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Dryland Winter Wheat Production and Its Relationship to Fine-Scale Soil Carbon Heterogeneity—A Case Study in the US Central High Plains

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Abstract: Soil carbon plays a key role in maintaining soil quality, but its direct impact on crop yields depends on the interplay of different factors. This study aims to study fine–spatial variation soil properties and their effect on grain productivity in fallow–wheat cropping systems in the US central High Plains. We evaluate wheat yields in relation to soil macro and micronutrients, total C (TC), and texture as well as subtle variations in field elevation. To document soil–yield relationships at a fine spatial scale, soil sampling (0–15 and 15–30 cm depths) was conducted using a regular 30 m grid spacing in eleven adjacent fields. Interpolated yield maps indicated that the availability of key nutrients and textures contributed to the spatial distribution of wheat productivity. Random forest (RF) showed that these soil attributes were able to explain slightly under 30% of the spatial variation in crop yields. Our findings demonstrate that TC can often serve as a reliable proxy for delineating yield-based management zones, even in inherently low C soils. In addition, Fe, Zn, SO_4-S, sand, and subtle topographic changes were also critical factors affecting wheat yield. Our results highlight that developing management zones in these soils relying exclusively on soil information is not straightforward. However, the high level of within-field spatial variability observed needs to be addressed.

Keywords: dryland systems; grain yield; decision making; organic matter; precision agriculture; soil heterogeneity; winter wheat

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1. Introduction

Wheat is one of the most important dryland crops in the Central Great Plains of North America and globally. Soils in these regions are often characterized by low soil organic matter (SOM), poor fertility, and low overall productivity. Therefore, nutrient supply is especially needed in this region [1]. Moreover, rising temperatures and erratic precipitation during the last few decades, along with a continued use of tillage and fallow periods, have degraded soil quality and threatened the profitability and productivity of dryland agriculture in the region [2,3].

While climate is often the most crucial factor in crop productivity, the basis for adapting and mitigating climate change effects on crop yields largely depends on soils and their capacity to retain nutrients or water [4–6]. Therefore, considerable attention has been focused on soil attributes, such as soil carbon (C), which is a critical quality indicator that can affect the availability of water and limiting nutrients for plant growth [7–9]. However, despite the expected ability of soil C to modulate nutrient retention, inconsistent effects of

C and nutrient availability on wheat yields have been reported [10,11]. In some instances, crop production and quality have been related to crop management practices and soil texture rather than soil chemical properties [12–14]. Typically, soil chemical and physical properties are important for yield variations at small scales, while topography as well as hydrological and climatic processes can operate at large scales [15–17]. It is known that climate is often more significant than soil spatial variability, especially in regions that depend solely on precipitation for crop production [3,4]. Therefore, downscale regional soil responses to a higher spatial resolution can potentially reveal hidden interactions with crop yields in localized environments [18].

Soil C distribution depends on the cumulative impact of topography, hydrology, and fertility distribution [19]. Moreover, inherently high primary productivity in specific field sections can result in further net additions of soil organic matter (SOM) over years and centuries [20]. Therefore, the relative contributions of C to yields should be expected to fluctuate across neighboring fields [21,22]. Although previous regional-level studies have analyzed key driving factors related to variability in crop yields [16], few studies have specifically examined the role of C on spatial yield distribution at the field-scale level. This is especially relevant for delineating a strategic management based on soil fertility.

Fine-scale soil research is critical because the site-specific influence of soil on crop yields might not apply to other regions or even neighboring fields within a farming operation [23]. In this study, we investigated the fine-scale spatial variability of soil quality attributes and its effect on grain productivity in fallow–wheat cropping systems located in eleven adjacent experimental plots with considerable variability in grain yields in the US central High Plains. We hypothesize that changes in within-field grain yields are slightly explained by the spatial variation of soil C in the central High Plains due to the region's inherently low C content. To this end, we aimed to (1) document the spatial variability of grain yields and soil parameters at the field-scale level, (2) identify soil characteristics associated with high crop productivity within multiple fields, and (3) assess the soil C contribution to crop productivity in soils inherently low in organic matter.

2. Materials and Methods

2.1. Study Site

This study was conducted at the USDA-ARS Central Great Plains Research Station in Akron, Colorado (40°9.24′ N, 103°8.19′ W). All research fields are on slopes below 3 percent at an elevation of 1384 m.a.s.l. The individual fields ranged from 2.5 to 4.3 ha in area (Figure 1). Soils in the study area included Ascalon sandy loam (Fine-loamy, mixed, superactive, mesic Aridic Argiustolls), Platner loam (fine, smectitic, mesic Aridic Paleustolls), Rago silt loam (Fine, smectitic, mesic Pachic Argiustolls), and Weld silt loam (fine, smectitic, mesic Aridic Argiustolls) [24].

2.2. Climate Data

Climate data 2017–2019 were obtained from a meteorological station adjacent to the experimental fields. Mean annual precipitation during the study period was 388 mm, mean annual pan evaporation was 1851 mm, and mean annual temperature was 10.2 °C. Total precipitation during the growing season (April to July) was 348 mm in 2018 and 254 mm in 2019 (Figure 2). During the grain-filling period in May, mean temperature was 16.3 °C in 2018 and 10.6 °C in 2019. Between September and December, corresponding to the early vegetative phase of winter wheat, 61 mm and 46 mm of precipitation were recorded in the 2017/18 and 2018/19 seasons, respectively.

