were weighed to obtain the biomass (in kg ha^{-1}).

2.6. Soil Apparent Electrical Conductivity (ECa) and Topographic Altitude Processing

Estimating EC_a at unsampled locations was carried out with the ordinary point kriging method. This produced kriged maps showing the spatial distribution of EC_a in each experimental field based on the estimated values. Although there are many algorithms that can be used for interpolation, the advantages of using geostatistical techniques [25] are well recognized considering the spatial variation of the studied variable, which is EC_a in this case. The geostatistical analyses were carried out with the extension, Geostatistical Analyst of ArcGIS (version 10.5, ESRI, Inc., Redlands, CA, USA), and the kriged maps of EC_a were produced with the ArcMap module of ArcGIS software.

Digital elevation model (DEM) surfaces were generated for each field using the triangulated irregular network (TIN) interpolation tool from the ArcGIS. The TIN algorithm uses sample points to create a surface formed by triangles based on nearest neighbor point information. Then, the vector layers were converted into grid surfaces with the spatial analyst tools of ArcGIS.

2.7. Definition and Validation of Homogeneous Management Zones (HMZ)

Descriptive statistical analysis (mean, standard variation and range) was performed for all soil and pasture parameters.

After obtaining the EC_a maps for each field, homogeneous zones were delimited using a classification technique in ArcGIS. Topography was also considered since it is an important factor that can affect the potential zones [26]. Consequently, the final classified maps were generated using an unsupervised classification technique on two sets of input data: the EC_a and the altitude layers. The ISO Cluster approach in ArcGIS was used to perform the classification. This algorithm organizes the data in the input raster into a user-defined number of groups to produce signatures, which are utilized to classify the data using the "Maximum Likelihood Classifier" (MLC) function. The number of groups was fixed at three in this study (less, intermediate and more potential), as only a few homogeneous zones should be delineated, from a practical perspective.

Soil parameters (texture, pH, OM, P_2O_5 and CEC), and pasture biomass and vegetation index (NDVI) data at sampling locations were employed to check their differences. The delimitation of each zone in each experimental field was evaluated by computing the differences in the mean values of these soil and pasture parameters. In the case of soil parameters, because they were based on a small number of samples (only 8 composite samples in each experimental field), they were used as an indication of trends. The pasture parameters (biomass and NDVI), resulting from 8 composite samples obtained on 4 dates (a total of 32 samples in each experimental field) were treated 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 since 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 indicates that at least two groups were different but cannot indicate 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 was performed by means of the Dunn test as a post-hoc non-parametric test.

To facilitate the validation process of management zones based on soil and pasture samples, a global index (*GI*) was calculated for each parameter, in the set of six experimental fields. In this calculation, the coefficient "1" was assigned to the highest value of the parameter in each experimental field, in the set of 3 management zones. The value of the same parameter in the remaining two zones was transformed into a decimal fraction of this maximum value (relative value of each parameter, *RV*), corresponding to the ratio between the value in question and the maximum value (Equation (1)). After calculating the ratios, for each zone and each experimental field, the average value of the *GI* for each parameter in the set of six experimental fields was calculated (Equation (2)).

$$RV_{ijk} = \frac{AV_{ijk}}{Max.V_{i,j=1.to.m,k}} \tag{1}$$

$$GI_{jk} = \sum_{i=1}^{n}\left(\frac{RV_{jk}}{n}\right) \tag{2}$$

where: *RV*—relative value of each parameter; *AV*—absolute value; *Max.V*—maximum value; *i*—location; *j*—homogeneous management zones; *m*—number of homogeneous management zones; *k*—parameter measured; *n*—number of locations of each *j-k* pair.

3. Results

Descriptive statistics of altitude, soil and pasture parameters for the six experimental fields are shown in Tables 3–5, respectively.

Table 3. Descriptive statistics (mean, standard deviation and range) of the altitude in each of the six experimental fields used in this work.

Altitude (m)	Azinhal	Cubillos	Grous	Murteiras	Padres	Tapada
Mean	84.1	336.8	153.5	277.8	331.9	346.0
SD	6.5	5.2	5.2	6.0	7.9	8.5
Range	66.7–95.8	322.2–349.0	142.4–166.6	261.6–294.2	312.8–353.2	327.2–367.1

Table 4. Descriptive statistics (mean, standard deviation and range) of the soil parameters in each of the six experimental fields used in this work.

Parameter	Azinhal	Cubillos	Grous	Murteiras	Padres	Tapada
Clay (%)						
Mean	9.2	23.5	16.8	8.5	6.6	7.0
SD	3.0	1.6	7.2	4.7	2.0	6.4
Range	4.7–12.8	20.7–25.4	11.5–30.7	3.2–17.0	4.6–10.4	3.7–20.0

