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# On-farm experimentation of precision agriculture for differential seed and fertilizer management in semi-arid rainfed zones

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## Abstract

**Introduction** This study explores the integration of precision agriculture technologies (PATs) in rainfed cereal production within semi-arid regions.

**Methods** utilizing the Veris 3100 sensor for apparent soil electrical conductivity (ECa) mapping, differentiated management zones (MZs) were established in experimental plots in Valsalada, NE Spain. Site-specific variable dose technology was applied for seed and fertilizer applications, tailoring inputs to distinct fertility levels within each MZ. Emphasizing nitrogen (N) management, the study evaluated the impact of variable-rate applications on crop growth, yield, nitrogen use efficiency (NUE), and economic returns. For the 2021/2022 and 2022/2023 seasons, seeding rates ranged from 350 to 450 grains/m$^2$, and basal fertilizer dosages varied between high and low levels. Additionally, the total nitrogen units were distributed differently between the two seasons, while maintaining a uniform topdressing fertilizer dose across all treatments.

**Results** Results revealed a significant increase in yield in MZ 2 (higher fertility) compared to MZ 1 (lower fertility). NUE demonstrated notable improvement in MZ 2, emphasizing the effectiveness of variable-rate N applications. Economic returns, calculated as partial net income, showed a considerable advantage in MZ 2 over MZ 1, resulting in negative outcomes for low-fertility areas in several of the analyzed scenarios, and highlighting the financial benefits of tailored input management.

**Conclusion** This research provides quantitative evidence supporting the viability and advantages of adopting PATs in rainfed cereal production. The study contributes valuable insights into optimizing input strategies, enhancing N management, and improving economic returns in semi-arid regions.

**Keywords** Variable Dose Technology · Apparent soil electrical conductivity · Nitrogen management · Rainfed crops · Semi-arid regions

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## Introduction

In recent years, a shift from the traditional practice of applying uniform management strategies across agricultural plots to the adoption of site-specific management has been observed. This transition is driven by the recognition of the significant spatio-temporal heterogeneity inherent in agricultural soils, influencing production outcomes and yields (Munnaf et al., 2020). PATs serve as valuable complements to human visual inspection, facilitating the identification and characterization of intra-plot variability. These technologies encompass an array of tools, including global navigation satellite systems (GNSS), Geographic Information Systems (GIS), soil apparent electrical conductivity (ECa) surveyors, yield monitors, onboard sensors for vehicles, and multispectral sensors on satellites. In the specific case of Spain, while precision agriculture (PA) has found widespread application in extensive irrigated crops (Jat et al., 2018; Maresma et al., 2019) and high-value horticultural crops such as vines and other fruit species (Bonilla et al., 2015; Uribeetxebarria et al., 2018a), its integration in extensive rainfed crops remains relatively limited. These rainfed systems, where homogeneous doses are predominantly applied, cover approximately 85% of the total agricultural area dedicated to cereals in Spain, representing a substantial sector with extensive territorial coverage (MAPA, 2022). Within this category of agricultural systems, the economic return is notably limited, and productive outcomes are intricately linked to the spatio-temporal distribution of precipitation over the course of the year.

The analysis of the economic sustainability linked to the implementation of PATs in cereal crops has been studied in less depth compared to other rotation systems, as identified in the work of Finco et al. (2023), after studying the evolution of scientific publications on this topic by country from 1997 to 2023. The application of PA emerges as a pivotal strategy in optimizing inputs, reducing environmental costs, and enhancing traceability across the production process within these rainfed systems. However, the cost of its implementation is frequently questioned among farmers and specialists within the framework of these edapho-climatic conditions. Additionally, numerous farmers have access to suitable technology for implementing variable-rate input applications, but often lack the necessary knowledge or proper guidance to effectively put it into practice. As an example, in a questionnaire distributed among farmers, from the NE region of Spain, by the research group authoring this research paper, the availability of machinery for variable rate application (VRA) of inputs was assessed. Of the 141 farmers surveyed, 55% owned machinery for VRA (fertilizer spreaders, sprayers, and seeders), but only 28% had implemented VRA maps on certain occasions. The primary challenge in implementing PATs lies in accurately identifying zones of variability within a given plot. This involves not only recognizing spatial heterogeneity but also formulating recommendations tailored to these variable zones. Additionally, assessing the economic feasibility of implementing PA technologies adds another layer of complexity to the adoption process (Jat et al., 2018; Maresma et al., 2019).

In the absence of yield maps, apparent soil electrical conductivity (ECa) maps or satellite images currently stand out as the primary tools for delineating zones of variability within a field (Uribeetxebarria et al., 2018b; Gupta et al., 2019). These tools play a pivotal role in guiding PA strategies when yield data is unavailable. Furthermore, the utility of ECa values has been confirmed in predicting wheat and barley yields, making this source of information highly reliable due to its greater stability over the time compared to yield maps (Heil et al., 2018; Serrano et al., 2023).

The integration of site-specific variable dose technology enhances PA practices. By understanding the distinct behavioral patterns of crops in each sector of a plot, this technology facilitates the precise application of inputs in smaller, more homogeneous zones or subunits within the field (Martínez-Casasnovas et al., 2018). This targeted approach to input application proves especially valuable in the presence of significant variability in production factors across the plot, resulting in corresponding variations in yields (Virnodkar et al., 2020).

Nitrogen (N) represents a key input with a profound impact on economic performance, being a mobile nutrient in the soil crucial for optimizing grain yield. The conventional uniform N application often results in N excess in certain areas and deficiencies in others due to spatial variability. Numerous studies have emphasized the potential of site-specific N dosing in extensive cereal crops, highlighting its efficacy in mitigating the emission of greenhouse gases, reducing leaching issues and enhancing N use efficiency (Diacono et al., 2013; Peralta et al., 2015; Basso et al., 2016; Argento et al., 2021; Finco et al., 2023). However, a more precise quantification of plot variability in terms of N status and plant growth is imperative to establish a threshold for determining the feasibility of variable-rate application. The adjustment of topdressing fertilizer rates can be refined based on the crop´s vegetative state through the analysis of vegetation index or real-time sensor data, as has been stated in previous studies (Jat et al., 2018; Morari et al., 2018; Bijay-Singh et al., 2020; Corti et al., 2020; Argento et al., 2021). However, it is noteworthy that the conventional methodology for calculating the basal fertilization needs typically relies on the average potential yield observed in a given region. In semi-arid rainfed areas, such as the focus of this study, yields are closely tied to rainfall distribution, often exhibiting significant variability in the productivity history characterized by sawtooth patterns. This variability results in situations of over-fertilization in years when the potential yield is not achieved. Additionally, better understanding soil N-mineralization and related N-uptake by plants is needed for further optimization of in-season N-fertilization, as was confirmed in the studies conducted by Bijay-Singh et al. (2020) and Argento et al. (2021).

In recent years, there has been a growing number of farmers who rely on soil analyses for fertilizer calculations. It is anticipated that this trend will further intensify with the implementation of the new Regulation on Sustainable Nutrition (RD) that will govern fertilizer practices in agricultural plots in Spain. The establishment of this legislation responds to the need to mitigate the environmental impact of applying fertilizer products to agricultural soils. At the European level, the "Farm to Fork" strategy aligns with the European Green Deal and sets forth highly ambitious environmental objectives. Among these objectives is the commitment to reduce nutrient losses by at least half by 2030, without compromising soil fertility. Additionally, the strategy aims to decrease fertilizer usage by a minimum of 20% by the year 2030 (European Union, 2020).

