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Soil quality indices of paddy soils in Guilan province of northern Iran: Spatial variability and their influential parameters

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ABSTRACT

Soil quality (SQ) is an important issue in soil science, ecology, agronomy, and environmental sciences that has been received increased attention due to its importance in the sustainability of ecosystem and soil management. Biological and physicochemical soil traits, as sensitive variables to changes in soil functions, mainly used as major parameters in SQ assessment. Soil quality index (SQI) is the most suitable index to evaluate the quality of soils. This study aimed to 1) evaluate the quality of paddy-field soils using three approaches (integrate quality index, IQI; physical index, PI; Fuzzy) to develop a credible SQI for rice cultivation and 2) model the spatial variability of the SQIs. 120 soil samples were taken from rice cropping land within the study area (Shaft and Fouman counties, Guilan province, and north of IR Iran). Fifteen soil variables were considered to calculate SQI of the paddy soils. Principal component analysis (PCA) approach applied to choose the minimum data set (MDS). Both non-linear and linear scoring procedures used to compute the SQI. Four principal components (PC) explained nearly 70% of the overall SQI variability. Fuzzy method clearly investigated the main limiting soil factors in paddy fields and the GIS-based SQ maps could be useful for decision-makers. The correlation coefficients (r) between the fuzzy results by non-linear scoring and rice yields were relatively good (0.70). Whereas, the results of Gupta model and yield had very low correlation ($r = 0.24$). Application of fuzzy sets with non-linear scoring function provided a more accurate assessment of SQ as compared with that obtained in other approaches. Majority of the study area had low SQ and the most severe limitation ($SQI < 0.58$) and need better management practices for improving soil quality.

1. Introduction

Spatial variability of soil traits, diseases, and weeds affect crop yield (Gotway et al., 1997). Considering the spatial variability of soil properties and their effects on the growth and yield of crops is an important issue in sustainable and site-specific management systems (Juhos et al., 2016). Different biological, chemical, and physical aspects primarily characterize the soils (Bouma, 2002). Soil traits vary in space and time from a field to larger regional scales as a result of extrinsic and intrinsic factors (Sun et al., 2003; Moosavi and Sepaskhah, 2012; Moradi Choghamarani et al., 2016). The soil intrinsic variability is determined by soil forming factors including parent material, relief, climate, organisms, and time. On the other hand, extrinsic variability is mainly defined by the soil managerial activities e.g. crop rotation, fertilization, and irrigation (Ortega et al., 1999). Soil biological and physicochemical properties affect soil quality (SQ) and subsequently the yield of crops. SQ is the capacity of soil for functioning under natural conditions or boundaries of managed ecosystem for sustaining productivity of plants, maintaining the quality of environment and promoting the health of plants and animals (Karlen and Stott, 1994). Therefore, evaluation of SQ is vital to monitor the sustainability of agricultural systems (Abdelrahman and Tahoun, 2019). Determining the quality of soil is very difficult because the relationships between SQ and yield of crops is extremely complex and depends on complex relations among soil biological, chemical, and physical attributes and the other external factors (Juhos et al., 2016). Many researchers have studied the relationships among chemical and physical prosperities of soils and yield of crops (Ortega et al., 1999; Li et al., 2018; Gavili et al., 2018, 2019). Soil quality index (SQI) that is the main approach to assess the quality of soils (Sun et al., 2003) is used to evaluate land management systems in terms of their spatiotemporal variations (Erkossa et al., 2007). Indeed, the goodness of soil management practices and sustainability of land

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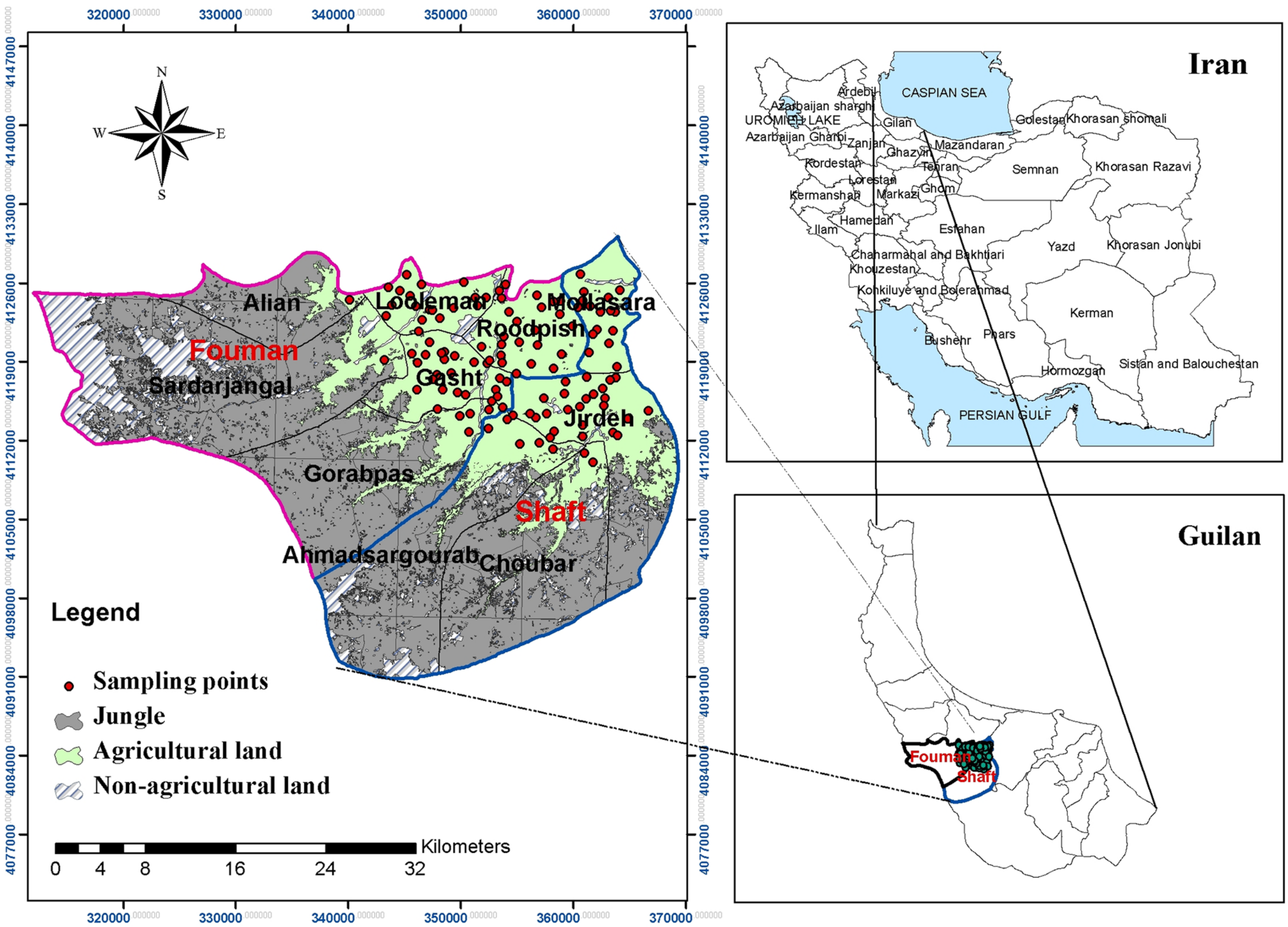

Fig. 1. Schematic view of the study area along with the experimental points.

use can be evaluated by identifying SQ indicators (Qi et al., 2009; Dagnachew et al., 2019). On one hand, direct field or laboratory measurement of SQ is not possible and it only can be derived from soil properties (Mukherjee and Lal, 2014). On the other hand, the solitary soil traits cannot be sufficient indicator of SQ (Mukherjee and Lal, 2014) because of the interactions among the soil physicochemical and biological attributes. The responses of solitary indicators to the management systems may be different and confounding their effects due to the fact that they are often interdependent. Therefore, combining the indicators to a single SQI may improve the evaluation (Bucher, 2002).

Indexing SQ has three steps: 1) selecting indicators, 2) scoring the indicators, and 3) integrating the values of scores. Indicators are selected by different methods such as expert opinion (Andrews et al., 2002a) and statistical methods such as principal component analysis (PCA) and regression methods (Masto et al., 2008). In expert opinion approach, the minimum data set (MDS) variables are selected from the available total data set (TDS) variables according to scientist's knowledge or recommendations in the literature (Pal et al., 2013), common management concerns, and consensus of the project investigators. PCA is a multivariate approach for investigating relationships among various quantitative soil variables. It reduces the dimension of large-volume data to facilitate selection of indicators by classifying soil variables into PCs. The values of indicators should be converted into 0 to 1 scores by linear or non-linear relationships before they are integrated into an index (Andrews et al., 2004; Masto et al., 2008). However, the SQI obtained by linear scoring was reported lower than that of the non-linear scoring method (Masto et al., 2008). The importance of each soil variable is described by assigning a value from 0 to 1. There is various SQ indexing methods such as additive and weighted methods (Andrews et al., 2004). Many quantitative models (e.g. Nemero quality index, NQI and integrated quality index, IQI) have been introduced to for calculation of SQI.