Table 4. *Cont.*

Parameter	Azinhal	Cubillos	Grous	Murteiras	Padres	Tapada
Silt (%)						
Mean	17.0	39.0	25.5	15.9	15.4	14.8
SD	3.8	0.6	3.9	10.7	2.2	9.9
Range	12.0–20.9	38.2–39.6	20.0–31.5	5.1–34.7	13.2–19.1	5.1–30.2
Sand (%)						
Mean	73.8	37.5	57.6	75.6	78.0	78.2
SD	5.6	1.9	8.9	14.6	2.6	9.0
Range	66.7–79.9	35.6–40.9	43.7–67.1	48.5–88.3	73.9–80.3	64.8–89.1
pH						
Mean	6.7	5.5	5.8	6.0	6.4	6.0
SD	0.2	0.3	0.3	0.5	0.5	0.3
Range	6.2–6.9	5.2–5.9	5.4–6.3	5.3–6.6	5.7–7.0	5.7–6.4
OM (%)						
Mean	1.9	3.1	2.5	2.7	2.7	2.2
SD	0.2	0.2	0.9	0.5	0.2	0.8
Range	1.5–2.2	2.6–3.3	1.0–3.7	2.1–3.3	2.3–2.8	1.2–3.3
P_2O_5 (mg kg^{-1})						
Mean	8.5	11.5	24.3	29.2	23.7	7.5
SD	3.8	2.9	21.5	21.7	6.7	3.2
Range	4.4–14.0	8.0–16.0	3.9–63.0	10.0–67.0	18.0–33.0	4.0–13.0
CEC (cmol kg^{-1})						
Mean	11.3	15.2	11.2	8.6	15.5	7.2
SD	3.9	2.4	1.8	2.8	1.3	2.5
Range	7.5–18.5	11.4–18.5	8.9–13.8	5.2–12.4	14.3–17.6	3.5–10.1
EC_a (mS m^{-1})						
Mean	14.5	15.4	7.0	13.8	18.6	6.1
SD	6.1	3.0	3.5	5.4	2.9	4.7
Range	3.7–45.6	3.4–23.8	0.2–48.3	0.9–33.9	0.1–32.5	0.2–48.5
SMC (%)						
Mean	2.5	7.3	2.5	10.1	6.6	6.3
SD	1.2	1.8	1.6	2.3	1.4	1.4
Range	1.7–5.3	5.1–10.3	0.9–5.9	6.5–12.9	4.3–8.6	4.3–9.1

OM—organic matter; CEC—cationic exchange capacity; EC_a—apparent electrical conductivity; SMC—soil moisture content.

Table 5. Descriptive statistics (mean, standard deviation and range) of the pasture parameters in each of the six experimental fields used in this work.

Parameter	Azinhal	Cubillos	Grous	Murteiras	Padres	Tapada
Biomass (kg ha^{-1})						
Mean	5291	8164	5917	6088	6551	7445
SD	3136	2501	3185	4808	2697	4698
Range	1167–12,037	4233–12,800	1767–14,500	1267–18,603	3050–11,853	2053–17,000
NDVI						
Mean	0.495	0.732	0.564	0.537	0.668	0.589
SD	0.134	0.048	0.188	0.077	0.119	0.080
Range	0.250–0.682	0.592–0.784	0.241–0.797	0.354–0.710	0.432–0.819	0.410–0.697

NDVI—normalized difference vegetation index.

It is evident (Table 4) that soil clay content is generally low (<10%), while in two of the experimental fields, clay content is higher (17% in "Grous" and 23.5% in "Cubillos"). The pH of these soils is usually low (<6.0), except in "Padres" (mean of 6.4) and "Azinhal" (mean of 6.7), which explains the usual practice of applying lime amendment. Soil organic matter (OM) presents average values of 2.5–3%, except in "Azinhal" (1.9%) and "Tapada" (2.2%). Average P_2O_5 contents are low in all experimental fields (<30 mg kg^{-1}), which explains the usual practice of applying phosphorous fertilizer in these dryland pastures. Average pasture productivity (biomass) varies between 5300 kg ha^{-1} ("Azinhal") and 8164 kg ha^{-1} ("Cubillos") (Table 5). It is important to highlight the high intra and inter field spatial variability (Table 4). The coefficient of variation (CV), for example, varies between 7% and 91% for clay, between 3% and 8% for pH, between 7% and 36% for OM, between 8% and 35% for CEC, between 16% and 77% for EC_a, between 5% and 23% for SMC, between 30% and 80% for biomass and between 7% and 37% for NDVI. The seasonality of pasture production throughout the vegetative cycle is represented by the wide amplitude of the productivity (biomass) and of the vegetative vigor of the pasture (NDVI) in the set of six experimental fields: respectively between 1167 ("Azinhal") and 18,603 kg ha^{-1} ("Murteiras") and between 0.241 ("Grous") and 0.819 ("Padres"). Figure 5 shows the significant linear correlation between the mean values of biomass and the mean values of NDVI, in the set of six experimental fields.

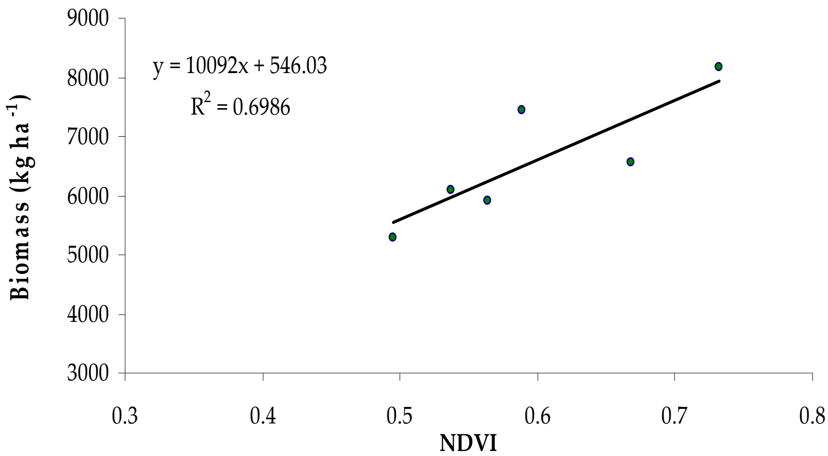

Figure 5. Linear correlation between mean pasture productivity (biomass) and mean pasture vegetative vigor (NDVI) in the set of six experimental fields used in this study.

Figures 6–11 show the altitude (a), EC_a (b) and homogeneous management zone (c) maps of the six experimental fields.

