Relationship between Spatial Variability Pattern of Wheat Yield and Soil Properties

Alidad Karami[1*] and Sadegh Afzalinia[2]

[1]*Department of Soil and Water Research, Fars Agricultural and Natural Resources Research and Education Center, AREEO, Shiraz, Iran.*
[2]*Department of Agricultural Engineering Research, Fars Agricultural and Natural Resources Research and Education Center, AREEO, Shiraz, Iran.*

Authors' contributions

This work was carried out in collaboration between both authors. Author AK designed the study, performed the statistical analysis, wrote the protocol and wrote the first draft of the manuscript. Author SA managed the literature searches, contributed in results interpretation and wrote the final draft of the manuscript. Both authors read and approved the final manuscript.

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ABSTRACT

Aims: Determining effects of spatial variation of some soil properties on wheat quantity and quality variation in order that proper soil and inputs management can be applied for sustainable wheat production.
Study Design: Analyzing data of a field with center pivot irrigation system and uniform management using the geostatistical method.
Place and Duration of Study: Soil and Water Research Department, Fars Agricultural and Natural Resources Research and Education Center, Darab, Iran, from September 2013 to February 2014.
Methodology: Wheat yield data harvested by class lexion 510 combine from 25 m^2 plots (11340 locations) with the corresponding geographical location were used. Besides, soil properties and wheat yield were measured at 36 randomly selected points on the field. Interpolation of parameters was predicted with the best semi-variogram model using kriging, inverse distance weighted (IDW), and cokriging methods.

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*Corresponding author: E-mail: ad.karami@areeo.ac.ir, alidad_karami@yahoo.com;

Results: Results showed that wheat yield varied from 2 to 10.08 tons per hectare. Cokriging with cofactor of kernel weight interpolator had more accuracy compared to the combine default interpolator (kriging). A logical, linear correlation was found between different parameters. The best variogram model for pH, OC, and ρb was exponential, for EC, TNV, SP, soil silt and clay percentage was spherical, and for soil, percentage sand was Gaussian model. Data of soil sand, silt, and clay percentage, EC, TNV, and SP had strong spatial structure, and soil pH, OC, and ρb had moderate spatial structure. The best interpolation method for soil pH, EC, sand and silt percentage was kriging method; while, for TNV, SP, OC, ρb, and clay percentage was IDW.
Conclusion: There was a close relationship between wheat yield variation and changes in the soil properties. Soil properties and wheat yield distribution maps provided valuable information which could be used for wheat yield improvement in precision agriculture.

1. INTRODUCTION

Applying identical and similar management to different parts of a field can make sever problem in the long term. Using synthetic fertilizers and intensive irrigation are two important environmental problems that associated with degradation of soil [1]. Crop production and soil management can influence soil carbon formation, decomposition, and soil sustainable productivity [2]. Junqueira et al. [3] showed that soil fertility negatively correlated with plot size, distance, and length of the cultivation period. Farmers may make a considerable variation in soils at very fine scales when developing and adapting their cultivation strategies [4]. Human activity has an adverse effect on global cycle of carbon, nitrogen, and phosphorus which play a significant role in climate change and influences entire organisms and ecosystem [5,6].

Climate and topography conditions combined with soil properties could explain the soil organic carbon (SOC) variations across the tropical region; also high SOC is related to high clay content and high root development [7]. Global warming and climate change is an important challenge; therefore, the high potential of topsoil to sequester C is an indicator of soil health and soil potential to mitigate climate change [8]. The soil organic carbon could affect the soil biological activity and diversity, soil fertility and nutrient cycles, soil hydraulic parameters, and soil structure, thus their results have a positive impact on plant productivity [8,9]. Therefore, applying precision agriculture and site-specific management to each part of field is necessary for conserving of soil organic matter.

Accurate estimation of soil properties is very important in precision farming, because optimization of these properties has positive effect on soil productivity and crop yield [10,11]. Recognizing potentials and limitations of different locations of field is very important for effective scheduling and field management. On the other hand, extrapolation of results obtained from point sampling, scattering experiment, and field measurements creates high uncertainty when generalizing to larger scales. Having a comprehensive knowledge about soil texture, moisture content, bulk density, and cation exchange capacity is necessary for evaluating soil quality and applying precision agriculture [12]. Therefore, several methods such as spatial variables theory and geostatistical method have been introduced to solve this problem [13].

Point or station study has limitation like a low number of sampling and comparing with a contortion of soil parameters pattern, provides small amount of information [14]. Variability of natural soil increased at different spatial and temporal scales, because of, complicated soil formation process and application of materials on soil with cultivation [15]. Soil variability increased with different agricultural crop management [16]. Variation of a relationship between soil properties was also reported at sugar-cane lands with uniform management and with aid of precision agriculture [17]. Also, nowadays geostatistical methods are using for explain of variability. Variability of soil organic carbon severely depends on natural processes and human activities [18]. Soil organic carbon at different locations has been estimated with geostatistical methods especially kriging method [19,20]. Soil physical and chemical properties are varied because of parent material nature and location of soil at the nature [21].