SQI of paddy soils have been studied in a few studies only by using a limited number of soil properties. For instance, Gupta (1986) and Gupta and Abrol (1993) used only soil physical and hydraulic properties to create a Boolean SQI for assessing the soil production potential of a paddy field. Dobermann and Oberthur (1997), Supriyadi et al. (2017) and Dengiz (2019) used only soil fertility-related properties to evaluate soil quality. It is supposed that soil physical, hydraulic and engineering properties affect rice productivity through affecting water movement and retention, nutrient transportation, soil swelling and shrinkage, crack formation and root damage. Amirinejad et al. (2011) evaluated spatial variation of soil physical health for rice and wheat by physical index. They found a fairly good ($R^2 = 0.67$) correlations between the grain yield of both plants and soil physical index. Kumar et al. (2014) reported that the majority of their studied region had physical index of < 0.4 for subsurface layer of soils under wheat cultivation indicating that the yield cannot be higher than 0.7 of its potential even under normal conditions or higher inputs. Some of investigators used fuzzy methods (Delsuz Khaki et al., 2017) or combination of fuzzy membership functions with Monte Carlo simulation (Dobermann and Oberthur, 1997) to produce maps of soil fertility indices for rice cultivation.

Paddy fields of Guilan province in north parts of Iran with an area of 200,000 ha are the most important areas for rice cultivation. The soils of these lowland areas are submerged for easier transplant of seedling, better water retention and weed control. In these conditions, soil structure is destroyed by soil tillage and addition of water, and a mud conditions is created. In spite of the significance of rice cultivation in the study area, integrated soil physical and chemical properties and SQ conditions have been not conducted widely. In other words, to the best of our knowledge, evaluation of different methods for obtaining soil quality indices and determining their spatial variability structures particularly for paddy soils have been not carried out. Besides, the most soil limiting factors for rice production in the paddy soils have been not determined. Therefore, the present study aimed to: 1) assess SQ status of the paddy fields using different methods by identifying effective physical and chemical properties of the soils (establishing a MDS), appropriate scoring functions (linear and non-linear), and an efficient SQI, and jointing fuzzy membership functions and Gupta (1986) and Gupta and Abrol (1993) methods, 2) investigate the limiting factors for rice production in the paddy fields, and 3) identify the spatial variability structure of the soil chemical and physical properties and the resultant SQIs in order to map their spatial distribution.

2. Materials and methods

2.1. Study area

Located in the Shaft and Fouman counties, Guilan province in the north of Iran (Fig. 1), the study area (paddy fields) ranged across nearly 280 km^2. The location is situated in the geographic coordinates 36° 56́ to 37° 18́ N, 48° 52́ to 49° 10́ E. The study area with a mean annual precipitation of about 1260 mm and mean annual temprature of 16 °C is characterized by a sub-humid (moderately moist) climate. Low land, alluvial plains, and few old plateaus are the major physiographic units in the study area. Texture classes of the soils vary from clay (high expansive smectite and moderate expansive vermiculite) to loam (Davatgar et al., 2005). The study area is almost flat (slope degree < 1%). Rice paddy fields are the major land use, Aquept is the predominant soil group, and water distribution network of Sepidrud dam is the main source of irrigation water in the study area. Land preparation practices including plowing, puddling, harrowing, and leveling are annually performed 7 to 30 days before transplanting in early spring. Soil water status of the puddled soils varies between field capacity (FC) and saturation and is submerged for creating anaerobic conditions. Puddling reduces hydraulic conductivity (to maintain soil water) through creation of a plow layer (Mousavi et al., 2009) which results in the loss of water percolation and the increased water and nutrient use efficiency. Furthermore, puddling supports weed control and homogenizes the soil by destroying aggregates and macropores (Janssen and Lennartz, 2007).

2.2. Soil sampling and laboratory analyses

Well scattered disturbed soil samples were collected from a depth of 0–30 cm in 120 experimental points. Furthermore, volumetric samples were taken from each sampling locations before land preparing and early plowing to measure the dry (BD_{dry}) and wet bulk density (BD_{wet}). BD_{dry} and BD_{wet} are the ratios of the mass of the oven- dried and wet (saturated) soils to the total (bulk) volume of the soil samples, respectively (Klute, 1986). The soil water retention curve (SWRC) and its relevant parameters were also determined using the collected disturbed samples. Schematic view of the entire study area along with the experimental points has been represented in Fig. 1.

The disturbed soil samples were air-dried and passed through a 2 mm sieve, before being transferred to the laboratory for further analysis. Selected chemical and physical attributes of the soils were measured using the following standard methods: Soil textural components (sand, silt, and clay contents) by hydrometer (Klute, 1986); particle density (PD) by pycnometer (Klute, 1986); soil organic carbon (OC) by wet oxidation method (Page et al., 1982), cation exchange capacity (CEC) by ammonium acetate displacement method (Page et al., 1982), total nitrogen (TN) by Kjeldahl method (Page et al., 1982); available phosphorus (P_{av}) by Olsen method (Olsen et al., 1954); and available potassium (K_{av}) by extraction with ammonium acetate (Chapman and Pratt, 1962). Undisturbed samples were also used to determine BD_{wet} and BD_{wet} by core method (Klute, 1986); saturated water content (θ_s) by oven drying method (Klute, 1986); saturated hydraulic conductivity (Ks) by falling head method (Booltink and Buma, 2002). Furthermore, water contents (θ) at 33 (field capacity, θ_{FC}), 80, 130 and 1500 kPa (permanent wilting point, θ_{PWP}) were measured by pressure plate (Dane and Hopmans, 2002). The soil water content at 80 kPa tension is an important threshold limit beyond which transpiration and relative growth of rice leaves begin to decrease (Davatgar et al., 2009). The water content in 130 kPa tension is another threshold causing 50% loss in the maximum yield of rice (Davatgar et al., 2009). The S parameter that is the slope of SWRC at its inflection point was determined (Dexter, 2004). Available water (AW) and non-capillary porosity (NCP) were determined as follows (Amirinijad et al., 2011):

$$AW = \theta_s - \theta_{PWP} \tag{1}$$

$$NCP = \theta_s - \theta_{FC} \tag{2}$$

The plastic (PL) and liquid (LL) limits (plasticity or Atterberg limits) were measured on the fine soil particles (< 0.425 mm diameter). PL was determined using the standard rolling thread test and the LL was measured using the Cassagrande apparatus (ASTM, D4318., 2011). Plasticity index (PI) was also determined as follows (McBride, 1993):

$$PI = LL - PL \tag{3}$$

Coefficient of linear extensibility (COLE) as an indicator for describing the shrinkage-swelling potential of soil (Reeve et al., 1980) was determined using the following equation (Bronswijk and Evers-Vermeer, 1990):

$$\mathrm{COLE} = \left(\frac{\mathrm{BD_{dry}}}{\mathrm{BD_{wet}}}\right)^{\frac{1}{3}} - 1 \tag{4}$$

where BD_{wet} and BD_{dry} are the bulk density (g cm^{-3}) of soil at water saturated and oven dry conditions, respectively. Paddy soils are usually submerged and their water contents are higher than FC conditions. Therefore, for determining COLE, instead of the usual method for measuring soil volume at 33 kPa and air drying conditions, the method proposed by Bronswijk and Evers-Vermeer (1990) was used. In this method, the volume of soil is measured at saturated and oven dry conditions (Yazdani et al., 2014). Planting and harvesting dates and the other needed data such as the type and amount of fertilizer used, water resources and number of irrigation were collected by visiting the farmers and preparing a questionnaire.

2.3. Processing of SQ indicators

2.3.1. Indicator selection using PCA

To improve the efficiency of the SQ evaluation, a MDS of 15 physical and chemical properties was selected through PCA. PCA can help to decrease the number of required variables for indexing through investigating PCs that best represent the variability and minimize redundancy of the data (Tesfahunegn, 2014). In PCA, the highest eigenvalue belongs to the first component (PC1) and gradually decreases with increasing the component number. It should be noted that in this method, each component is independent of the other components (Yao et al., 2013). Based on the MDS indicator selection approach proposed by Andrews et al. (2002a), PCs with eigenvalues of greater than one were selected in our study. Within each PC only variables with the absolute values within 10% of the highest loading factor (highly-weighted variables) were maintained for the MDS (Andrews et al., 2002b). For the significantly correlated ($r > 0.60$, $p < 0.05$) variables, only the variable with the highest loading factor was maintained in the MDS and all of the other variables were excluded to avoid redundancy (Andrews et al., 2002b).