In contrast, the sustained increase in fertilizer prices in recent years (Finco et al., 2023; Tenreiro et al., 2023) has prompted management decisions to be increasingly guided by economic criteria. This shift in focus has contributed to a reduction in over-dimensioned fertilizer doses, as farmers strive to optimize profitability based on the specific conditions of each season and minimize costs associated with excessive fertilization.

Simultaneously, the choice of seeding density is a critical production factor, and the relationship between plant density and yield must be defined in various environmental resource scenarios. Existing site-specific seeding approaches rely on arbitrary recommendations based on the fertility of management zones. Optimal plant density is a function of the interaction between variety and environment. For increased yields, adjusting seeding rates according to soil zones is recommended. Higher-yielding soil zones may benefit from higher seeding rates, while lower-yielding zones may achieve better yields with lower seeding rates or plant populations (Munnaf et al., 2020). Establishing a linkage between this parameter and soil typology remains a challenge without established rules, as varieties exhibit varying abilities to compensate for low or high seeding rates. These compensatory mechanisms involve modifications in cereal crops components, including the number of ears, the number of stems per $m^2$, the number of grains per ear, and the grain weight (Šarauskis et al., 2022).

The development of variable-rate protocols, both for seeding and fertilizer application, is further complicated by the substantial influence of climatic conditions in rainfed areas on crop response persistence. The primary objective of this study is to implement available PA technologies for the differentiated management of seed and fertilizer dosing in agronomic trials conducted in extensive semi-arid rainfed crops. The specific objective is to develop work protocols for the establishment of differentiated management zones and associated recommendations based on fertility variability within each productive zone.

## Materials and methods

### Location and edapho-climatic characteristics of the experimental plot

The experimental trial was carried out on a rainfed area located in the village of Valsalada, (Almudévar, Huesca, Spain). The study area consisted of three plots with a total area of approximately 30 ha (coordinated at 42°03×08.4´´N 0°39×06.3´´W; 422 m a.s.l). The topography of most of the surface exhibited slopes ranging from 0.1 to 5.0%, while approximately 10% of the total surface showed slopes of up to 15%. At the beginning of the trial, all three plots exhibited an identical management history with regards to crop rotations (alternating durum wheat with barley and introducing a legume crop such as peas or vetch every 3/4 years), input applications, and no-till farming practices. The soils were Typic Xerorthents and Gypsic Xerochrepts (USDA, 2014), called gypsiferous Xerorendsinas.

The average annual precipitation in the zone is below 451 mm per year, with a large thermal oscillation (average annual temperature of 14 °C), high evapotranspiration, a marked water deficit, and irregularity in the distribution of precipitation. Due to these climatic characteristics, the area is considered a semi-arid dryland in the Ebro Valley (FAO, 2007). In 2021/2022 and 2022/2023 cropping seasons, during which the experiments were conducted, an accumulated precipitation of 108.9 mm and 76.6 mm, respectively, was recorded between the months of January and May. There was a pronounced difference in the distribution of precipitation, particularly due to the low precipitation observed during the critical months for crop development in February (2021/2022) and March-April (2022/2023), as illustrated in Fig. 1.

### Apparent soil electrical conductivity

To analyze the intra-plot variability of soil properties, a soil ECa map was created. For this purpose, the Veris 3100 sensor (Veris Technologies, Salina, KS, USA), which is a contact

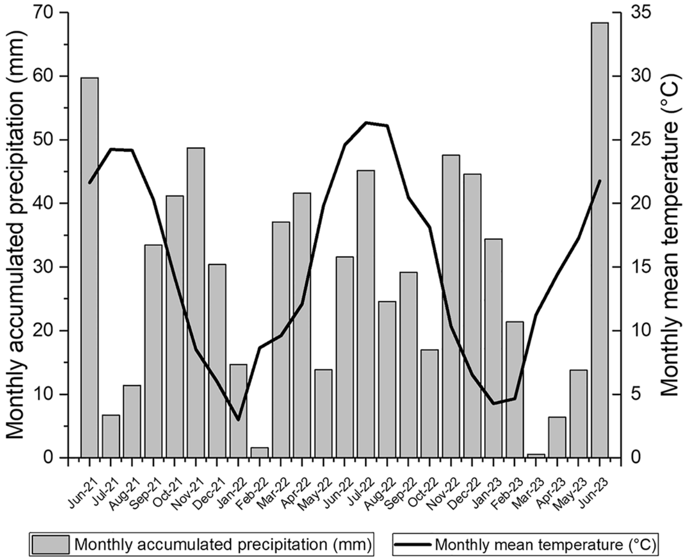


**Fig. 1** Ombrothermal diagram of the cropping seasons from the experimental trials

(or galvanic) ECa-meter, was used. The sensor provided ECa values from the shallowest soil layer (0–30 cm) and deeper layers (0–90 cm). In this study, measurements from the 0–90 cm depth range were utilized to mitigate potential influences from surface-level agricultural tillage management, and due to the higher correlation exhibited by the values with the results of the soil properties analyses (detailed in Sect. Management zones). From these data, an interpolation grid with 2×2 m pixels was generated. ECa values were estimated through local kriging using VESPER (Variogram Estimation and Spatial Prediction Plus Error) V. 1.62 (Minasny et al., 2005) and QGIS V. 3.16.4 software.

### Soil characterization and establishment of differentiated management zones

Considering the soil ECa map generated and its associated histogram, a targeted soil sampling was carried out to characterize the variability of soil properties in five zones with a gradient of ECa values (0–5, 5–10, 10–20, 20–30, > 30 mS $m^{-1}$). Considering the high variability detected in one of the plots, a grid of sampling points was stablished for systematic sampling, consisting of 46 composite samples. Additionally, 36 complementary samples were collected from different ECa zone categories, distributed across the three plots comprising the experimental set. The samples were taken using a cylindrical cane auger (Eijkelkamp, Netherlands) at a depth ranging from 0 to 30 cm, as gypsum outcomes prevented further penetration. All samples were composed by aggregating material from 5 points around the georeferenced point. Figure 2a displays the systematically distributed soil sampling points in the central plot and those conducted in the adjacent zones, based on the initial categorization of ECa. In order to delve into the factors governing the intra-plot variability of the experimental plots, additional sources of cartographic information were consulted, such as the images captured during the 1956 American flight conducted in Spain, as depicted in Fig. 2b.

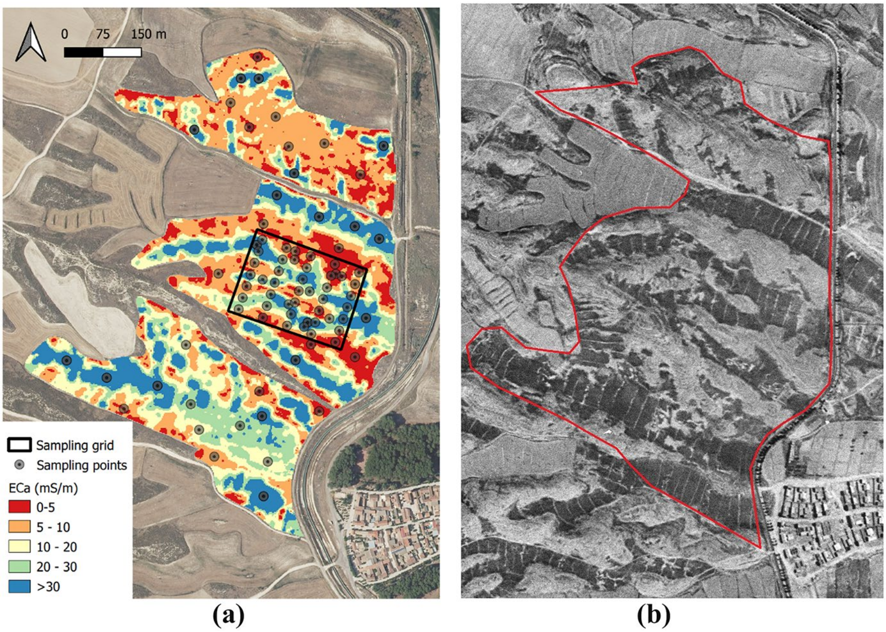


**Fig. 2** (**a**) Cartography generated from the sensing of ECa (0–90 cm) and associated soil sampling points. (**b**) Image captured during the 1956 American flight (ICEARAGON, 2023)

In Fig. 2, it can be observed that the areas formerly under cultivation (in dark color) exhibited higher ECa values. The subsequent agricultural land clearance resulted in seemingly homogeneous plots, yet their soil still reflects the previously high variability.

