ASSESSMENT OF PRODUCTION SERVICE CAPACITY BY SOIL QUALITY EVALUATIONS

Article *in* Fresenius Environmental Bulletin · October 2019

Nurullah Acir
Ahi Evran Üniversitesi

ASSESSMENT OF PRODUCTION SERVICE CAPACITY BY SOIL QUALITY EVALUATIONS

Nurullah Acir*

Kirsehir Ahi Evran University, Faculty of Agriculture, Department of Soil Science and Plant Nutrition, Kirsehir 40100, Turkey

ABSTRACT

The ability of a soil to provide the productivity service depends on the fulfillment of the functions that enable the realization of productivity service (PS). This study was conducted to determine and map the PS capacity of surface and subsurface soils in a 195-ha farmland located at Amasya province of Turkey. Functions that contribute to the provision of PS have been identified, and effective indicators ensuring the realization of functions have been identified. Indicator values were converted to unitless scores using non-linear scoring functions defined in soil management assessment framework. Simple additive (SA) and weighted additive (WA) methods were used to calculate soil functions scores and PS index values. The weights representing the contribution ratio of each indicator to soil functions as well as each function to PS index were obtained by employing the Analytical Hierarchy Process (AHP). Soil functions scores were calculated by summing of the weighted indicator scores, and the PS index value was obtained by summing the weighted function scores. Ordinary kriging, inverse distance weighting and radial basis function methods were used to produce maps for functions and PS index values. Root mean squared error and mean absolute error values were used as criteria to determine the most accurate interpolation method. The AHP technique revealed that nutrient cycle function had the highest (34%) contribution to the provision of PS, while the durability and resistance function (15%) had the lowest contribution. The PS index value was calculated as 0.57 and 0.59 by SA and WA methods, respectively. The PS index values and soil functions, except the resistance and resilience, calculated both by SA and WA were slightly different for surface and sub-surface soils. The results revealed that organic carbon is the most influential indicator affecting the soil functions and consequently the PS of soils.

KEYWORDS:
Ordinary Kriging, Productivity service, SMAF, Soil functions, Soil quality

INTRODUCTION

Soil quality assessments are a crucial component to understand the functioning capability of the ecosystem and to ensure the sustainable use of soil resources [1]. The most important functions of soils include nutrient cycling, water relations, physical stability and support, resilience and resistance, filtering and buffering, biodiversity and conservation of habitats [2]. Direct measurement of soil quality is not possible due to the various sources contributing the quality of soils; therefore, the use of indicators is the most preferred method in the evaluation of soil quality [3]. Definition of the indicators that are effective in the realization of soil functions is extremely important to accurately assess of the relevant function. Indicators should have high correlations with the function desired to be assessed [4].

The most important management goal in agricultural practices is the productivity that evaluates the impact of soil characteristics on crop yield [5]. Productivity of soils is defined to increase or maintain the quantity and quality of production, but to ensure the sustainability of growing the economically important crops [2]. Different methods have been used in the assessment of soil quality and various indicators have been used in each of the soil quality assessment methods. Score cards [6], soil quality test kits [7], soil conditioning index (SCI) [8], agricultural ecosystem performance assessment tool (AEPAT) [9], agro-ecological decision support system (MicroLEIS DSS) [10], soil management assessment framework (SMAF) [2] and Cornell soil health test are some of the tools used to assess soil quality. The SMAF method developed by Andrews et al. (2004) [2] has been widely used and tested for soil quality assessments conducted in USA [11-13], Brasil [14, 15], Spain [16], Turkey [17,18], South Africa [19], Nepal [20], Ethiopia [21], and so on. The SMAF reflects the dynamic soil quality, which is influenced by the management decisions, rather than genetic quality, that is resulted from soil formation factors such as climate, topography and parent material

The researchers assessing the quality of soils under different climatic, vegetation and topography conditions have developed different approaches depending on the management objectives [11, 22-

26]. The strategies can be grouped under two main titles as simple additive [4, 14]and weighted additive [23, 27, 28]. The easiest method to combine the scored indicators within the soil quality index (SQI) is the simple additive method, which is obtained by summing the indicator scores and dividing them by the total number of indicators [2, 11, 23]. The simple additive method considers equal contribution of each characteristic in the data sets to the soil quality. Soil quality should reflect the combined effects of physical, chemical and biological soil properties. However, the overall SQI cannot adequately be representative in this method when the numbers of indicators for physical, chemical and biological characteristics in the data set are not equal [24]. Therefore, the weighted additive method was recommended to determine the contribution of individual indicators to the overall SQI [14, 26, 28-32]. The most commonly used methods to attain weights for individual indicators in weighted additive method are the principal component analysis (PCA) [23, 26, 33-35], expert opinion [23, 36] and Analytical Hierarchy Process (AHP) [37-41]. The AHP, developed by Saaty (1980) [42], is a multi-faceted decision-making mathematical method that evaluates qualitative and quantitative variables considering the experts opinions for the sensitive assessment of soil quality [43]. The AHP also reduces the bias in decision-making by controlling the consistency of decision-makers' assessments [39].

The surface properties of soils can be easy to measure and evaluate, however some soil functions are strongly related to pedogenic processes which may not be explained only by using the characteristics of the surface layer [28]. Therefore, the assessment of soil quality using both surface and subsurface soil properties can provide sufficient information help to more accurately describe soil properties which have the maximum effect on soil functions. Merril et al. (2013) [44] recommended to use the properties of subsurface horizons which are important for soil classification in soil quality assessments. In this study, soil quality assessments have been carried out both for surface and subsurface soil layers. Assessing the quality of soils and figuring out capacity of each soil function will contribute to the general review of the agricultural practices applied by the users. However, soil properties can vary within a few meters of a field [45]. Therefore, the spatial distributions rather than the mean values of functions and overall soil quality will provide more useful information to the land users. The information obtained on soil quality can be more useful by determining the spatial distribution of soil quality and functions. Soil characteristics and functions determined to evaluate the sustainability of soil management practices are site specific which only provide information about the quality of the sampling point. However, various interpolation methods have been used to predict the values in non-sampled locations using the sampling points [46, 47].

The main aim of this study was to evaluate the various functions of surface and subsoil soils located in a large farm where intensive agricultural activities have been carried out. The contribution (weight) of individual indicators and functions have been determine by using expert opinion and AHP. Simple additive and weighted additive methods were used to obtain final function and quality scores. Three different interpolation methods were compared to obtain most accurate predictions for unsampled locations. Spatial distribution maps of soil productivity index were produced by using the values obtained with the most accurate prediction method.