Kaiser-Meyer-Olkin (KMO) and Bartlett's (BTS) tests were used to evaluate the appropriateness of the data for PCA. The KMO test was used to evaluate the correlation between the input variables. If the value of KMO test is > 0.6, the data is suitable for PCA (Jolliffe, 1986). BTS is the second confirmatory test performed before PCA. If the value of BTS test is significant ($p < 0.05$), it indicates the correlation between the variables and the suitability of PCA. In the present study, the KMO statistic was > 0.6 and the BTS test was significant. Therefore, the data was suitable for PCA. Based on PCA, the COLE, clay content, AK, CEC, TN, AP, and θ_{80} were selected as MDS. More explanation for this analysis is presented at the results section.

2.3.2. Indicator transformation (Scoring)

After choosing the MDS through PCA, the following standard scoring function (SSF) was applied to transform (score) all variables of MDS for inclusion in the SQI:

2.3.2.1. Linear scoring function (LSF). The homothetic transformation equations [Eqs. (5) and (6)] were applied for "more is better" and "less is better" scoring functions, respectively. Combination of the both equations was used for "optimum is better" scoring function to transform the values of soil variables to a common range from 0.1 to 1.0 regarding their effects on SQ (Velasquez et al., 2007):

$$Y = 0.1 + \left(\frac{(x-b)}{(a-b)}\right) \times 0.9 \tag{5}$$

$$Z = 1 - \left(\frac{(x-b)}{(a-b)}\right) \times 0.9 \tag{6}$$

where Y and Z are the transformed x variable. b and a are the minimum and maximum threshold values of the x (non transformed or true variable), respectively.

2.3.2.2. Nonlinear scoring functions (NLSF). The NLSF proposed by Masto et al. (2008) used to normalize SQ indicators as below:

$$Y = \frac{1}{[1 + e^{-\beta(x-\alpha)}]} \tag{7}$$

where α is the baseline value of soil variable where the score is 0.5 or nearly the mean value of the upper and lower thresholds, and β is the slope. Baselines are usually considered as the lowest target values. If the value of a soil indicator is located within the threshold (control) limits, an acceptable condition can be considered for the system. If the value lies outside the control limits, it is considered as a degraded system (Masto et al., 2008). Different parameters of the scoring functions have been summarized in Table 1.

2.3.3. Integration of soil indicators into indices

After scoring the selected indicators, a weighted additive approach (WAA) was applied to integrate them into the indices (Andrews et al., 2002b). In the present study, weights of the MDS indicators were assigned by the ratio of variance of each variable to the total cumulative variance to get a certain weight value under a special PC (Tesfahunegn, 2014).

After weighting the scored MDS indicators, the integrated quality index (IQI) was calculated using the following equation (Qi et al., 2009):

$$IQI = \sum_{i=1}^{n} W_i N_i \tag{8}$$

where W_i and N_i are the weight and score of indicator i, respectively.

2.4. Fuzzy method

The MDS variables (COLE, clay content, AK, CEC, TN, AP and θ_{80}) were used to evaluate the SQ based on the Fuzzy rule using the joint membership function (JMF). Fuzzy set theory is a mathematical method used in data and functional relationships to characterize uncertainty and imprecision. Application of a fuzzy set will be useful to characterize uncertainty using standard statistical measures. One of the aspects of the field of fuzzy mathematics is fuzzy logic (McBratney and Odeh, 1997).

In Boolean set theory, the membership of a set is defined as true (1) or false (0). Membership of a fuzzy set, however, is expressed on a continuous scale from 0 to 1. In other words, a fuzzy membership function (FMF) converts variable Z to FMF value (FMF) on a continuous scale of 0 to 1. The FMF values of 0 and 1 indicate no and full memberships to the set, respectively (Dobermann and Oberthur, 1997). There are several fuzzy membership functions. In this study, linear and non-linear membership function was used. Whatever the value of element (FMF) is closer to 0, the grade of membership is lower and whatever the value of element (FMF) is closer to 1, the grade of membership is higher and the SQ will be better.. Therefore, the following equation was also used to evaluate the SQ based on the fuzzy min-operator (McBratney and Odeh, 1997):

$$\mathrm{JMF} = \mathrm{Min}(\mathrm{FMF}_{\mathrm{COLE}\geqslant 0.09}, \mathrm{FMF}_{\mathrm{CEC}\geqslant 20}, \mathrm{FMF}_{\mathrm{clay}\geqslant 35}, \mathrm{FMF}_{\mathrm{AK}\geqslant 120}, \mathrm{FMF}_{\theta 80\geqslant 45}, \mathrm{FMF}_{\mathrm{TN}\geqslant 0.2}, \mathrm{FMF}_{\mathrm{AP}\geqslant 12)} \tag{9}$$

Based on Equation (9), among the variables selected in MDS, the variable with the minimum scoring value was selected as JMF and had the most determinative role in determining soil quality. In this model, all stable soil variables are of high inherent potential and favorable for intensive rice cropping.

2.5. Gupta (1986) method

A physical index (PI) was suggested by Gupta (1986) and Gupta and Abrol (1993) that was calculated for each soil sampling location by considering the rating of each eight studied physical variables as follow:

$$PI = A \times B \times C \times D \times E \times F \times G \times H \tag{10}$$

Table 1
Soil quality (SQ) indicators, scoring function, thresholds, and the baseline limits used for assessing SQ in the present study.

Soil variables	Threshold					Reference
	Scoring function	Lower	Upper	Slope	Baseline	
Coefficient of linear extensibility, COLE[a]	More is better	0.03	0.09	–	–	Parker et al. (1977)
Clay content (%)	More is better	27	35	−0.3	15	Dobermann and Oberthur (1997)
Cation exchange capacity, CEC ($cmol_+ \ kg^{-1}$)	More is better	10	20	−0.5	10	Dobermann and Oberthur (1997)
Total nitrogen, TN (%)	More is better	0.1	0.2	−34	0.1	[b]RRII expert knowledge and experimental data
Available (sodium bicarbonate- extractable) phosphorus, AP ($mg \ kg^{-1}$)	More is better	6	12	−0.55	6	RRII expert knowledge and experimental data
Available (ammonium acetate- extractable) potassium, AK ($mg \ kg^{-1}$)	More is better	80	120	−0.09	80	RRII expert knowledge and experimental data
Volumetric water content at 80 kpa, θ_{80} (%)	More is better	35	45	−0.5	35	RRII expert knowledge and experimental data

[a] In this study, COLE was higher than 0.09, as a result it received score of 1.
[b] Rice Research Institute of Ira

where *A* is the depth of soil (cm), B is the BD (Mg m^{-3}) of the top 100 cm, C is the apparent hydraulic conductivity or infiltration rate (cm h^{-1}), D is the capacity of available water storage (cm) of the top 100 cm, E is the aggregation in terms of organic matter content (%), F is non-capillary porosity (%) of the top 60 cm, G is the depth of water table (cm), and H is the land slope (%). In the present study, score of each PI component for the paddy soils was calculated based on the method proposed by Gupta (1986) and Gupta and Abrol (1993). It should be noted that the active depth of roots and puddling conditions of the studied paddy soils is mainly limited to the surface horizons due to hardness of the plowing layer. Therefore, in the present study the information of surface horizons was used for Gupta (1986) model.

2.6. Evaluation of SQ indices

Sensitivity of the methods used for SQ indexing was evaluated by the following sensitivity analysis introduced by Masto et al. (2008):

$$Sensitivity = \frac{SQI_{\max}}{SQI_{\min}} \quad (11)$$

where SQI_{min} and SQI_{max} are the minimum and maximum SQI obtained from each dataset selection and scoring procedures. Methods with the higher values of sensitivity are more preferable as they are more susceptible to managerial practices and perturbations.

The yield of rice at the experimental locations was measured at 1 × 1 plots and correlated with the mentioned SQIs.

2.7. Statistical and geostatistical analyses

Descriptive statistics including the min., max., median, standard deviation, variance, mean, kurtosis and skewness coefficients, and the coefficient of variation (CV) were calculated for the soil variables. Furthermore, the Kolmogorov-Smirnov test ($p < 0.05$) was used to check the normality of the data.

