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Variable rate phosphorus fertilizer recommendations for rainfed wheat

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ABSTRACT

A uniform application of phosphorus (P) fertilizers to spatially variable soils often results in under-fertilization in low P-localities and over-fertilization in high P-localities. This study aimed to evaluate the variable rate applicability of P fertilizers on a 300-ha sloping landscape under rainfed winter wheat cultivation for over 70 years. The soils were sampled (155 samples) using a random spatial sampling technique based on visual differences in soil color and topographic factors. Plant available soil P content (P_{av}) and other variables of soil samples were analyzed. The spatial variability of P_{av} was evaluated and the area was divided into three uniform zones (low, medium, high) for fertilizer P application based on the spatial variation of P_{av}. The values of P_{av} showed moderate variablity (CV= 21.3%). The fertilizer recommended by the Ministry of Agriculture and Forestry (MAF) was calculated for five identically-sized sub-regions. The results showed that P fertilizer rates calculated for all five sub-regions based on MAF were identical, suggesting that the MAF was insensitive to spatial variability of P_{av} in the study soils. Both semivariograms and surface maps of soil properties indicated a strong spatial association between P_{av} and each of plant available water content (PAWC) and aggregate stability index (ASI), suggesting that yield limitation casued by PAWC should be considered in a variable P-application program in the study area. A more comprehensive study is needed to evaluate the efficiency and cost-benefit economics of variable P application in the study soils.

1. Introduction

Application of commercial fertilizers contributes to crop growth to a considerable extent, resulting in a substantial yield increase in agricultural crops. However, uniform use of fertilizers has induced economical losses and caused pollution of the surface and groundwater, due to the spatial variability of soils, across the world (Vadas et al. 2004). The importance of the spatial variability of soil properties has long been recognized, emphasising the need for precise site-specific applications of agricultural fertilizers (Kassa et al. 2022; Sharma et al. 2022; Abera et al. 2022). Uniform fertilizer application may lead to over-fertilization in some localities and under-fertilization in others, resulting in improper fertilizer applications (Günal 2021). Site-specific fertilizer applications help equilibrate and stabilize the content of soil nutrients and yield (Sanches et al. 2021). Therefore, when high spatial variability of soil nutrient content is the case, application rates of those fertilizers should be adjusted site-specifically to optimize the nutrient supply to crops across the field (Ruffo et al. 2005).

Site-specific crop management (SSCM) considers variability in soil and crop parameters to optimize use of inputs such as fertilizers and pesticides (Sudduth et al. 1997). However, without an adequate knowledge of the spatial variability of soils, site-specific application of soil nutrients is impossible (Sawyer 1994). Conventional soil testing methods, used in determining spatial variability of soils, are costly and time-consuming. In addition, the time and cost required for intensive sampling in the SSCM can limit the implementation of a variable-rate fertilizer application.

Spatial variability management of soil chemical attributes is one of the means of precision agriculture (PA) to increase yield (Raddy et al. 2021; Beneduzzi et al. 2022). Understanding the variability in crop yield in relation to the spatial variations in soil properties can help more efficiently apply agricultural inputs on site-specific basis (Ameer et al. 2022; Ameer et al. 2023). Fertilizer application relying on soil characteristic map-based fertilizer recommendations may help reduce fertilizer input without sacrificing crop production (Yadav et al. 2023).

Several factors, such as differences in crop response to applied fertilizers and in exisiting nutrient pools in the soil, are considered in delineating nutrient management zones (MZs) on fields (Abera et al. 2022). Many researchers considered identifying existing nutrient pools in the soil to provide reliable fertilizer recommendations. Mapping of soil fertility is a practical and effective means to delineate the soils into low, medium, and high nutrient status zones (Ameer et al. 2022). These delineated internally homogeneous MZs, in terms of soil fertility and crop productivity management, can be treated separately for the precise application of fertilizers (Ameer et al. 2023). Some other techniques such as remote sensing (RS), geographical information system (GIS) (Yadav et al. 2023) and their combination (Trivedi et al. 2022) have been used successfully in site-specific crop and fertilizer management. Modern geospatial tools such as RS, GIS, and Global Positioning System (GPS) have provided tremendously powerful means for surveying, mapping, monitoring, delineating, and charaterizing soil resources (Trivedi et al. 2022; Beneduzzi et al. 2022; Kumar et al. 2023).

In Türkiye, ferilizer recommendations under the fertilizer support program rely on the "Fertilizer Calculator" provided by the Ministry of Agriculture and Forestry of Türkiye (MAF)", which roughly considers variability in soil properties and concentrations of major nutrients in soil at the sampling time. This study aimed to 1) evaluate sensitivy of MAF-fertlizer recommendations to the varability in soil properties and 2) formulate a variable-rate P recommentation, based on spatial variation in P_{av}, for rainfed winter wheat, in a 300-ha land exhibiting differences in soil and slope properties.

2. Materials and Methods

2.1. Material

This study was carried out on a 300-ha sloping farmland, located 20 km from the center of Çankırı cith along the Çankırı-Ankara highway (Fig. 1). The study area comprises many scondary hillslopes characterized by varying aspects, steepness, and shapes, located on a sloping landscape with a general linear slope resulting from a liner increase in elevation toward the north. The area has been under rainfed winter wheat production for more than 70 years. Variation in slope properties and distribution of parent materials are key factors affecting yield variability. The prominent differences in soil color highlight substantial soil spatial variability potentially leading to variation in crop yield thoroughout the study area.