The samples were air-dried in the laboratory and sieved to 2 mm to calculate the percentage of coarse elements (>2 mm).The following physicochemical parameters were analyzed on the sieved fraction: pH (potentiometry), soil texture (USDA method), cation exchange capacity (spectrometry), oxidable organic matter (potentiometric titration), electrical conductivity (electrometry), calcium carbonate equivalent (potentiometric titration), water holding capacity (WHC—gravimetry—difference in water content between field capacity and permanent wilting point through Richards chambers), N (N-$NO_3$—spectrophotometry), P (Olsen— spectrophotometry), K and Mg (ammonium acetate extract buffered at pH 7). Additionally, a measurement of arbuscular mycorrhizal fungi (AMF) spore concentration was conducted as an indicator of soil biological activity ( Jaizme-Vega, 2015; García-González et al., 2016; Jaizme-Vega, 2019) in each of the composite sample. AMF spores were extracted from 20 g of each air-dried soil sample by triplicate using the wet sieving method outlined by Gerdemann and Nicholson (1963), with modifications introduced by Sieverding (1991). Once the spores were extracted, they were counted on the final filter (0.45 µm) using a stereomicroscope and the spore concentration was calculated for 100 g of dry soil. Based on the data obtained from the composite samples, a data matrix was formed, ordered by the five previously established ECa categories.

The average NDVI (Normalized Difference Vegetation Index - Rouse et al., 1974) for the last 5 years was calculated on a representative date during the crop growth (April), as explained in Sect. Crop vegetation index monitoring and final yield data. The distribution of the average NDVI values was studied in conjunction with the previously explained data to delve deeper into the detected variability.

Differences in the distribution of parameters among zones were assessed through the Kruskal-Wallis statistical analysis of variance using the IBM SPSS Statistics V.26 software. A predictive linear regression model was stablished using R Commander Package V. 2.7–2. The data set was divided into calibration (70%), and validation (30%) sets (Guerrero & Mouazen, 2021), verifying the predictive level for the ECa zone. Multiple Linear Regression (MLR) was applied to explain the relationship between soil ECa and independent variables.

## Experimental design of variable seeding rate and fertilization

Based on the ECa map and the soil physicochemical results, differentiated management zones (MZs) were established. An experimental design was conducted in two specific zones within the plots, identified as homogeneous areas with ECa values associated with the lowest (MZ 1) and highest (MZ 2) fertility levels, respectively. In this respect, MZ 1 was characterized by a loamy texture and moderate levels of N, P, and K at 9.3 mg kg$^{-1}$, 6.38 mg kg$^{-1}$, and 109.3 mg kg$^{-1}$, respectively. Similarly, MZ 2 was characterized by a clayey-loam texture and higher levels of macronutrients, with average values of 24.3 mg kg$^{-1}$ for N, 7.7 mg kg$^{-1}$ for P, and 150.7 mg kg$^{-1}$ for K. Three factors were established as independent variables: ECa zone, seeding rate and basal fertilizer dosage, each with two levels (high and low) associated with them. In the 2021/2022 cropping season *Triticum durum* L. var. Filón was the selected crop, while *Hordeum vulgare* L. var. Asteroid was chosen for the subsequent season (2022/2023). The range of seeding rates applied in both experimental campaigns varied within the interval of 350 and 450 grains m$^{-2}$, calculating the equivalent dose (kg ha$^{-1}$) based on thousand kernel weight. Two different doses of fertilizer (diammonium phosphate with an NPK ratio of 18-46-0) were applied to represent high and low basal fertilizer dosages. The chosen dosage range for basal fertilizer varied significantly between cropping seasons. They were determined based on recommendations for the region, considering the potential productivity of the plots in years with adequate precipitation distribution, the economic cost of inputs (with a significant increase in 2020), and previous yields. Seeding and fertilization were carried out, based on prescription maps, on November 6th 2021 and December 5th with a John Deere 750 A direct disc planter (6 m of working width) and a Rauch Axis 40.2 M-EMC-W mounted centrifugal disk fertilizer spreader (with hydraulic actuation and variable dosing capacity determined by prescription map inserted in the cab console and recognized by ISOBUS system), respectively. The seeding and fertilizing speeds were 11 and 12 km h$^{-1}$, respectively, and the working width of the fertilizer spreader was 24 m. Nitrogen fertilization was completed in February 2022 and 2023 (tillering stage) using the same fertilizer spreader. The dosage of topdressing fertilizer applied was uniform in both experimental cropping seasons, consisting of solid urea (46% N). In 2021/2022, 200 kg ha$^{-1}$ of N were applied, representing the majority of nitrogen units applied as a topdressing (80–90%). During the barley season, 100 kg ha$^{-1}$ were applied, indicating a 34% reduction in the total N application for this season. Table 1 summarizes the doses applied for each level of independent variables (high and low) in each experimental cropping season.

The experimental area in the plots was subdivided into experimental units defined by rectangles of 50 m long and 24 m wide, this involved 8 passes of the seeder and 3 passes of the fertilizer spreader to complete the prescriptions in the total width of the experimental

**Table 1** Summary of the applied dosage ranges for each input in the two experimental growing seasons

| Inputs | 2021/2022 | | 2022/2023 | |
|---|---|---|---|---|
| | Low | High | Low | High |
| Crop/cultivar | Wheat/ Filón | | Barley/Asteroid | |
| Seeding rate (kg ha$^{-1}$) | 130.0 | 167.0 | 135.0 | 173.0 |
| Basal fertilizer rate (kg ha$^{-1}$) | 70.0 | 130.0 | 120.0 | 180.0 |
| Total basal N applied (kg ha$^{-1}$) | 12.6 | 23.4 | 21.6 | 32.4 |
| Topdressing nitrogen fertilizer (kg ha$^{-1}$) | 200.0 | 200.0 | 100.0 | 100.0 |
| Total N applied (kg ha$^{-1}$) | 104.6 | 115.4 | 67.6 | 78.4 |