The data were checked for existence of probable trend, outliers, and departure from normal distribution before applying geostatistical approaches (Robinson and Metternicht, 2006). In the cases that deviation from normal distribution was significant, natural log or square root transformations was used. The geostatistical analyses were performed using GS^+ (5.1) software packages to evaluate the spatial distribution and correlation of the soil attributes. After calculating SQIs using the mentioned approaches, the map of the best SQI was produced using the kriging and inverse distance weighting (IDW) methods using Arc GIS (10.4). According to the SQ grades proposed by Qi et al. (2009) the studied SQIs, were classified into four classes namely the most suitable (≥ 0.78), suitable (0.78 – 0.68), severe limitation (0.68 – 0.58) and the most severe limitation (< 0.58).

3. Results and discussion

3.1. Descriptive statistics

Texture of the studied soils belonged to six different classes of loam (4%), clay (9%), silt loam (10%), clay loam (11%), silty clay loam (23%), and silty clay (43%) based on the USDA texture triangle (Fig. 2). Regarding the median values (Table 2), results indicated that the soils were high in clay content (40%) and most (75%) of the soils were classified as heavy textured (clay, silty clay, and silty clay loam) soils (Fig. 2).. Results of Kolmogorov-Smirnov test showed that the studied variables (except for AP, AK, OC, Ks, and OC) followed normal distribution. Normal distribution of the data that may resulted from the uniform parent materials, flatness of area (slope < 1%), and the similar managerial practices (puddling process), indicates that the soil attributes have uniform variance and there are no outliers.

CV that is the standardized variability (ratio of standard deviation to the mean value), varied from 2% (for PD) to 92.25% (for AP). The

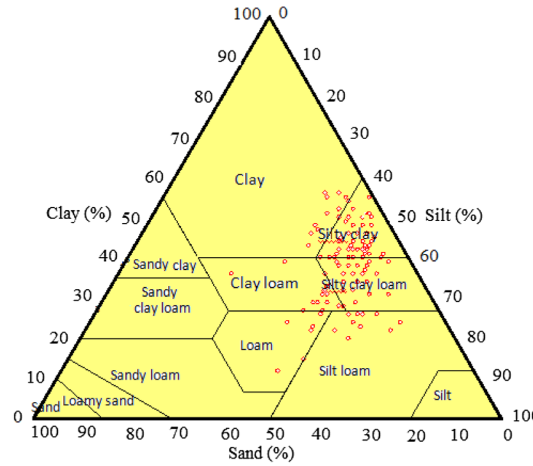

Fig. 2. Textural classes of the studied soils (components are in mass percent).

studied variables were grouped into three classes of the low (COLE, PD, BD_{dry}, θ_s, θ_{130}, and θ_{80} with CV < 15%), the moderate (CEC, OC, TN, AK, clay content, PI, and S index with CV values of 16 to 35%), and the high (AP and Ks with CV > 35%) variability regarding the variability classes proposed by Wilding and Dress (1983). To put it another way, almost all of the variables (except for AP and Ks) belonged to the low to moderate variability categories. Most of the attributes were positively skewed and the highest kurtosis coefficients were observed for AP. The PD and AP had the lowest and the highest skewness coefficients, respectively (Table 2). Furthermore, a relatively great difference between the median (3650 kg ha^{-1}) and the maximum (4563 kg ha^{-1}) values of grain yield (Table 2) may resulted from limitation in soil properties or inappropriate managerial practices in most of the studied fields.

Pearson correlation coefficients (r) between the studied variables have been shown in Table 3.

3.2. Variogram analysis and modeling spatial variability

Majority of the studied soil physical and chemical attributes showed spatial correlation with dominant spherical models. Spherical models with the nugget effect of 0.001 to 42, sill values of 0.0034 to 116, and the range parameters of 1.3 to 18 km were the best models fitted to the variograms of θ_{130}, θ_{80}, θ_s, clay content, BD, OC, AP, CEC, TN, Ks, and SQI (Fuzzy). Whereas, exponential models with the nugget effect of 0.0002 to 450, sill values of 0.0003 to 1945, and range parameters of 1.1 to 3.5 km were the best models fitted to the variograms of COLE, AK, PD, and PI (Table 4). The results were in accordance with the findings of the other researchers who showed that exponential and spherical models are the best models fitted to spatial structure in the majority of soil chemical and physical (Moosavi and Sepaskhah, 2012) and hydraulic attributes (Moradi Choghamarani et al., 2016). The range parameter that indicates the domain extent of spatial correlation was considerably different and > 1.1 km for all of the studied variables. The highest range parameter (18 km) was observed for variogram of clay that is greatly larger than that of the other variables (Table 4). This may correspond to the uniformity of parent material in the study area and existence of high amounts of clay particles in almost all of the experimental points.

The nugget (C_0) to sill (C_0 + C) ratio that is the ratio of the random to total variance of a variable can be applied to evaluate the spatial correlation (structure). If the ratio is < 25%, 25 to 75%, and > 75%, the spatial structure of the studied variable are classified as strong, moderate, and weak, respectively (Cambardella et al., 1994). The nugget:sill ratio for CEC, OC, and AK was 24%, 20%, and 23%, respectively and they showed the strong spatial structure.

Table 2
Summary statistics of the studied soil attributes the grain yield of rice.

Soil attributes	Minimum	Maximum	Mean	Median	Standard deviation	Skewness	Kurtosis	Coefficient of variation (CV)	Variability classes [a]	Kolmogorov-Smirnov statistics
Volumetric water content at 130 kpa, θ_{130} (%)	28.28	47.65	34.16	33.96	3.16	1.30	3.90	9.25	Low	0.81
Volumetric water content at 80 kpa, θ_{80} (%)	29.82	52.79	36.84	36.95	3.35	1.62	5.84	9.10	Low	1.19
Saturated water content, θs (%)	44.38	71.20	59.29	58.91	5.59	−0.088	−0.197	10.61	Low	0.52
S Index	0.04	0.10	0.07	0.07	0.01	0.50	0.36	17.98	Moderate	1.04
Cation exchange capacity, CEC ($cmol_+ kg^{-1}$)	10.00	47.00	29.16	28.50	7.09	0.11	−0.01	24.31	Moderate	0.74
Organic carbon, OC (%)	1.16	4.28	2.40	2.25	0.69	0.62	−0.38	28.75	Moderate	1.39*
Total nitrogen, N (%)	0.11	0.43	0.23	0.21	0.06	0.77	0.45	26.36	Moderate	1.03
Available phosphorus, AP ($mg\ kg^{-1}$)	1.90	82.80	12.81	9.40	11.82	3.31	13.82	92.25	High	2.46**
Available potassium, AK ($mg\ kg^{-1}$)	37	258	135	130	47.14	0.55	−0.19	34.87	Moderate	1.47*
Bulk density, BD ($g\ cm^{-3}$)	0.72	1.23	0.92	0.90	0.08	1.14	2.59	8.57	Low	1.06
Particle density, PD ($g\ cm^{-3}$)	2.43	2.72	2.60	2.61	0.06	−0.65	0.70	2.17	Low	1.10
Clay content (%)	12.00	56.00	38.51	40.00	9.46	−0.35	−0.38	24.56	Moderate	0.96
Saturated hydraulic conductivity, Ks ($cm\ day^{-1}$)	0.05	0.51	0.21	0.17	0.10	1.21	1.02	50.24	High	1.48*
Coefficient of linear extensibility, COLE	0.11	0.19	0.16	0.16	0.16	−0.33	−0.22	10.60	Low	0.66
Plasticity index, PI (%)	12.87	33.68	22.68	22.82	4.28	0.07	−0.39	18.87	Moderate	0.85
Grain yield of rice, GY ($kg\ ha^{-1}$)	1760	4563	3509	3650	609	−0.682	0.894	17.36	Moderate	0.79

[a] Variability classes adopted by Wilding and Dress (1983) (1983) as low, moderate, and high variability classes which correspond to the coefficient variations (CV) of < 15%, 15% to 35%, and higher than 35%, respectively.
* and ** Significant at $p < 0.05$ and $p < 0.01$, respectively.

Table 3
Pearson correlation coefficient (r) between the studied soil attributes [a.]