Table 6 shows mean values of soil parameters (clay, pH, OM, P_2O_5 and CEC) in the management zones of each experimental field. Due to the small number of composite samples (only eight), they were used only as an indication of trends. Given that the establishment of sampling areas was carried out before the EC_a and altitude surveys, and therefore, before the definition of the HMZ in some experimental fields ("Azinhal", "Murteiras", "Padres" and "Tapada"), one of the three identified zones was not sampled (soil and pasture). The trend for some soil properties, which are related to soil fertility, is in accordance with the proposed zoning. This is the case for CEC in "Azinhal", "Cubillos", "Grous", "Murteiras" and "Tapada", of clay contents in "Azinhal", "Grous", "Murteiras" and "Tapada" or OM in "Cubillos", "Grous" and "Murteiras", where higher values were found in zones with more soil fertility potential. When compared to other important soil parameters in Mediterranean pastures, the low levels of the P_2O_5 in all experimental fields, which is one of the main limitations of these soils, do not show a consistent trend, despite the areas with more potential in "Crous" and "Murteiras" registering clearly higher values of this nutrient. Among the five parameters considered in this study, soil pH seems to be the one with the lowest sensitivity for validating the management zones.

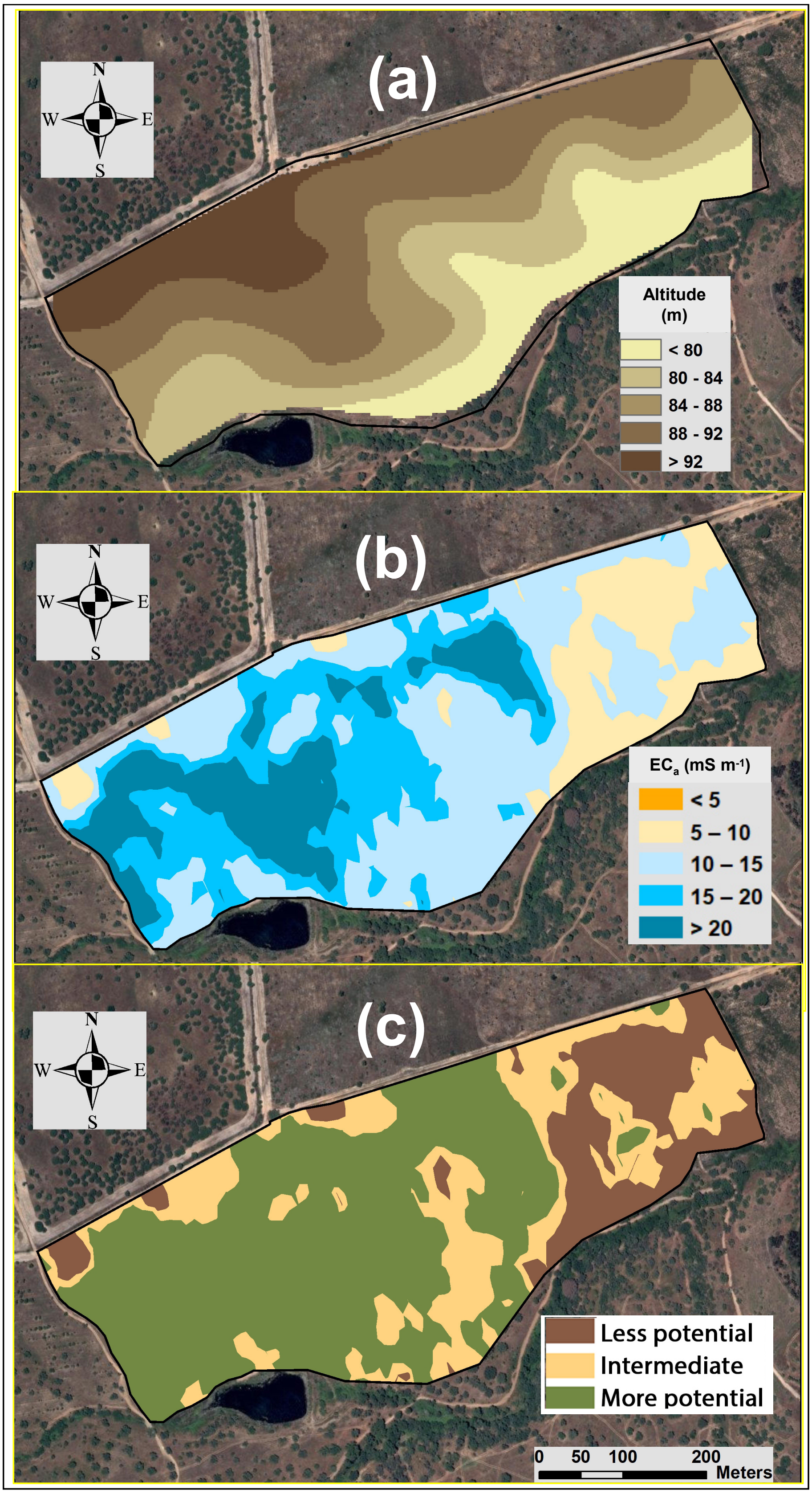

Figure 6. Altitude (**a**), soil apparent electrical conductivity (EC$_a$; (**b**)) and homogeneous management zones (**c**) of "Azinhal" experimental field.