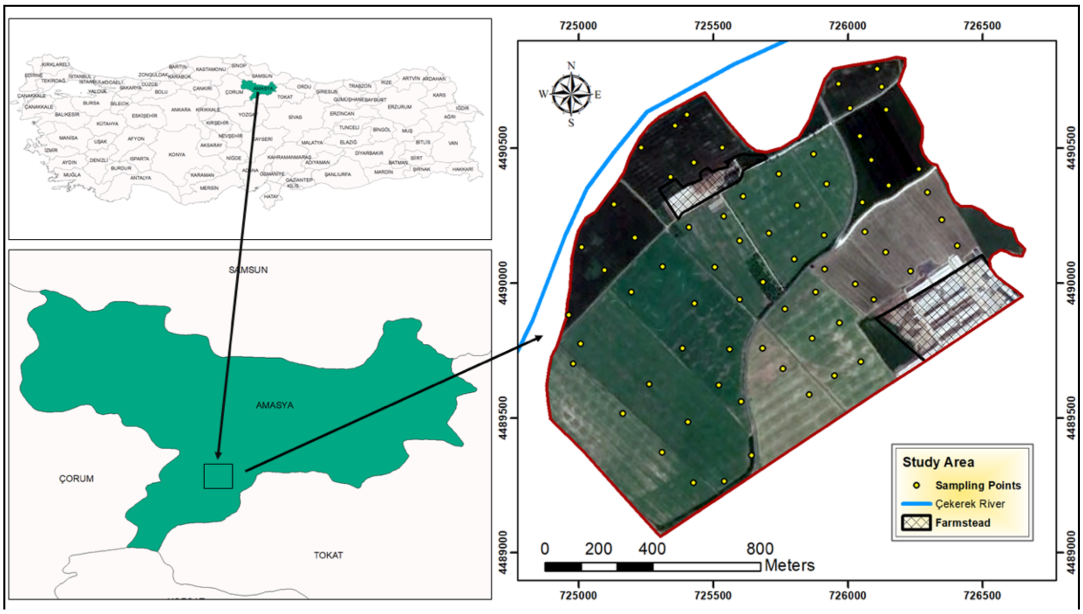

FIGURE 1
Location of study area and sampling points

MATERIALS AND METHODS

Study Area. The study area located in Amasya province between Gözlek and Kutu villages and is bounded to Çekerek River (UTM 724,800-726,800 E-W longitude and 4,489,100-4,490,800 N-S latitude). The coverage area of study area is 182 ha. Long-term average total rainfall of the region is 473.7 mm and the average temperature is 13.7 ºC. Soil moisture regime of the study area is Ustic and the temperature regime is Mesic [48]. Soil samples were collected from alfalfa (51 samples), corn (15 samples), tomato (1) and apple orchard (2) fields.

Soil Sampling and Laboratory Analysis. The study area was divided into 100 m X 100 m square grids and the soil samples were taken at the corner points of the grids at 0-20 and 20-40 cm depths. The texture was determined by hydrometer method using sodium hexametaphosphate [49]. Aggregate stability was determined according to wet sieving method in soil particles between 2.0 and 1.0 mm [50]. The organic matter was analyzed according to the "modified Walkey-black" method described by Nelson and Sommers (1982) [51]. Plant available phosphorus was determined by sodium bicarbonate ($NaHCO_3$) method of Olsen (1954) [52]. Extractable potassium was analyzed using 1 N ammonium acetate solution [53]. Lime content was calculated according to the volume of carbon dioxide released in Scheibler Calcimeter [54]. Total organic carbon is calculated on the basis of carbon in organic matter [55]. Soil reaction (pH) and electrical conductivity (EC) were measured in 1 soil: 2.5 pure water mixture by using a pH and EC meter [56]. Field capacity, wilting point, available water content and bulk density were determined according to Saxton et al. (1986)[57].

Soil Quality Assessment. Soil Management Assessment Framework (SMAF). This study was carried out to determine the productivity potential of soils under intensive agricultural production. Nutrient cycle, water relations, physical stability and support and resilience and resistance functions were determined to define status of productivity management in the study area. Organic carbon, aggregate stability, pH, electrical conductivity, useful water content, bulk density, plant available phosphorus and extractable potassium were chosen as the indicators to determine the capability of above stated functions.

The SMAF which is a three-step soil quality assessment tool [2] has been used to assess the quality of soils in the study area. The first step in SMAF is to determine the soil indicators which are selected from the physical, chemical and biological characteristics of the soil and sensitive to the changes in management [58, 59]. The second step of the SAMF is interpretation of indicators by using non-linear scoring functions. The algorithms of scoring curves for the indicators were developed under the SMAF approach. Three different scoring curves have been developed based on “more is better”, “less is better” and “optimum is better” algorithms. Scoring curves take specific conditions of the field or the crop to be grown into account and scores change accordingly. For example, the score of available water content indicator significantly changes depending on climate, texture and organic matter content. The third step of SMAF is to integrate the scored values of indicators and soil functions into a soil quality index [2]. Simple additive (Eq. 1) and weighted additive (Eq. 2) methods were used in the integration step.

$$SQI_{SA}\sum_{i=1}^{n}\frac{Si}{n} \tag{1}$$

$$SQI_{WA}\sum_{i=1}^{n}WiSi \tag{2}$$

where, *Si* is the indicator score, *n* the number of indicators integrated in the index and *Wi* the weighted value of the indicators. The weights of indicators and soil functions were determined by expert opinion and AHP technique.

Analytical Hierarchy Process (AHP). The weights of indicators and functions in AHP technique were assigned in 3 steps. In the first stage, dual comparisons are performed and matrices are created by considering the impact of indicator or function on the specific function or the management goal. In the second step, the priority is calculated for each of the indicators or functions that are compared. The final step of AHP is to control the accuracy of the weights obtained by comparing each parameter with the generated comparison matrix. The most important factor to test the reliability of the final decision is the consistency of the expert decisions in the comparison matrix. The consistency ratio should be less than 10% to accept the weight obtained for each indicator or function [60].

Geostatistical Analyses. Three different interpolation methods such as ordinary kriging (OK), inverse distance weighting (IDW) and radial basic functions (RBF) were compared in the accuracy of predictions for the values at non-sampled locations. The root mean squared error (RMSE) and mean absolute error (MAE) values were used as the criterion to decide the most appropriate interpolation method [61, 62]. The OK is based on the principle of estimating a value of variable at any unknown location by using the value of known locations, assuming that the variables are stationary and the mean is constant [63]. The IDW method uses the inverse distance functions of the distances in calculating the value of unknown location using the value of known location. The IDW method is based on the assumption that the similarity decreases as the distance from the known location to the targeted point decreases [64]. The RBF method is used to interpolate the multidimensional data. The RBF is generally used in prediction with a limited number of data or locations. The most important advantage which makes RBF different from other methods is being easily used in any dimension without a general restriction [65].

Statistical Analyses. The lowest, the highest, mean, standard deviation, coefficient of variation, skewness and kurtosis values of the parameters, soil quality indicators, functions and productivity management goal were calculated by using SPSS (SPSS 21) software. The values of soil functions and management goal quality scores obtained by simple additive and weighted additive methods were compared with paired t-test.