Soil attributes	θ_{130}	θ_{80}	θ_s	S Index	CEC	OC	TN	AP	AK	BD	PD	Clay	Ks	COLE
θ_{130}	1													
θ_{80}	0.936**	1												
θ_s	0.503**	0.485**	1											
S Index	−0.057	0.005	0.164	1										
CEC	0.445**	0.354**	0.510**	0.070	1									
OC	0.224*	0.199*	0.270**	0.256**	0.307**	1								
TN	0.198*	0.191*	0.167	0.215*	0.285**	0.931**	1							
AP	−0.151	−0.164	−0.229*	−0.191*	0.020	−0.188*	−0.129	1						
AK	0.328**	0.297**	0.491**	−0.006	0.490**	−0.043	−0.013	0.107	1					
BD	0.122	0.179	−0.325**	−0.252**	−0.370**	−0.510**	−0.469**	0.163	−0.139	1				
PD	−0.066	−0.067	−0.105	−0.058	−0.080	−0.458**	−0.418**	0.227*	0.003	0.314**	1			
Clay content	0.476**	0.377**	0.650**	−0.073	0.529**	0.006	−0.129	−0.217*	0.502**	−0.193*	−0.029	1		
Ks	−0.307**	−0.234*	−0.289**	0.061	−0.311**	0.077	0.108	−0.026	−0.304**	−0.082	−0.256**	−0.438**	1	
COLE	0.214*	0.160	0.768**	0.274**	0.547**	0.443**	0.352**	−0.236**	0.422**	−0.805**	−0.236**	0.546**	0.125	1
PI	0.627**	0.606**	0.511**	0.041	0.277**	−0.084	−0.172	−0.267**	0.397**	0.105	−0.008	0.597**	−0.288**	0.283**

θ_{130}: Volumetric water content at 130 kpa; θ_{80}: Volumetric water content at 80 kpa; θ_s: Saturated water content; CEC: Cation exchange capacity; OC: Organic carbon; TN: Total nitrogen; AP: Available phosphorous; AK: Available potassium; BD: Bulk density; PD: Particle density; Ks: Saturated hydraulic conductivity; COLE: Coefficient of linear extensibility; PI: Plasticity index
* and ** Significant at $p < 0.05$ and $p < 0.01$, respectively.

Table 4
The best models fitted to variogram of the studied soil variables along with their parameters and modeling statistical measures.

Soil properties	Model	Method	Nugget effect (C_0)	Sill (C_0 + C)	Rang (A) (m)	$C_0/(C_0 + C)$ (%)	R^2	RSS	Spatial structure classes
θ_{130} (%)	Spherical	OK	2.65	6.2	1300	43	0.49	1.65	Moderate
θ_{80} (%)	Spherical	OK	3.5	6.1	1750	57	0.45	1.85	Moderate
CEC ($cmol_+ kg^{-1}$)	Spherical	OK	12	49.5	3400	24	0.90	26.9	Strong
OC (%)	Spherical	OK	0.009	0.044	2000	20	0.72	8.5×10^{-5}	Strong
TN (%)	Spherical	OK	1.07×10^{-3}	0.0034	2300	31	0.69	5.68×10^{-7}	Moderate
AP (mg kg^{-1})	Spherical	OK	0.4	0.66	4500	61	0.83	0.0116	Moderate
AK (mg kg^{-1})	Exponential	OK	450	1945	1100	23	0.91	64,696	Strong
Clay content (%)	Spherical	OK	42	116	18,000	36	0.95	352	Moderate
COLE	Exponential	OK	0.0002	0.0003	3600	74	0.58	1.37×10^{-9}	Moderate
SQI (Fuzzy)	Spherical	OK	0.0055	0.1	3200	55	0.83	3.08×10^{-6}	Moderate
θ_s (%)	Spherical	OK	0.006	0.0085	3800	71	0.7	1.16×10^{-6}	Moderate
BD (g cm^{-3})	Spherical	OK	0.0025	0.0037	5000	68	0.655	5.99×10^{-7}	Moderate
PD (g cm^{-3})	Exponential	OK	0.0023	0.0028	5500	82	0.77	3.09×10^{-8}	Weak
K_s (cm day^{-1})	Spherical	OK	0.085	0.29	2000	29	0.72	7.11×10^{-3}	Moderate
PI (g g^{-1})	Exponential	OK	0.0014	0.002	6000	70	0.62	1.04×10^{-7}	Moderate

θ_{130}: Volumetric water content at 130 kpa; θ_{80}: Volumetric water content at 80 kpa; CEC: Cation exchange capacity; OC: Organic carbon; TN: Total nitrogen; AP: Available phosphorous; AK: Available potassium; COLE: Coefficient of linear extensibility; SQI: Soil quality index; R^2: Coefficient of determination, RSS: Residual sum of square, OK: Ordinary kriging
If the ratio of nugget to sill is < 25%, 25 to 75%, and > 75%, the spatial structure of the variable are classified as strong, moderate, and weak, respectively (Cambardella et al., 1994).

3.3. Developing PCs

The KMO test statistic of 0.676 and the significant ($p < 0.001$) Bartlett's spherical test (BTS) showed that PCA is useful in the present study (Table 5).

The extracted principal components have been shown in Table 6. PCA revealed that there are four PCs with eigenvalues of > 1.0 (Table 6). Considering the eigenvalues > 1.0, among 15 PCs (that are equal to the number of studied variables), four PCs representing 70.62% of the total variance were selected.

In the first PC, which explained 32% of the total variation, the high positive factor loadings were obtained for CEC, AK, θ_s, clay content, and COLE. Among the mentioned five variables, COLE had the highest factor loading (0.813) and significant correlation ($r = 0.77$) with θ_s (Table 3). Due to the effect of CEC, clay content, θ_s and COLE (which is a criterion of soil shrinkage and expansion) on the AK content and release, this component named as the effective factor for soil potassium.

PC2 explained 19% of the total variance and had the highest positive coefficient and the highest factor loadings for TN and OC. A strong correlation ($r = 0.93$) was observed between these two variables (Table 3). Due to the direct and effective role of organic matter in nitrogen availability, this component named as an effective factor in nitrogen availability. The third component explained 11% of the total variation and had high positive coefficient and high factor loading for soil volumetric water content at 80 and 130 kPa tensions. There was a strong correlation between these two variables ($r = 0.94$). Therefore, the third component can be mentioned as the critical soil water content factor that is effective in reducing yield. The fourth component that explained only 9% of the total variation, had a high negative coefficient with AP, and was considered as the soil phosphorus availability factor. Because of high significant correlation ($r > 0.60$, $p < 0.05$) between some variables in each PC, the variable with the highest factor loading remained in the component and the other variables were omitted. Therefore, θ_s of the first component, OC of the second component and θ_{130} of the third component were omitted due to the strong and significant correlation with COLE, TN, and θ_{80}, respectively (Table 6). Based on the principal component analysis, TN, AP, AK, clay content, CEC, COLE, and θ_{80} (critical soil water content) were selected as MDS. There were soil variables related to physical, fertility, and engineering properties in the selected MDS. PCA showed that the seven soil properties selected in the MDS could be used to generate SQI and consequently improving soil conditions in the study area. The other researchers also applied the PCA method to evaluate SQI (Juhos et al., 2016; Rangel-Peraza et al., 2017; Xu et al., 2017; Juhos et al., 2019). Hereafter, the mentioned soil factors (MDS) are discussed in detail.

Table 5
The results of KMO and Bartlett tests for the studied soil traits.

Kaiser-Meyer-Olkin measure of sampling adequacy		0.676
Bartlett's test of sphericity	Approximate Chi-Square	1400
	Degree of freedom	105
	Significance	0.000

Table 6
Initial eigenvalues, proportion of variance, and communality estimates for soil attributes.

Soil attributes	PC1	PC2	PC3	PC4	Communalities
Eigenvalue [a]	**4.77**	**2.91**	**1.68**	**1.25**	–
% of total variance	31.78	19.36	11.17	8.30	–
Cumulative variance (%)	31.78	51.15	62.32	70.62	–
Eigenvectors					
CEC	0.739	0.289	0.139	−0.190	0.686
OC	0.111	0.940	0.032	0.108	0.909
TN	0.039	**0.956**	0.028	−0.003	0.916
AP	−0.003	−0.097	−0.138	**−0.857**	0.763
AK	0.752	−0.102	0.119	−0.199	0.630
BD	−0.494	−0.519	0.528	−0.199	0.831
PD	0.007	−0.565	−0.018	−0.246	0.380
θ_s	0.782	0.140	0.243	0.256	0.755
Clay content	0.785	−0.173	0.254	0.198	0.749
COLE	**0.813**[b]	0.357	−0.218	0.301	0.926
PI	0.483	−0.238	0.594	0.355	0.769
Ks	0.072	0.081	−0.324	0.182	0.150
θ_{130}	0.379	0.184	0.859	0.037	0.917
θ_{80}	0.298	0.177	**0.871**	0.083	0.886
S Index	0.071	0.225	−0.198	0.480	0.325

CEC: Cation exchange capacity; OC: Organic carbon; TN: Total nitrogen; AP: Available phosphorous; AK: Available potassium; BD: Bulk density; PD: Particle density; θ_s: Saturated water content; COLE: Coefficient of linear extensibility; PI: Plasticity index; Ks: Saturated hydraulic conductivity; θ_{130}: Volumetric water content at 130 kpa; θ_{80}: Volumetric water content at 80 kpa.