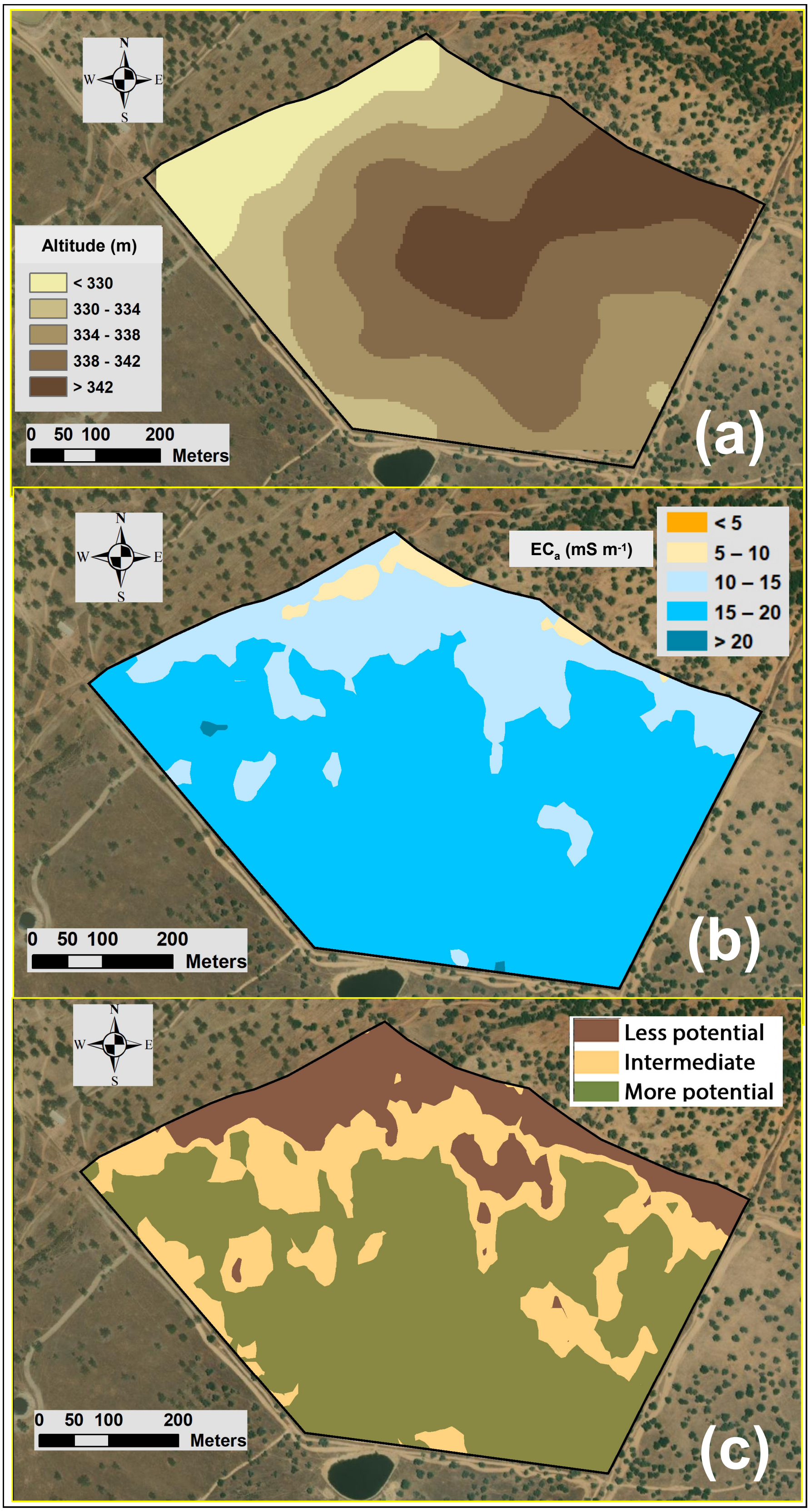

Figure 7. Altitude (**a**), soil apparent electrical conductivity (EC$_a$; (**b**)) and homogeneous management zones (**c**) of "Cubillos" experimental field.