RESULTS AND DISCUSSION

Descriptive statistics of soil quality indicators. Descriptive statistics of physical and chemical properties were given in Table 1. The EC values of the soils formed in semi-arid climate varied between 0.72 and 0.68 dS m^{-1} which indicates a safe soil environment for salinity. Mean lime content in 0-20 cm depth was 9.54% and 9.72% in 20-40 cm depth (Table 1). The average pH value (8.54) was strong alkaline which significantly affects the availability plant nutrients and therefore, may reduce the agricultural production [66]. High lime content and relatively high soil pH may negatively affect the availability of plant nutrients in root zone. However, plant available phosphorus and exchangeable potassium concentrations of most soil samples were adequate due to the continuous use of phosphorus fertilizers and high potassium content of parent materials of soils. The soils of study area generally had low organic matter content. Organic matter content in some places of the study area was very low and insufficient as 0.32% and organic matter content was relatively high as 3.53% in some part of the study area.

The variation coefficient (CV) is often used to express the variability of soil properties in a data set. If the coefficient of variation is less than 15%, the parameter is considered as less variable, between 15% and 35% as moderately variable and >35% as highly variable [67]. The soils in study area had less variable in pH, $CaCO_3$, bulk density, field capacity and available water content (Table 1).

TABLE 1
Descriptive statistics of soil properties

0-20	Unit	Depth (cm)	Minimum	Maximum	Mean	Std. Devistion	CV*	Skewness
Clay	%	0-20	22.48	65.00	49.54	10.26	20.71	-1.20
		20-40	20.00	65.00	49.60	9.66	19.49	-1.16
Silt		0-20	19.55	48.13	26.74	6.86	25.65	1.51
		20-40	14.82	47.50	25.95	6.34	24.44	1.79
Sand		0-20	11.98	42.70	23.72	6.75	28.46	0.86
		20-40	12.70	42.70	24.45	6.51	26.64	0.79
pH		0-20	8.08	8.85	8.54	0.13	1.49	-0.89
		20-40	8.16	8.84	8.54	0.13	1.49	-0.45
Electrical Conductivity	dS m^{-1}	0-20	0.20	0.72	0.34	0.10	29.84	1.65
		20-40	0.19	0.68	0.36	0.10	28.22	1.01
CaCO3	%	0-20	7.69	12.56	9.54	1.21	12.65	0.63
		20-40	7.69	12.56	9.72	1.11	11.46	0.53
Organic Matter		0-20	0.32	3.53	1.54	0.45	29.23	1.14
		20-40	0.34	2.29	1.28	0.39	30.60	-0.03
Phosphorus	mg kg^{-1}	0-20	10.35	124.18	23.72	14.83	62.50	4.87
		20-40	5.74	91.22	21.35	12.87	60.28	3.75
Potassium		0-20	63.70	901.89	338.31	149.70	44.25	1.40
		20-40	86.70	677.32	290.80	123.65	42.52	0.88
Bulk Density	g cm^{-3}	0-20	1.18	1.40	1.25	0.05	3.79	1.51
		20-40	1.18	1.40	1.25	0.04	3.55	1.42
Aggregate Stability	%	0-20	24.67	88.70	68.81	14.64	21.27	-1.44
		20-40	19.52	86.81	66.93	14.21	21.24	-1.34
Permanent Wilting Point		0-20	13.59	38.54	28.43	6.13	21.58	-0.99
		20-40	12.48	38.54	28.38	5.83	20.54	-0.86
Field Capacity		0-20	26.53	51.76	42.03	5.95	14.16	-1.01
		20-40	26.59	51.76	41.88	5.69	13.57	-0.78
Available Water Content		0-20	12.03	16.53	13.60	0.81	5.96	1.39
		20-40	10.99	16.38	13.50	0.76	5.61	0.49

*CV: Coefficient of Variation

Clay, sand and silt contents in both soil depths had moderate variability. The surface and subsurface clay contents were 49.54 and 49.60%, respectively and the majority of soils had clayey textures (Table 1). The soils with high clay content (>52%) extend, in the form of a spring, from the south-west corner of the farm to the north-east corner. The average sand content in 0-20 and 20-40 cm depths was 23.72 and 24.45%, respectively. Sand content of soils close to the Kelkit river were around 42% which indicates the effects of sedimentation deposited by the river on the textures of soils. Bulk density values at both soil depths ranged from 1.18 to 1.40 g cm^{-3}, with an average of 1.25 g cm^{-3}. Pierce et al. (1983) [68] reported that the root growth in soils with >45% clay was adversely affected when bulk density is greater than 1.39 g cm^{-3}, and root growth is significantly restricted at a bulk density greater than 1.47 g cm^{-3}. The researchers also stated that bulk density up to 1.40 g cm^{-3} in sandy clayey loam, loamy and sandy soils will not cause any problem for crop production. Mean bulk density of soils (1.25 g cm^{-3}) clearly shows that bulk density is not a limiting factor for root development in study area. High aggregate stability ensures the improved physical conditions and better water and nutrients uptake [69]. The aggregate stability (AS) values (68.8 and 66.9%, respectively) in surface and subsurface depths had moderate variability in study area. Available water content of surface and subsurface soils varied between 13.60 and 13.50% (Table 1).

Descriptive Statistics of Soil Quality Indicator Scores. Descriptive statistics of soil quality indicators and soil quality index values were presented in Table 2. Mean organic carbon score which was determined by using "higher is better" algorithm was 0.16 and ranged from 0.03 to 0.73 in surface soils. The algorithm developed for scoring the organic carbon indicator takes the total organic matter content, soil texture and climate into account for scoring. The climate is a constant parameter for the study area, therefore the most influential variables affecting the variability of the organic carbon indicator were organic matter content and soil texture. High variability in soil texture within the study area, which is located adjacent to the Cekerek River, is the major cause for the variability of the organic carbon indicator. Organic carbon has a significant effect on functioning capability of soils due to the impact on formation of aggregates, higher water retention, drainage and resistance to compaction [70]. The average AS, phosphorus, EC and potassium scores of surface soils were 0.99, 0.99, 1.00 and 0.98, respectively. The AS, which helps improving water and nutrient retention and soil resistance to water and wind erosion, was very high in the majority of the study area, however, AS was 0.73 where organic carbon content was very low and sand content was high.

High soil pH values, which is scored using "optimum point is better" algorithm, caused the pH scores range between 0.48 and 0.77. The results revealed that pH controlling the availability of plant nutrients in agricultural production limits the functioning capabilities of soil to a certain extent. Bulk density of soils is widely used as an indicator of soil functioning due to the great impact on aeration, available water content, infiltration and hydraulic conductivity and resistance to erosion [71]. Bulk density score, which is an indicator of soil compaction, ranged from 0.58 to 0.90 and the average value was 0.74. The areas with bulk density scores (0.58) are located adjacent to the river and had high sand and insufficient organic carbon contents. The average available water content functions 60% of the capacity and is closely related to the relatively

TABLE 2
Descriptive statistics of surface and subsurface soils for soil quality indicators and indices