For estimation of spatial pattern of soil properties (pH, EC, CaCO$_3$), universal kriging model is more suitable compared to the other methods (ordinary kriging, IDW, and splines) [22]. The best interpolator for calcium and soil electrical conductivity is cokriging method, for saturation percentage, magnesium, sodium, and silt and clay percentage is disjunctive kriging and for zoning of potassium and sand percentage is ordinary kriging method [23].

Also, Pearson correlation and regression analysis are used for determining relationship between soil electrical conductivity and other soil properties [24]. Understanding relationships between crop yield and soil parameters is useful for making accurate decision and applying better field management. There is a significant correlation between soil texture and soil salinity and moisture content of 0-20 cm soil depth; soil salinity and moisture have high variability, but soil organic carbon and total nitrogen of 0-20 cm soil depth have low variability [25]. Soil electrical conductivity has a correlation with soil clay content [26], soil water content [27], and amount of soil organic carbon [43]. Reduction in agricultural inputs utilization (e.g. organic farming), biodiversity conservation, and improving water, soil, and air quality are proposed for conserving environment [28,29].

Crop yield is affected by inherent soil properties and management factors; therefore, for optimum using of inputs, protecting the environment, producing healthy food, using variable rate fertilizer spreaders, adapting irrigation system designs, and sustainable and economic producing, a comprehensive understanding of variability pattern of soil properties and yield is necessary.

The target of this research was to determine the spatial variability of wheat yield and soil properties and choose the best geostatistical model for characterizing these spatial variations. In addition, soil properties and wheat yield distribution map were provided using the best interpolator and obtained results were analyzed.

2. MATERIALS AND METHODS

Fars province and Darab plain is one of the most important regions in Iran for producing agricultural products. In this plain, a field with 40 ha area, which irrigated with a center pivot irrigation system was selected. This field was located from 28°, 46$^{'}$, 59$^{''}$ N to 28°, 47$^{'}$, 23$^{''}$ N and from 54°, 16$^{'}$, 47$^{''}$ E to 54°, 17$^{'}$, 14$^{''}$ E (Fig. 1). The moisture and temperature regimes of this area are Aridic-Ustic and Hyperthermic, respectively. Wheat yield data harvested by class lexion 510 combine from plots of 25 m^2 areas (11340 points) with the corresponding geographical location were used. In addition, soil samples were randomly taken from 0-30 cm soil depth of 36 sites (points) of this field and analyzed for soil EC, pH, Total Neutralizing Value (TNV), OC, SP, and soil sand, silt and clay particles [30]. Wheat yield was also measured by manual harvesting 2 m^2 area of these sites. Besides, soil bulk density was measured by taking undisturbed soil samples from 0-15 and 15-30 cm soil depths. Collected data were analyzed using Microsoft Excel 2007, SPSS 16, AGRO-MAP 4, Surfer 10, and GS$^+$ 7 software's. Data were Interpolated for parameters at the points without measured data using kriging, inverse distance weighting, and cokriging methods by fitting spherical, exponential, linear, and Gaussian models to the experimental semi-variograms.
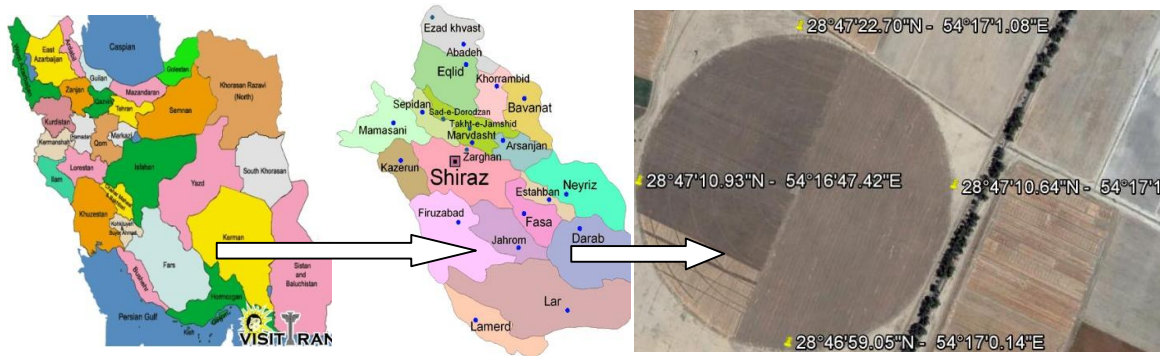

Fig. 1. Schematic of study area

Firstly, spatial variation of studied property was shown based on regionalized variable theory according to the following formula:

$$Z(x) = m(x) + \varepsilon(x) \tag{1}$$

Where, $Z(x)$ is regionalized variable, $m(x)$ is structural variation, and $\varepsilon(x)$ is random component.