A dry sub-humid/semi-arid continental Anatolian type climate prevails in the study area (Iyigun et al. 2013). Long term mean annual precipitation ranges from 406.0 to 538.0 mm, mean annual temperature from 9.1 to 11.1°C and relative humidity from 61.0 to 66.0%. The long term means of minimum temperature range from −5.0 to −2.7°C (in January) and maximum temperatures from 26.4 to 30.9°C (in July). The lowest extreme temperature ever recorded was −25.0°C on 25 January 1950, and the highest was 42.0°C on 30 July 2000 (MGM 2024). Soils of the study area are Gypsic Haplustepts and Gypsic Ustorthents according to Soil Survey Staff (2014). The parent materials are gypsum/calcium carbonate mixed with colluvium in the majority of cases. Also, gypsum over lacustrine residuum generally appears on the flat to slightly sloping landscape positions.

2.2. Methods

2.2.1. Soil sampling and laboratory analyses

In this study, 155 soil samples were taken based on random geostatistical sampling technique from the plow depth (0-20 cm). The sampling was designed with a minimum distance between two samples set at least 5 m, ensuring an adequate number of lags at close proximity to safely model the semivariogram near the origin. A global positioning system (GPS) was used to address sample coordinates. Soil samples were transferred to a laboratory, dried at room temperature, passed through a 2-mm sieve and stored for analysis. The soil variables analyzed and the methods used in the analyses are given in Table 1.

2.2.2. Delineating uniform phosphorous application zones

The study area was conveniently divided into five equal-sized sub-regions based on visual differences in soil color and topography, and P recommendation-values were calculated with mean data for each of the sub-regions using the fertilizer recommendation calculator of the Ministry of Agriculture and Forestry of Türkiye (MAF). The recommendation for P for all five sub-regions was identical, indicating that the MAF was insensitive to spatial variability of P_{av} in the study area. For delineating variable P fertilizer management zones (MZs), the fertilizer recommendation was calculated for each of the sampling points using P_{av} and expected wheat yield. The expected wheat yield was determined based on farmer's statement, and it was taken as 4000 kg ha^{-1}. The mean and standard deviation of P_{av} and P recommendation values were calculated for the study area and then used to delineate MZs as follows:

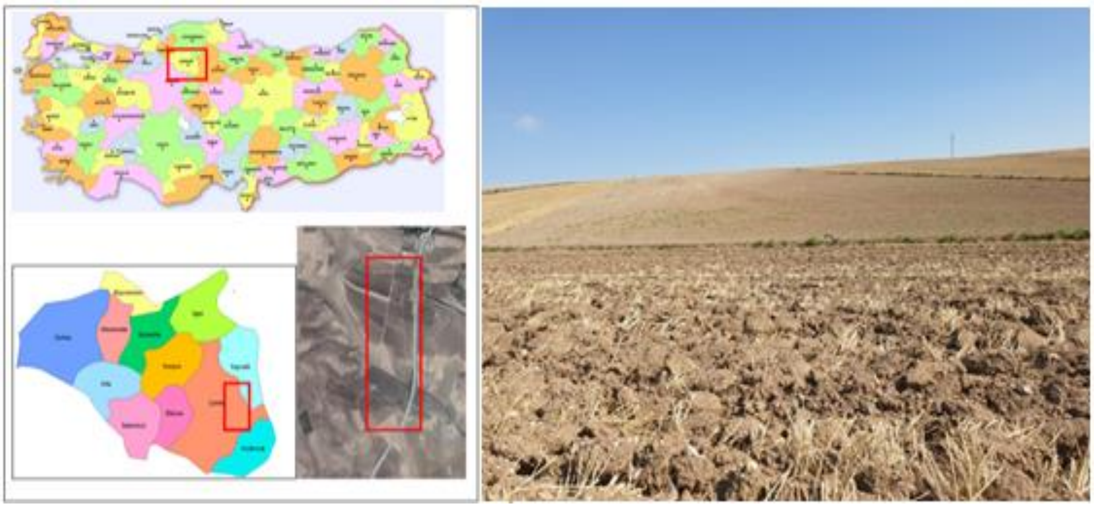

Figure 1. Location and view of the study area. The lighter colors indicate low fertility localities.

$$If\ P_{avi} < (M_{Pav} - SD_{Pav})\ then\ FP_i = M_{FP} + SD_{FP} \quad [1]$$

$$If\ P_{avi} > (M_{Pav} + SD_{Pav})\ then\ FP = M_{FP} - SD_{FP} \quad [2]$$

$$If\ (M_{Pav} - SD_{Pav}) < P_{avi} < (M_{Pav} + SD_{Pav})\ then\ FP_i = M_F \quad [3]$$

Where, SD_{Pav} is the standard deviation and M_{Pav} is the mean of P_{av}-values, and M_{FP} is the mean and SD_{FP} is standard deviation of fertilizer P recommendations, calculated using P_{av} and mean yield (4000 kg ha^{-1}) in the study area. P_{avi} is the plant available soil P content and FP_i is the fertilizer P recommended for sampling site *i*. For example, let SD_{Pav}= 3, M_{Pav}= 15, M_{FP}= 17, SD_{FP}= 4, and P_{avi}= 6, then FP_i for the site *i* can be calculated as follows: As P_{avi}= 6 < (15-3) = 12, the Eq. (1) should be used. Therefore, according to Eq. (1), FP_i= 17+4= 21 kg ha^{-1}. Thus, the 21 kg ha^{-1} application zone should include the sampling site *i*.