	Depth (cm)	Minimum	Maximum	Mean	Std. Deviation	CV*	Skewness
Organic Carbon	0-20	0.03	0.73	0.16	0.10	59.63	3.52
	20-40	0.03	0.29	0.12	0.06	47.79	0.99
Aggregate Stability	0-20	0.73	1.00	0.99	0.05	5.16	-4.13
	20-40	0.65	1.00	0.98	0.06	6.20	-4.65
pH	0-20	0.48	0.77	0.58	0.05	8.58	1.24
	20-40	0.50	0.75	0.58	0.05	8.50	1.03
Phosphorus	0-20	0.95	1.00	0.99	0.01	1.28	-2.03
	20-40	0.74	1.00	0.98	0.03	3.36	-5.92
Bulk Density	0-20	0.58	0.90	0.74	0.07	8.97	0.01
	20-40	0.57	0.90	0.74	0.07	9.36	-0.18
Electrical Conductivity	0-20	1.00	1.00	1.00	0.00	0.00	
	20-40	1.00	1.00	1.00	0.00	0.00	
Available Water Content	0-20	0.45	0.73	0.60	0.06	10.24	-0.41
	20-40	0.40	0.73	0.60	0.06	10.34	-0.22
Potassium	0-20	0.62	1.00	0.98	0.06	6.20	-4.52
	20-40	0.60	1.00	0.97	0.08	7.76	-3.90
Soil Quality Indices	0-20	0.65	0.85	0.76	0.03	3.66	-0.60
	20-40	0.66	0.81	0.75	0.03	3.88	-1.14

*CV: Coefficient of Variation

low bulk density and organic carbon content of soils. The soil quality index calculated with the arithmetic mean of individual soil quality indicators ranged from 0.65 to 0.85 in surface, from 0.66 to 0.81 in subsurface soils and mean value for surface and subsurface soils was 0.76 and 0.75, respectively. The indicators that cause soils in study area functioning under the full capacity are organic carbon, pH, available water content and bulk density, respectively.

Soil Quality Functions and Indices. The nutrient cycle, water relations, physical stability and support and resistance and resilience functions were defined to determine the functioning capacity of soils under intensive agricultural production. The minimum data sets required to identify these functions were chosen by expert opinion and the weights indicating the contribution of the indicators to the functions were determined by the AHP and expert opinion (Table 3).

Equal weights were assigned for the indicators defining the functions and the functions. However, different weights were assigned to the indicators and functions in AHP method. The highest indicator weights for the nutrient cycle, water relations and physical stability and support functions in AHP were attained for pH (0.45), Organic carbon (0.30) and aggregate stability (0.38), respectively (Table 3.). According to the AHP method, the highest weight value of the functions that affect the productivity management target was occurred for the nutrient cycle (0.34) and the lowest weight value was in the resistance and resilience (0.15) function (Table 3.).

Nutritional cycle (NC) function indicates the capability of soil to provide optimum amounts of plant nutrients and which can be toxic to plants and directs concentrations of excess nutrients that can be harmful to air or water [2]. The mean NC value calculated by the SA (0.79) and WA (0.72) was significantly different from each other (Table 4). The weights calculated by WA for phosphorus, potassium and available water content indicators were lower compared to the pH indicator in assessing the NC function of soils. The pH indicator with the lowest mean score (0.58) is the most important indicator that limits the production in the study area.

The scores of water relations (WR) and physical stability and support (PSS) functions calculated by SA and WA were similar to that in the NC. Mean scores for both functions were 0.70 and 0.62 in SA, whereas the scores calculated by using the WA were 0.61 and 0.63, respectively (Table 4). However, the WR and PSS function scores did not significantly change with soil depth. The WA method resulted in higher weight value of organic carbon indicator defined under the WR function. Providing available water is a major determinant of the soil productivity in arid and semi-arid climates [72]. The WR function enables the percolation of water and movement of plant nutrients and beneficial soil organisms in solution and helps the soils to resist against erosive forces [2]. Lower organic carbon compared to other indicators defined under the WR function limits the WR function and therefore caused to the low productivity. The PSS function supports physical structure of soils which increases the resistance to disruptive forces and provides a better environment for plant roots [73]. The weights of aggregate stability and organic carbon indicators under the PSS function were higher in AHP compared to pH and bulk density indicators.

TABLE 3
Weight for soil functions and indicators calculated by expert opinion and analytical hierarchy process (AHP)

Management Goal	Soil Function	Weight		Indicator	Weight	
		AHP	EO		AHP	EO
Productivity	NC	0.34	0.25	pH	0.45	0.25
				Phosphorus	0.19	0.25
				Potassium	0.13	0.25
				Available Water Capacity	0.23	0.25
	WR	0.21	0.25	Aggregate Stability	0.21	0.20
				Organic Carbon	0.30	0.20
				Available Water Capacity	0.25	0.20
				Bulk Density	0.15	0.20
				Electrical Conductivity	0.09	0.20
	PSS	0.31	0.25	Aggregate Stability	0.38	0.25
				Organic Carbon	0.31	0.25
				pH	0.13	0.25
				Bulk Density	0.18	0.25
	RR	0.15	0.25	Organic Carbon	1.00	1.00

*AHP: Analytical hierarchy process, EO: Expert Opinion, NC: Nutrient cycle, WR: Water relations, PSS: Physical Stability and support, RR: Resistance and resilience, SQI: Soil quality index

TABLE 4
Comparison of management goal and soil function scores obtained by simple additive (SA) (EO)and weighted additive (WA)

	SA				WA				Paired Sample t-test
	Min.	Max.	Mean	Skewness	Min.	Max.	Mean	Skewness	
					0-20 cm				
NC	0.65	0.84	0.79	-1,664	0.61	0.81	0.72	-0,188	**
WR	0.61	0.81	0.70	0,383	0.50	0.78	0.61	0,999	**
PSS	0.52	0.80	0.62	1,289	0.52	0.83	0.63	1,283	**
RR	0.03	0.73	0.16	3,517	0.03	0.73	0.16	3,517	ns
SQI$_{\text{Productivity}}$	0.45	0.80	0.57	2,093	0.48	0.80	0.59	1,819	**
					20-40 cm				
NC	0.66	0.86	0.79	-1,584	0.61	0.82	0.71	-0,352	**
WR	0.59	0.77	0.69	-0,279	0.48	0.69	0.59	-0,166	**
PSS	0.50	0.69	0.61	-0,206	0.47	0.69	0.62	-1,118	**
RR	0.03	0.29	0.12	0,986	0.03	0.29	0.12	0,986	ns
SQI$_{\text{Productivity”}}$	0.47	0.64	0.55	0,110	0.47	0.67	0.58	-0,216	**

* SA: Simple Additive, WA: Weighted Additive, NC: Nutrient cycle, WR: Water relations, PSS: Physical Stability and support, RR: Resistance and resilience, SQI: Soil quality index, ** Correlation is significant at P<0.01 level (2-tailed). ns: not significant

TABLE 5
Cross-validation results of soil quality index for productivity goal and soil functions according to interpolation methods

	SQI-SA$_{\text{Productivity}}$		SQI-WA$_{\text{Productivity}}$		SQI-SA$_{\text{Productivity}}$		SQI-WA$_{\text{Productivity}}$	
	0-20				20-40			
	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE
OK	**0.04339**	**0.02745**	**0.04062**	**0.02554**	**0.03387**	**0.02362**	**0.03411**	**0.02335**
IDW	0.04409	0.02750	0.04120	0.02585	0.03389	0.02435	0.03420	0.02405
RBF	0.04570	0.02865	0.04273	0.02720	0.03447	0.02499	0.03476	0.02485