The resulting graph of semi-variance versus different lag distances that called experimental semi-variogram was drawn for each parameter. For obtained data, empirical semi-variogram was calculated using the following equation:

$$\gamma(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} [Z(X_i) - Z(X_i + h)]^2 \tag{2}$$

Where, $\gamma(h)$ is Semi-variance, $Z(x_i)$ is the observed value of variable Z in X_i, $Z(Xi+h)$ is the observed value of variable Z in X_i+h, h is lag distance, and $N(h)$ is the number of comparisons between a given distance h. Spatial structure of data was determined by fitting spherical, exponential, linear, linear to sill and Gaussian models to the experimental semi-variogram [31,32]. In order to compare the spatial correlation of different semi-variograms, nugget variance to sill [$C_0/(C_0+C)$] ratio was used. When this ratio was ≤0.25, the measured variable was considered strongly spatially dependent; when the ratio was between 0.25 and 0.75, the measured variable was considered moderately spatially dependent; and when the ratio was >0.75, the variable was considered weakly spatially dependent [33]. Coefficient of determination of the best model fitted to the semi-variogram was also used to compare the spatial correlation of different semi-variograms. When this coefficient was <0.5, the spatial correlation was considered week [34].

In kriging method, the weights are chosen in such a way that the estimate $Z^*(x_0)$ of the true value $Z(x_0)$ is unbiased and the prediction variance is minimized. In the kriging method, the predictor $Z(x_0)$ for a non-sampled location x_0, is calculating as follow [35]:

$$Z^*(x_o) = \sum_{i=1}^{n} \lambda_i Z(x_i) \tag{3}$$

Where λ_i, is weight associated with the sampling point i, $Z(x_i)$ is amount of observation data around of un-sampled point, and x_i is location

of observation points. The best fitted model to the experimental variogram was determined, and kriging, cokriging, and IDW interpolators were used for explanation of spatial variability of each parameter. For evaluation of models and geostatistic estimation validity, mean absolute error (*MAE*), mean biased error (*MBE*), root mean square error (*RMSE*), and variance of error (*MSDR*) criteria were used by the following equations [36]:

$$MAE = \frac{1}{2} \sum_{i=1}^{n} |\hat{Z}(x) - Z(x)| \tag{4}$$

$$MBE = \frac{1}{n} \sum_{i=1}^{n} [\hat{Z}(x) - Z(x)] \tag{5}$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (\hat{Z}_{(x)} - Z_{(x)})^2} \tag{6}$$

$$MSDR = \frac{1}{n} \sum_{i=1}^{n} \left(\frac{\hat{Z}_{(x)} - Z_{(x_i)}}{\sigma(x)}\right)^2 \tag{7}$$

Where n is number of samples, $\hat{z}(x)$ is amount of estimated value at point x, $Z(x)$ is amount of measured, and $\sigma(x)$ is standard deviation at point x. Amounts of values calculated for criteria showed the amounts of biased values. Positive biased values showed overestimation of predicted data and negative biased values showed underestimation of predicted data. For cokriging method, experimental cross semi-varogram function $[\gamma_{ij}(h)]$ was used as follows [37]:

$$\gamma_{ij}(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} \{[Z_i(x_{k+h}) - Z_i(x_k)][Z_j(x_{k+h}) - Z_j(x_k)]\} \tag{8}$$

Where, $[\gamma_{ij}(h)]$ is sample cross semi-variance to the distance h, $N(h)$ is the number of sample pair of points separated by the distance h, Z_i and Z_j are the values of the main variable and co-variable, respectively at locations of x_k and x_{k+h}. After calculating cross semi-variogram, theoretical models were fitted to the experimental cross semi-variogram. Cokriging interpolator equation is as follows:

$$\hat{Z}_u(x_o) = \sum_{v=1}^{V} \sum_{i=1}^{n} \lambda_{iv} Z(x_{iv}) \tag{9}$$

Where, U is main variable, V is co-variable, λ_{iv} is weight of each observation for co-variable, $Z_{(x_{iv})}$ is measured amount of co-variable at location x_{iv}

and $\hat{Z}_{u(x_\circ)}$ is amount of estimated main variable at non sampled point $x_\circ$.

In IDW method, the highest weight was allocated to the nearest sample and lowest weight was allocated to the sample with the maximum distance from estimated value. In this method, amount of variable for each points of without data was calculated using the following equation:

$$Z = \frac{\sum_{i=1}^{n} \frac{Z_i}{d_i^m}}{\sum_{i=1}^{n} \frac{1}{d_i^m}} \tag{10}$$

Where, Z is estimated value of variable at non-sampled point, d_i is distance of non-sampled point from the estimated point, n is number of samples, and m is exponent of distance (d).