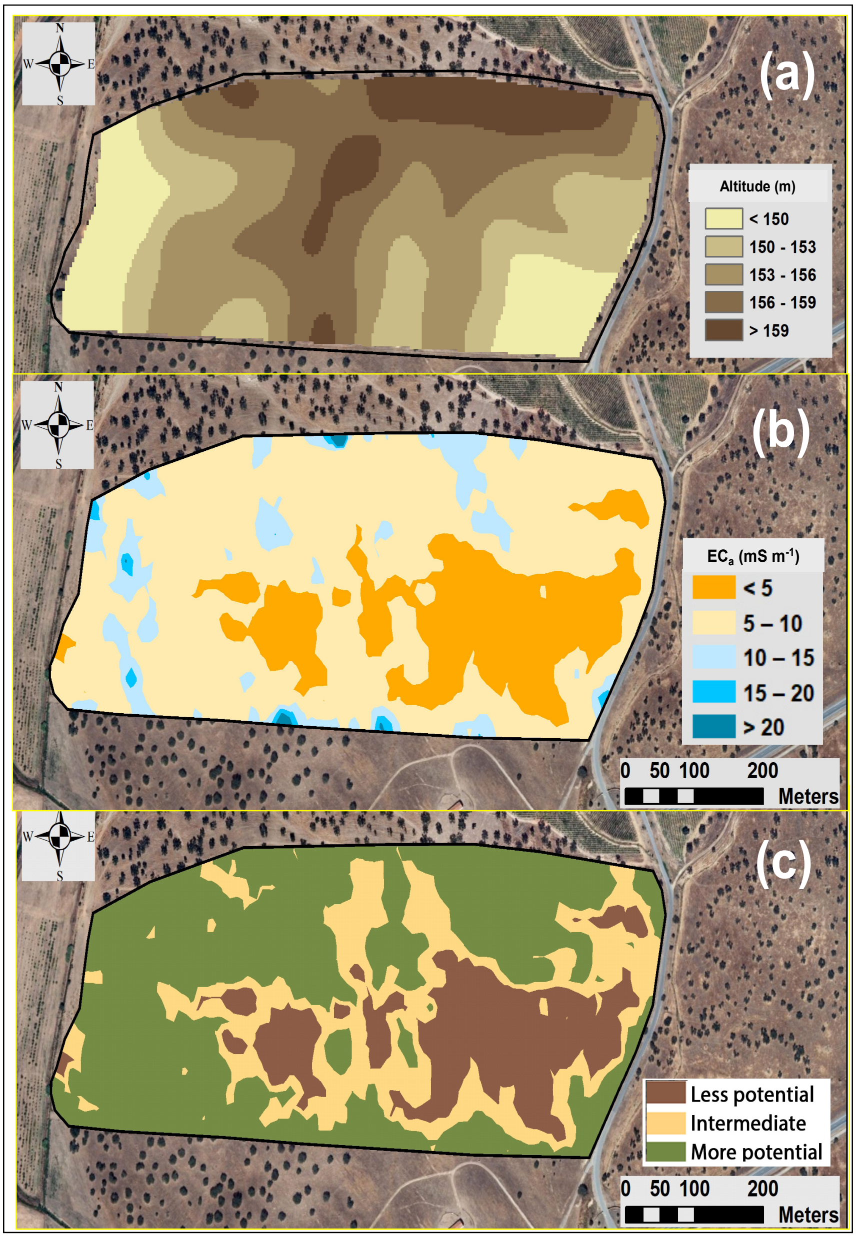

Figure 8. Altitude (**a**), soil apparent electrical conductivity (EC_a; (**b**)) and homogeneous management zones (**c**) of "Grous" experimental field.

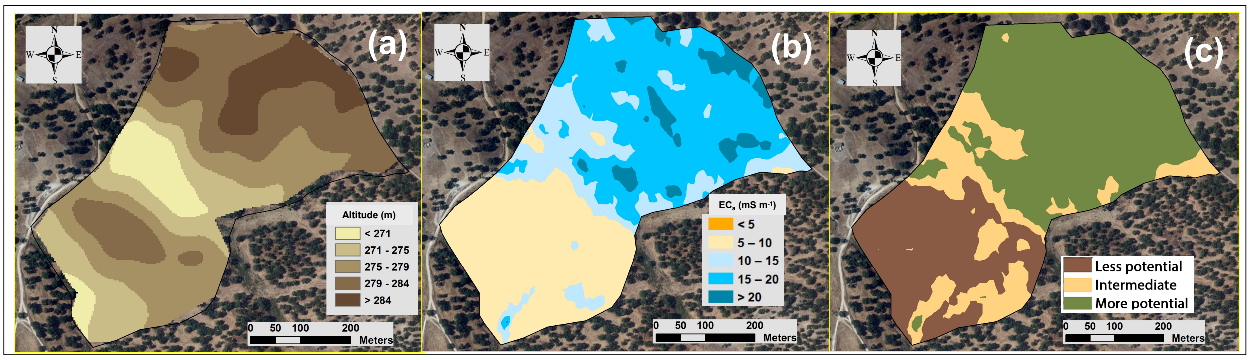

Figure 9. Altitude (**a**), soil apparent electrical conductivity (EC_a; (**b**)) and homogeneous management zones (**c**) of "Murteiras" experimental field.

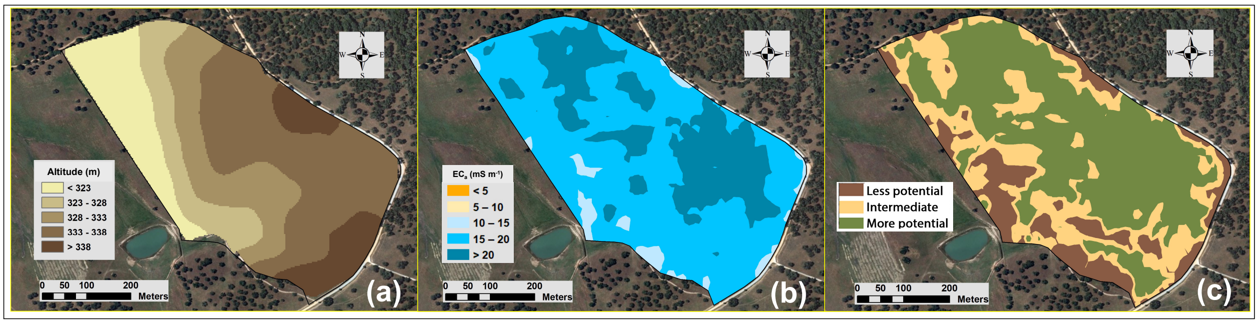

Figure 10. Altitude (**a**), soil apparent electrical conductivity (EC_a; (**b**)) and homogeneous management zones (**c**) of "Padres" experimental field.