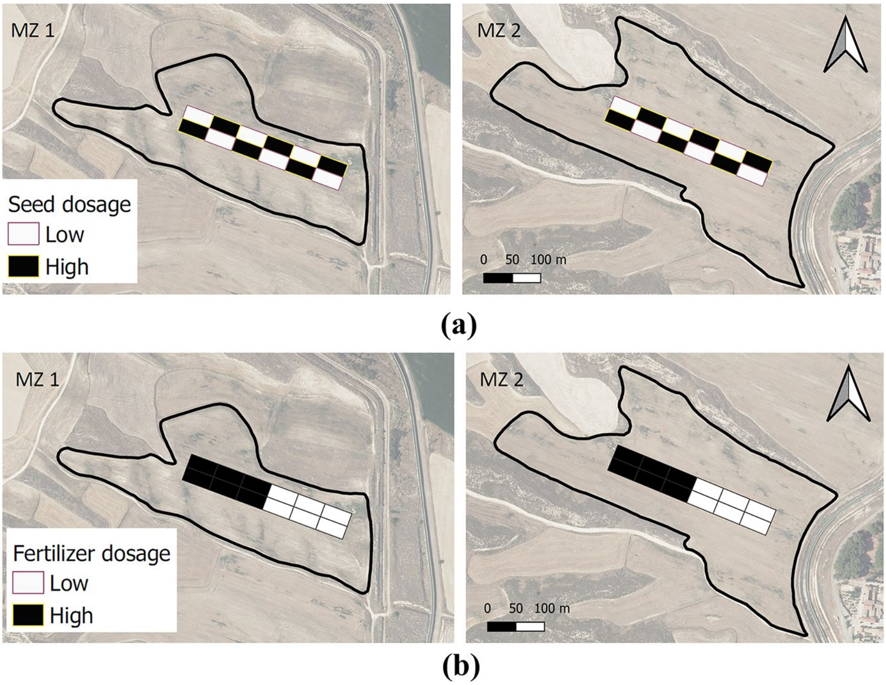


**Fig. 3** Experimental design adopted in the two studied plots. (**a**) Seeding variable rate and (**b**) basal fertilizer variable rate.

subunits. The dimensions were selected to facilitate the adaptation of the treatments to the working width of the machinery and the subsequent statistical analysis of the data. The homogeneity detected in the selected zones allowed the establishment of a balanced experimental design, with all doses covering both differentiated MZs.

Figure 3a and b show the experimental design of seeding rates and fertilization adopted in the experimental plots.

The prescription maps were generated using QGIS V 3.16.4 software and exported to shapefile format to be loaded into the machinery through the task management platform of the monitor (Operations Center, John Deere). Data collection on this platform allowed, once the tasks were completed, to download the maps of actual application to check for possible errors and percentage variations compared to the preset doses, which were found to be less than 5% in all cases.

The occasional and localized errors were subsequently considered when setting random sampling points in QGIS for statistical analyses (as described in Sect. Statistical analysis of results).

### Crop vegetation index monitoring and final yield data

The vegetative growth of the crop was monitored through the NDVI. NDVI was computed using data extracted from satellite images provided by the Planet Scope constellation (Planet Labs, San Francisco, CA, USA) with bands covering the visible and near-infrared spectrum. These images featured a spatial resolution of 3×3 m pixel size and possessed a daily temporal resolution. The imagery spanned from the tillering stage of the crop to its harvest (02/18/22 to 06/15/22, 02/15/23 to 06/03/2023), with 10 cloud-free images used for calculating the cumulative NDVI. The processing level applied was Surface Reflectance, incorporating atmospheric scattering correction to the image bands. NDVI computation from the images was executed using Google Earth Engine software and the accumulated NDVI (NDVIa) was derived as the sum of distinct NDVI values for each analyzed date.

The harvest in both cropping seasons was carried out using a John Deere W660 combine equipped with yield sensors and monitoring systems. The yield data were exported in shapefile format, corrected to 14% moisture content, and subjected to statistical interpolation through local kriging using VESPER V 1.6. software.

### N use efficiency

Nitrogen use efficiency (NUE) was determined through the partial balance method (Basso et al., 2016; Dahal et al., 2020), with the calculation involving inputs such as grain yield and the quantity of nitrogen applied. The Eq. (1) for its calculation is as follows:

$$NUE = \frac{Yield\ \left(kg\ ha^{-1}\right)}{N_{app}\ \left(kg\ ha^{-1}\right)} \tag{1}$$

where $N_{app}$ is the N fertilizer amount.

### Economic return

In this research, the financial advantages of spatially variable rate fertilization were assessed through the examination of the partial net income, determined utilizing Eq. (2) (Wang et al., 2023):

$$N_I = (C_Y \times\ C_p) - (F_{app} \times\ F_p) - (S_{app} \times\ S_p) \tag{2}$$

where $N_I$ is the partial net income (€ $ha^{-1}$), $C_y$ is cereal grain yield (kg $ha^{-1}$), $C_p$ is grain price (€ $ha^{-1}$), $F_{app}$ is fertilizer applied amount (kg $ha^{-1}$), $F_p$ is fertilizer price (€ $ha^{-1}$), $S_{app}$ is seed applied amount (kg $ha^{-1}$), and $S_p$ is seed price (€ $ha^{-1}$).

Table 2 summarizes the prices associated with the studied variable inputs and grain selling price in both growing seasons.

As specified, the calculated net return is partial and solely related to the evaluated inputs. In this study, other costs associated with phytosanitary treatments or management activities have not been factored in, considering them common across all treatments.

### Statistical analysis of results

The correlation between the physicochemical parameters determined from the soil samples and the ECa measurements was evaluated through de Spearman test, after confirming the non-normality of physicochemical data distribution. The average NDVIa and yield results was obtained for each experimental subplot using the zonal statistics tool from QGIS software. Three-way ANOVA was conducted to analyze the effect of factors (ECa, seeding rate, and fertilizer rate) and their interactions on the response variables were analysed. Univariate ANOVA was conducted to evaluate the means distribution as a function of treatments (combination of factors). Means comparisons were combined with the HSD Tukey´s test with a significance level of 0.05. The software used for these analyses was IBM SPSS Statistics V.26.

## Results and discussion

### Management zones

The distribution of the obtained measurements from the deep-ECa (0–90 cm) sensing, showed in Fig. 2, were very similar to those obtained for shallow-ECa (0–30 cm). The ECa values obtained ranged from 0 to 206 mS $m^{-1}$, with the majority of the data falling between 5 and 80 mS $m^{-1}$. No values indicative of potential salinity were detected. In the case study, the initial representation of potential intra-plot variability linked to ECa (shallow and deep) measurements was similar, with slight variations in the data, which exhibited smoother transitions between zones in the case of shallow-ECa. However, the analysis of the correlation between these values and the results obtained from physicochemical analyses of soil samples revealed a higher correlation with the deep-ECa. Table 3 presents the results of the Spearman correlation test.

This higher correlation of deep-ECa with the studied properties is in line with previous studies (Simón et al., 2013), where the strongest correlations were established between soil texture class, specifically clay content, and its relationship with moisture content. In this study, relatively constant parameters over the time have been analysed, considering that the detected variability responds more to natural patterns than differences in specific nutrients.

**Table 2** Prices associated with the studied variable inputs and grain selling (€/Mg)

| Inputs | 2021/2022 | 2022/2023 |
|---|---|---|
| Diammonium phosphate (18-46-0) | 770 | 984 |
| Urea (46%) | 864 | 518 |
| Seed R-2 wheat | 420 | - |
| Seed R-2 barley | - | 512 |
| Grain selling price | 340 | 220 |

**Table 3** Correlation level between ECa (deep and shallow) and soil properties. Spearman test

| | ECa (0–30 cm) | | ECa (0–90 cm) | |
|---|---|---|---|---|
| | Spearman correlation coefficient | p-value | Spearman correlation coefficient | p-value |
| Clay | 0.665 | < 0.0001 | 0.778 | < 0.0001 |
| Sand | –0.629 | < 0.0001 | –0.732 | < 0.0001 |
| Silt | –0.442 | 0.003 | –0.535 | < 0.0001 |
| CEC | 0.724 | < 0.0001 | 0.801 | < 0.0001 |
| Coarse elements | –0.720 | < 0.0001 | –0.810 | < 0.0001 |
| $CaCO_3$ | 0.598 | < 0.0001 | 0.671 | < 0.0001 |
| WHC | –0.116 | 0.365 | –0.221 | 0.272 |
| pH | 0.290 | 0.147 | 0.490 | 0.001 |
| CE (ext. 1:5 $H_2O$) | –0.307 | 0.048 | –0.475 | 0.001 |

Figure 4 depicts the main differences observed in the distribution of soil physicochemical and biological parameters analysed, and average NDVI, based on the sampled ECa zones (deep). The figure displays the results of parameters whose distribution showed a clear (direct or inverse) relationship with ECa values.