3. RESULTS AND DISCUSSION

Results showed that variation range of wheat yield was from 2 to 10.08 ton/ha which was very high (Table 1). Reason of this high variation was existence of effective parameters on spatial heterogeneous including amount of soil organic matter, non-leveled farm, micro-relief, vegetation accumulation, soil texture, drainage, erosion, cultivation system and tillage, crop rotation, and similar fertilizing system in all part of a field. These factors are strongly affected by human activities which should be effectively managed.

Evaluation of wheat yield at 11340 points with area of 25 m^2 for each point indicated that 321 points had zero wheat yields. These data points where the points located at the borders of the field with very shallow or without crop canopy; therefore, software installed on the combine was not able to record data for these points. Therefore, these data points were eliminated from the collected data and the rest were analyzed again. Variation of wheat grain yield showed that wheat yield and yield components could be considerably increased by applying precision agriculture, improving management system, and eliminating existing limitations at the field.

Exponential model was the best fitted to the grain yield data with the maximum coefficient of determination and the minimum residual sum of squares, and wheat yield and 1000 kernel weight had strong spatial structure (Table 2).

Based on evaluation criteria, accuracy of point kriging method for estimating wheat grain yield was higher than IDW method (Table 3). Spatial distribution of wheat grain yield using point kriging interpolator is shown in Fig. 2, and wheat grain yield had very high variability. Diacono et al. [38] also found high spatial variations for durum wheat yield and quality parameters, and related these variations to the spatial variability of effective factors on crop yield. Kernel weight of wheat grain was influenced by soil properties and soil salinity had the higher effect on the kernel weight than the others. According to the findings of Martínez et al. [39] and Ben Hassine et al. [40], drought and salinity are two important abiotic stresses in the world that reduce crop vegetation and increase soil erosion. In the studied field, variation of soil properties such as: soil texture, soil salinity, and uniform field management and fertilizer application caused to variation of wheat yield. Sambatti and Caylor [41] and Rozema and Flowers [42] also found that drought and salinity reduced crop yield considerably. Therefore, divided of field to uniform parts and doing proportional management and using variable and sufficient rate of fertilizer or irrigation water for every part of field will be leading to more yield and sustainability of production.

Wheat kernel weight had significantly negative correlation with soil salinity and soil silt percentage. Also, there was positive correlation between soil saturation percentage and soil organic carbon and fine particles (soil silt and clay percentage), but soil saturation moisture had significantly negative correlation with sand percentage and TNV. Besides, Soil pH had positive correlation with soil clay percentage, but negative correlation with EC. Also, soil EC had positive correlation with soil organic matter and negative correlation with soil clay percentage. Correlation between TNV, and soil sand percentage was positive; while, correlation between this factor and soil organic carbon and clay percentage was negative. Soil organic carbon had positive correlation with soil silt percentage (Table 4).

There was no significant correlation between soil bulk density and soil other properties including soil OC, EC, pH, SP, TNV and soil sand, silt and clay percentage. Results of previous researches have also shown contradictory correlation between soil bulk density and other soil parameters [43]. Similar to results of this

Table 1. Descriptive statistics of wheat grain yield harvested by class lexion combine

Variable	Unit	Minimum	Maximum	Average	Variance	Skewness	Kurtosis
Wheat yield	tons/ha	2	10.8	5.1	1.5	1.19	2.9
Kernel weight	g	23	43	36.3	26.4	-0.93	0.24

Table 2. Fitted model to the experimental semi-variogram and summary of geostatistical information of wheat yield harvested by combine and cross semi-variogram information of kernel weight with co-factor of soil salinity

Factors	Model	C_0	C_0+C	$\dfrac{C_0}{C_0+C}$	A_0	R^2	RSS
Wheat yield	exponential	0.032	0.064	0.02	117.2	0.94	$1.43*10^{-5}$
Kernel weight-EC	Gaussian	-0.001	-0.332	0.003	229	0.96	$6.9*10^{-3}$

C_0: nugget effect, $C+C_0$: sill, $[C_0/(C_0+C)]$: spatial correlation ratio, A_0: range (m), R^2: coefficient of determination, RSS: residual of sum of square.

Table 3. Evaluation of different interpolation methods for wheat yield harvested by combine

Interpolation method	*MBE*	*MAE*	*RMSE*	*MSDR*
Inverse distance weighting	-0.0672	0.6848	0.9404	0.0012
Kriging	-0.0156	0.6863	0.9386	0.0012

Table 4. Simple correlation coefficient between wheat yield characteristics and measured soil properties

