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GEO-SPATIALLY INTEGRATED SOIL QUALITY EVALUATION: A CASE OF TOBA TEK SINGH, PAKISTAN

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Abstract

Agricultural development and rapid human population growth are among the key prevalent factors that have caused soil degradation in several terrestrial ecosystems. Soil quality is being increasingly affected by water and wind-related erosion, aridity, salinity due to misuse, and erroneous agrarian practices. Evaluating soil quality is an essential tool for crop management and soil sustainability; this is exclusively unique in semi-arid and dry regions where the observation of soil quality offers a prospect to gauge land management systems. Here, we evaluated the soil quality in the agricultural district Toba Tek Singh, Punjab, Pakistan. For this purpose, the Integrated Quality Index (IQI) model was executed through Total Dataset (TDS) and Minimum Dataset (MDS) methods of data selection. TDS shows the soil quality results of all the selected indicators (i.e., EC, pH, CaCO3, OM, P, K, SP). To select the MDS, the Principal Component Analysis was used and three indicators were selected including pH, EC, and OM. Among the two indices (IQI_{TDS} and IQI_{MDS}), moderate and low soil quality were recognized as a leading grade for soil quality of the study area. The reason for low-quality soil was a considerably low percentage of OM, a lower amount of $CaCO_3$ in soil, a high rate of pH and EC, and a lesser amount of Phosphorous and K in the soil of the study area. The results for TDS and MDS were found to be appropriate to each other as confirmed by the Geographically Weighted Regression (GWR) model (Adjusted R^2 0.81). Thus, this approach might be used as a helpful tool for the development of quantitative techniques to estimate soil quality. This is helpful to identify areas where soil quality is low and can be improved with better management practices and maintain a suitable amount of fertilizers in the soil.

Key words: Soil quality, Agriculture, IQI, MDS, TDS, Geographical information systems (GIS), Geographically weighted regression (GWR).

Introduction

Soil quality is considered an essential component besides water and air quality, playing a critical role in sustaining environmental quality (Bünemann *et al*., 2018). Agricultural sustainability also greatly relies on the quality and health of soil (Lal, 1998; Vasu *et al*., 2020). Soil quality is defined as "the capacity of soil to function to sustain plant and animal productivities, to maintain or enhance water and air quality, and to support human health and habitation" (Karlen *et al*., 2003). Soil is the major contributor to the earth's biosphere. It tends to provide purification of water, cycling of nutrients, and providing habitats for biodiversity to maintain the environmental quality at a global scale. Soil health is affected by different factors that are related to soil management and also by soil formation factors (Rinot *et al*., 2019). Soil quality is particularly essential to maintain the sustainability of an agricultural country.

Soil quality assessment is considered an inevitably necessary process to observe the quality of the soil (Li *et al*., 2019) such as the production of agriculture, forest, nature protection, and recreational sites, or urban development. It is broadly recognized that; the concept of soil quality is most valuable in a global context, specifically in the evolving agro-ecosystems. In the evaluation of soil quality, it is necessary to respond to two questions. First, how does the soil function, and second, what procedures are suitable for making the assessment? After this assessment procedure, a range of parameters is to be taken into account, which indicates that the soil functions can be calculated using characteristics of landscapes, understanding the occurrence of dynamic processes in soil, and the knowledge of pedogenesis (De la Rosa & Sobral, 2008; Vasu *et al*., 2020).