2.2.3. *Geostatistical analysis of spatial variability of soil variables*

A typical geostatistical analysis was conducted at three stages: an exploratory data analysis, a semivariogram analysis, and a spatial interpolation of the variable of subject (Isaaks and Srivasta 1989) The data for experimental semivariograms were modelled using commonly employed theoretical models (spherical, exponential, Gaussion models). Geostatistical analysis of soil variables of pH, EC, sand, silt, clay, OM, $CaCO_3$ and K contents and PAWC and ASI was conducted besides P_{av}. According to Webster (2001), variables with a skewness >|1.0| are assumed to be strongly skewed and log-transformed and those between |0.5| and |1.0| are assumed to be moderately skewed and square root-transformed, while those <|0.5| are assumed to be slightly skewed and do not need to be transformed. The data for EC were log-transformed to decrease its skewness below absolute |0.5|. The log-transformation resulted in a small decrease in skewness. However, after removing one data point and repeating the log-transformation this resulted in a tremendous decrease in skewness of the data for EC (Table 2). Similarly, to EC, removing four data points and then square root-transforming resulted in a substantial decrease in skewness for PAWC. As both full and reduced datasets for pH, clay content, silt content, and P_{av} were insensitive to data transformations, data were removed from those data sets until the values of skewness fell below absolute |0.5|. Table 2 shows descriptive statistics of full and reduced datasets and results for log- and square root-transformation for EC and PAWC, respectively.

Table 1. Soil variables and the methods used in their analysis

Soil property	Methods/device	Reference
Soil texture	By mechanical analysis	Gee and Bouder (1986)
Plant available potassium content	With a flame photometer	Kacar (1996)
Field capacity and wilting point	With pressure chambers	Cassel and Nielsen (1986)
Plant available water content	Difference between field capacity and wilting point	Cassel and Nielsen (1986)
Electrical conductivity	With an EC electrode in 1:2.5 soil-water suspension	Rhoades et al. (1999)
Soil pH	With a pH electrode in 1:2.5 soil-water suspension	Rhoades et al. (1999)
Organic matter content	By Walkley-Black method	Nelson and Sommers (1982)
$CaCO_3$ content	With a Scheibler calcimeter	McLean (1982)
Plant available P content	By Olsen method	Olsen (1954)
Aggregate stability index	By wet sieving	Kemper and Rosenau (1986)

Table 2. Descriptive statistics of soil properties in study area

Soil property	N	Min	Max	Mean	SD	Skewness	Kurtosis	CV, %
pH (1:2.5)	155	6.80	7.69	7.15	0.23	1.70	1.49	3.21
pH (1:2.5)	&128	6.90	7.20	7.06	0.055	-0.20	-0.04	0.77
EC (mS cm^{-1})	155	2.49	2630.00	472.10	521.3	3.16	9.31	110.40
#EC	&154					-0.41	9.22	
Sand (%)	155	7.97	63.56	26.24	7.97	0.24	-0.48	30.37
Clay (%)	155	16.75	69.70	53.80	7.43	-0.97	3.37	13.81
Clay (%)	&153	29.80	69.70	53.94	7.08	-0.42	0.66	13.13
Silt (%)	155	5.45	47.05	20.18	5.61	0.96	3.00	27.80
Silt (%)	&153	5.45	35.00	19.94	5.14	0.41	0.46	25.82
$CaCO_3$ (%)	155	4.65	32.76	17.12	6.22	0.38	-0.34	36.32
OM (%)	155	0.62	2.95	2.19	0.53	-1.10	0.65	18.27
OM (%)	&145	1.09	2.95	2.28	0.41	-0.77	-0.06	17.98
Na (mg kg^{-1})	155	5.90	37.69	15.78	15.78	0.70	2.57	75.91
K (mg kg^{-1})	145	13.51	65.10	38.94	12.98	-0.01	-0.92	33.33
PAWC (%)	155	2.90	52.08	20.87	11.69	0.87	-0.16	54.94
## PAWC	&151					0.38	-0.60	
ASI (%)	155	0.33	0.611	0.49	0.05	-0.21	0.20	11.16
P (mg kg^{-1})	155	3.42	20.11	15.26	3.25	-1.73	2.83	21.29
P (mg kg^{-1})	&140	12.21	20.11	16.25	1.65	-0.43	-0.41	10.15

N: Number of soil samples, Min: Minimum, Max: Maximum, SD: Standard deviation, CV (%): Coefficient of variation EC: Electrical Conductivity, OM: Organic Matter, Na: Sodium, K: Potassium, P_{av}: Plant available phosphorus, FC: Field capacity, WP: Wilting point, ASI: Aggregate stability index.
#: log-transformed, ##: Square root-transformed, &: Number of data points retained to decrease the corresponding value of skewness below |0.50|.