	Yeild	KW	SP	pH	EC	TNV	OC	ρb_{15}	ρb_{30}	Sand	Silt	Clay
Yeild	1											
KW	.61**	1										
SP	-.02	-.33	1									
pH	-.24	-.04	-.03	1								
EC	.12	-.39*	.27	-.62**	1							
TNV	.13	.30	-.60**	.06	-.11	1						
OC	-.05	-.29	.73**	-.23	.54**	-.39*	1					
ρb_{15}	.08	.07	-.05	.02	-.14	.20	-.19	1				
ρb_{30}	-.01	.01	-.10	-.17	.12	.24	-.19	.37	1			
Sand	.16	.17	-.64**	-.32	.32	.65**	-.28	.14	.28	1		
Silt	-.17	-.39*	.51**	-.08	.25	-.58**	.36*	-.31	-.28	-.60**	1	
Clay	-.07	.06	.44**	.46**	-.57**	-.40*	.10	.04	-.15	-.83**	.04	1

KW: Kernel weight, SP: Saturation percentage, TNV: Total neutralized value, OC: Organic carbon, ρb: Bulk density

Table 5. Descriptive statistics of measured soil properties at the study area

Variable	Unit	Minimum	Maximum	Average	Variance	Skewness	Kurtosis
pH	-	7.7	8.1	7.9	0.01	-0.33	-0.35
EC	dSm^{-1}	0.57	0.98	0.76	0.01	0.09	-0.95
OC	%	1.01	1.66	1.32	0.02	-010	-0.01
TNV	%	42	52.5	47.5	7.48	-0.12	-0.64
SP	%	48	63	54.9	9.3	0.35	0.34
ρb_{15}	$grcm^{-3}$	1.22	1.54	1.38	0.01	0.26	-0.78
ρb_{30}	$grcm^{-3}$	1.37	1.77	1.54	0.01	0.19	-0.46
Sand	%	22.2	39	28.4	17.3	0.65	-0.79
Silt	%	37.4	46.6	42.3	5.44	-0.21	-0.46
Clay	%	21	35	29.3	11.2	-0.39	-0.46

SP: Saturation percentage, TNV: Total Neutralized Value, OC: Organic carbon, ρb: Bulk density

research, Martins da Silva et al. [44] also reported negative correlation between soil silt and soil sand percentage. Soil sand had the maximum variation across the studied field and pH, EC, and ρb showed the minimum variations. Soil properties in the nature are variable because of variability in parent material and soil location [21]. Data of soil organic carbon, silt and clay percentage, pH, and TNV had a normal distribution, but distribution of soil EC, SP, sand percentage, and bulk density was not normal; therefore, these data were converted to the normal distribution using logarithmic transformation (Table 5).

Soil particle size percentage and SP had the maximum variation across the farm area. Bevington et al. [45] also reported that soil hydraulic properties were site dependent because of soil intrinsic heterogeneous. The best semi-variogram model for soil pH, organic carbon, and soil bulk density at the soil depth of 15 and 30 cm was exponential. The best semi-variogram model for soil EC, TNV, SP, and soil silt and clay percentage was spherical and for soil sand percentage was Gaussian. Selection of the best model for semi-variogram was done based on the maximum determination coefficient and the minimum residual sum of squares (RSS) (Table 6).

Soil EC, TNV, SP, and soil sand, silt, and clay percentage had strong spatial structure; while, soil pH, organic carbon, and soil bulk density had moderate spatial structure. In the most cases of soil properties, nugget effect was very low, determination coefficient was high, and residual sum of squares was very low (Table 6). The best cross-variorum model for SP with cofactor of soil clay percentage and for soil EC with cofactor of

soil pH and soil potassium was spherical model. The best cross-variogram model for soil EC with cofactor of organic matter was exponential. In these cross semi-variograms, nugget effect was small, determination coefficient was high, and residual of sum of squares was low. The best interpolator method for soil pH, EC, organic carbon, sand and silt percentage was kriging and for TNV, saturation percentage, bulk density at 0-15 and 15-30 cm, and soil clay percentage was IDW method. Having knowledge about spatial variations of soil parameters is an important tool to assess the region potentials and effective land management manners. Access the soil salinity and sodicity information can be used as a useful tool for making proper decision by policy makers at critical times [46].

Variation maps of soil properties were drawn using the best semi-variogram model and the best interpolation method. In the northwest of the field, that soil salinity as a limitation factor was high, the amount of yield and kernel weight were low (Fig. 2). The r value of wheat grain yield after cokriging was 0.93.

Variation of wheat yield depends on limitation factors at different part of the field. Kihara et al. [47] reported that limited water holding capacity, poor infiltration rate, high surface runoff, and poor management practices may contribute to the limited availability of water to the crop. Different responses of wheat yield to the identical management across the field are the most important challenge and require site specific management at each specific part of the field. Rather attention should be devoted to improve the wheat production through improving soil water management and application of organic resources to increase SOC and fertilizer

Table 6. Fitted model to the experimental semi-variogram and summary of geostatistical information of soil properties