[a] Boldface eigenvalues correspond to the PCs examined for the quality index.

[b] Boldface factor loadings are the highest weighted loading in each principal component and the underlined factor retain in MDS.

3.4. Soil factors of MSD

The CEC, clay content, θs, COLE, and AK were selected in the first component (PC1). There was significant positive correlation among these variables (Table 3). The value of CEC reflects the capacity of soils to retain the essential nutrients (e,g., calcium, magnesium, and potassium) for plants (Wu et al., 2015).

The clay content as a soil textural component plays a vital role in cultivation of rice. It is a main factor controlling most of the soil chemical, physical, and hydrological attributes and is one of the most significant physical SQ indicators. Clay content can affect water retention/transportation and the stability of soil aggregates. Furthermore, clay soils due to the high retention capacity for water and nutrients are appropriate for rice production (Dengiz, 2013). Saglam et al. (2015) reported that the content of clay is the most soil attribute that is used as a SQ indicator for paddy soils. The amount of clay in most of the paddy fields in the Guilan province is high and the high (smectite) and moderate (vermiculite) expansive clays are the predominant minerals (Davatgar et al., 2005). Therefore, when the soils are submerged, they will swell and retain more water.

Spatial distribution of clay content, CEC, AK, and COLE (the capacity of a soil for swelling when moist) represented in Fig. 3. The CEC and COLE had similar spatial distribution.

3.4.1. Available potassium (AK)

The soils with > 120 mg kg^{-1} AK were located in the areas with high CEC and COLE values. The amount of AK was higher than its critical level (120 mg kg^{-1}) in the west, south, and northeast of the study area; whereas, there was moderate to severe deficiency of AK in the southeast, southwest, and northwest parts. Although the average concentration of AK was 135 mg kg^{-1} in the studied paddy soils (Table 2); but 44% of the paddy fields had a potassium deficiency based on the critical level (120 mg kg^{-1}) and are likely to have a relative positive response to application of potassium fertilizers (Fig. 3). Despite deficiency of AK in the studied paddy soils, the spatial distribution of AK fertilizer application was not appropriate in the paddy fields (i.e., questionnaire evaluation of farmers showed that 55% of the farmers did not use potassium fertilizers and only 10% of the farmers used potassium fertilizers adequately). In the study area, nitrogen fertilizers were used more than potassium fertilizers, which are deficient in soils. In this area, the farmers usually do not use potassium fertilizer due to the lack of knowledge for the positive roles of potassium in increasing the quantity and quality of rice yield, lack of sufficient resources of potassium fertilizers, and the increased price of potassium fertilizers.

3.4.2. Total nitrogen (TN)

Nitrogen is one of the most significant essential nutrients playing key roles in the vegetative growth stages and productivity of plants. Therefore, it is used as a key indicator in SQ assessment (Ren et al., 2014). TN varied from 0.11% to 0.43% in the studied paddy soils. It was sufficient in large areas and its deficiency was mostly observed in the west, northeast, and southeastern parts of the study area. Up to 70% of the studied soils had TN of > 0.2%. A highly significant correlation (r = 0.93) between TN and OC was observed. Dengiz (2019) also

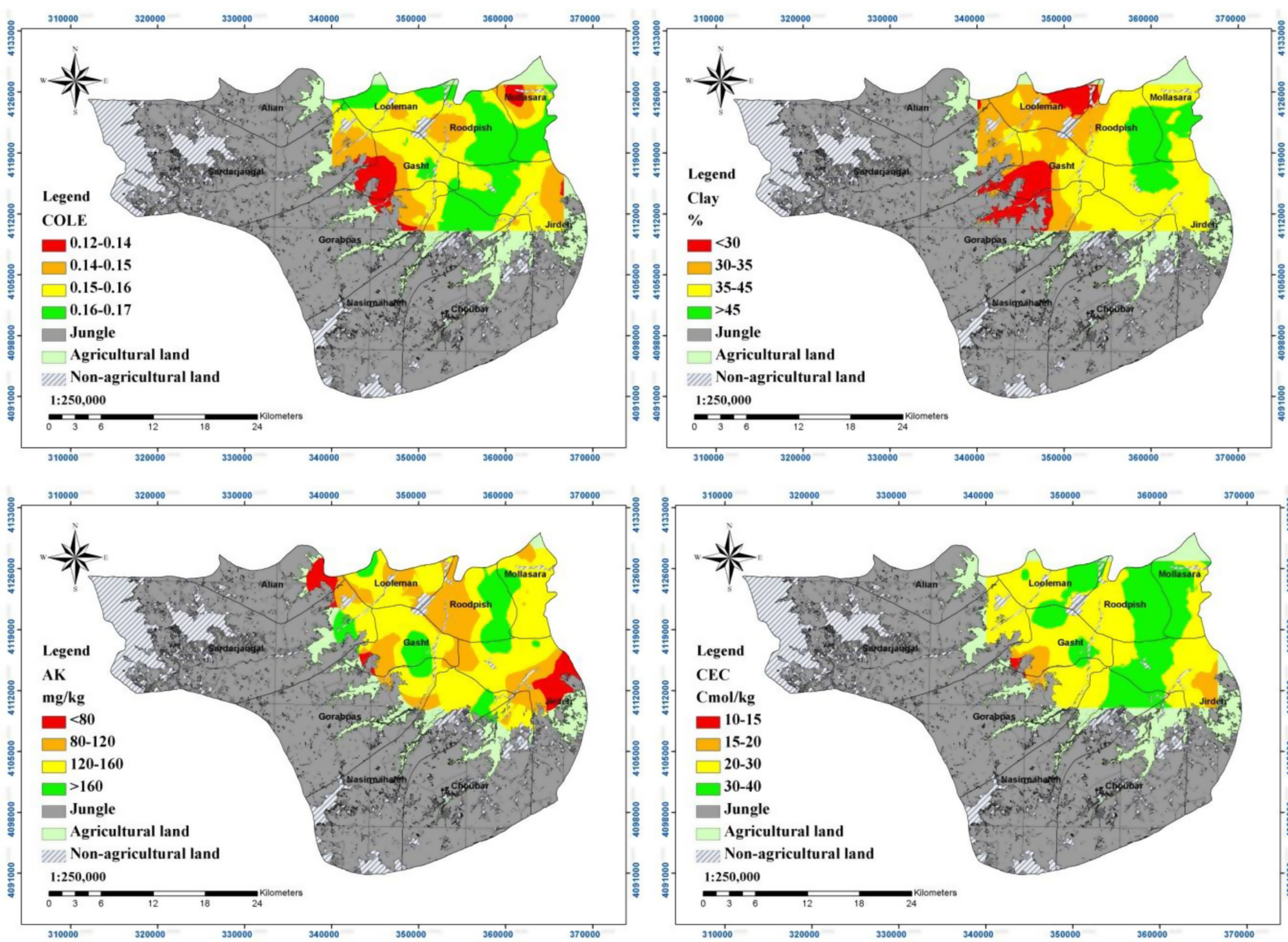

Fig. 3. Spatial distribution maps of the krigied coefficient of linear extensibility (COLE), clay content, cation exchange capacity (CEC) and available potassium (AK) in the studied paddy soils.