The spatial structure of soil variables including P_{av} was modeled and ordinary kriging (OK)-interpolations were conducted using geostatistical software (GS^+ 2022). The most suitable semivariogram model was selected based on the highest R^2 and lowest SSE-values for semivariogram fitting. In addition, cross-validation correlation coefficient (r_{CV}) was considered to judge if the theoretical semivariograms could adequately represent the experimental semivariograms. For sand content, $CaCO_3$ content, and ASI full data (155 data points); for EC log-transformed and PAWC square root-transformed reduced data; and for rest of the soil variables reduced data were used in geostatistical analysis (Tables 2 and 3).

We used variable lag-distances to increase the quality of semivariogram fits. Also, some data points were removed from some lags to increase modeling performance, especially for increasing R^2 and decreasing RSSE-values. Table 3 shows the number of data points used in semivariograms modeling. OK-interpolations were conducted using parameters (sill, range (A), and nugget variance) from the corresponding theoretical semivariograms. A minimum of 10 and a maximum of 13 neighboring data were used in OK interpolations. We applied inverse distance with varying power when the OK-interpolation performed inadequately. The data were interpolated by normal distance interpolation when r_{CV} was insignificant in both of IDW and OK-interpolations.

3. Results and Discussion

3.1. Descriptive statistics of soil properties

The variability of soil attributes plays a crucial role in defining uniform nutrient management zones. The sand and silt contents of soil textural components were highly similar in CV compared to clay content (Table 2). Sand and silt content were moderately and clay content was slightly variable according to (Mulla and McBratney 2002), who noted that a soil attribute with CV< 15% is deemed slightly, between 15 and 36% moderately and >36% highly variable. Silt content was moderately and sand and clay contents were slightly right-skewed according to Webster (2001). The values for K and Na showed highly dissimilar statistical distributions as suggested by their corresponding values of skewness, kurtosis, and CV. Values for Na were highly variable, while those for K were moderately variable. The values of $CaCO_3$ content ranged from 2.49 to 32.76 and were moderately variable and slightly right-skewed. The mean for $CaCO_3$ suggested that the majority of the study soils were highly calcareous (Table 2). The values of OM content were moderately variable and strongly left-skewed, indicating that some extremely low OM-valued localities were present in the study area. Aggregate stability index (ASI) is an important indicator of soil physical quality. Values for ASI were between 33 and 61% and showed a slightly left-skewed distribution and little variability. The values for ASI indicated that the study soils were structured weakly to moderately in strength. Soil pH has a strong influence on the soil P availability to plants (Tisdale et al. 1993). The values of soil pH ranged from 6.80 to 7.69 (Table 2). The range indicated that soil pH would be a limiting factor of P-availability, especially at some high pH-localities in the study area. Values for EC showed a highly asymmetric and flat distribution as suggested by high positive skewness and kurtosis. Also, the greatest value of CV occurred for EC. The ranges for EC and pH indicated that no salinity or alkalinity problems were the case in the study area. Values for FC and WP showed somehow dissimilar statistical distribution, while they were highly similar in variability, they were highly different in skewness and kurtosis. Plant available water content (PAWC) was highly variable (CV%= 54.7); its values ranged from 2.74 (very low) to 48.74 (very high). The value for skewness (0.79) indicates the presence of some relatively high-valued localities of PAWC across the study area.

3.2. Spatial variation of plant available soil phosphorous content as related to uniform phosphorous application zones

Values for P_{av} ranged from 6.84 to 23.53 mg kg^{-1} and exhibited a medium variability (CV= 21.29%) (Table 2). High positive skewness indicated that some high P_{av}-valued localities are present in the study area. High short-range variability (nugget variance) and short geostatistical range (A= 20 m) indicated that P-availability was affected by numerous soil factors as noted elsewhere (Trangmar et al. 1985). Table 3 shows that the geostatistical range for P_{av} is 20 m, and that the values are moderately spatially dependent according to Cambardella et al. (1994), who suggested that a variable with percent nugget effect < 25 is dependent strongly, between 25 and 75 moderately, and > 75 weakly. Figure 2b shows spatial pattern in P_{av} across the study area. The P_{av} was interpolated by OK using the parameters of semivariogram given in the Table 2, and results are shown in Table 3. The cross-validation correlation coefficient (r_{cv}) suggested that the kriging interpolation performed poorly, which may be attributed to a short-range of influence (small A) and a high short-range variability (relatively high nugget variance) for P_{av} as indicated corresponding semivariogram (Fig. 2a and Table 3). The inverse distance weighted (IDW) interpolation technique was tried using different power-values, again, the results were unsatisfying.