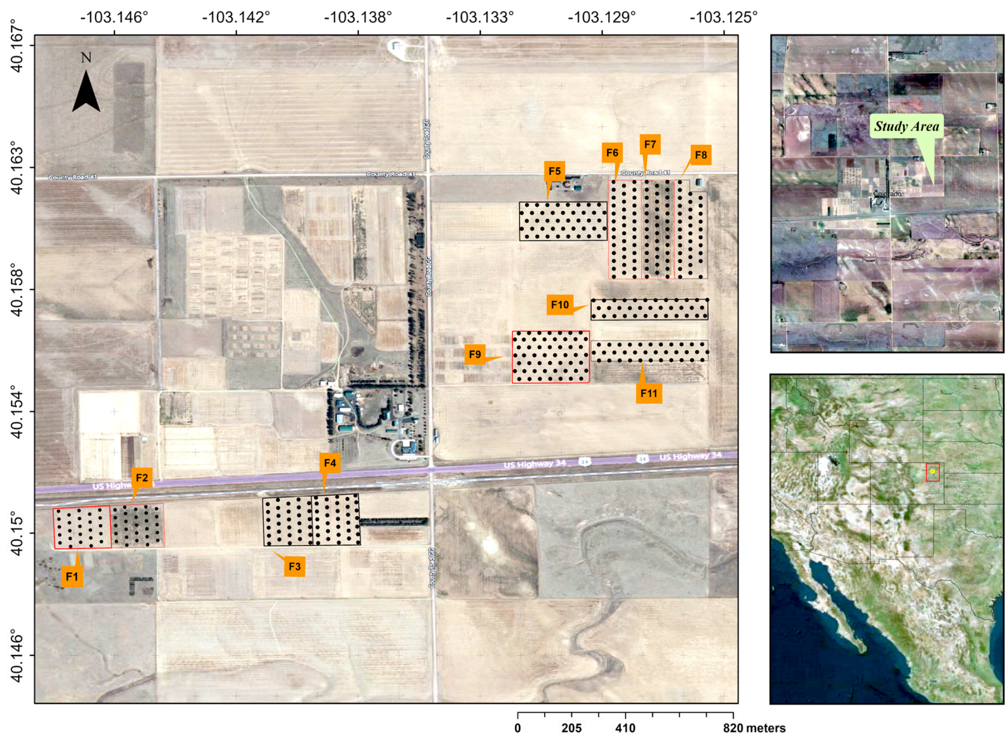

Figure 1. Study area showing field numbering and soil grid sampling points for fields (F) harvested in 2018 (**red**) and 2019 (**black**). Each field was sampled using a grid pattern of 30 m × 30 m equidistant spacing. Soil samples were collected at each point and analyzed for different physicochemical properties.

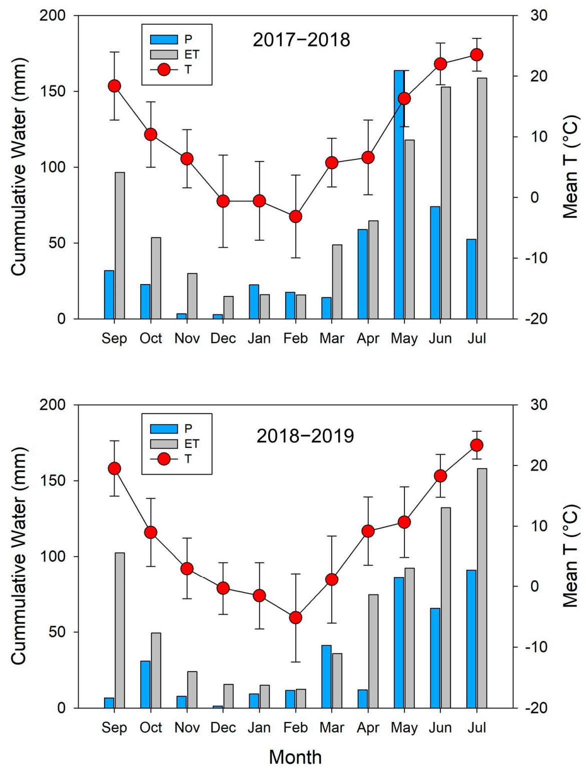

Figure 2. Monthly precipitation (P), evapotranspiration (ET) based on Hargreaves-Samani method, and mean temperature received during the winter wheat growth seasons 2017/18 and 2018/19 (October through June) in Akron, CO, USA.

2.3. Experimental Design and Cropping Practices

The experiment included five winter wheat fields planted in fall 2017 and six different wheat fields planted in fall 2018, with a total area of 58 ha. It should be noted that none of the research fields could be sampled in consecutive years given that they were on a winter wheat–fallow rotation. Because of this, no definitive conclusions about climate effects should be derived from this data set. We were able to obtain a greater sample size by including different fields in consecutive years, all planted with hard red winter wheat, and within the Central Great Plains Research Station.

Wheat (*Triticum aestivum* L., variety Langin) was planted in fields with chemical fallow for 14 months. There were two tillage operations prior to planting wheat: a sweep tillage with horizontal v-blades (8–10 cm deep) in August, followed by a disc tillage immediately before planting. Weeds were controlled during both cropped and non-crop periods by glyphosate, 2,4-D herbicide, dicamba (3,6-dichloro-2-methoxybenzoic acid), paraquat (1,1′-dimethyl-4,4′-bipyridinium dichloride), Thifensulfuron-methyl, Tribenuron-methyl, or Metsulfuron-methyl. Phosphorus (P_2O_5) and urea ammonium nitrate as nitrogen (N) fertilizer were dribbled over the row during the planting operation according to pre-plant soil nitrate tests, organic matter (OM) content, and an expected crop yields of 3.36 t ha^{-1}. Fertilizers were applied uniformly throughout the fields at an average rate of 84 kg N ha $^{-1}$ and 45 kg P ha $^{-1}$ each year.

2.4. Soil Sampling and Laboratory Analysis

To characterize the spatial variation in soil properties across the eleven fields, each field was sampled using a grid pattern of 30 m $\times$ 30 m equidistant spacing in July 2018 (Figure 1). Without a priori knowledge of the spatial soil heterogeneity in the study area, the 30 m grid spacing was acquired due to the extreme flat relief characteristics across the study area as well as the plot's sizes considered in this project. In a flat terrain scenario, we do not expect soil variability to change drastically over short distances to consider higher sampling density. On the other hand, since our experimental plots are relatively small, larger grid intervals might not be appropriate for this study. A total of 776 samples, at two sampling depths, were collected from 388 different grid points. One soil core per grid point was obtained using a 5 cm diameter Giddings hydraulic probe and separated into 0−15 and 15−30 cm depths. Samples from both depths were oven-dried at 38 °C and ground to pass through a 2-mm sieve for subsequent analyses. Total carbon (TC) was determined using a combustion total CNS analyzer (LECO CHNS-2000). Olsen P, which measures plant-available P, was determined using ammonium acetate DTPA [25]. Potassium (K), magnesium (Mn), zinc (Zn), iron (Fe), copper (Cu), and sulfur (SO_4-S) were determined using methods described by [26]. The pH, electrical conductivity (EC), soil texture, and cation exchange capacity (CEC) were analyzed using standard methods [27]. Soil OM was determined by loss on ignition (LOI) in a muffle furnace at 550 °C for 24 h. Elevation was collected separately with a tractor-mounted VERIS 3100 instrument (Veris Technologies, Inc., Salina, KS, USA), which was pulled through transects across each field using Real-Time Kinematic (RTK) for corrections.