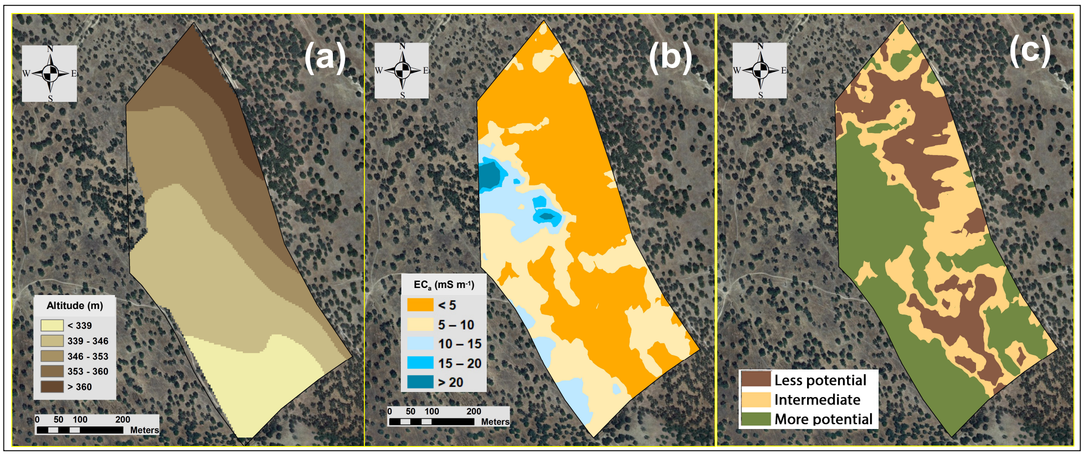

Figure 11. Altitude (**a**), soil apparent electrical conductivity (EC_a; (**b**)) and homogeneous management zones (**c**) of "Tapada" experimental field.

Table 6. Mean values of the soil parameters in each management zone (less, intermediate and more potential) within each experimental field.

Parameter	Azinhal	Cubillos	Grous	Murteiras	Padres	Tapada
Clay (%)						
Less potential	-	23.1	12.9	5.2	-	4.2
Intermediate	7.2	24.9	19.8	-	6.5	-
More potential	9.6	22.6	27.2	10.2	6.7	8.5
pH						
Less potential	-	5.3	5.4	5.4	-	5.9
Intermediate	6.6	5.6	5.8	-	7.0	-
More potential	6.9	5.5	5.9	6.3	6.2	6.1
OM (%)						
Less potential	-	2.6	2.4	2.2	-	2.2
Intermediate	1.9	3.1	2.2	-	2.8	-
More potential	1.9	3.2	3.1	3.0	2.6	2.2
P_2O_5 (mg kg^{-1})						
Less potential	-	11.0	10.0	17.0	-	4.5
Intermediate	12.0	10.5	17.6	-	23.0	-
More potential	7.8	12.3	41.5	53.5	23.8	9.0
CEC (cmol kg^{-1})						
Less potential	-	11.4	10.7	5.5	-	6.4
Intermediate	9.9	14.9	10.0	-	16.6	-
More potential	18.5	16.7	13.3	10.2	15.3	8.9

OM—organic matter; CEC—cationic exchange capacity.

Figure 12 shows the GI calculated for five soil parameters based on Equations (1) and (2). This figure confirms that pH is the only soil parameter that does not allow the differentiation of the established HMZ. The remaining soil parameters (clay, OM, P_2O_5 and CEC) systematically show higher values in areas with more potential.

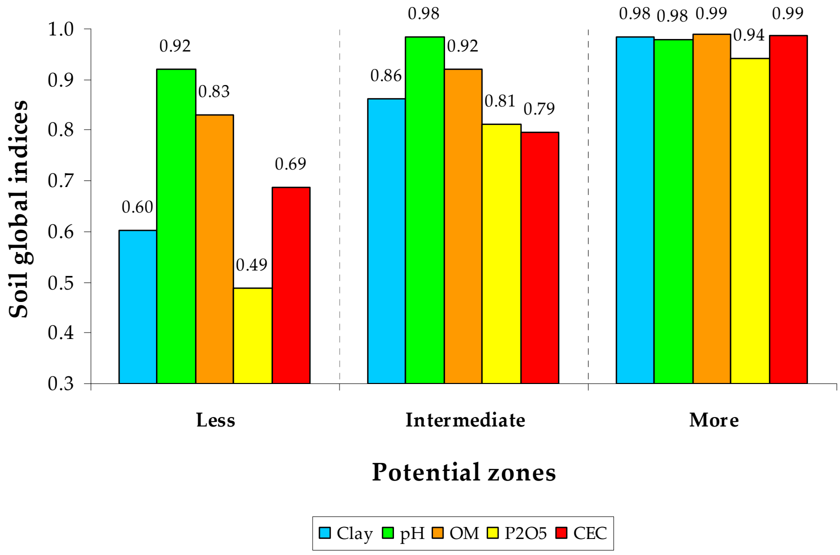

Figure 12. Global index of five soil parameters for each homogeneous management zone in the set of six experimental fields.

Table 7 shows mean values of pasture parameters (biomass and NDVI) in each management zone for each experimental field. Within each column, different letters indicate significant differences ($p < 0.05$) between zones performed by the Dunn test. Biomass was the most useful variable to characterize homogeneous zones, systematically presenting, in all experimental fields, significantly higher productivity values in zones with more potential. On the other hand, it was apparent that the use of NDVI was not suitable to differentiate HMZ, since mean values were similar in the various potential homogeneous zones in many experimental fields ("Cubillos", "Murteiras" and "Padres").

Table 7. Mean values of the pasture parameters in each management zone (less, intermediate and more potential) within each experimental field. Different letters indicate significant differences ($p < 0.05$) according to the Dunn test.

Parameter	Azinhal	Cubillos	Grous	Murteiras	Padres	Tapada
Biomass (kg ha^{-1})						
Less potential	-	7525a	5226a	5204a	-	5315a
Intermediate	4361a	7810a	6200b	-	6104a	-
More potential	5601b	8752b	6041b	6971b	6820b	8154b
NDVI						
Less potential	-	0.73a	0.55a	0.53a	-	0.55a
Intermediate	0.44a	0.72a	0.55a	-	0.66a	-
More potential	0.51b	0.74a	0.60b	0.5a	0.68a	0.60b

NDVI—normalized difference vegetation index.