Soil quality parameters are used to determine soil functions. Soil attributes will vary by selection, and they depend on the capacity of soil under consideration. Classification of the characteristics of soil is based on three groups: physical indicators, biological indicators, and chemical indicators (Marzaioli *et al*., 2010; Brejda *et al*., 2000). Attribute selection of indices must be established on land use, functions of soil, measurement of consistency, spatiotemporal variations, changes in the management of soil, and required skills for interpretation (Nortcliff, 2002). To date, several methods for the evaluation of soil quality are developed including card design, testing kits, soil quality indexing, and other geostatistical methods (Sun *et al*., 2003; Qi *et al*., 2009). However, the most widely used method is soil quality indices owing to its quantitative flexibility and easy handling. It also has the additional benefit of validation of soil quality assessment and management with spatial-temporal evidence while analyzing the soil quality from regional or local levels (Andrews & Carroll, 2001; Qi *et al*., 2009). Previously, researchers have used soil quality assessment and quality indices to estimate the influence of crop production, litter management, agricultural practices, and regional scale soil management (Karlen *et al*., 2003; Andrews *et al*., 2002). The soil quality index is developed by following the indicator's selection, scoring of assigned indicators, and then making a composite index by integrating all the indicators. For indicators selection, two well-adopted methods include Total Dataset (TDS) and Minimum Dataset (MDS). TDS-based indicator collection is performed according to particular soil features, and in the MDS technique, indicators are selected as per association within indicators and simplicity of measurement (Gómez *et al*., 2009). Various addition, multiplication, and weighted-mean protocols make it possible to integrate the normalized indicators into a quality index (Andrews *et al*., 2002). The best examples of such calculations are the Integrated Quality Index (IQI) and Nemoro Quality Index (NQI). The NQI-based model exploits the minimum and average indicator scores and does not consider the respective weights. On the other hand, IQI indexing is based on combining the chosen indicators and weights using a simplified scoring equation to make an index. The NQI and IQI models based on TDS followed by MDS analysis were utilized in agricultural land of different provinces in China and Iran, where researchers recognized the blend of the IQI analysis model. This is proved to be an excellent tool to evaluate soil quality (Qi *et al*., 2009; Rahmanipour *et al*., 2014).

Over-exploitation of ecosystems with land-use changes from natural pastures and forests to croplands have negatively influenced soil quality. Inappropriately, with the agricultural advancement, degradation in soil health is increasing by the water and wind-related erosion, aridity, and salinity due to misuse and erroneous agrarian practices. Soil fertility decreases day by day due to continuous crop cultivation in the soil, and it also affects soil nutrients. Therefore, soil quality assessment is crucial for better crop and soil management. In this context, the present study assessed the soil quality in the agricultural district Toba Tek Sigh, Punjab, Pakistan-an agrarian country in South Asia, using IQI indices model with TDS and MDS methods.

Methodology

Study area: The study area for this study is Tehsil Toba Tek Singh located in District Toba Tek Singh, central Punjab. The study area is situated between 30°34' to 31°3' N, and 72°07' to 72°47' E, and on 152 meters elevation above mean sea level (Fig. 1). The total land area of tehsil Toba Tek Singh is 2,240 km² and the topography is flat and plain. The study area has an arid or desert sort of climate. According to the Köppen climate classification, this region falls in BWh climate.