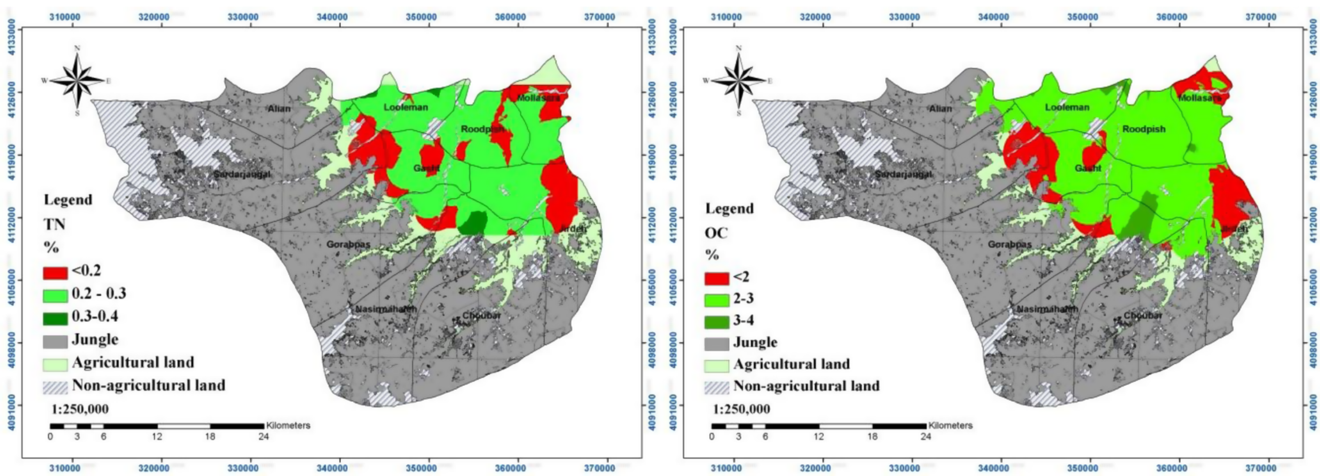

Fig. 4. Spatial distribution maps of the krigged soil organic carbon (OC) and total nitrogen (TN) contents in the studied paddy soils.

showed that clay content, OC, and TN of the soils are the main factors for assessing SQI for paddy soils. Soil OC is an important SQ indicator that has strong and indirect influences on the physical quality of soils (Reynolds et al., 2009). OC plays a key role in maintaining crop productivity and environmental quality due to its determinant effects on soil biological, chemical, and physical properties e.g. nutrient cycling, root growth, water retention and availability, gas flow intensity, soil conservation, and nitrogen supplying and transformation. Therefore, OC is the most significant and key factor affecting SQ and it has a great potential to vary due to different agricultural management systems. It was reported that soil health is low and yield may be constrained when soil OC is $< 1\%$ (Kay and Angers, 1999). It this study, OC and TN have similar spatial distribution patterns (Fig. 4).

The mean value of TN was 0.22% in the study area (Table 2) which is higher than its critical level of 0.2% (Table 1). However, nitrogen deficiency was observed in some parts of the study area. In these N deficient-areas, the OC was also low (Fig. 4). In these areas, nitrogen fertilizers should be used to increase crop yield.

3.4.3. *Critical soil water content (CSWC)*

In the studied paddy fields, the threshold limit and 50% of yield reduction occurs in water tension of about 80 and 130 kPa, respectively (Davatgar et al., 2009). Bouman et al. (2001) also reported that the threshold limit for rice crop reduction occurred at tension of 70 kPa. The reason for the stress occurring in these low tensions is due to the high clay content and dominant smectite type (Davatgar et al., 2005). Therefore, with reducing the water content from the saturated conditions, cracks develop in the paddy fields, and in addition to damage to the root, a large amount of water is lost through the cracks. Sadradini and Salahshour Dalivand, 2012 showed that the cracks develop at the tension of 2 kPa in the paddy fields of Guilan province.

Results revealed that the spatial distribution of θ_{130} and θ_{80} were relatively similar and showed that the paddy fields of the western parts were more sensitive to drought stress (Fig. 5). Results also indicated that there was a positive significant correlation ($r = 0.94$, $p < 0.01$) between θ_{130} and θ_{80}.

3.4.4. *Available phosphorus (AP)*

Phosphorus is of the primary essential nutrients for plant growth. It is necessary to sustain the optimum plant production and quality. Phosphorus plays a vital roles in root branching and the morphology of lateral roots (Razaq et al., 2017), supplying and transferring of energy for biochemical processes (Choudhury et al., 2007). The critical level of AP in the paddy soils is 12.8 mg kg^{-1} (Table 1) and the average concentration of AP in the studied paddy soils was 12 mg kg^{-1} (Table 2). Although, the large areas of the studied soils, especially in the east and central parts had insufficient AP (Fig. 6) and it is expected that the response of plant to application of phosphorus fertilizers will be remarkable. Therefore, phosphorus can be considered as a limiting factor for rice production in the paddy fields. The results of this study are in accordance with that of the other investigators. For instance, Liu et al. (2015) stated that MDS including TN, AP, and some soil biological variables represents 82% of SQ variation in the Chinese paddy fields. Furthermore, Li et al. (2013) reported that the most appropriate soil quality indicators including soil OM, available nitrogen (AN), AP, slowly AK and sand content accounted for 77.9% of the quality variation among their studied subtropical paddy soils of China. They also reported that SQI among the studied soils varied from nearly 0.22 to 0.84 and had a significant correlation with rice yield. Salam et al. (2011) stated that AP, OC, and clay content were the major factors causing SQ variation in the paddy soils.

3.5. *Soil quality index (SQI)*

In the present study, a MDS consisted of CEC, TN, AP, AK, clay conternt, COLE, and θ_{80} were selected to evaluate SQIs by non-linear and linear scoring functions and their spatial variability. Weighing factor is the ratio of variance of each variable to the total cumulative variance (Tesfahunegn, 2014). Result of the final normalized PCA-based integrated quality index (PCA- IQI) is presented as below:

$$\begin{aligned} \text{IQI} \\ &= 0.191(\text{CEC}) + 0.191(\text{AK}) + 0.191(\text{Clay}) + 0.191(\text{COLE}) + 0.117 \\ &\quad (\text{TN}) + 0.067(\theta_{80}) + 0.05(\text{AP}) \end{aligned} \tag{13}$$

The coefficients of determination between the obtained SQIs determined using different approaches and the yield of rice as well as the results of sensitivity analysis have been brought in Table 7.

In this study, SQI determined using the Fuzzy rules (by non-linear scoring function) had larger range and more sensitivity than that of the other applied methods (Table 7). It seems that this method is more sensitive to perturbations and management practices. The SQI determined using the Fuzzy method had the most significant correlation ($r = 0.70$) with the yield of rice. It seems that this SQI can better explain rice yield variations. Liu et al. (2014, 2015) reported that the correlation between SQI and rice yield were 0.54, 0.69, and 0.59, respectively. In the present study, SQI determined using the PCA- IQI and Gupta approaches had less correlation with rice yield than that of the Fuzzy method. Consequently, they are not recommended.

In the IQI method, the final score of an index is a summative score that is the sum of each indicator value multiplied by its weight, both ranging from zero to one. Since multiplying two quantities smaller than

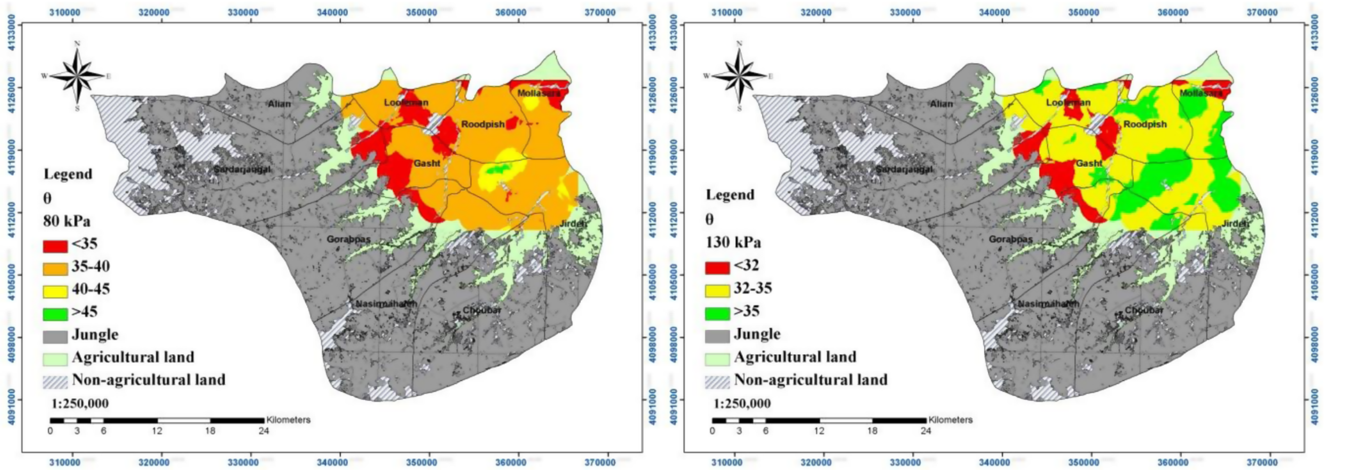

Fig. 5. Spatial distribution maps of the krigged volumetric water content measured at 80 and 130 kPa tensions (θ_{80} and θ_{130}, respectively) in the studied paddy soils.