* SQI: Soil Quality Index; EO: Expert Opinion, AHP: Analytical Hierarchy Process; RMSE: Root Mean Square Error; MAE: Mean Absolute Error; OK: Ordinary Kriging, IDW: Inverse Distance Weighting, RBF: Radial Basis Function

The mean SQI obtained by SA and WA were significantly different from each other. According to the SA, the SQI, which reflects the productivity target, ranged from 0.45 to 0.80, and the mean SQI value was 0.57. The SQI obtained by using the WA was ranged between 0.48 and 0.80, and the mean SQI for WA was 0.59 (Table 4). The main difference is the higher weights assigned to NC and PSS functions by the WA method. Furthermore, the SQI values obtained by SA and WA methods revealed that soils in the study area are functioning almost at half of their natural productivity functioning capacity. Low levels of total and organic carbon in soils are considered a serious threat to the sustainability of soil functions [74]. The most important reason for the low functioning capacity of soils in study area is the low value of RR function which was defined only by a single indicator (organic C). The organic C is a major source of nutrients and depletion of organic matter is associated with the loss of soil productivity [75]. The low content of organic carbon in the study area is the primary agent of the low overall SQI scores. Accurate land use and management planning has an important role in improving the soil quality [76]. Therefore, adaptation of agricultural practices (animal manure, green fertilization etc.) to increase the organic carbon content of soils in the study area will enhance the ability of soils to function.

Interpolation of Soil Quality Functions and Indices. Monitoring and quantification of soil variability are vital to evaluate the effects of management techniques and to plan more effective agricultural practices [77]. Geostatistical approaches have been frequently used for spatial analysis of soil properties [78,79]. In this study, productivity SQI values of surface and subsurface soils at unsampled locations were predicted by ordinary kriging (OK), inverse distance weighting (IDW) and radial basic functions (RBF) methods and the results were given in Table 5.

Different comparison methods have been used to assess the relationship between the measured actual and the estimated values, and to choose the best interpolation method provides closest values to the measured values. The root-mean squared error (RMSE) and the mean absolute error (MAE) are the most commonly used methods in comparison of the estimated and actual values in soil data [47, 61-63].

The OK interpolation method provided the lowest RMSE and MAE values in the prediction of the productivity management goal scores at non-sampling points both for the simple additive and weighted additive methods. Similarly, Bhunia et al. (2018) [47] compared the efficiency of OK, IDW, RBF, local polynomial interpolation (LPI) and Empirical Bayes kriging (EBK)interpolation methods. Similar to the results of the current study, the

OK interpolation method performed better than the other interpolation methods and considered as the most appropriate interpolation method due to the lower RMSE value. Zare-Mehrjardi et al. (2010) [80] also showed that the OK interpolation method yielded reliable results compared to the IDW method in predicting the spatial distributions of soil properties. The maps of productivity SQI obtained by OK interpolation method were presented in Figure 2 and 3.

The lowest productivity goal SQI values obtained by simple additive and weighted additive methods are located in the fields adjacent to the Çekerek River and the SQI values increase as moving away from the river. High sand and low organic carbon contents near the river cause low productivity scores in these fields. Soil texture of alluvial plains has a very high variability even at very short distances [81]. The variation in the soil texture in an alluvial plain significantly affects spatial variability of water holding capacity, available water content and the water movement in the profile [82].

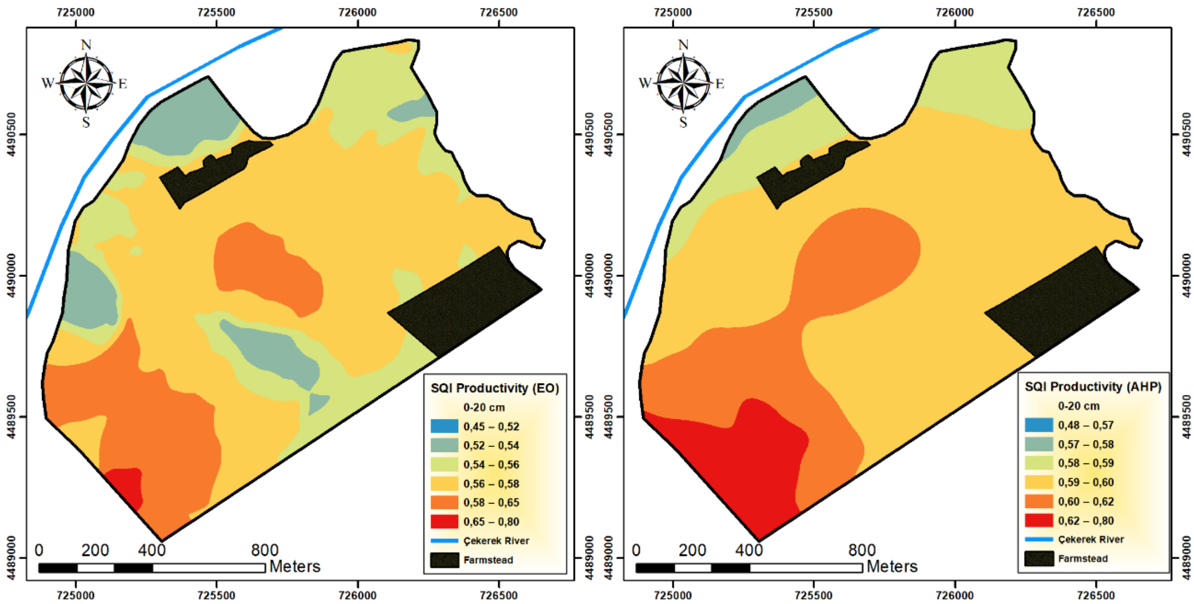

FIGURE 2
Spatial distribution of productivity quality index scores of surface soil in study area