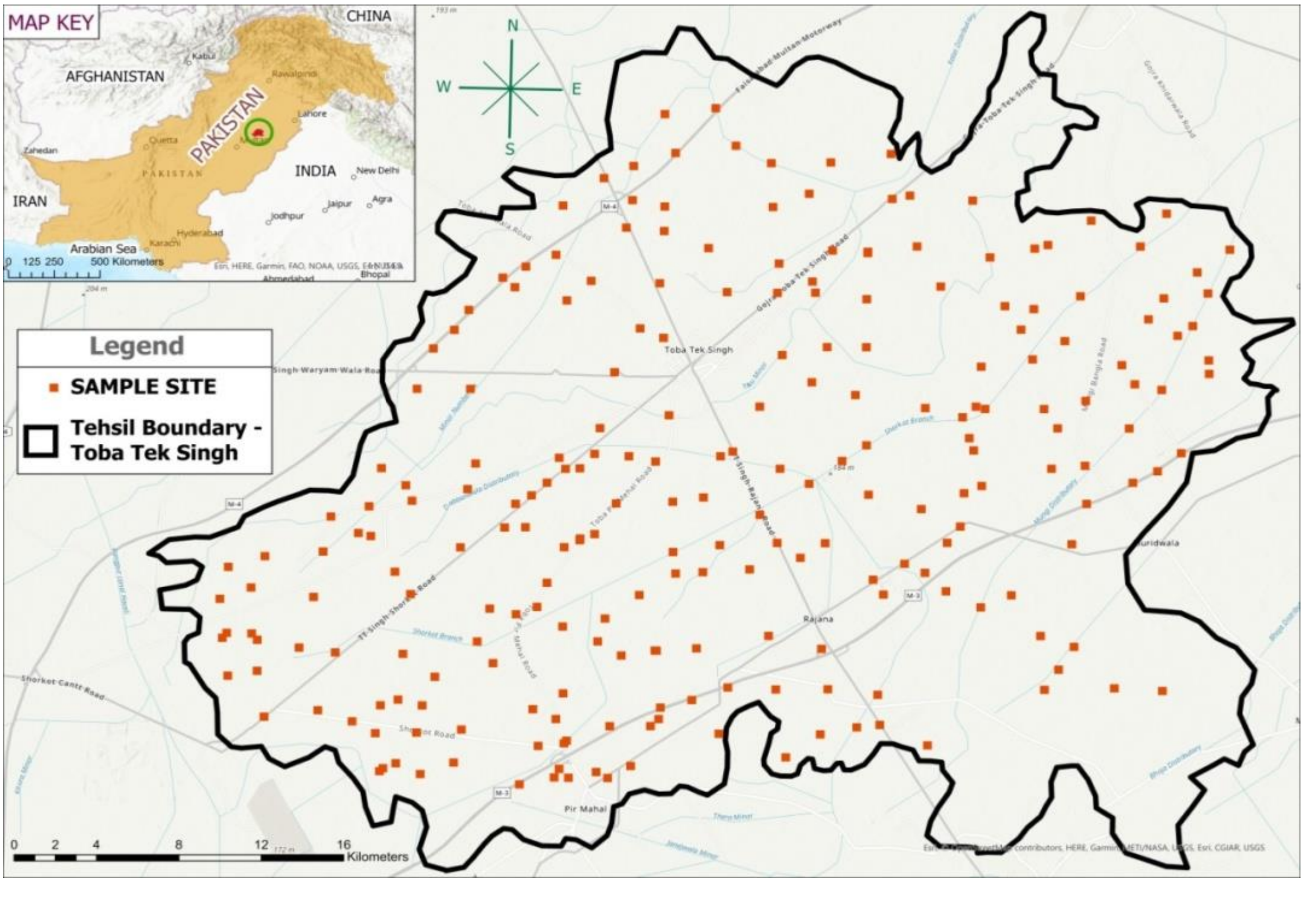

Fig. 1. The study area of the Tehsil Toba Tek Singh.

June is the hottest month and January is the coldest. The average temperature in the hottest months is 40.7 °C and the average temperature of the coldest months is 6°C. The average annual maximum temperature is 35 °C with annual precipitation of 254 to 381 mm (Rehman *et al*., 2011; Khan *et al*., 2010). This area is of great importance in terms of agriculture. The main crops cultivated in the region are wheat, oilseed, sugarcane, cotton, and maize (Supplemental Appendix 1). The yield per acre for most cultivated crops in the area is given in Supplemental Appendix 1.

Keeping in view the importance of this agriculturally important area and its land usage (Supplemental Appendix 2), the present study was designed to investigate the soil quality, a critical issue faced by the study area, by utilizing statistical and geo-statistical methods. Firstly, the most influential parameters were chosen through a comprehensive literature review and then modeled as a TDS and MDS using IQI. The detailed workflow of the methods is provided in (Fig. 2).