2.5. Processing of Yield Data and Mapping

Yield maps were obtained at harvest in July 2018 and 2019 using Trimble software integrated with the harvester. Yield data were cleaned using the open-source Yield Editor software (version 2.0.7) [28] to remove positional artifacts caused by abrupt speed changes and ramping of grain flow while entering or leaving a field. Cleaned yield monitor data were interpolated with Empirical Bayesian Kriging (EBK) implemented in the ArcGIS Pro Geostatistical Analyst (version 3.1). EBK is a geostatistical interpolation method that differs from classical kriging methods because it automates the most challenging aspects of building a valid kriging model by using semivariogram models from subsets of data to reduce the standard errors of the prediction [29–31]. A leave-one-out cross-validation method was used to assess the predictive performance of the EBK. Results of EBK cross-validation for wheat grain yields across the eleven fields are shown in Supplementary Table S1. The accuracy of the EBK interpolations was estimated based on metrics such as root mean square error (RMSE), mean error, average continuous ranked probability score (CRPS), average standard error (ASE), and the number of validation data values inside a 90% and 95% confidence interval. In addition, RMSE and mean error were standardized by dividing by the standard deviation. If the average standard error (ASE) of the prediction is close to the RMSE values, the model is correctly assessing the variability in the predictions [32]. In a high-quality interpolation, standardized values of RMSE and mean error should be close to 1 and 0, respectively [33]. The continuous ranked probability score (CRPS) should be as small as possible. Our results show that the EBK interpolation method is reliable for predicting grain yields in the eleven fields studied (Supplementary Table S1), given that the values of standardized RMSE were close to 1 in all fields. In addition, the standardized mean error was close to 0, while RMSE values were close to the ASE.

2.6. Statistical Analysis

We extracted the grain yield values (t ha^{-1}) from the raster yield maps shown in Figure 3 using the same grid points as for the soil samples (Figure 1). After tests of normality by Shapiro–Wilk test, non-parametric Kruskal–Wallis tests, $p < 0.05$, were combined with Bonferroni multiple comparisons test to determine significant differences among grain yield at different fields ($p < 0.01$). One-tailed Spearman's correlation analysis was used to test correlations between soil variables and yields ($p < 0.05$). Principal component analysis (PCA) was carried out between soil variables and independent fields for exploratory analysis, making visualizing the relationship between different groups easier. Prior to principal component analysis (PCA), we removed multicollinearity among explanatory variables for the wheat yields by using both the Spearman's correlation coefficient and computing the variance inflation factor (VIF) of the explanatory variables. Multicollinearity is present when the VIF is higher than 5. All statistical analyses were carried out using R Statistical Software, version R 4.1.1 [34]. VIF was calculated using R package 'car_3.0-11' [35]. Subsequently, PCA was carried out using Canoco v.5.0. Random Forest (RF) was used as a selection method because it efficiently handles the non-linear classification task [36]. To carry out RF analysis, we used randomForest and caret packages in R with the default and optimized settings [37]. The parameters for model optimization in the R package randomForest are the number of variables to be considered at each split (mtry) and the number of trees (ntree). The final values used for the model were mtry = 4; ntree = 500. RMSE was used as a criterion to select the optimal model through repeated k-fold CV. RF also provides an assessment of the relative importance of the different variables (varImp). For each tree, the prediction accuracy on the out-of-bag portion is calculated. In addition, the feature contribution is calculated by randomly permuting the values of a predictor variable and keeping all the other predictor variables fixed. The mean squared error (MSE) is computed on the out-of-bag, and then, MSE is recomputed after permuting a variable. The differences in MSE are averaged and normalized by the standard error.

3. Results

3.1. Spatial Variability of Wheat Grain Yield

In general, we observed considerable spatial variation in grain yields in all eleven fields (Figure 3). The yield means of these fields collected at each grid point ranged from 2.1 to 8.3 t ha^{-1} (Figure 4). A pairwise comparison revealed significant differences among grain yields at different fields. Fields 1, 2, 4, and 5 showed a higher average yield while Field 8 was significantly lower when compared to the rest of the fields ($p < 0.01$). The mean wheat grain yield was 4.7 $\pm$ 0.9 t ha^{-1} in 2018 and 4.2 $\pm$ 1.2 t ha^{-1} in 2019.

Figure 3. Spatial distribution of the wheat yields (2018 and 2019) for each field (F) as calculated by kriging from harvester-based yield maps. Colors denote areas spanning higher (red, 11.20 t ha^{-1} maximum), intermediate (yellow), and lower (green, 1.30 t ha^{-1} minimum) wheat yields.

3.2. Relating Soil Attributes to Wheat Yield

Mean values for soil chemical and physical properties at 0−15 cm depth are shown for the fields harvested in 2018 (Table 1) as well as those harvested in 2019 (Table 2). Note that these are not interpolated values, but rather those measured on a 30 m × 30 m grid (Figure 1). The TC content in the fields harvested ranged from 0.6 to 1.4% (Tables 1 and 2). The fields differed markedly in pH, ranging from 5.9 to 6.8. Clay varied between 19.8% and 28.0%, while sand content varied between 28.8% and 63.6%.