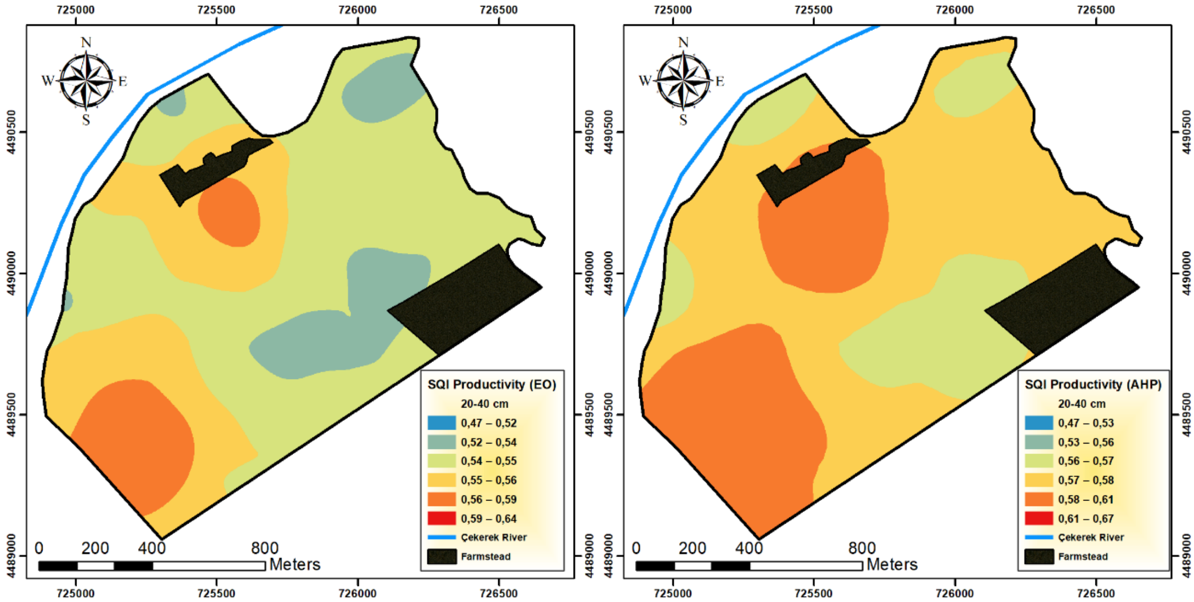

FIGURE 3
Spatial distribution of productivity quality index scores of sub-surface soil in study area

The SQI scores for the productivity of subsoil soils were slightly lower than the surface soils. Hewitt (2004) [83] stated that the fertility of soils is significantly affected by subsurface characteristics. Vasu et al. (2016) [28] stated that genetic characteristics along with the dynamic characteristics of the soils will help to identify the relationship between soil functions and soil properties.

CONCLUSIONS

The productivity SQI of soils, which were mostly formed over alluvium parent materials, were scored using the nonlinear scoring curves of the SMAF method, weighted by expert opinion and AHP methods and calculated by simple additive and weighted additive methods. The SQI values obtained with the weighted additive and simple additive methods were quite similar to each other. Natural productivity capacities determined by the simple additive method were 57 (0-20 cm) and 58% (20-40 cm) and 57 (0-20 cm) and 59% (20-40 cm) by the weighted additive method. The resistance and resilience function had the highest impact the productivity of soils and the organic carbon is the major contribute to this function. The maps with the highest accuracy for soil functions and productivity service index values were produced by the ordinary kriging method.

REFERENCES

[1] Garrigues, E., Corson, M.S., Angers, D.A., van der Werf, H.M., Walter, C. (2012) Soil quality in Life Cycle Assessment: Towards development of an indicator. Ecological indicators. 18, 434-442.

[2] Andrews, S.S., Karlen, D.L., Cambardella, C.A. (2004) The soil management assessment framework. Soil Science Society of America Journal. 68, 1945-1962.

[3] Ditzler, C., Tugel, A. (2002) Soil quality field tools: experiences of USDA-NRCS soil quality. Agronomy Journal. 94, 33-38.

[4] Andrews, S.S., Karlen, D., Mitchell, J. (2002) A comparison of soil quality indexing methods for vegetable production systems in Northern California. Agriculture, Ecosystems and Environment. 90, 25-45.

[5] Juhos, K., Czigány, S., Madarász, B., Ladányi, M. (2019) Interpretation of soil quality indicators for land suitability assessment – A multivariate approach for Central European arable soils. Ecological Indicators. 99, 261-272.

[6] Romig, D.E., Garlynd, M.J., Harris, R.F. (1996) Farmer-Based Assessment of Soil Quality: A Soil Health Scorecard 1. Methods for Assessing Soil Quality. 39-60.

[7] Liebig, M.A., Doran, J.W., Gardner, J.C. (1996) Evaluation of a field test kit for measuring selected soil quality indicators. Agronomy Journal. 88, 683-686.

[8] NRCS, U. (2003) Interpreting the soil conditioning index: A tool for measuring soil organic matter trends. US Department of Agriculture, Natural Resources Conservation Service, Soil Quality-Agronomy Tech Note.

[9] Liebig, M.A., Miller, M.E., Varvel, G.E., Doran, J.W., Hanson, J.D. (2004) AEPAT: Software for Assessing Agronomic and Environmental Performance of Management Practices in Long-Term Agroecosystem Experiments. Agronomy Journal. 96, 109-115.

[10] De la Rosa, D., Mayol, F., Diaz-Pereira, E., Fernandez, M., de la Rosa Jr, D. (2004) A land evaluation decision support system (MicroLEIS DSS) for agricultural soil protection: With special reference to the Mediterranean region. Environmental Modelling and Software. 19, 929-942.

[11] Karlen, D.L., Cambardella, C.A., Kovar, J.L., Colvin, T.S. (2013) Soil quality response to long-term tillage and crop rotation practices. Soil and Tillage Research. 133, 54-64.

[12] Beniston, J.W., Lal, R., Mercer, K.L. (2016) Assessing and Managing Soil Quality for Urban Agriculture in a Degraded Vacant Lot Soil. Land Degradation and Development. 27, 996-1006.

[13] Veum, K.S., Sudduth, K.A., Kremer, R.J., Kitchen, N.R. (2017) Sensor data fusion for soil health assessment. Geoderma. 305, 53-61.

[14] Cherubin, M.R., Karlen, D.L., Cerri, C.E., Franco, A.L., Tormena, C.A., Davies, C.A., Cerri, C.C. (2016) Soil Quality Indexing Strategies for Evaluating Sugarcane Expansion in Brazil. PLoS One. 11, e0150860.

[15] Lisboa, I.P., Cherubin, M.R., Satiro, L.S., Siqueira-Neto, M., Lima, R.P., Gmach, M.R., Cerri, C.C. (2019) Applying Soil Management Assessment Framework (SMAF) on short-term sugarcane straw removal in Brazil. Industrial Crops and Products. 129, 175-184.

[16] Apesteguía, M., Virto, I., Orcaray, L., Bescansa, P., Enrique, A., Imaz, M., Karlen, D. (2017) Tillage effects on soil quality after three years of irrigation in northern Spain. Sustainability. 9, 1476.

[17] Ozgoz, E., Gunal, H., Acir, N., Gokmen, F., Birol, M., Budak, M. (2013) Soil quality and spatial variability assessment of land use effects in a typic haplustoll. Land Degradation and Development. 24, 277-286.

[18] Şeker, C., Özaytekin, H.H., Negiş, H., Gümüş, İ., Dedeoğlu, M., Atmaca, E., Karaca, Ü. (2017) Identification of regional soil quality factors and indicators: a case study on an alluvial plain (central Turkey). Solid Earth. 8, 583-595.

[19] Swanepoel, P., du Preez, C., Botha, P., Snyman, H., Habig, J. (2015) Assessment of tillage effects on soil quality of pastures in South Africa with indexing methods. Soil Research. 53, 274-285.

[20] Kalu, S., Koirala, M., Khadka, U.R., Anup, K. (2015) Soil quality assessment for different land use in the Panchase area of western Nepal. International Journal of Environmental Protection. 5, 38-43.