Table 3. Semivariogram analysis of study soils

SV	M	C_o	C	C_o/C0+C	A	RSSE	R^2	r_{CV}	n
Sand (%)	E	33.30	66.60	0.34	276.0	349.00	0.86	0.54	151
Clay (%)	E	16.80	58.00	0.29	690.0	149.00	0.94	0.62	152
Silt (%)	E	8.37	30.00	0.29	51.0	71.40	0.74	0.29	153
OM content (%)	E	0.11	0.23	0.33	192.0	6.48×10^{-3}	0.63	0.01	145
pH	E	0.001	0.003	0.47	24.0	1.84×10^{-7}	0.53	0.01	128
EC (ms cm^{-1})	G	0.25	0.50	0.50	51.9	0.07	0.49	0.60	154
$CaCO_3$ content (%)	S	6.24	33.80	18.00	25.0	430.00	0.38	0.56	150
PAWC (%)	E	0.60	1.46	0.41	21.0	0.03	0.72	0.01	150
ASI	S	6.30×10^{-3}	2.8×10^{-2}	0.23	20.0	6.00×10^{-7}	0.62	0.26	150
P (mg kg^{-1})	E	1.27	3.18	40.93	18.0	1.45	0.62	0.05	140

SV: Soil variable, M: Model type (E exponential, S: spherical, G: Gaussian), Co: Nugget variance, C: sill, A: geostatistical range, RSSE: Residual sum of squared error, R^2: Coefficient of determination for semivariogram fit, r_{CV}: Correlation coefficient between cross validated and actual values, n: number of data points (out of 155 data points (full data)) included in the geostatistical analysis, EC: Electrical conductivity, OM: Organic matter, P_{av}: Plant available phosphorus, FC: Field capacity, WP: Wilting point, PAWC: Plant available water content, ASI: Aggregate stability index.

Therefore, we used the normal distance interpolation technique to build a surface map for P_{av} (Fig. 2b). Fig. 2b shows that most of the low P_{av} sites were located in the southern and northern part of the study area. Please notice that the "north" in the GS+-produced surface maps is different from the absolute north on the Google Earth Map for the study area.

Figure 2c shows uniform P fertilizer management zones (MZs) determined based on spatial distribution of P_{av}-values shown in Fig. 2b. Three MZs were defined: High, medium and low P application zones (Fig. 2c) Medium P application sites were located mainly in northeast and southwest, while high P application sites oriented from southeast to northwest (Fig. 3c). The reverse was the case for spatial pattern for P_{av} (Fig. 2b). The M_{FP} was 24 kg P ha^{-1} for the uniform application across the study area. The uniform P application could result approximately 450 kg P to be saved. However, plants in the high P application zones (sites) would suffer P deficiency due to the application of P fertilizer in inadequate amounts, which may result in significant

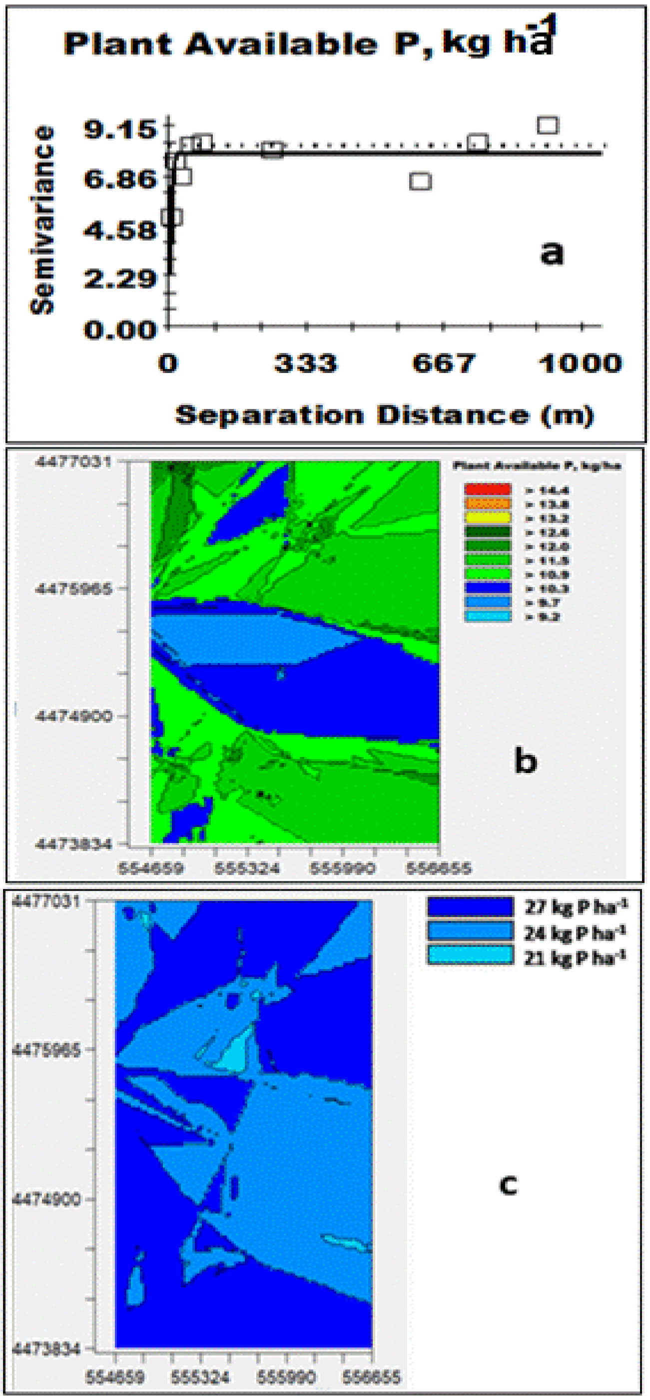

Figure 2. (a) Semivariogram and (b) spatial distribution pattern for plant available P content in study soils, (c) delineated uniform P application zones and corresponding fertilizer P requirements for each of the zone. The surface map in b was built by normal distance weighted interpolation. See text for explanation.