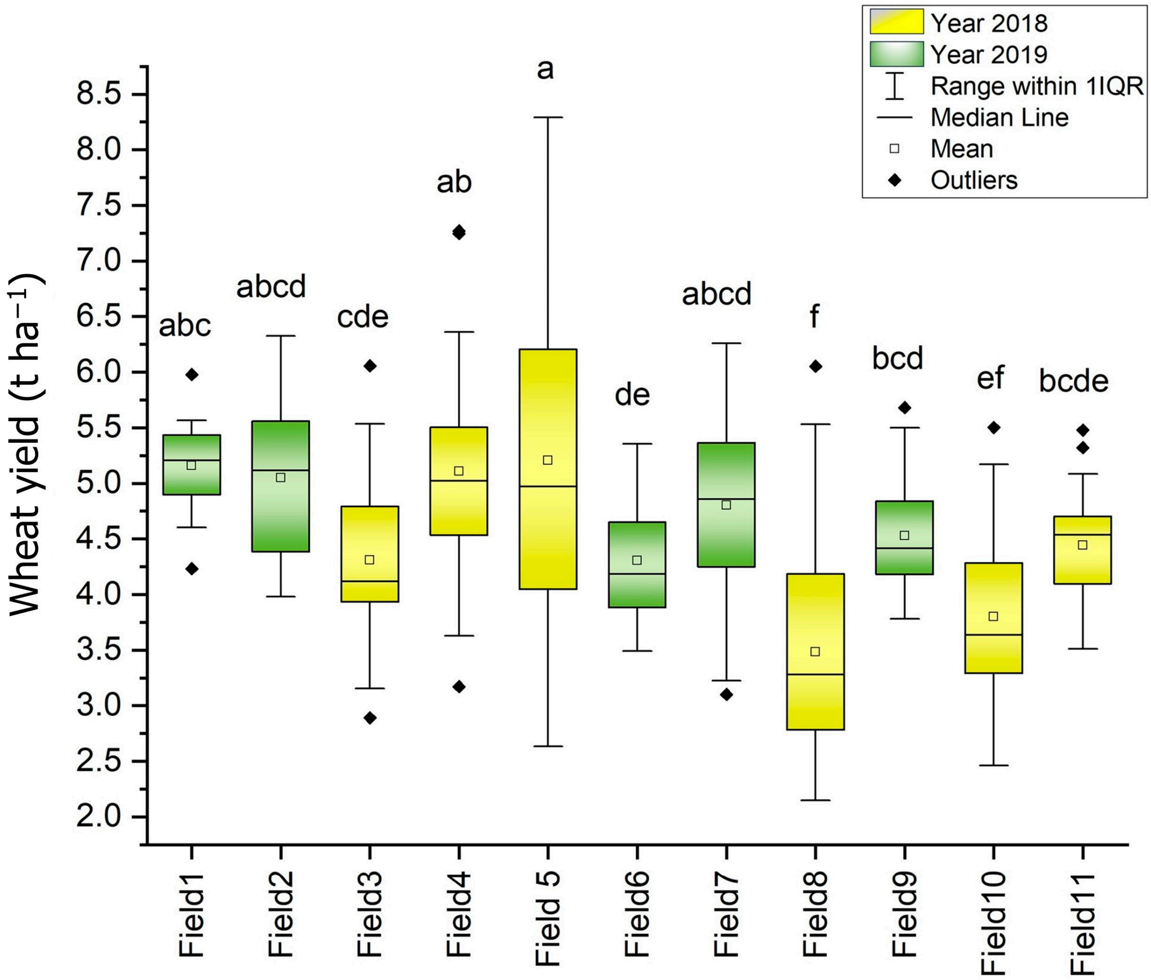

Figure 4. Wheat grain yields for fields harvested in 2018 (**green**) and 2019 (**yellow**). Different letters indicate significant differences in medians among fields. Bonferroni post hoc test was used for pairwise comparisons ($p < 0.01$).

Table 1. Mean soil properties (0−15 cm depth) and standard deviation of samples points in the grid within wheat fields harvested in 2018. The soil parameters are: electrical conductivity (EC), organic matter (OM), total carbon (TC), cation exchange capacity (CEC), phosphorus (P), potassium (K), sulfates (SO_4-S), zinc (Zn), iron (Fe), manganese (Mn), copper (Cu), calcium (Ca), magnesium (Mg), sodium (Na), and elevation (Elev).

	pH	EC	OM	TC	CEC	P	K	SO_4-S	Zn	Fe	Mn	Cu	Ca	Mg	Na	Sand	Clay	Elev
		dS m^{-1}	wt %	wt %	cmol(+) kg^{-1}	mg kg^{-1}	mg kg^{-1}	mg kg^{-1}	mg kg^{-1}	mg kg^{-1}	mg kg^{-1}	mg kg^{-1}	mg kg^{-1}	mg kg^{-1}	mg kg^{-1}	%	%	m
Field 1 (n = 25)																		
Mean	6.6	0.1	2.6	1.2	18.6	20.9	705	9.3	0.8	27.4	25.8	1.0	2553	378	8.0	32.6	28.0	1388
SD	0.5	0.1	0.4	0.1	3.6	7.5	61	1.6	0.5	9.8	10.5	0.2	740	63	1.4	4.2	2	1
Field 2 (n = 27)																		
Mean	6.5	0.2	2.7	1.4	21.3	31.8	766	10.9	0.7	28.2	30.9	1.0	2749	378	9.3	34.2	27.3	1387
SD	0.6	0.1	0.4	0.2	4.0	14.3	97	1.6	0.2	10.3	12.4	0.2	965	54	2.5	7.5	2.1	1
Field 6 (n = 38)																		
Mean	6.4	0.1	1.3	0.6	11.7	10.3	315	16.2	0.5	19.0	19.7	0.7	1478	280	6.1	63.6	19.8	1382
SD	0.4	0.1	0.2	0.1	3.1	4.8	78	3.0	0.4	11.0	7.5	0.2	558	87	1.8	6.1	3.2	1
Field 7 (n = 38)																		
Mean	6.4	0.1	1.6	0.7	11.5	13.1	366	15.4	0.6	21.8	23.7	0.8	1401	258	6.1	57.2	21.1	1382
SD	0.4	0	0.3	0.2	2.1	4.5	92	3.0	0.9	6.7	8.6	0.1	336	78	2.0	8.6	3.7	1
Field 9 (n = 52)																		
Mean	6.4	0.1	1.9	0.9	20.1	32.1	599	11.7	0.5	29.7	31.2	1.0	2487	343	10.1	41.3	25.4	1383
SD	0.8	0	0.3	0.2	4.1	13	107	8.8	0.1	14.4	15.9	0.2	1218	109	2.6	6.4	2.9	0

Table 2. Mean soil properties (0−15 cm depth) and standard deviation of samples points in the grid within wheat fields harvested in 2019. The soil parameters are: electrical conductivity (EC), organic matter (OM), total carbon (TC), cation exchange capacity (CEC), phosphorus (P), potassium (K), sulfates (SO_4-S), zinc (Zn), iron (Fe), manganese (Mn), copper (Cu), calcium (Ca), magnesium (Mg), sodium (Na), and elevation (Elev).