Figure 13 shows soil and pasture global indices: a soil fertility GI (including the set of all the measure soil parameters), a pasture biomass GI and a pasture NDVI GI. Both soil fertility GI and pasture biomass GI consistently differentiate the previously defined HMZ's. However, pasture NDVI GI, similar to individual analysis, field by field (Table 7), did not show sufficient sensitivity to differentiate HMZ.

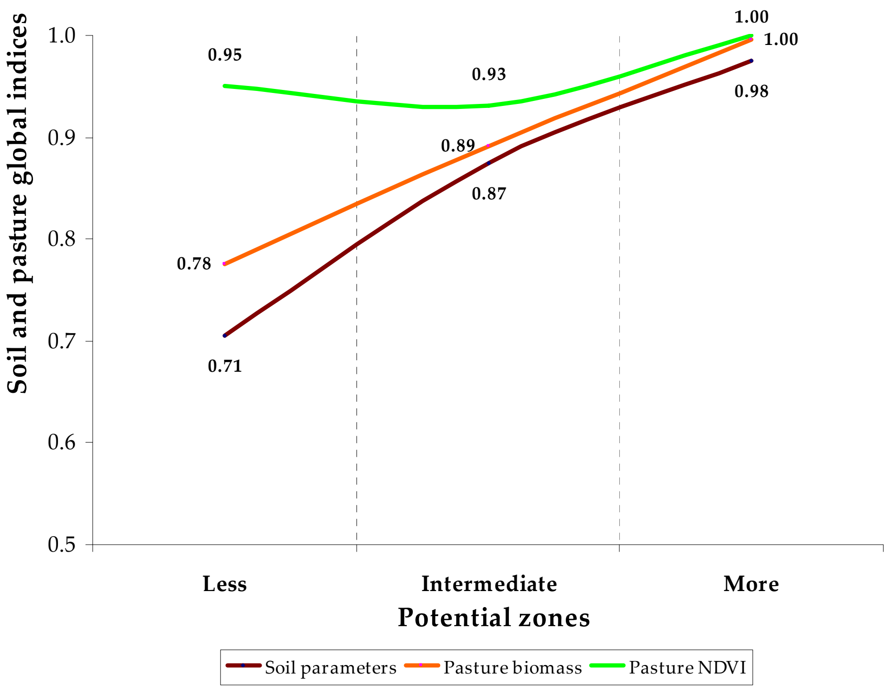

Figure 13. Global index of soil and pasture parameters for each homogeneous management zone in the set of six experimental fields.

4. Discussion

Based on EC_a and topographic surveys, the objectives of this study were: (i) to evaluate the soil spatial variability and generate HMZ maps; and (ii) validate these HMZ through soil, biomass and NDVI measurements.

In the last decade, numerous works have been published that replicate the use of EC_a sensors and geostatistical techniques to define HMZ in very different crops, for example, in corn [27], vineyards [28], olive orchards [29] or pastures [9,10,15,30].

The methods used to validate HMZ are very diverse, with the intensive soil sampling being the most common process [5,31–33], but often it is not technically feasible for large-scale application [34]. In addition, some soil variables (such as the pH in our study) correlate inconsistently with EC_a mainly as a consequence of complex interactions between soil properties [29], and a temporal component of variability that is only weakly detected by an expected constant variable such as EC_a [35]. Alternatively, these soil properties can be used to formulate a soil fertility index [2,7]. The use of a global soil fertility index (GI_{soil}), such as the one presented in this study, that encompasses several relevant parameters with direct influence on soil fertility (including phosphorous, OM, pH, clay content and CEC), is a simplified approach which has been proposed in several works [2,7]. In this way, it is possible to reduce the complexity assumed by geostatistical techniques, based, for example, on the Rasch model clustering process [5,7] or on principal component analyses [2]. The GI_{soil} showed the ability to validate areas of different potential, identified through EC_a and altitude data, which is in agreement with several other works [32,36,37].

The validation based on biomass assumes the well-studied relationship between soil characteristics and crop productivity [5,29]. In cereal crops (wheat, corn, among others), the incorporation of calibrated commercial yield monitors in combines equipped with differential GPS antenna provides crop yield maps [32], which is interesting spatial information for use as a validation tool specifically for this type of crop [2]. However, in livestock production systems, which is the case here, it is difficult to quantify the spatial variability of biomass production because forage is usually harvested by animals [6], which requires manual and representative sample collection. Alongside the GI_{soil}, the pasture yield (biomass) showed the ability to validate potential management zones defined in this study. However, since this is an exhaustive and expensive process, there is a growing interest in studies based on rapid sampling and validation methodologies [16]. One option increasingly used for this purpose [12] is indirectly via plant growth measurements that rely on vegetation indices [36]. Remote or proximal sensing provides an attractive opportunity to obtain the NDVI or other indices [12] related to pasture development throughout the vegetative cycle [16]. In this study, NDVI was not consistent in the validation of HMZ, which is in line with other studies [5]. One problem attributed to NDVI is its insensitivity to changes in environment and/or biomass when environmental conditions and biomass reach a certain threshold [16,38]. According to Moral et al. [14], the spatial variability detected by optical sensors at vegetation level is not related to the spatial pattern of soil fertility and not suitable to detect the spatial variability between zones. Serrano et al. [13] showed that NDVI reflects the plant chlorophyll content and, therefore, has greater potential to monitor the evolution of pasture quality, namely the crude protein content, than the productivity predicted in the three HMZ defined in this study.

The results of this study show the interest in multi-variable HMZ validation approaches, which consider soil and landscape attributes, yield data (biomass) and/or multi-temporal vegetation measurements (time-series of vegetation indices obtained by proximal or remote sensing) [12]. The combination of different validation methods can alleviate the difficulty in interpretating EC_a readings, which are highly location and soil-specific [35].