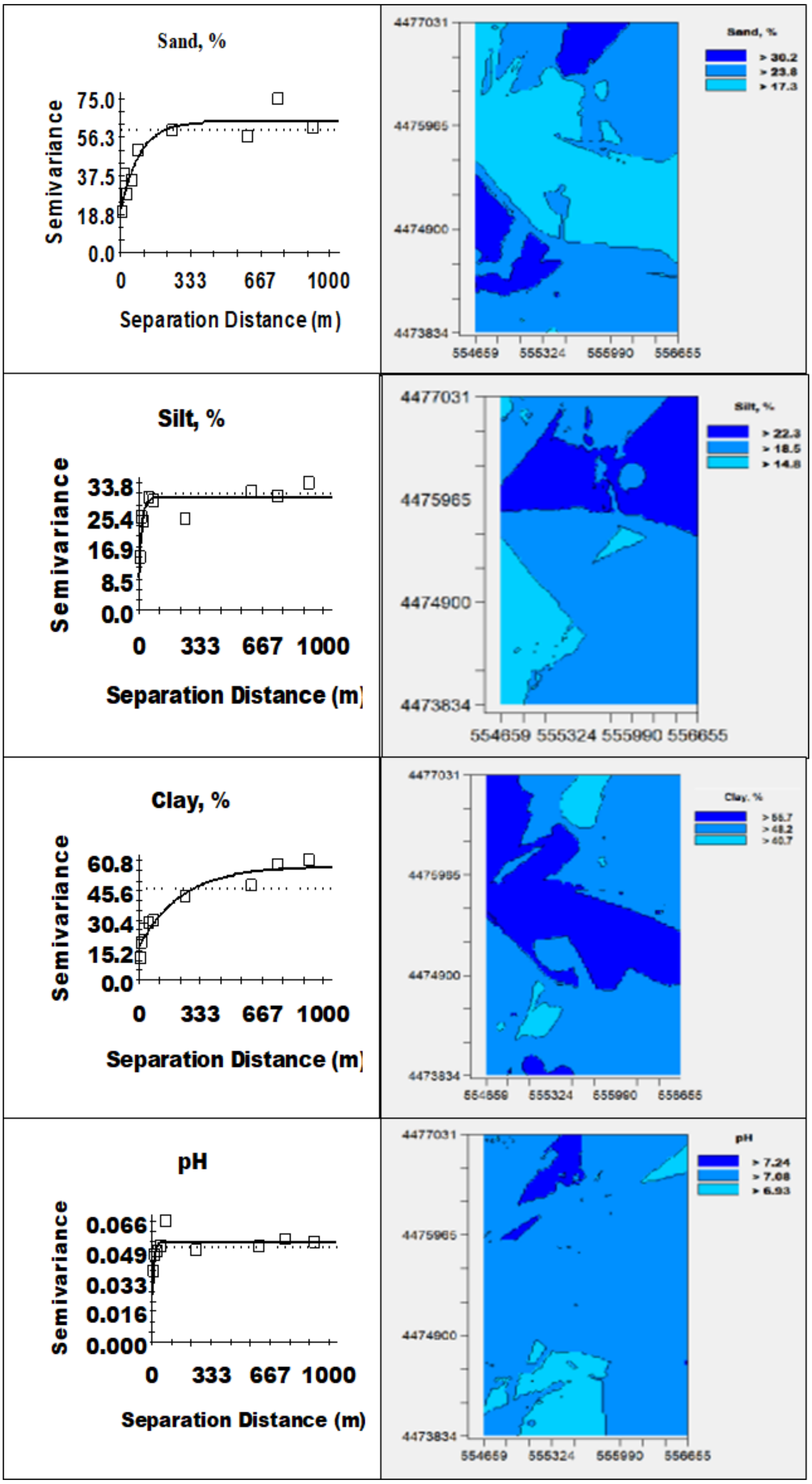

Figure 3. Semivariograms and corresponding surface maps of soil variables. The surface maps for OM content, pH, and PAWC were built by normal distance weighted interpolation.