	pH	EC	OM	TC	CEC	P	K	SO_4-S	Zn	Fe	Mn	Cu	Ca	Mg	Na	Sand	Clay	Elev
		dS m^{-1}	wt %	wt %	cmol(+) kg^{-1}	mg kg^{-1}	mg kg^{-1}	mg kg^{-1}	mg kg^{-1}	mg kg^{-1}	mg kg^{-1}	mg kg^{-1}	mg kg^{-1}	mg kg^{-1}	mg kg^{-1}	%	%	m
Field 3 (*n* = 30)																		
Mean	5.9	0.1	2.3	0.9	16	33.6	746	7.3	0.5	22.8	27.3	0.8	1790	458	10.2	37.2	28.1	1387
SD	0.3	0	0.3	0.2	1.9	7.1	90	2.6	0.3	6.2	9.4	0.1	303	111	3.0	5.2	2.8	1
Field 4 (*n* = 33)																		
Mean	6.4	0.2	2.3	0.9	17.9	26.5	747	7.1	0.5	18.3	22.3	0.8	2237	521	13.3	36.2	29.3	1387
SD	0.5	0.1	0.2	0.1	4.9	6.2	77	1.6	0.2	5.6	6.5	0.1	843	139	7.5	4.0	3.0	1
Field 5 (*n* = 42)																		
Mean	6.3	0.1	1.8	0.8	12.8	23.2	475	6.0	0.5	39	26.3	0.7	1425	292	6.5	54.4	22.7	1381
SD	0.4	0	0.7	0.3	2.3	16.3	170	6.0	0.3	23.1	10.4	0.2	299	78	1.1	14.0	4.9	1
Field 8 (*n* = 34)																		
Mean	6.3	0.1	1.7	0.7	13.1	14.4	370	5.8	0.3	16.8	16.6	0.6	1711	293	7.8	57.7	21.1	1382
SD	0.7	0	0.3	0.1	5.0	5.2	66	1.5	0.2	7.9	7.9	0.1	905	116	2.8	8.3	3.7	1
Field 10 (*n* = 35)																		
Mean	6.3	0.1	2.0	0.8	14.9	26.4	549	9.7	0.6	25.9	23.5	0.8	1808	293	7.4	48.8	23.4	1383
SD	0.6	0.1	0.4	0.2	3.6	5.7	89	2.5	0.4	8.5	8.7	0.1	881	72	1.0	7.4	3.0	1
Field 11 (*n* = 34)																		
Mean	6.8	0.1	2.1	0.8	17.2	22.4	554	6.1	0.6	15	17.1	0.6	2254	430	7.7	46.3	27.0	1384
SD	0.6	0.1	0.3	0.2	2.9	9.5	75	3.7	0.7	8.8	9.9	0.1	769	112	0.9	8.0	3.2	0

Figure 5 represents an interpolated kriging map in a 30 m × 30 m grid to show spatial heterogeneity in the distribution of TC in the 0−15 cm depth. High spatial TC variability with distinct hotspots occurs in six of eleven fields. Relatively higher TC content was observed in sections of fields 1 and 2 at the southwestern edge of the site in slightly higher elevation areas. The influence of soil TC on wheat yields was significant (r = 0.35, $p < 0.05$); however, the TC relationship with localized grain yields was not consistent among the fields.

Spearman's rank correlations were carried out using yields specific to each soil sampling grid point and soil attributes within the eleven experimental fields. Several of the soil variables were correlated to each other. For the 0−15 cm depth soil samples, soil TC was positively correlated with K, OM, CEC, silt, and clay but negatively related with sand (Figure 6). Sand had a strong negative relationship with several measures of soil quality, such as P, K, and CEC. The Spearman's correlation for the 15−30 cm soil data and grain yields followed a similar pattern for the topsoil layer (Supplementary Figure S1), but OM and TC had slightly weaker correlations with the yield when the 15−30 cm depth soil samples were analyzed.

We carried out a principal component analysis (PCA) to explore the relationship between soil properties (0−15 cm depth) and wheat grain yields across the eleven fields (Figure 7). The CEC, silt, Na, and OM were not included in the PCA due to multicollinearity (VIF > 10) brought about by the high correlation of these variables with TC. Fields 1 and 2, which have some of the highest average yields (Figure 4), also have high clay, K, and TC content. (Figure 7). Fields 8 and 6, which were the lowest yielding on average, also have high sand content and low TC. The highest grain yields observed were also dependent on clay and Na. We also observed a positive relationship between wheat yield, P, and Cu, especially in the 0−15 cm layer.

Figure 5. Spatial distribution of surface total C (TC, 0−15 cm, 2018–2019) for each field (F) as calculated by kriging from a 30 m × 30 m soil sampling grid. Colors denote areas spanning higher (red, 2% by weight maximum), intermediate (orange), and lower (yellow, 0.4% by weight minimum) TC content.

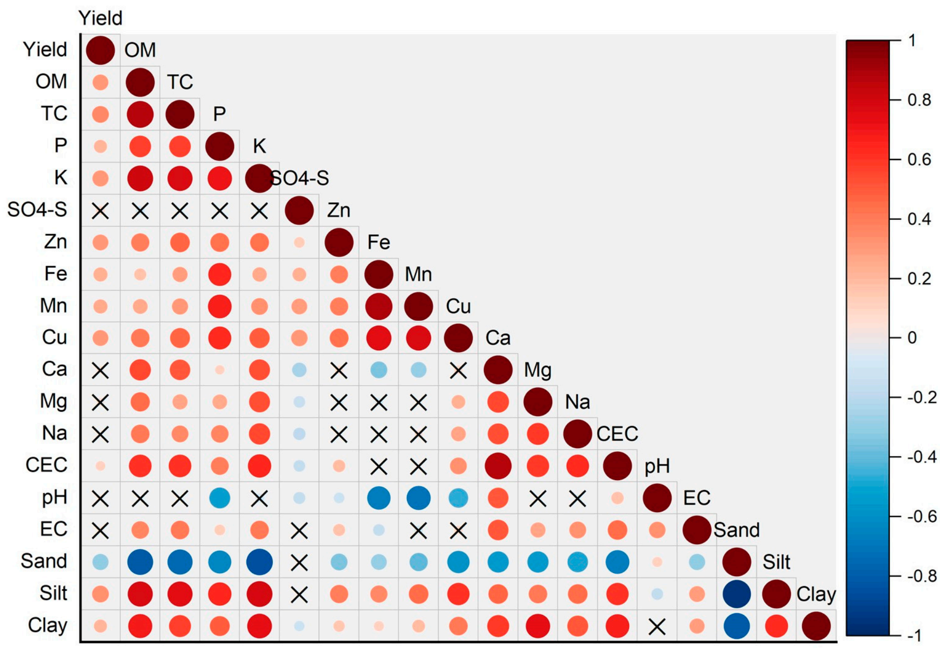

Figure 6. Spearman 's rank correlation matrix of all variables included in the analyses. Only the 0−15 cm depth soil samples were included. Data from both 2018 and 2019 fields were combined to calculate the coefficients. Values show the Spearman's rank results (only significant correlations are shown $p < 0.05$), OM: organic matter, TC: total carbon, P: phosphorus, K: potassium, SO_4-S: sulfates, Zn: zinc, Fe: iron, Mn: manganese, Cu: copper, Ca: calcium, Mg: magnesium, Na: sodium, CEC: cation exchange capacity, EC: electrical conductivity.