Variability is a fundamental component of the PA concept. This associates an exponential incorporation of technology to support decision making in complex agricultural and livestock production scenarios [6]. The definition of HMZ meets the major aim of PA [2]: to optimize crop management by addressing spatial variability and thus optimizing the use of farm inputs [12]. For example, the published works of Cicore et al. [30], Moral et al. [5] or Bonecke et al. [33] show algorithms and methodologies to predict and quantify the needs for the variable rate application of nitrogen fertilizer, phosphorous fertilizer or lime amendment.

Soil spatial variability is one of the main parameters, especially in Montado's Alentejo region, southern Portugal [4], impacting the productivity of dryland pastures and, consequently, the extensive animal production systems [39]. The results obtained in this study confirm this variability, reflected in the high soil coefficients of variation, intra and inter experimental fields, and highlight some of the main limitations of these soils: in general, low pH (mean between 5.5 and 6.7), usually with coarse texture and low amounts of phosphorous (P_2O_5 < 30 mg kg^{-1}). The combination of these factors substantiates the widespread practice in these dryland pastures of soil phosphorous fertilization [4]. However, this is a complex process. Given that the relative agronomic effectiveness of phosphorus fertilizers and the availability of this nutrient in the soil environment is governed by reactions in the soil matrix that are highly influenced by the pH [40], pH correction might be required before P fertilizing [13]. Additionally, Carvalho et al. [41] mention the need to improve the Mg/Mn ratio in order to reduce the problems of Mn toxicity, which has long been recognized as the major limiting factor of pasture and forage production on acid cambisoils of Portugal. Therefore, these authors suggest that pH correction should be carried out through the application of dolomitic limestone, which provides $CaCO_3$ but also Mg. Nevertheless, the dominant practice of the farmers in this region, is to apply the same rate of fertilizer over whole fields and even whole farms. Given the spatial variability of soil properties that was observed in all the experimental fields that were studied in this work (which is a good indicator for differentiated management), this practice leads to frequent over and under-application of fertilizers, a critical challenge to sustainable crop production and long-term soil and environmental quality [13].

Site-specific management is an attractive and intuitive approach to increasing the fertilizer use efficiency by adjusting fertilizer rates to the soil and crop variability [9]. The practice of defining HMZ should extend to the dynamic management of animal grazing and its impact on pasture degradation. Pasture degradation is a complex phenomenon that involves causes and consequences, which lead to gradual decrease in productivity. These include inadequate grazing practices, such as the use of stocking rates or grazing intervals, that do not consider pasture growth cycle, or inadequate pasture management practices, such as the absence of periodic soil fertility replenishment [42]. Loss of pasture quality reduces the economic return of this silvo–pastoral ecosystem [8], since it increases the need for animal feed supplementation, in a context of extremely marked climate change in the Mediterranean region [13,43].

In Portugal, site-specific management in agriculture or animal production based on the EC_a surveys is still in an initial phase of adoption among farmers and, as suggested by Córdoba et al. [32], further studies should be conducted in the next years to evaluate these subfield homogeneous zones and to better understand the agronomic significance of this classification. This would not only provide for the fusion of the data for multiple sensors or sources, by extracting complementary information [35], it would also provide the expansion of an emerging market for technological service providers to support the farmers.

5. Conclusions

Precision Agriculture is one the pillars of the Common Agricultural Policy ("CAP 2023–2027") and of the national strategic plans (e.g., the Portuguese Plan for Recovery and Resilience, PRR). The incorporation of farming technologies is a challenge for today's farmers and provides the building blocks for the future, especially for the new generation of young farmers and agricultural managers, who are knowledgeable, have received qualified training and have ecological awareness and high standards.

The results of this study show that data based on temporally stable EC_a and topographic surveys can be used to define HMZ and implement site-specific management in soils with dryland permanent pastures. A new global index, which integrates relevant soil and pasture parameters, was proposed for the validation process. This is a rational way to improve the efficiency of the use of inputs by adjusting them to soil and pasture variability. The limits of these HMZ may be dynamic, allowing the farm manager, in the following years, to make adjustments based on new accumulated knowledge (obtained, for example, by soil and pasture smart sampling and/or a time series of vegetation indices obtained by proximal or remote sensing).

This is an exploratory work in the Alentejo region of southern Portugal. The large-scale implementation of this concept requires further medium and long term validation studies, both in terms of cost–benefit analysis (economic and environmental), as well as in terms of impact on pasture productivity and biodiversity, and, consequently, on the livestock production system. An extensive database should also be the starting point for the development of algorithms that allow the evaluation of the agronomic significance of this classification (subfield homogeneous zones) and establishing more general methods of mapping and quantifying variable input prescriptions.

Author Contributions: Conceptualization, J.S.; methodology, J.S., L.P., J.M.d.S. and F.M.; software, J.S., L.P., J.M.d.S., F.M. and L.P.; validation, J.S., S.S. and F.M.; formal analysis, J.S. and F.M.; investigation, J.S.; resources, J.S.; data curation, J.S. and S.S.; writing—original draft preparation, J.S.; writing—review and editing, J.S. and S.S.; visualization, J.S.; supervision, J.S.; project administration, J.S.; funding acquisition, J.S. All authors have read and agreed to the published version of the manuscript.

Funding: This work was funded by National Funds through FCT (Foundation for Science and Technology) under the Project UIDB/05183/2020 and by the projects PDR2020-101-030693 and PDR2020-101-031244 ("Programa 1.0.1-Grupos Operacionais").

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

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