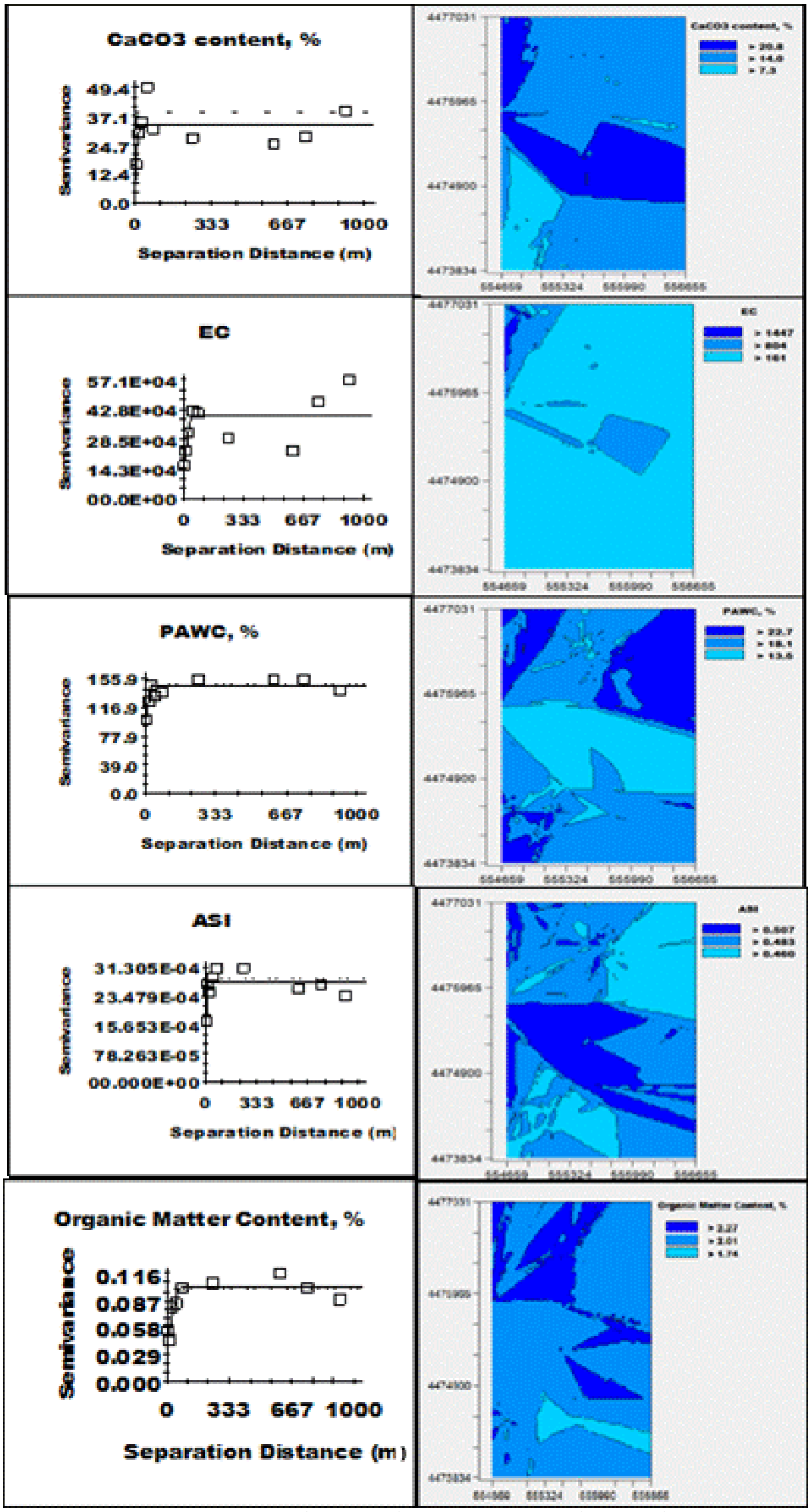

Figure 3. (continued) Semivariograms and corresponding surface maps of soil variables. The surface maps for OM content, pH, and PAWC were built by normal distance weighted interpolation.

decrease of the yield. A further study is needed to evaluate the cost: benefit economics of variable P applications in the study area. On the other hand, the size of management zone 1 is negligible (the isolated lighter blue-colored spots oriented from northwest to southeast, Fig. 2c); therefore, the study area was divided into two management zones: a medium P application zone including low P application spots and a high P application zone.

The study area is located on a sloping landscape with ridges and eroded hilltops, characterized by shallow topsoil and exposed subsoils. Overall, eroded soils, where low P_{av}–valued sites are located, had a lighter color than the other sites. Similarly, Fleming et al. (2001) reported lower yield for corn (*Zea mays* C.) on upper slope positions in Nebraska. Additionally, a strong correlation between P_{av} level and winter wheat yields in northeast Colorado was reported. In western Iowa, crop yields on footslope positions surpassed those on backslopes and side-slope positions, which was attributed to higher soil organic matter and available water content for plants in more productive localities (Bonfil et al. 2006).

The variable fertilizer application yields benefits in the majority of cases. For example, similar to our study, Bhatti et al. (1998) calculated varying rates of fertilizer for their area, divided into three homogenous MZs. They calculated the net profits as \$321 for MZ1, \$392 for MZ2, and \$416 ha^{-1} for MZ3. Their cost: benefit ratios were 4.33, 5.28, and 5.62 for MZ1, MZ2, and MZ3, respectively. They suggested that hybrid selection and hybrid-specific fertilizer management are also important in management of N fertilizers.

3.3. Spatial variability of soil properties as related to plant available soil P content in the study area

Table 3 presents the results of semivariogram analysis, and Figure 3 shows the semivariograms and spatial pattern of the soil properties within the study area. The findings in Table 3 indicate that the majority of the soil variables are moderately spatially dependent similar to P_{av}. In addition, many of the soil variables are poorly interpolated as low r-values for cross validation (r_{CV}) indicated. Silt and clay contents were highly different from the rest of the soil variables in A, while $CaCO_3$ content, FC, WP, PAWC, ASI and P_{av} were similar. In addition, the spatial structure of P_{av} was highly similar to those of ASI and PAWC in both model type and A. Except ASI and $CaCO_3$ content, all the soil attributes, including P_{av}, were moderately spatially dependent.