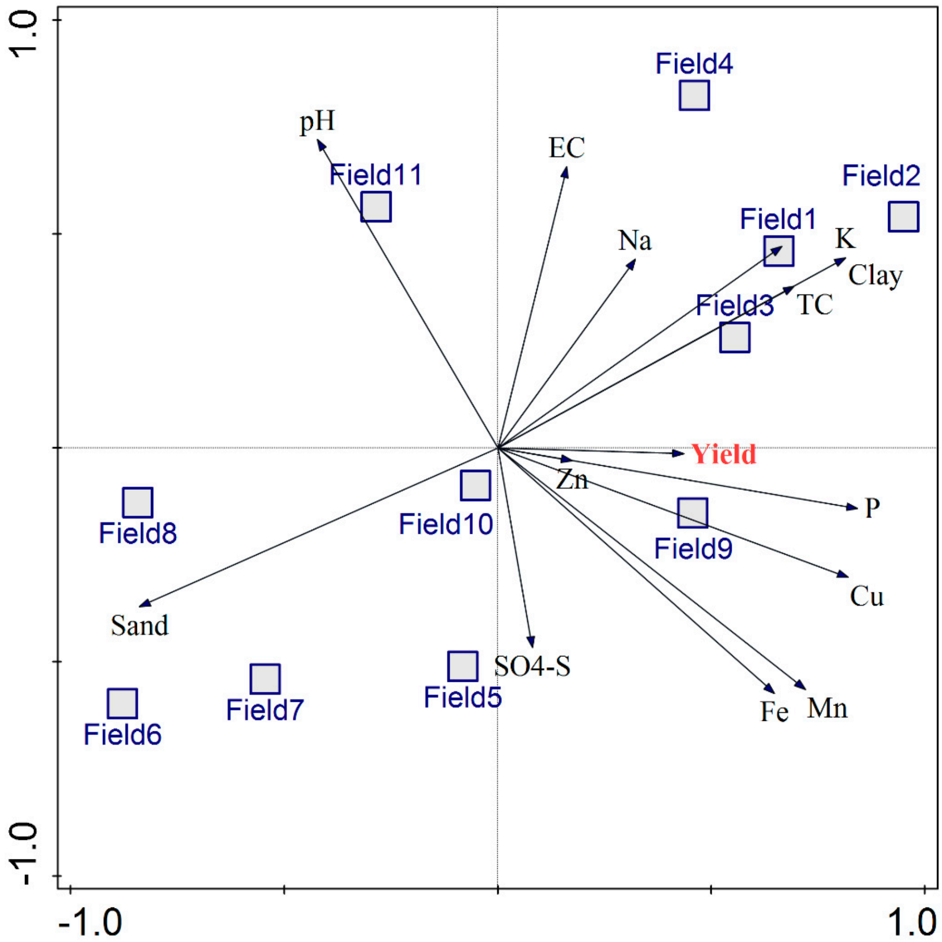

Figure 7. Principal component analysis (PCA) representing the relationship between soil properties and wheat grain yields at grid points across eleven fields. The grain yields were recorded in 2017/2018 19 and 2018/19 cropping season for a recently implemented long-term experiment. The samples were collected at 0–15 cm depth and wheat fields are denoted by squares in gray. Arrows in black represent soil parameters: clay, copper (Cu), electrical conductivity (EC), iron (Fe), manganese (Mn), pH, phosphorus (P), potassium (K), total carbon (TC), sand, sulfates (SO_4-S), and zinc (Zn).

Despite the relatively subtle topography of these wheat fields, we found that elevation differences affected the relationship between yields and soil properties in two of the eleven fields. A significantly negative correlation between yield and elevation was observed in fields 4 and 5 ($p < 0.05$) (Figure 8). Field 5 displayed the most pronounced spatial grain yield variability (Figure 3), associated with higher TC, clay, Zn, P, Mn, S, and Fe at lower elevations (Supplementary Figure S2). In field 4, in contrast, low elevation/high yielding areas were not always associated with high TC (Supplementary Figure S2). Zn alone had the highest positive correlation to wheat yields, whereas clay content and EC were negatively correlated with the yield.