A very distinct inflection point was observed at 10 mS $m^{-1}$ for all variables, with a smoother variation in the case of NDVI. In the conditions of this study, ECa zones with values above 10 mS $m^{-1}$ exhibited significantly higher values of organic matter, CEC, clay content, $CaCO_3$ content, and concentrations of AMF spores, which are closely associated with higher soil quality and fertility. These high ECa zones coincided with areas formerly under cultivation in the region, specifically valley bottoms surrounded by slopes. In contrast, the zones with low ECa values were those not cultivated prior to parcel concentration, where scrubland predominated in the past. These zones can be associated with lower fertility levels, regulated in this case by soil properties that vary little over the long term, and directly influence the nutrient content. This result is consistent with the findings reported by Uribeetxebarria et al. (2018b), where the results of intra-plot variability measured from soil ECa are linked to the previous management of the plots, highlighting the spatial pattern reflected by ECa as a consequence of the previous parceling process.

The distribution of AMF spore concentration based on ECa zones is noteworthy, showing a clear behavioral pattern similar to the other analyzed parameters. The inclusion of indicators of biological activity for the delineation of differentiated management zones has not been widely studied, and low correlations of some indicators (microbial biomass carbon, released $CO_2$ carbon, and metabolic coefficient) have been reported in a previous study (Machado, 2009) conducted in the northern region of Spain.

Figure 5 illustrates the categorization of ECa zones that exhibited significant differences in the studied parameters, thus being susceptible to differentiated management.

In the Fig. 5, it can be observed that the experimental design proposed in this trial was situated in two relatively homogeneous zones in terms of high and low ECa values.

## ECa explanation: multiple Linear regression model (MLR)

The value of ECa could be estimated as the expression in Eq. (3):

$$ECa\ \left(mS\ m^{-1}\right) = I + a \cdot\ sand + b \cdot\ CIC + c \cdot\ lime + d \cdot\ organic\,matter + e \cdot\ coarse\ element \quad (3)$$

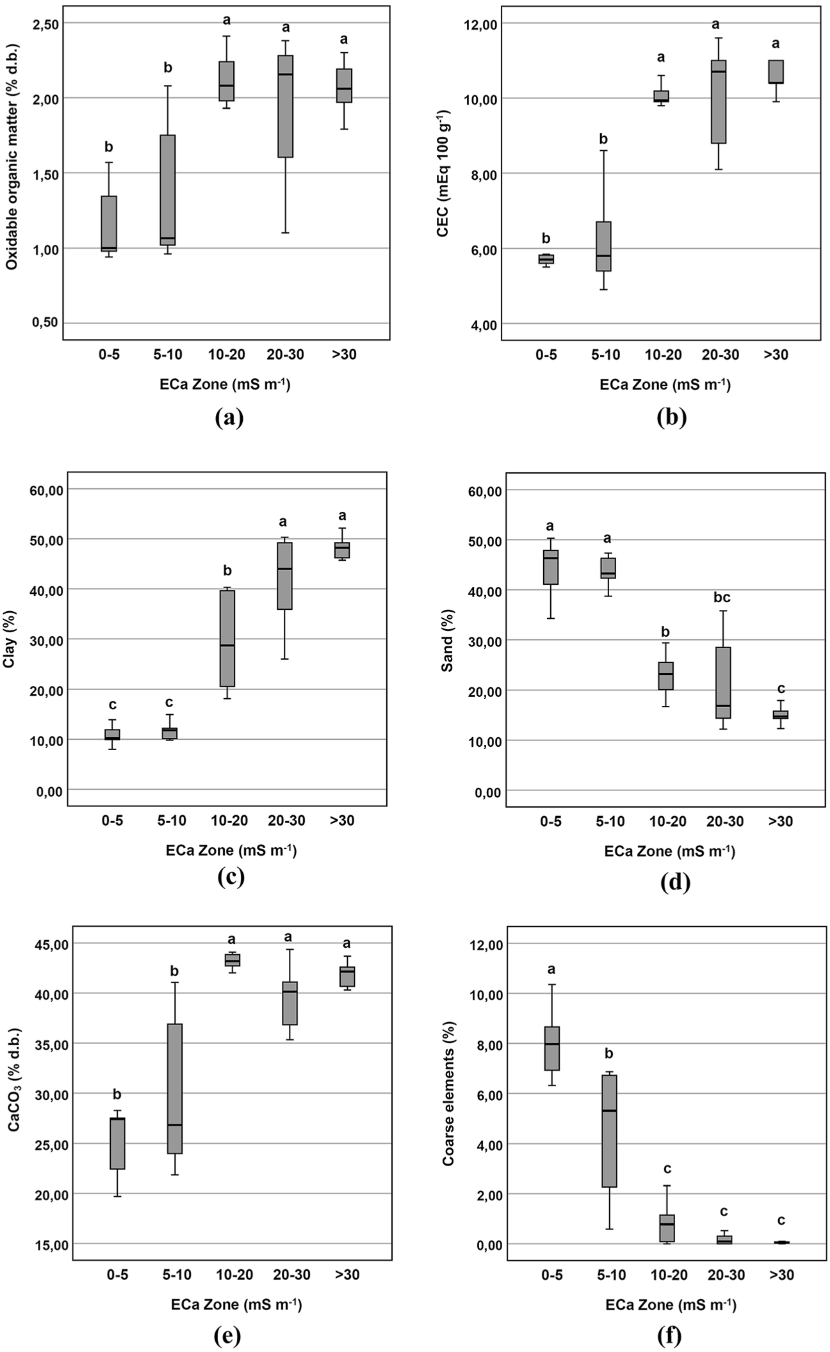


**Fig. 4** Distribution of values for different physicochemical and biological parameters based on the ECa zone. The boxes represent the median and interquartile range, and the bars indicate the maximum and minimum values. Different letters indicate significant differences based on Kruskal-Wallis ANOVA ($p \leq 0.05$)

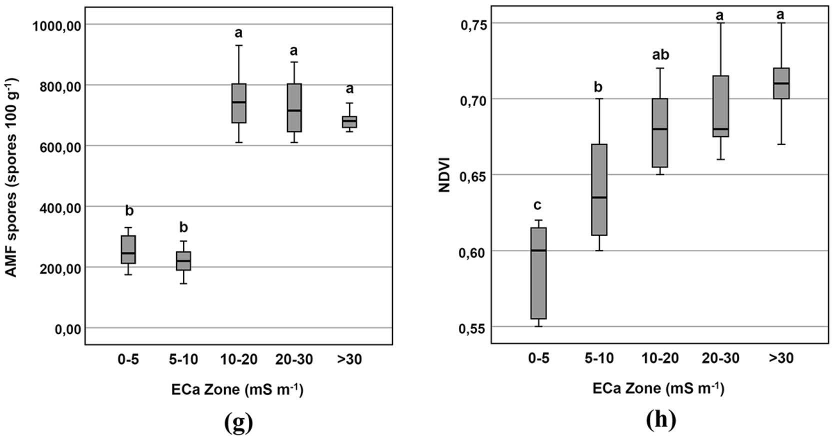


**Fig. 4** (continued)

where *I* is the intercept, and *a*, *b*, *c*, *d*, and *e* the coefficients of the equation obtained in the regression analyses.