Figure 3 shows the spatial pattern of soil variables across the study area. Greater values of sand content and lower values of clay content are generally co-located on the medium P application zone. The spatial pattern for OM content showed no clear spatial association to the spatial pattern of P_{av} in the study area, while those for $CaCO_3$ content and wilting point showed that their greater values tended to be located in the medium P application zone. Similarly, a spatial relationship between ASI and P_{av} is evident, while soil pH and EC showed no apparent spatial relationship with P_{av}. When semivariogram and the spatial pattern for P_{av} are compared to those for rest of the soil properties, it can be concluded that the greatest spatial relationship occurred between P_{av} and ASI and PAWC. The close spatial relationship with PAWC and P_{av} should be considered in variable P application as low P_{av} and low PAWC tend to co-exist in the study area. In many cases, especially in dryland farming conditions, low PAWC is one of the most important yield limiting factors. If this is the case in the study area, the expected benefit may not be obtained from greater fertilizer applications on the low-P sites.

The results revealed that OK- interpolations for many of the soil variables performed poorly due probably to the same reasons behind unsatisfactory interpolation of P_{av}. Just like with P_{av}, we experimented with different lagging and modeling approaches to improve the success of OK-interpolation for other soil properties. Although performance for semivariogram modelling increased tremendously in many cases as indicated by increased R^2 and/or decreased RSSE, no significant improvement was the case in the corresponding r_{CV}-values. A different sampling configuration may yield a highly different modeling performance (Kravchenko 2003). Actually, there were adequate numbers of samples in close distances (between 0 and 50 m), while greater number of samples were needed in medium distances (50-200 m) to safely model semivariograms in those proximities. There are also adequate numbers of samples to calculate semivariograms in distances longer than 200 m. However, the fact that the data enabled the detection of close spatial associations between P_{av} and PAWC is very important in practice as PAWC can limit the benefit from greater P application on the low PAWC-sites.

The On Farm Management Information Systems (FMIS) seem promising to facilitate the implementation of precision agriculture for small-scale farmers in Türkiye. The On-Farm Experimentation (OFE) is an innovative process in which farmers and professional researchers collaborate to improve farm management by generating data from agronomic experiments on farmers' own fields (Tanaka et al. 2023). Lack of data availability is another key obstacle in the implementation of precision farming, worldwide (Tanaka et al. 2023; Kumar et al. 2023). Many different tools and techniques are used to gather the information needed for precision agriculture. Tools and technologies such as Global Positioning System (GPS), Geographic Information System (GIS), sensor technology, yield monitoring systems, software, and spatial interpolation of soil resources can be used for gathering the information needed for implementing variable rate application of fertilizers across the world (Kumar et al. 2023). Those same techniques and tools can be used in Türkiye to facilitate the application of variable fertilizer management across the nation.

4. Conclusions

The main objectives of this study were to identify the field scale spatial variability in soil P_{av} and some soil properties to develop uniform P management zones (MZs) for site-specific applications of P fertilizers. Characteristics of semivariograms and spatial patterns related to both P_{av} and most of the studied soil properties indicated the presence of high short-range variability of soil attributes in the study area. Results of cross-validation analyses suggested that a different soil sampling configuration with a greater sampling density is needed to safely apply geostatistics to delineate uniform P application MZs.

Two MZs were identified based on the spatial variation of P_{av}. The soil attributes such as PAWC and ASI were highly spatially related to P_{av} as their greater values co-located with greater values of P_{av}, and vice versa. The close spatial association between P_{av} and PAWC is very important in practice. A greater P application may not yield the expected benefit on low PAWC-sites as low PAWC may still limit the yield increase at those sites. The variable P application management zones (MZs), identified through observed yield differences, may not fully capture soil factors that limit yield beyond P_{av}. Therefore, the spatial variability in soil variables should be considered along with spatial variability in yield to correctly identify the yield differences and factors responsible for the differences in developing a successful variable fertilizer application program.

An extensive literature search for this research revealed that Türkiye is just in the early stages of adopting and beginning to embrace precision agriculture, aligning with the global trend observed in numerous other nations across the world. However, the strategic support from both public and commercial sectors is still in the infancy stages. The advancement of precision agriculture (PA) in Türkiye faces obstacles and various challenges, including a lack of information, connectivity issues in rural areas, and a lack of funding. The main factor impeding the advancement of precision agriculture, and a key reason for its slow implementation, is the constraint posed by insufficient financial resources. Issues related to the adaption of the farmers, organization, and functioning of the economy to increase its profitability, employment, and staff development should be solved in order to implement precision agriculture on a national scale. The small field size and lack of financial resources are obstacles for small-scale farmers. These problems force the farmers to apply traditional methods in production.

Future studies may explore how current variable rate fertilizer and pesticide management techniques and approaches may increase food production, limit environmental effects, and cut costs. Studies should be conducted to achieve the integration of precision farming into everyday farming operations in Türkiye. The obstacles that force the farmers to apply traditional methods in production should be studied holistically, considering the technical, financial, and social aspects of the problem. The On Farm Management Information Systems (FMIS) may facilitate the implementation of precision agriculture, especially by small-scale farmers. Therefore, we propose research on the orientation of FMIS to be given priority in future studies in Türkiye.

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