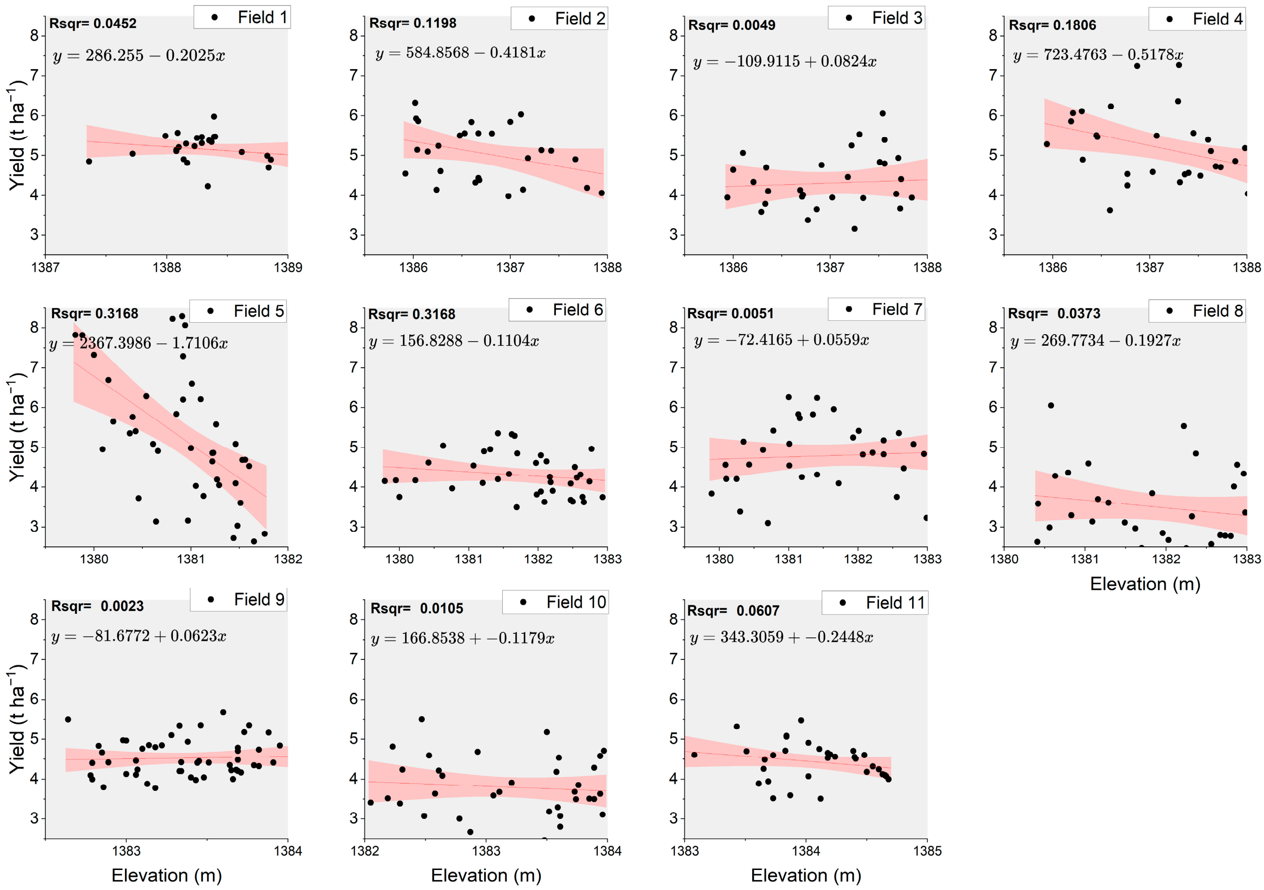

Figure 8. Relationship between elevation (m) and wheat yields in eleven individual fields across Central Great Plains Research Station in Akron, Colorado. A simple linear regression was used to determine the relationship between variables. The shaded areas represent the 95% confidence intervals for each studied field.

3.3. RF Variable Importance Analysis

The RF shows the relative contribution of each underlying soil attribute to spatial yield prediction for all the fields together (Figure 9). Unlike the PCA analysis, RF assesses non-linear relationships between yield variability and its predictors. It should be noted that variable importance could be due to either positive or negative relationships. The most highly ranked 0−15 cm soil variables for predicting wheat yields were TC, Fe, Zn, SO_4-S, and sand. The RF model in the 0−15 cm depth explained 26% of wheat yield variability. At the 15−30 cm depth, soil variables explained about 28% of grain yield. The importance of soil variables was not uniform across depths. For example, TC and Zn were major drivers at 0−15 cm but had a lesser importance at 15−30 cm. Interestingly, other physical indicators of soil quality, such as pH, clay, and EC, were not found to be important predictors of yields at either depth. Clay was related to grain yields in individual fields (Supplementary Figure S2), but when all the fields were analyzed together, it lost its importance (Figure 9). Sand was ranked among the five most important variables for predicting wheat yields (Figure 9) due to a negative relationship that is demonstrated by the PCA (Figure 7).

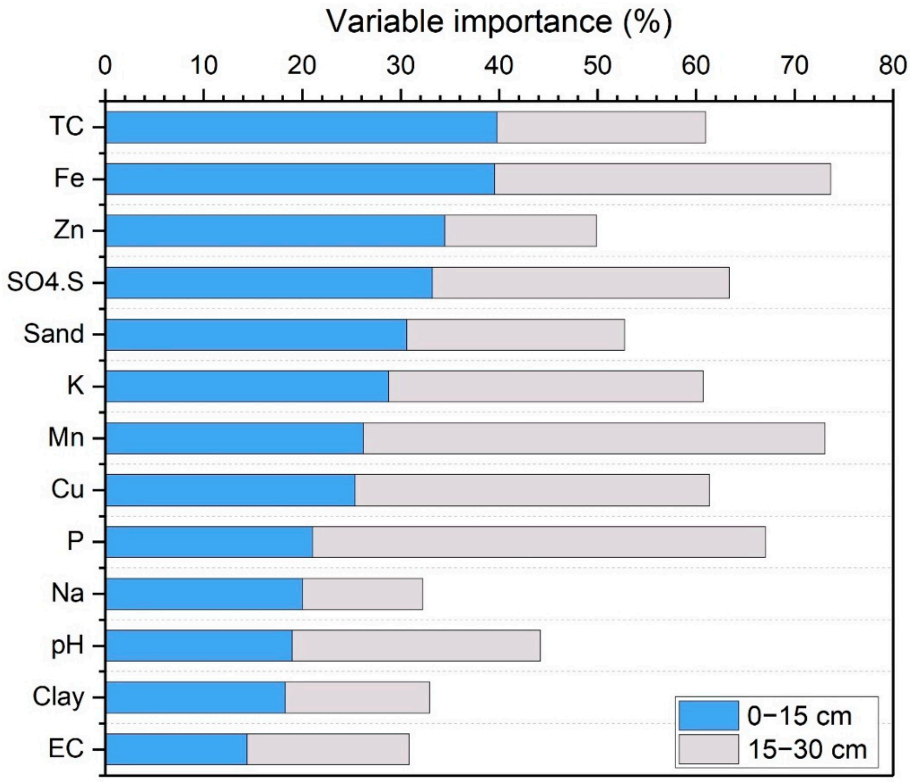

Figure 9. Variable importance analysis based on random forest (RF) to assess the relative contribution of soil attributes on wheat yields at two depths 0−15 cm (**blue**) and 15−30 cm (**grey**).

4. Discussion

Understanding soil spatial variability and its relationship to crop yields is critical for improving crop performance. In this study, we documented fine-scale soil heterogeneity associated with spatial variations in grain yields across eleven fields under wheat–fallow systems in the semiarid central High Plains of the USA (Figure 1). It should be noted that in this dryland environment, soil moisture dynamics should be expected to have an important role in driving both spatial and temporal variability in grain yields. However, repeated measurements of soil moisture at the 388 sampling points were beyond the scope of resources and objectives for this project; thus, this work concentrates on the relationship between soil quality distribution and grain productivity. We found that soil TC, P, and sand content as well as several micronutrients were crucial factors controlling the spatial variation of grain yields. In contrast, other variables, such as pH and EC, were not related to grain production in these fields.

4.1. Spatial Distributions of Soil C and Wheat Grain Productivity

Our analysis shows high spatial variation in TC across all fields in this experiment (Figure 5), which was positively related to grain yields. Our results suggest that TC content enhances nutrient availability and recycling to crops, contributing to higher wheat grain productivity. Generally, the fact that TC involves spatial variability in yields agrees with previous studies showing such association and improvements in plant nutrition, soil structure, water holding capacity, and soil buffering capacity [38–40].