The results (intercept, coefficients and model determination coefficient) are shown in Table 4, for an adjusted $R^2 = 0.865$ and $p < 0.0001$.

Component and residual plots of the model (not shown) provided insight into the model´s fit and the potential for improvement through polynomial equations. However, attempts to improve it with raw polynomial or natural spline adjustments did not yield improvements over the linear regression model.

The model was validated by predicting 30% of initially not introduced values. The validation goal was not to obtain the exact ECa value based on soil properties but to achieve a value classified within the range of the 5 pre-established ECa categories (0–5, 5–10, 10–20, 20–30, >30 mS m$^{-1}$), which was validated in 97% of cases. In practical terms, this implies that differentiated management zones could be established in the study area based on soil ECa measurements and regularly analyzed soil data. Additionally, the results of targeted soil sampling, based on other sources of information (yield and/or biomass index maps), could be related to ECa categories and therefore to soil fertility real levels.

In line with previous studies (Castro & Costa, 2012; Liao et al., 2014; Machado, 2009; Simón et al., 2013; Uribeetxebarria et al., 2018b, Arnó et al., 2018), a strong influence of soil texture on the ECa values was confirmed. However, a significant influence of clay content and WHC would have been expected in the model. In this case, sand and silt content proved to be significant parameters intimately linked to clay content, but a direct influence of WHC, which is also related to texture, was not observed.

## Effect of factors on crop growth and yield

Figure 6 depicts the distribution of values obtained for the dependent variables: yield (kg ha$^{-1}$) and NDVIa, in each experimental cropping season.

As can be seen, intra-plot variability was mapped for both NDVIa and yield results. The average value obtained for NDVIa in 2021/2022 was 4.55 ± 0.25 (minimum of 4.18 and maximum of 5.06). For that cropping season, the final average yield of the wheat crop

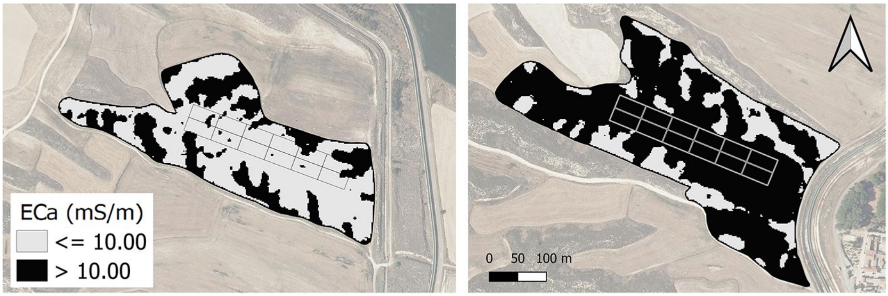


**Fig. 5** Distribution of differentiated management zones with significantly different soil properties represented by their ECa values

**Table 4** Regression coefficients for ECa values (mS $m^{-1}$) as a function of sand content (%), $CaCO_3$ content (%), CEC (mEq 100 $g^{-1}$), AMF spore's concentration (spores 100 $g^{-1}$), lime content (%), oxidable organic matter (%), NDVI and coarse elements (%) – adjusted $R^2$ = 0.865

| Parameter | Estimate | Standard error | *p*-value |
|---|---|---|---|
| Intercept | 24.623 | 6.164 | < 0.001 |
| Sand | –0.246 | 0.074 | < 0.01 |
| CEC | 2.886 | 0.561 | < 0.0001 |
| Silt | –0.249 | 0.065 | < 0.001 |
| Organic matter | –8.909 | 2.324 | < 0.001 |
| Coarse elements | –0.637 | 0.224 | < 0.01 |

reached a value of 1012.13 ± 179.48 kg $ha^{-1}$ (minimum and maximum values of 654.33 and 1391.97 kg $ha^{-1}$, respectively). The low precipitation in January and February, and the high temperatures recorded in May and June (final growth stage and grain-filling period) led to a considerable reduction in the final yield. Regarding the 2022/2023 growing season, the average value of NDVIa was 10.76 ± 2.27 (minimum of 8.00 and maximum of 14.06). The final average yield of the barley crop was 1422.46 ± 802.09 kg $ha^{-1}$ (minimum and maximum values of 604.32 and 2575.99 kg $ha^{-1}$, respectively). In this agricultural season, barley cultivation suffered from the low rainfall in the months of March, April, and May, resulting in significant, widespread reductions in overall yields across the productive averages of the region.

Results of three-way ANOVA concerning the effect of ECa, seeding rate (SR) and fertilization rate (FR) on the vegetation index and final yield are shown in Table 5.

As can be seen from the above results, of the three analyzed factors (ECa zone, seeding and fertilization rate), ECa, and hence soil variability, had the highest effect on NDVIa and final yield, in line with the results obtained in the previous experimental cropping season (Minuesa, 2021). The seeding rate did not show a significant effect on the NDVIa or yield in either of the two cropping seasons, nor did its interaction with the other factors show a significant effect. The variable base fertilizer dosage exerted a significant and pronounced influence on NDVIa across both experimental growing seasons. However, its impact on final yield differed between experiments, showing statistical significance only in the 2022/2023 barley campaign. Figures 7 and 8 show the results of the one-way ANOVA conducted to evaluate the distribution of NDVIa and yield values for each combination of influent factors, therefore, treatments should be understood as the combination of ECa and FR.

In the 2021/2022 cropping season, and selecting by ECa values, in MZ 1 (ECa ≤ 10 mS $m^{-1}$) an average value of 4.39 ± 0.15 for the NDVIa was obtained, which was significantly lower than the 4.70 ± 0.23 obtained for MZ 2 (ECa > 10 mS $m^{-1}$). Regarding the yield, a significantly higher value was also obtained in MZ 2 as compared to MZ 1, with values of 1081.69 ± 177.36 and 942.57 ± 159.20 kg $ha^{-1}$, respectively. It should be noted that, although the differences in the average values were statistically significant, these differences are reduced at a practical level, especially considering such a low yield level as that of the crop growing season studied in this experiment. However, at this practical level, the differences observed on the behavior of the crop under the seeding and fertilization variable rates were interpreted in order to formulate recommendations to avoid the risk of yield losses.

Considering the variable fertilization dosing, it was observed that the higher levels of fertilizer were associated with increased NDVIa and yields, both in MZ 1 and MZ 2, which could warn of the risk of reducing the dose of basal fertilizer in both zones. This result complements the conclusions obtained in the previous growing season, in which basal fertilizer had a significant effect on the NDVIa only in zones with lower values of ECa (Minuesa, 2021).

In contrast, the seeding rate could be reduced in both MZ without compromising the yield, demonstrating that the relationship between plant density and yield is not directly proportional in all edapho-climatic situations. This result is in line with recommendations contained in the reviews of some authors (Munnaf et al., 2020; Šarauskis et al., 2022) and it would be explained through the concept of the wheat plasticity.

In the 2022/2023 cropping season, based on ECa values, MZ 1 yielded an average NDVIa value of 8.62 ± 0.43, significantly lower than the 12.89 ± 0.84 recorded for MZ 2. Similarly, the yield in MZ 2 was significantly higher compared to MZ 1, with values of 1991.60 ± 297.57 and 664.24 ± 48.10, respectively.