[21] Gelaw, A., Singh, B., Lal, R. (2015) Soil quality indices for evaluating smallholder agricultural land uses in northern Ethiopia. Sustainability. 7, 2322-2337.

[22] Armenise, E., Redmile-Gordon, M., Stellacci, A., Ciccarese, A., Rubino, P. (2013) Developing a soil quality index to compare soil fitness for agricultural use under different managements in the Mediterranean environment. Soil and Tillage Research. 130, 91-98.

[23] Mukherjee, A., Lal, R. (2014) Comparison of soil quality index using three methods. PloS one. 9, e105981.

[24] Cherubin, M.R., Karlen, D.L., Franco, A.L., Cerri, C.E., Tormena, C.A., Cerri, C.C. (2016) A Soil Management Assessment Framework (SMAF) evaluation of Brazilian sugarcane expansion on soil quality. Soil Science Society of America Journal. 80, 215-226.

[25] Hammac, W.A., Stott, D.E., Karlen, D.L., Cambardella, C.A. (2016) Crop, Tillage, and Landscape Effects on Near-Surface Soil Quality Indices in Indiana. Soil Science Society of America Journal. 80.

[26] Yu, P., Liu, S., Zhang, L., Li, Q., Zhou, D. (2018) Selecting the minimum data set and quantitative soil quality indexing of alkaline soils under different land uses in northeastern China. Science of the Total Environment. 616, 564-571.

[27] Lima, A.C.R., Brussaard, L., Totola, M.R., Hoogmoed, W.B., de Goede, R.G.M. (2013) A functional evaluation of three indicator sets for assessing soil quality. Applied Soil Ecology. 64, 194-200.

[28] Vasu, D., Singh, S.K., Ray, S.K., Duraisami, V.P., Tiwary, P., Chandran, P., Anantwar, S.G. (2016) Soil quality index (SQI) as a tool to evaluate crop productivity in semi-arid Deccan plateau, India. Geoderma. 282, 70-79.

[29] Biswas, S., Hazra, G.C., Purakayastha, T.J., Saha, N., Mitran, T., Singha Roy, S., Basak, N., Mandal, B. (2017) Establishment of critical limits of indicators and indices of soil quality in rice-rice cropping systems under different soil orders. Geoderma. 292, 34-48.

[30] Lin, Y., Deng, H., Du, K., Li, J., Lin, H., Chen, C., Zhang, G. (2017) Soil quality assessment in different climate zones of China’s Wenchuan earthquake affected region. Soil and Tillage Research. 165, 315-324.

[31] Mishra, G., Marzaioli, R., Giri, K., Borah, R., Dutta, A., Jayaraj, R. (2017) Soil quality assessment under shifting cultivation and forests in Northeastern Himalaya of India. Archives of Agronomy and Soil Science. 63, 1355-1368.

[32] Raiesi, F. (2017) A minimum data set and soil quality index to quantify the effect of land use conversion on soil quality and degradation in native rangelands of upland arid and semiarid regions. Ecological Indicators. 75, 307-320.

[33] Askari, M.S., Holden, N.M. (2015) Quantitative soil quality indexing of temperate arable management systems. Soil and Tillage Research. 150, 57-67.

[34] Cheng, J., Ding, C., Li, X., Zhang, T., Wang, X. (2016) Soil quality evaluation for navel orange production systems in central subtropical China. Soil and Tillage Research. 155, 225-232.

[35] Raiesi, F., Kabiri, V. (2016) Identification of soil quality indicators for assessing the effect of different tillage practices through a soil quality index in a semi-arid environment. Ecological Indicators. 71, 198-207.

[36] Fernandes, J.C., Gamero, C.A., Rodrigues, J.G.L., Mirás-Avalos, J.M. (2011) Determination of the quality index of a Paleudult under sunflower culture and different management systems. Soil and Tillage Research. 112, 167-174.

[37] Negaresh, H., Rakhshani, Z., Firoozi, F., Alinia, H. (2016) Desertification assessment using the analytic hierarchy process and GIS in southeast Iran. Geografiska Annaler: Series A, Physical Geography. 98, 1-14.

[38] Arami, S., Ownagh, M. (2017) Assessment of desertification hazard, risk and development of management plans. Desert. 22, 51-67.

[39] Kumar, N., Singh, S.K., Mishra, V.N., Reddy, G.P.O., Bajpai, R.K. (2017) Soil quality ranking of a small sample size using AHP. Journal of Soil and Water Conservation. 16.

[40] Liu, J., Wu, L., Chen, D., Li, M., Wei, C. (2017) Soil quality assessment of different Camellia oleifera stands in mid-subtropical China. Applied Soil Ecology. 113, 29-35.

[41] Budak, M., Gunal, H., Celik, I., Yildiz, H., Acir, N., Acar, M. (2018) Soil Quality Assesment Of Upper Tigris Basin. Carpath J Earth Env. 13, 301-316.

[42] Saaty, T.L. (1980) The analytic hierarchy process McGraw-Hill. New York 324.

[43] Salehpour Jam, A., Tabatabaei, M., Sarreshtehdari, A. (2017) Pedological Criterion Affecting Desertification in Alluvial Fans Using AHP-ELECTRE I Technique (Case Study: Southeast of Rude-Shoor Watershed Area). ECOPERSIA. 5, 1711-1729.

[44] Merrill, S.D., Liebig, M.A., Tanaka, D.L., Krupinsky, J.M., Hanson, J.D. (2013) Comparison of soil quality and productivity at two sites differing in profile structure and topsoil properties. Agriculture, Ecosystems and Environment.179, 53-61.

[45] Cambardella, C., Moorman, T., Parkin, T., Karlen, D., Novak, J., Turco, R., Konopka, A. (1994) Field-scale variability of soil properties in central Iowa soils. Soil science society of America journal. 58, 1501-1511.

[46] Robinson, T., Metternicht, G. (2006) Testing the performance of spatial interpolation techniques for mapping soil properties. Computers and electronics in agriculture. 50, 97-108.

[47] Bhunia, G.S., Shit, P.K., Maiti, R. (2018) Comparison of GIS-based interpolation methods for spatial distribution of soil organic carbon (SOC). Journal of the Saudi Society of Agricultural Sciences. 17,114-126.

[48] Staff, S.S. (1999) Soil Taxonomy: A Basic System of Soil Classification for Making and Interpreting Soil Surveys: Department of Agriculture. Natural Resources Conservation Service, USDA.

[49] Gee, G.W., Bauder, J.W. (1986) Particle-size analysis 1. Methods of soil analysis: Part 1—Physical and mineralogical methods. 383-411.

[50] Kemper, W., Rosenau, R. (1986) Aggregate Stability and Size Distribution 1. Methods of Soil Analysis: Part 1—Physical and Mineralogical Methods. 425-442.

[51] Nelson, D., Sommers, L. (1982) Methods of soil analysis. Part 2. 539-579.

[52] Olsen, S.R. (1954) Estimation of available phosphorus in soils by extraction with sodium bicarbonate. United States Department of Agriculture: Washington.

[53] Thomas, G.W. (1982) Exchangeable cations. Methods of soil analysis Part 2 Chemical and microbiological properties. 159-165.