The RF machine learning algorithm was a valuable tool for assessing non-linear relationships between yield variability and its predictors in the topsoil considered here. We found that the total contribution of soil variables for explaining crop yield variability was 28% and 26% in the 0−15 and 15−30 cm depths, respectively (Figure 9). Therefore, approximately only one-third of the changes in yield variation can be attributed to the soil properties studied here. Our results show that several soil-related factors had different levels of importance in the 0–15 cm and 15–30 cm depths (Figure 9). For instance, TC greatly influenced yield variability at 0–15 cm; however, it was less evident at 15–30 cm. This relationship may be attributed to decreased soil C concentration and a narrower range of C variability at lower depths. We hypothesize that better soil conditions at shallower depths could be relevant to germination and stand establishment, ultimately having a measurable effect on yields. Our results show a general tendency towards decreased wheat yields with increasing sand content in soils (Figure 7), and we suspect that this is likely related to declining TC in the coarser textures soils. It has been demonstrated that sandy soils are more likely to be deficient in nutrients, such as P [41,42]. In addition, coarser texture and lower organic C content may result in low water holding capacity, leading to low precipitation use efficiency and water stress during grain-filling [13,43]. Sandier soils are less likely to sequester C and retain plant nutrients [44]. Therefore, sandy areas in fields could have a feedback mechanism that may perpetuate low yields.

4.2. Relationship of Grain Yields to Nutrient Availability

The RF analysis indicated that SO_4-S played a role in the spatial variability of wheat yields (Figure 9). The linear regression failed to detect a statistically significant association between SO_4-S and crop yields (Figure 6). However, we speculated a possible synergistic effect of SO_4-S on nutrient use efficiency reflected by a non-linear model (Figure 9). These results are in line with those obtained by previous studies [45–47], where SO_4-S can contribute to uneven grain yield distribution due to an interaction with macronutrients, such as N, P, and K, and also affect crop growth under severe Fe limitations. In our study, soil pH was not a significant factor directly influencing yield variation in these soils (Figures 6 and 9); however, slightly alkaline conditions in Field 11 (pH > 6.5) did seem to have a significant impact on nutrient availability (Table 2 and Figure 7). This is largely due to high pH affecting solubility and reducing nutrient uptake for some micronutrients [48–50]. An EC measurement has been proposed for mapping within-field variability in soil parameters that influence spatial crop growth because of its relationship to soil quality attributes, such as texture, organic matter, and salinity [51]. However, contrary to our expectations, EC was not helpful in distinguishing high-yielding from low-yielding soils in these particular fields (Figures 6 and 9).

Although the area covered by the research fields tends to have a very mild topography, we observed that a slight increase in elevation led to a significant reduction in wheat yields in two of the eleven fields studied (Figure 8). This is most likely due to a lower SOM, coarser texture, and occasionally shallower depth in the upland and sloping positions resulting from soil erosion and deposition processes [52,53]. However, in line with [16], there were still unresolved inconsistencies, indicating that the relationship between topography and crop yields is irregular across relatively flat areas. Due to data limitations, we were not able to assess geospatial differences in soil water storage and availability [54]. Numerous confounding factors might contribute to yield variability in this region, such as snow catch, runoff, soil depth, topography, previous land use, crop residue distribution, and stand establishment as well as pest and pathogen infestations [55]. Our results show that some soil properties do have a measurable role, as they may lead us to identify more controllable conditions in order to predict grain yield variability.

4.3. Insights and Future Prospects

Our results emphasize the need to address soil within-field variability; however, soil quality and fertility analysis should not be the only strategy adopted to delineate management zones within a field. Indeed, no single soil attribute can be used as a universal criterion for different fields since our findings indicate that the impact of soil parameters on crop productivity is not uniform across fields. Yet, we demonstrate that TC can often serve as a good proxy for delineating yield-based management zones, even in inherently low C soils. It should be noted that water availability, timing, and distribution is crucial for maximizing crop yield. However, under prolonged water stress conditions, their effect on crop yields largely depends on soils and their capacity to retain nutrients or water.

For example, TC content can enhance water-holding capacity, making soils more resilient to droughts.

Monitoring the geospatial and temporal variability of soil variables would require repeated sampling of thousands of points across a field, which is both prohibitively expensive and labor-intensive. Despite these limitations, fine-scale spatial heterogeneity needs to be addressed in order to optimize water management and fertilizer use as well as reduce soil erosion and nutrient runoff. Taking within-field soil variability into consideration is especially important for estimating fertilizer requirements, which are often calculated based on average core values without capturing the full extent of soil variation [56]. Therefore, efforts are underway to improve new technologies (e.g., handheld sensor, proximal sensing) for cost-efficient mapping to further reduce uncertainties regarding nutrient inputs and enhance agricultural sustainability and productivity.

5. Conclusions

Significant spatial variations in soil and crop yields were found among the fields studied in the central Great Plains. Soil attributes, especially TC, were able to explain a significant portion of the observed spatial variation in these wheat yields. However, the impact of these soil parameters on crop productivity was not uniform across all fields. Since soil contribution cannot be interpreted independently of other environmental variables, quantifying attributes, such as profile water storage capacity, pre-plant soil water, and plant-available water dynamics, could be helpful to adequately address site-specific soil conditions and crop yield anomalies. Our data show that the development of management zones in these soils relying exclusively on soil information is not a straightforward task; however, the high level of within-field spatial variability observed needs to be taken into account in order to improve nutrient use efficiency in a cost-effective manner. Understanding the drivers controlling yield spatial variability at the within-field level provides insight into the possibilities as well as the knowledge gaps that can potentially influence the effectiveness of precision management systems and the validity of crop yield simulations.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/agronomy13102600/s1. Table S1. Performance of the spatial interpolation to predict wheat grain yields per field. The spatial estimation method included Empirical Bayesian kriging (EBK) validated using a leave-one-out cross-validation. Figure S1. Spearman rank correlation matrix of all variables included in the analyses. Only the 15−30 cm depth soil samples were included. Data from both 2018 and 2019 fields were combined to calculate the coefficients. Values show the Spearman rank results (only significant correlations are shown $p < 0.05$). EC: electrical conductivity, OM: organic matter, TC: total carbon, P: phosphorus, K: potassium, SO_4-S: sulfates, Zn: zinc, Fe: iron, Mn: manganese, Cu: copper, Ca: calcium, Mg: magnesium, Na: sodium, CEC: cation exchange capacity. Figure S2. (A) Differential response of wheat yields to elevation and soil nutrients in (A) field 4 and; (B) field 5.

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