Considering variable fertilization, in this cropping season, the highest vegetation index and yields were obtained for the high basal fertilizer dose in MZ 2, while no significant differences were observed in the low fertility zone (MZ 1).

The debate over whether to adopt a higher (*King's* scheme – KS) or lower (*Robin Hood* scheme – RHS) input application in high/low fertility zones, respectively, intensifies in study areas such as the one covered in this research. Studies by Morari et al. (2018) and Guerrero and Mouazen (2021) have demonstrated the advantages of the RHS for N application, highlighting its benefits in cases where low fertility is not associated with significant issues or erosion. In situations like the one at hand, considering the low levels of organic matter, a soil fertility problem is evident, with questionable compensation through increased N application. The high-fertility zone responded to increasing fertilizer doses in the 2022/2023 growing season, with different distribution and reduction in nitrogen units compared to 2021/2022.

Once again, the seeding rate emerged as an input that could be reduced in these experimental conditions without compromising crop yield or growth rate, as evidenced in both MZs and under different fertilizer doses. In the study conditions, it is assumed that very few farmers conduct seed counts to determine appropriate sowing doses. Therefore, the proposed dose reduction is significant when compared to the doses commonly applied but less notable when considering recommendations for these cereals in grains $m^{-2}$. Studies such as those by Munnaf et al. (2020) and da Silva et al. (2021) highlight the possibility of reducing doses in low-fertility zones in various crops, partially aligning with the results of this study,

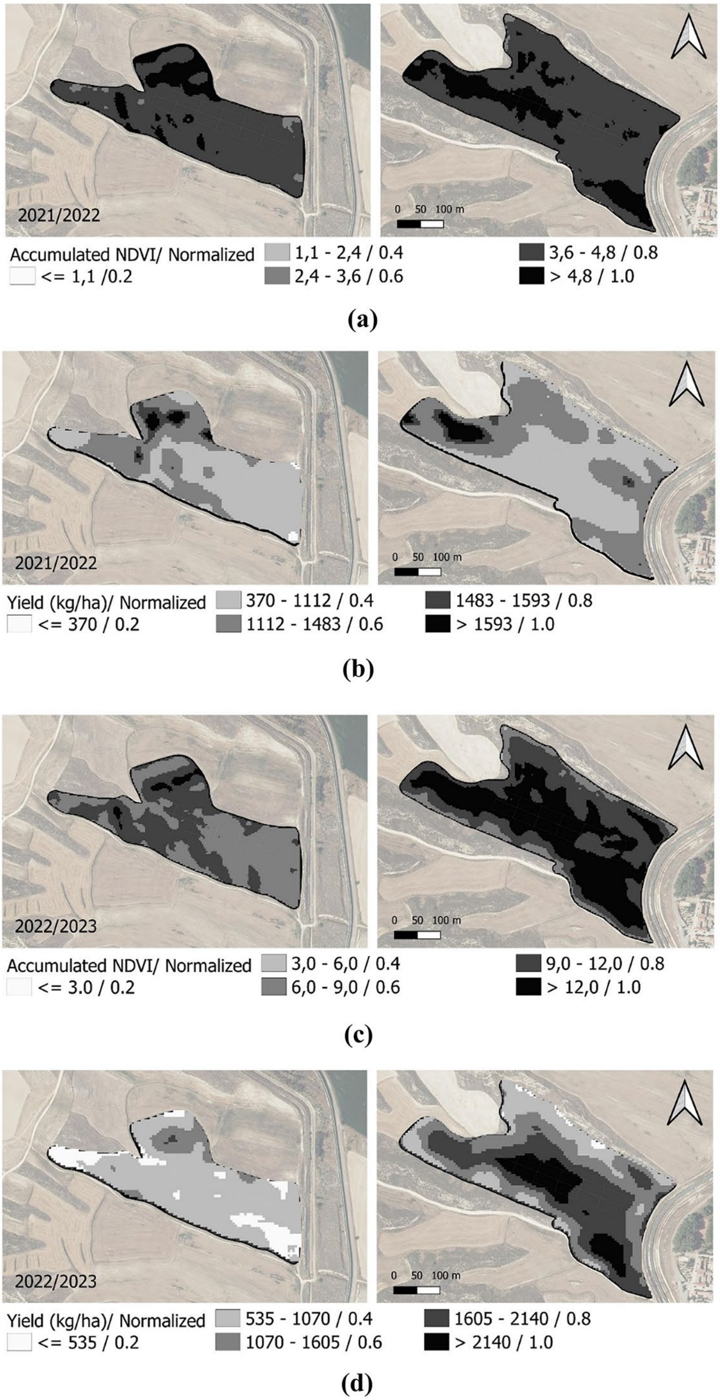


**Fig. 6** NDVIa map and yield map of the experimental plots in 2021/2022 (**a**, **b**) and 2022/2023 (**c**, **d**) cropping seasons

**Table 5** Three-way ANOVA results on the effects of apparent electrical conductivity (ECa), seeding rate (SR) and fertilization rate (FR) on NDVIa and final yield

| | 2021 / 2022 | | 2022 / 2023 | |
|---|---|---|---|---|
| Factor | NDVIa | Final yield | NDVIa | Final yield |
| **ECa** | < **0.0001** | 0.041 | < **0.0001** | < **0.0001** |
| **SR** | 0.619 | 0.831 | 0.855 | 0.629 |
| **FR** | < **0.0001** | 0.108 | < **0.001** | **0.020** |
| **ECa * SR** | 0.061 | 0.550 | 0.422 | 0.984 |
| **ECa * FR** | 0.251 | 0.600 | 0.486 | 0.057 |
| **SR * FR** | 0.523 | 0.925 | 0.315 | 0.411 |
| **ECa * SR * FR** | 0.689 | 0.665 | 0.950 | 0.876 |

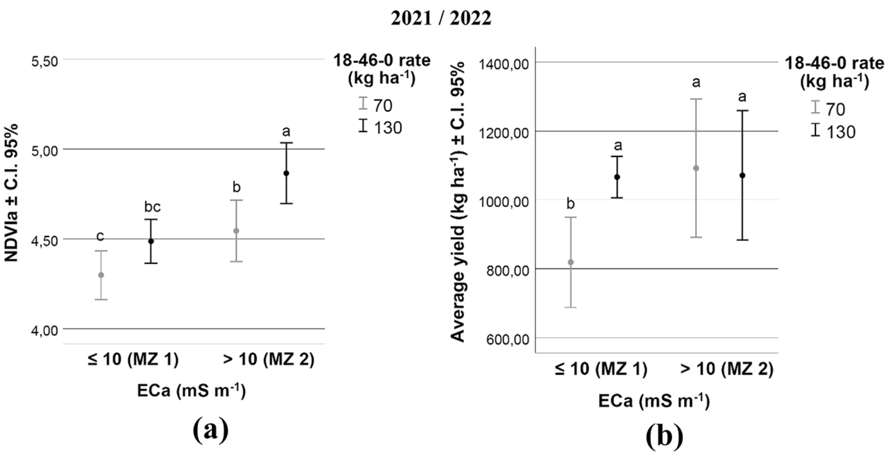


**Fig. 7** 2021/2022 growing season. Effects of ECa and fertilization rate on (**a**) NDVIa and (**b**) average yield. Different letters show statistically significant differences at $p \leq 0.05$ (Tukey´s test)