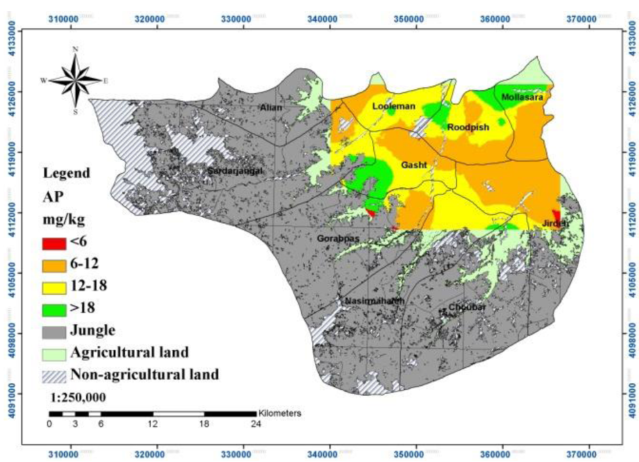

Fig. 6. Spatial distribution map of the krigged available phosphorus (AP) in the studied paddy soils.

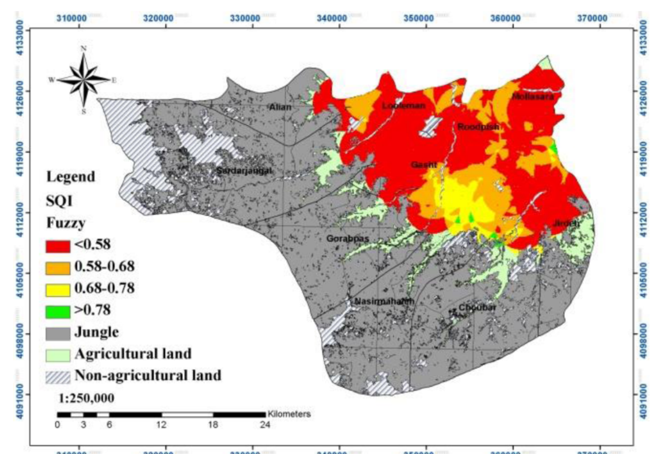

Fig. 7. Spatial distribution map of the krigged Fuzzy- SQI (as the most suitable SQI) in the studied paddy fields.

one result in a highly exaggerated smaller value; therefore, the mentioned approach may not reflect the reality of SQ in the study area.

The Gupta's (1986) model showed the lowest r value (0.24) with the yield of rice. In this method, only the soil physical attributes are used. While in reality, the soil chemical properties and soil fertility attributes affect the yield of plant. In the fuzzy method, all selected variables remain in the fuzzy dataset. Nevertheless, the soil variable that caused the most limitation is considered as the determinant factor and role of the other variables are ignored. The fuzzy method is similar to the Liebig minimum law, where yield is considered as a function of the minimum nutrient and the desirability of other elements has no role in increasing the yield. Based on Liebig's law, if a nutrient element is at a minimum level, the yield will be a function of that element and the other elements cannot do the functions of the restricted element (Reilly and Fugile, 1998).

In this study, the clay content, CEC, COLE, and θ_{80} values along with the macronutrients (TN, AK, and AP) were remained in the MDS. However, undoubtedly the clay content, CEC, and COLE could not play such a direct role similar to the nutrient elements and water (whose effect is reflected at θ_{80}) in plant. Therefore, yield may not be a direct function of their minimal level (in the study area, θ_{80}, AP, and AK were at the minimal levels in 56%, 33%, and 13% of the soils, respectively). However, it seems that in the study area, due to the high amount of clay (predominantly expandable smectite minerals), CEC and COLE are high. Consequently, in drought conditions these three variables can affect the shrinkage- swelling potential of the soils and the formation of cracks that may reduce the yield of rice through water loss and/or physical damage to the plant roots. Therefore, the mentioned variables may play roles that are more important in drought conditions.

Spatial distribution of the krigged Fuzzy, as the most suitable SQI in

Table 7
Values of the minimum and the maximum soil quality indices (SQIs) and the sensitivity index introduced by Masto et al. (2008) along with the regression relationships and their correlation coefficients (r) between the SQIs determined using the different approaches and the yield of rice.

Scoring methods	Soil quality index [a]	Minimum	Maximum	Sensitivity index	Relationship between yield and SQI	r
Linear	PCA- IQI	0.35	0.99	2.82	Yield = 1897.7 IQI + 1829.6	0.55
Non-linear	Fuzzy	0.10	0.81	8.00	Yield = 1678 SQI_{Fuzzy} + 3028	0.55
	PCA- IQI	0.53	0.99	1.87	Yield = 3481.9 IQI + 198.11	0.56
Boolean method	Fuzzy	0.10	0.98	9.80	Yield = 1576.4 SQI_{Fuzzy} + 2549.2	0.70
	Gupta	0.46	0.90	1.96	Yield = -1891.7 SQI + 4601.2	0.24

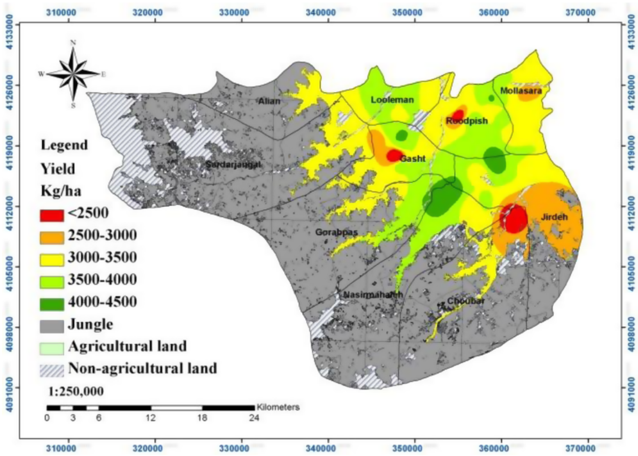

Fig. 8. Spatial distribution map of the krigged yield of rice in the studied paddy soils.

Table 8
Areal distribution of the Fuzzy- SQI values as the most suitable SQI in the study area.

Range of SQI	Area (ha)	Area (%)
< 0.58	18,862	67.2
0.58 – 0.68	6803	24.3
0.68 – 0.78	2225	7.9
> 0.78	154	0.6

the studied paddy soils (Fig. 7) showed that a large area of the studied paddy fields had poor quality and belonged to the quality classes of III and IV regarding the classification introduced by Qi et al. (2009).

Most (67%) of the studied paddy soils had the SQI of < 0.58. Spatial distribution of the predicted yield showed that the yield of rice was low at the west, southeast, and northwest parts of the studied paddy fields (Fig. 8). In the mentioned areas, the SQI was also low. A large part of this area had less θ_{80} or AP or AK than the other parts (Figs. 3, 5, and 6), which affected soil fertility, plant nutrition, and water retention. The mentioned reasons caused decrease in SQ and subsequently the yield of rice. Only small parts of the southern paddy fields (nearly 8% of the study area) had high SQI (> 0.768) (Table 8 and Fig. 7). The soils of this area had higher clay content, OC, COLE, CEC, and AK contents than the other parts (Figs. 3 to 5). Clay and OC had positive effects on the soil capacity to storage water; In addition, these properties are effective in maintaining exchangeable cations and supplying them to the rice plant (Doberman and Oberthur, 1997).

4. Conclusion

Soil physical and chemical quality is an important aspect of soil analysis. In the present study, SQIs of paddy soils were determined using different approaches for selecting the MDS, scoring and weighting the soil indicators, and integrating them to obtain SQI. Furthermore, the spatial structures of the selected SQI and their influential soil properties were modeled using the geostatistical approaches. A set of physical (clay content, θ_{80}, and COLE), chemical (CEC), and fertility (TN, AP, and AK) indicators were determined as the most influential parameters for SQI. The indicators include a set of static intrinsic and extrinsic factors. In the present study, SQI based on Fuzzy method could better explain rice yield variations and the correlation between them was high (0.70). Most of the studied paddy soils had poor quality (SQI of < 0.58). Results indicated that in areas with low clay content and COLE, water retention ability and consequently soil water content threshold of yield reduction were low. The low values of clay content and CEC had a negative effect on potassium exchange. It seems that extensive continuous rice cultivation without the use of potassium and phosphorus fertilizers has reduced the AK and AP concentrations in the studied paddy soils. Therefore, proper irrigation management and optimum consumption of fertilizers containing potassium and phosphorus is essential for sustainable economic production in the paddy fields in the study area. In general, monitoring SQ could be important to determine the optimum level of fertilizer application, to avoid imposing more cost on the farmers' production in terms of inputs consumption, and prevent the surface and ground water pollutions.

CRediT authorship contribution statement

Leila Rezaee: Methodology, Software, Data curation, Writing - original draft. **Ali Akbar Moosavi:** Data curation, Writing - review & editing, Methodology, Software. **Naser Davatgar:** Methodology, Data curation, Writing - review & editing, Software. **Ali Reza Sepaskhah:** Writing - review & editing.

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