[54] Kacar, B. (1994) Plant and Soil Chemical Analysis. 3rd Soil Analysis. Ankara Univ. Agric. Fac. Education Res. and Development Foundation Publications. (in Turkish).

[55] Tabatabai, M. (1994) Soil enzymes. Methods of soil analysis: part 2—microbiological and biochemical properties. 775-833.

[56] Rhoades, J., Chandubi, F., Lesch, S. (1999) Soil salinity assessment: methods and interpretation of electrical conductivity measurements. FAO, Roma (Italia). 9251042810 9251042810.

[57] Saxton, K., Rawls, W.J., Romberger, J., Papendick, R. (1986) Estimating generalized soil-water characteristics from texture 1. Soil Science Society of America Journal. 50, 1031-1036.

[58] Shukla, M., Lal, R., Ebinger, M. (2006) Determining soil quality indicators by factor analysis. Soil and Tillage Research. 87, 194-204.

[59] Imaz, M., Virto, I., Bescansa, P., Enrique, A., Fernandez-Ugalde, O., Karlen, D. (2010) Soil quality indicator response to tillage and residue management on semi-arid Mediterranean cropland. Soil and Tillage Research. 107, 17-25.

[60] Saaty, T.L. (2008) Decision making with the analytic hierarchy process. International journal of services sciences. 1, 83-98.

[61] Emadi, M., Baghernejad, M. (2014) Comparison of spatial interpolation techniques for mapping soil pH and salinity in agricultural coastal areas, northern Iran. Archives of Agronomy and Soil Science. 60,1315-1327.

[62] Rahmanipour, F., Marzaioli, R., Bahrami, H.A., Fereidouni, Z., Bandarabadi, S.R. (2014) Assessment of soil quality indices in agricultural lands of Qazvin Province, Iran. Ecological Indicators. 40, 19-26.

[63] Özdemir, Ş., Günal, H., Nurullah, A., Arslan, H., Özaydin, K.A., Kahyaoğlu, S.E. (2019) Deterministic and Stochastic Interpolation Methods in Estimation of Soil Salinity in Çerikli Irrigation Area. Soil Water Journal 8, 55-67. (in Turkish).

[64] Li, J., Heap, A.D. (2008) A review of spatial interpolation methods for environmental scientists. Geoscience AustraliaRecord 2008/23.

[65] Wright, G.B. (2003) Radial basis function interpolation: numerical and analytical developments. Thesis-Doctor of Philosophy. Faculty of the Graduate School of the University of Colorado.

[66] Taşkın, M.B., Türkmen, F., Akça, M.O., Soba, M.R., Öztürk, H.S. (2018) Investigation of fertility status of Ankara University Ayaş Research and Application Farm soils. Journal of Soil Science and Plant Nutrition. 6, 122-133. (in Turkish).

[67] Wilding, L. (1985) Spatial variability: its documentation, accommodation and implication to soil surveys. 166-194.

[68] Pierce, F., Larson, W., Dowdy, R., Graham, W. (1983) Productivity of soils: Assessing long-term changes due to erosion. Journal of Soil and Water Conservation. 38, 39-44.

[69] Saha, D., Kukal, S. (2015) Soil structural stability and water retention characteristics under different land uses of degraded lower Himalayas of North-West India. Land degradation and development. 26, 263-271.

[70] Becerra-Castro, C., Lopes, A.R., Vaz-Moreira, I., Silva, E.F., Manaia, C.M., Nunes, O.C. (2015) Wastewater reuse in irrigation: A microbiological perspective on implications in soil fertility and human and environmental health. Environment international. 75, 117-135.

[71] Li, Z., Liu, C., Dong, Y., Chang, X., Nie, X., Liu, L., Zeng, G. (2017) Response of soil organic carbon and nitrogen stocks to soil erosion and land use types in the Loess hilly–gully region of China. Soil and Tillage Research. 166, 1-9.

[72] Froment, M., Dampney, P., Goodlass, G., Dawson, C., Clarke, J. (1995) A review of spatial variation of nutrients in soil. MAFF final report for project CE0139, ministry of agriculture London, UK: Fisheries and Food.

[73] Bhaduri, D., Purakayastha, T., Patra, A., Chakraborty, D. (2014) Evaluating soil quality under a long-term integrated tillage–water–nutrient experiment with intensive rice–wheat rotation in a semi-arid Inceptisol, India. Environmental monitoring and assessment. 186, 2535-2547.

[74] Bizo, M.L., Levei, E.A., Kothe, E., Senila, M., Modoi, C.O., Ozunu, A. (2015) Chemical assessment of soil quality for ecological remediation strategies. Carpath J Earth Environ Sci. 10, 195.

[75] Bauer, A., Black, A. (1994) Quantification of the effect of soil organic matter content on soil productivity. Soil Science Society of America Journal. 58, 185-193.

[76] Rezaei, H., Jafarzadeh, A., Aliasgharzad, N., Alipoor, L. (2015) Soil quality investigation based on biological and micromorphological traits under different land uses. Carpathian Journal of Earth and Environmental Sciences. 10, 249-262.

[77] Sun, B., Zhou, S., Zhao, Q. (2003) Evaluation of spatial and temporal changes of soil quality based on geostatistical analysis in the hill region of subtropical China. Geoderma. 115, 85-99.

[78] Budak, M. (2018) Importance of Spatial Soil Variability for Land Use Planning of a Farmland in a Semi-Arid Region. Fresen. Environ. Bull. 27, 5053-5065.

[79] Surucu, A., Ahmed, T.K., Gunal, E., Budak, M. (2019) Spatial Variability of Some Soil Properties in an Agricultural Field of Halabja City of Sulaimania Governorate, Iraq. Fresen. Environ. Bull. 29,193-206.

[80] Zare-Mehrjardi, M., Taghizadeh-Mehrjardp, R., Akbarzadeh, A. (2010) Evaluation of Geostatistical Techniques for Mapping Spatial Distribution of Soil PH, Salinity and Plant Cover Affected by Environmental Factors in Southern Iran. Notulae Scientia Biologicae 2.

[81] Iqbal, M., Ali, A., Rizwanullah, M. (2005) Residual effect of tillage and farm manure on some soil physical properties and growth of wheat (Triticum aestivum L.). International Journal of Agriculture and Biology (Pakistan).

[82] Budak, M., Nurullah, A. (2019) The Use of Geostatistics and Geographical Information Systems Techniques in the Management of the Gökhöyük Agricultural Farm Lands in Turkey. Agricultural Research Journal. 6, 102-114. (in Turkish).

[83] Hewitt, A. (2004) Soil properties relevant to plant growth: A guide to recognising soil properties relevant to plant growth and protection. Manaaki Wenua Press. Lincoln, New Zealand.

Received: **03.05.2019**
Accepted: **03.07.2019**

CORRESPONDING AUTHOR

Nurullah Acir
Kırşehir Ahi Evran University,
Faculty of Agriculture,
Department of Soil Science and Plant Nutrition,
Kırşehir 40100 – Turkey

e-mail: nurullah.acir@ahievran.edu.tr