Factors	Model	C_0	C_0+C	$\dfrac{C_0}{C_0+C}$	A_0	R^2	RSS
pH	Exponential	0.0041	0.0111	0.369	115	0.725	$6.36*10^{-6}$
EC	Spherical	0.0093	0.0434	0.214	1328	0.960	$1.52*10^{-5}$
TNV	Spherical	1.700	9.098	0.187	517	0.911	7.07
SP	Spherical	$7.82*10^{-4}$	$3.79*10^{-3}$	0.206	491	0.932	$4.38*10^{-7}$
OC	Exponential	0.0142	0.0285	0.498	432	0.816	$1.02*10^{-5}$
ρb $_{15}$	Exponential	0.0029	0.0060	0.483	1030	0.885	$8.06*10^{-8}$
ρb $_{30}$	Exponential	0.0036	0.0073	0.493	1205	0.313	$1.3*10^{-6}$
Sand	Gaussian	0.006	0.1451	0.041	1052	0.912	$4.72*10^{-5}$
Silt	Spherical	1.99	9.989	0.199	1194	0.904	2.63
Clay	Spherical	0.26	21.51	0.012	925	0.955	7.09

*SP: Saturation percentage, TNV: Total Neutralized Value, OC: organic carbon, ρb: bulk density.*
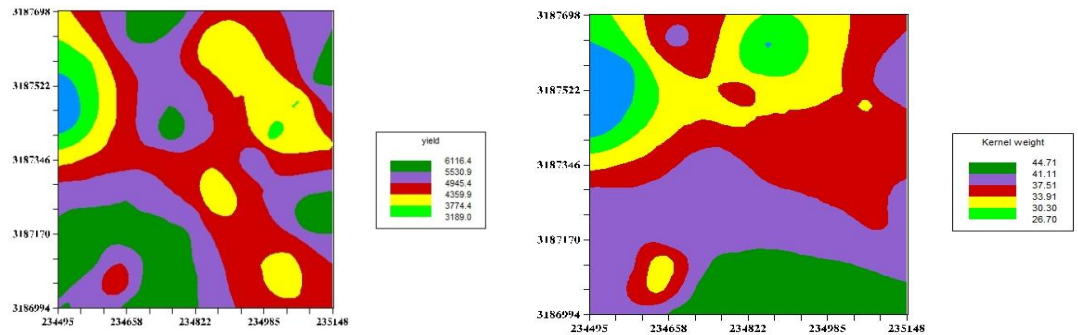
Fig. 2. Spatial distribution map of wheat grain yield using cokriging method with cofactor of kernel weight (left) and kernel weight with cokriging method using cofactor of soil salinity (right)

amendment in the different polygons of the field. Soil nutrient management through balanced crop nutrition and providing macro and micronutrients, manure, and other organic soil amendments is necessary to achieve optimum crop yield and sustainable production [47].

Because of dry climate and soil excessive exploitation, soil physical condition of lands in southern part of Iran such as studied area is unfavorable. Hebb et al. [48] also reported that intensive cropping system leads to the physical disruption, decreasing water content, and distortion of soil structure, thereby reducing macro-porosity and increasing bulk density. Frequently use of conventional tillage destroyed soil structure in the studied area. More frequent tillage operations can lead to aggregate disruption, which exposes intra-aggregate organic matter to microbial decomposition [49]. Following manure application, organic matter is

incorporated into stable soil aggregates [50]. Similar to our research area, long term inappropriate management practices may destroy soil physical condition and deplete soil C stocks, while adoption of best management practices can improve soil condition and reduce soil C losses [51]. Application of some useful practices within the agricultural systems such as conservation agriculture, including no-till or reduced tillage (RT), residue retention and crop-pasture rotation have been recognized as an effective approach to sustain productivity in dry land agro-ecosystems [52].

Results of soil pH variations showed that there was the higher amount of pH in the east half of the field and contrarily the lower amount of pH was observed in the west half of the study area. Especially, amount of soil pH increased from the southwest to the northeast of study area (Fig. 3).
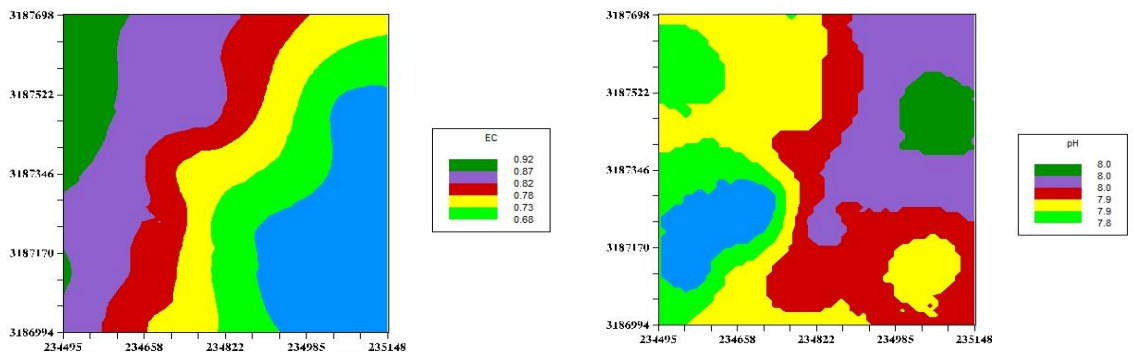
Fig. 3. Spatial distribution map of soil pH (right) and soil EC (left) using Kriging interpolation method