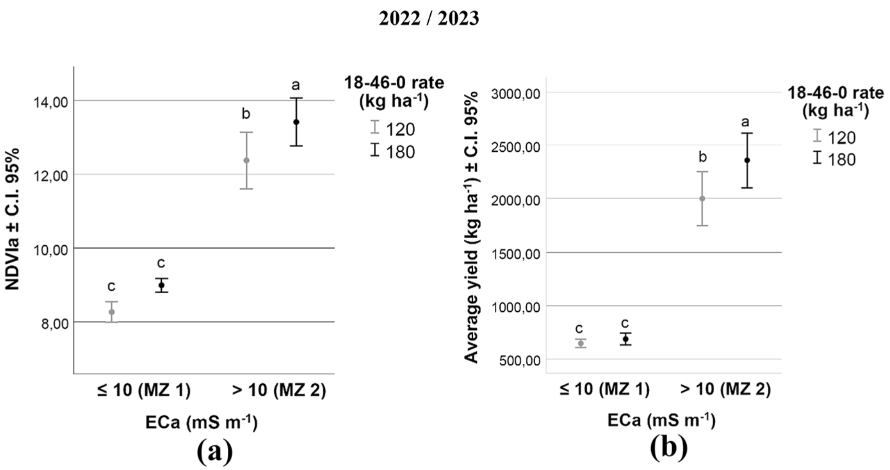


**Fig. 8** 2022/2023 growing season. Effects of ECa and fertilization rate on (**a**) NDVIa and (**b**) average yield. Different letters show statistically significant differences at $p \leq 0.05$ (Tukey´s test)

particularly in the case of barley cultivation and its association with specific nitrogen availability. The need to study other related factors, such as sowing depth, becomes evident, as it was not considered in this study and may have significant effects, as reflected in the studies by Ding et al. (2021) and Kazlauskas et al. (2021).

### N use efficiency and economic return

Table 6 presents the results obtained for NUE and partial net economic return in each of the studied treatments.

The data obtained raises concerns about the low efficiency of such agricultural systems in nitrogen utilization (ranging from a concerning 7.53% to a more favorable 30.85% in the best-case scenario), and consequently, in their contribution to pollution due to nitrogen loss. Faced with adverse climatic events in these growing seasons, such as uneven precipitation distribution and rising temperatures, the need to fine-tune nitrogen doses and distribution becomes evident. These data are incomparable with those from other studies conducted in rainfed areas (Basso et al., 2016; Tenreiro et al., 2023), which showed higher levels of NUE due to the soil typology under investigation. In the 2022/2023 season, with a total reduction in the applied N dose (but with a higher dose in the basal fertilization), the economic return from the low-fertility zone was negative. This emphasizes the need to refine the distribution of fertilizer doses in these areas and the necessity of reducing the seed dose.

### Future perspectives

The development of this experimental trial has been integrated into a participatory research model (on-farm experimentation), wherein conventional recommendations of the study area have been followed. The obtained results will enable a transition in the area towards more efficient management models, establishing a balance between environmental and economic sustainability. The variable-rate application technique has proven to be a valuable tool in this regard. However, in the face of recurring adverse climatic events in the area, it is necessary to combine such studies with the development of models capable of correlating climatic data with the potential yield for each year (Gobbo et al., 2022). The topography of agricultural plots in these systems is also a factor to consider, undoubtedly contributing to improving the characterization of differentiated management zones (Tenreiro et al., 2023).

## Conclusions

This study explored the distribution of ECa values, both shallow and deep, in the context of management zones. While the initial representation of intra-plot variability linked to ECa measurements exhibited similarities, correlations with soil properties were found to be higher for deep-ECa, aligning with previous research. The multiple linear regression model successfully explained ECa variability based on soil properties, allowing for the establishment of robust differentiated management zones. The impact of ECa zones on crop growth and yield was evident, with significant variations observed in NDVIa and yield across different seasons and treatments. The debate on input application schemes intensified, with the study highlighting the advantages of a lower input scheme in low-fertility zones. How-

**Table 6** N use efficiency (%) and partial net economic return (€ $ha^{-1}$) of the treatments ($N_{app}$: applied N; $BF_{app}$: basal fertilizer applied; $TF_{app}$: topdressing fertilizer applied; $S_{app}$: seed applied; $S_c$: seed cost; $F_c$: total fertilizer cost; $N_i$: partial net income)

| Growing season | ECa (mS $m^{-1}$) | $N_{app}$ (kg $ha^{-1}$) | $BF_{app}$ + $TF_{app}$ (kg $ha^{-1}$) | $S_{app}$ (kg $ha^{-1}$) | Average Yield (kg $ha^{-1}$) | NUE | $S_c$ (€ $ha^{-1}$) | $F_c$ (€ $ha^{-1}$) | $N_i$ (€ $ha^{-1}$) |
|---|---|---|---|---|---|---|---|---|---|
| **2021/2022** | **≤10** | 104.60 | 70+200 | 130 | 849.68 | 8.12 | 54.60 | 226.70 | 7.59 |
| | | 115.40 | 130+200 | 130 | 1061.64 | 9.20 | 54.60 | 272.90 | 33.46 |
| | | 104.60 | 70+200 | 167 | 787.95 | 7.53 | 70.14 | 226.70 | -28.94 |
| | | 115.40 | 130+200 | 167 | 1071.02 | 9.28 | 70.14 | 272.90 | 21.11 |
| | **>10** | 104.60 | 70+200 | 130 | 1053.33 | 10.07 | 54.60 | 226.70 | 76.83 |
| | | 115.40 | 130+200 | 130 | 1055.13 | 9.14 | 54.60 | 272.90 | 31.24 |
| | | 104.60 | 70+200 | 167 | 1131.19 | 10.81 | 70.14 | 226.70 | 87.76 |
| | | 115.40 | 130+200 | 167 | 1087.11 | 9.42 | 70.14 | 272.90 | 26.58 |
| **2022/2023** | **≤10** | 67.60 | 120+100 | 135 | 652.17 | 9.65 | 69.12 | 178.80 | -104.44 |
| | | 78.40 | 180+100 | 135 | 639.73 | 8.16 | 69.12 | 225.00 | -153.38 |
| | | 67.60 | 120+100 | 173 | 635.71 | 9.40 | 88.58 | 178.80 | -127.52 |
| | | 78.40 | 180+100 | 173 | 729.34 | 9.30 | 88.58 | 225.00 | -153.12 |
| | **>10** | 67.60 | 120+100 | 135 | 2020.47 | 29.89 | 69.12 | 178.80 | 196.58 |
| | | 78.40 | 180+100 | 135 | 2301.18 | 29.35 | 69.12 | 225.00 | 212.14 |
| | | 67.60 | 120+100 | 173 | 1982.61 | 29.33 | 88.58 | 178.80 | 168.80 |
| | | 78.40 | 180+100 | 173 | 2418.42 | 30.85 | 88.58 | 225.00 | 218.48 |

ever, depending on the climatic conditions of each agricultural season, it will be necessary to study de long-term effect of this strategy over several years, ensuring a minimum of nutrients available for the crop and assessing the opportunity to improve soil fertility through strategies of organic matter addition. The potential to reduce the seed rate without compromising the yield is an encouraging outcome that can be applied to PA practices in this edaphoclimatic zone. Concerns were raised regarding the low nitrogen use efficiency and economic return in the studied agricultural systems, underscoring the need for refined nitrogen dosing strategies. This study's results contribute to the ongoing efforts to transition the area towards more efficient and sustainable management models, leveraging variable-rate application techniques. However, the study acknowledges the importance of combining such approaches with climatic modeling and consideration of topography for a comprehensive understanding of differentiated management zones.

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**Conflict of interest** The authors declare that they have no conflict of interest.

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