Amount of soil EC increased from the southeast to the northwest of study area (Fig. 3). Variation of soil salinity together with other soil properties effect on crop yield. Therefore, using from precision agriculture and varied management at different part of field is necessary for better production and conservation of ecosystem. Intensive use of our area with cultivation of wheat-corn and burning residue caused soil degradation. Kurwakumire et al. [53] reported that crops in the degraded soils are non-responsive to fertilizer across different farming systems. Spatial variation map of soil properties showed that amount of TNV increased from north to the southwest, and soil saturation percentage increased from the southwest to northeast of the field (Fig. 4). At the condition of water and moisture shortage, soil saturation percentage plays the most important rule.

Spatial variation map of soil organic carbon showed that this property increased from south to the north and especially northwest, similar to pH distribution, higher amount of soil clay percentage was in the east half of the field and contrarily its lower amount was observed in the west half of the study area (Fig. 5). In this condition uniform management wasn't correct, and should be done varied suitable management at the different parts of field.

Soil bulk density increased from north to the south, results not presented. Soil organic carbon is an indicator for soil nitrogen and soil productivity. In this direction artificial adding organic materials and nitrogen to soil with nitrogen deficiency was caused increased of plant biomass, and should be useful for increasing carbon sequestration that can be effective in world carbon cycle [54]. Several study showed that soil organic matter is a soil quality indicator and very active part of soil. Soil organic matter is very important for soil productivity and also has positive effect on improving soil physical condition [55,56]. Conservation agricultural that can be increasing soil organic matter and environmental quality, and these practices was considered as sustainable activity [57].
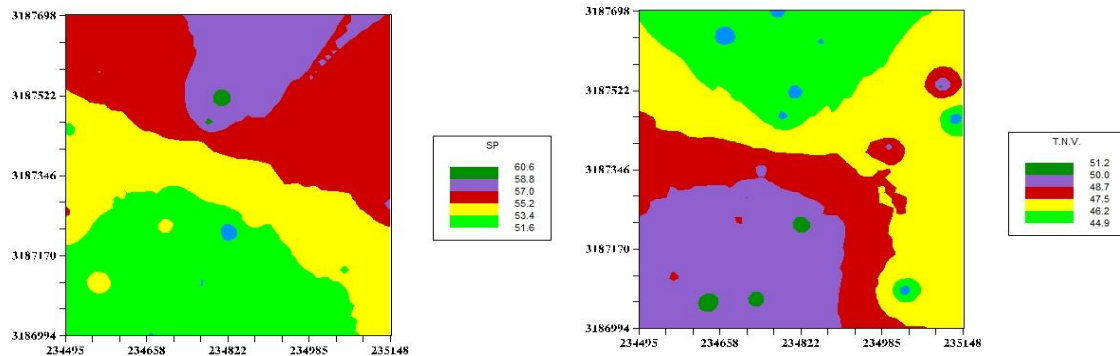

Fig. 4. Spatial distribution map of soil TNV (right) and soil SP (left) using IDW interpolation method
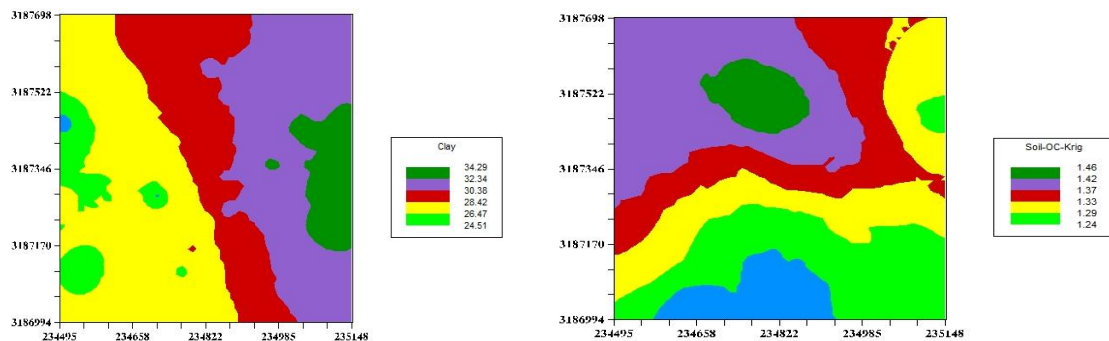

Fig. 5. Spatial distribution map of soil OC (right) and soil clay percent (left) using IDW interpolation method

Having sufficient knowledge about soil fertility and limitation factors of crop production is very important to develop appropriate soil and nutrient management. Also, existence of wide variability of crop response to nutrients, and manure application was reflecting a high degree of heterogeneity in soil characteristics and crop growing conditions at various spatial scales [47]. Thus site specific soil fertility management practices are necessary for sustainably increasing crop production [47,58]. Also attention to site specific and integrated nutrient management could be followed for increasing crop production, nutrient availability and soil carbon pools for long-term [59]. To achieve high soil quality and enhancing soil fertility and productivity, attention to SOC is necessary.

Accordingly, several studies showed that climate, elevation, and soil properties exerted a large influence on SOC distribution [60,61]. Climate, geology, and soil formation are affecting SOC in the long term, while vegetation disturbance and land cover change are the main factors affecting on soil C storage in the short period [62]. Changes in C stock were found to be potentially related to altitude, precipitation, temperature, soil texture, and root biomass [7]. In our studied area rotation is wheat – corn, and this cropping system isn't suitable. Because, perennial-based cropping systems are associated with increases in SOC [63], whereas annual cropping can cause a loss of organic matter due to lower levels of organic inputs and soil disturbance from frequent tillage [64]. Soil properties can also have effect on soil organic carbon. In this regard, Andriamananjara et al. [7] also showed that the SOC was positively correlated with the clay content in topsoil. In studied area soil organic

matter was low and variable, applying different sources and amounts of organic matter, proportional with different part of field, improved soil properties consistent with the findings of [65].

Spatial distribution map of soil sand percentage showed certain trend which was increasing from northeast to the southwest and soil silt percentage increased from south to north (Fig. 6).

Based on results of this research (Fig. 6) and previous research works, uniform irrigation and other uniform field management in all parts of field are incorrect. Besides of this, for anticipation of soil degradation and access to sustainable production, attention to the following cases is very effective in our region. Combination of field surveys with spatial data can be used to identify preference management for improving production at a variety of management levels [66]. Reduced soil disturbance increased physical protection of SOM within macro-aggregates [67,68]. Higher SOC can be accumulated in macro-aggregates in reduced or no-tillage systems [69]. Increasing plant residue, root and exudates production, crop rotational diversity, which increases microbial biomass and activity, will lead to increase in SOC, soil aggregation, and crop production [70,71,72]. Improvement of SOC and soil quality leads to increase soil water holding capacity [73] which is important in our region that drought frequency and intensity and climate change is developing. Our agricultural lands need an ecological engineering which increase resource-use efficiency, reduce fertilizer requirements and nutrient losses, and thereby enhance agricultural sustainability [74].
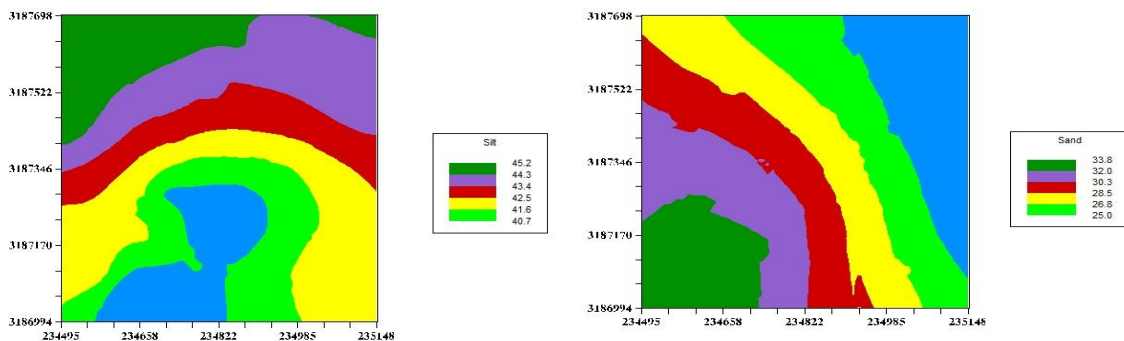
Fig. 6. Spatial distribution map of soil sand percent (right) and soil silt percent (left) using kriging interpolation method

The nutrient management perspective, better management of crop residue with sufficient chemical NPK fertilizers application, might be a better long-term fertilization practice in our region that consistent with the findings of [75].

4. CONCLUSIONS

Results showed that wheat yield variability was very high across the studied farm; however, wheat yield can be increased with eliminating or adjusting of the factors that have negative effect on wheat yield at different part of field. Evaluation of combine default interpolator showed that this interpolator had low accuracy; therefore, data collected by this system should be corrected. Wheat yield and yield components had significant correlation with soil properties which should be taken into account in designing a suitable management system for different part of each field. The best models of semi-variograms and the best interpolator for each soil property and crop parameter was determined and their variation maps were provided. Based on spatial distribution maps of soil properties and zoning of every of them are very useful for better management at different parts of field. Complexity, heterogeneity, and anisotropy of soil, can affected on crop yield. Therefore, long-term evaluation of soil properties, application inputs and circumstance of field management is very important for sustainable crop production and conservation of production resources.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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