Soil sampling and measurements: The first step in data collection was the feasibility survey with the help of experts, agricultural farmers, environmentalists, and soil scientists, by asking questions about the soil quality of the study areas. The feasibility survey was performed within every 5 km of the study area. It is observed that in some areas, the soil is fertile while in others, the quality of the soil is poor, and in the rest of the areas, the soil is moderate. As per these locational observations, samples were collected. There are more samples from the areas with poor and moderate soil as compared to the fertile soil locations.

A handheld GPS device was used to obtain the absolute location (Lat./Long.) of the sampling points, which was later used to generate the spatial points in ArcGIS 10.7 software. These GPS readings were taken on a notebook and also on the soil sample bags. Soil samples were taken by a special soil augur, which was designed for the collection of soil samples. Soil samples were taken from different crop cultivated areas, (*e.g*., maize, wheat, tobacco, sugarcane, and cotton) within every 2500 m^2. All the samples were collected in daylight and each sample was 250 g in terms of weight. A total of 235 samples were collected from the study area with absolute geographical location. Each sample was taken from upper 0-30 cm soil depth during April 2019 and preserved in plastic airtight bags (Fig. 3).

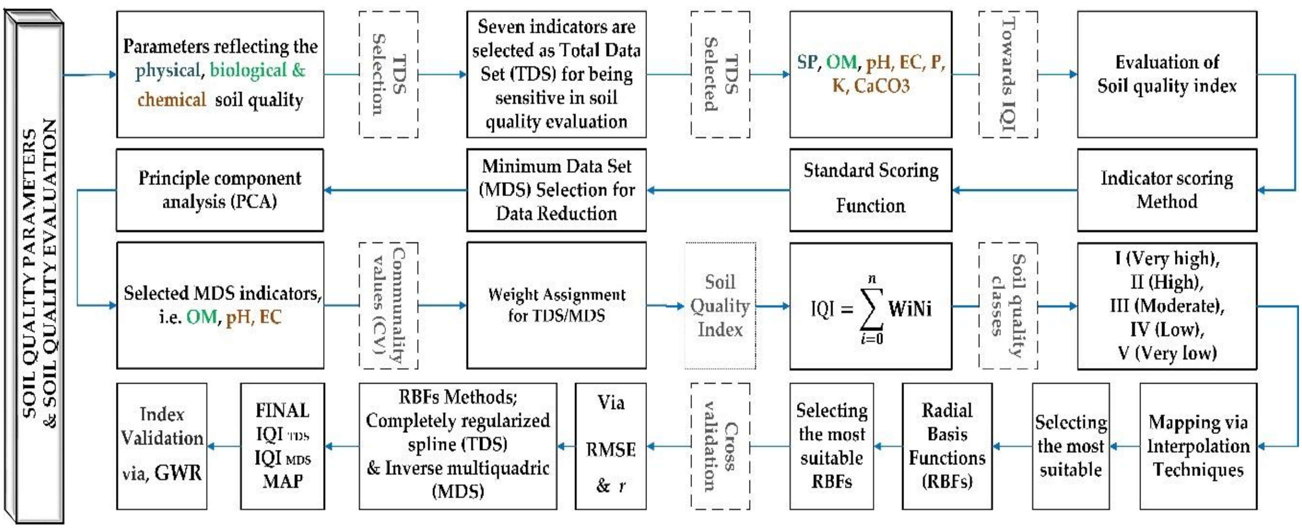

Fig. 2. The adopted methodology to assess the soil quality.

Fig. 3. A glimpse of different phases of soil sampling from Toba Tek Singh Tehsil.

Selected parameters to test the soil quality: The soil samples were sent to the Soil and Water Testing laboratory, Toba Tek Singh Ayub Agricultural Research Institute, for the determination of the selected parameters to ascertain the soil quality. Seven parameters reflecting the physical, chemical, and biological quality of the soil were selected. The selected parameters for physical soil quality were soil texture and saturation percentage (SP), for soil biological quality, soil organic matter (OM), and for the Soil chemical quality, soil reaction (pH), electrical conductivity (EC), phosphors (P), potassium (K), and calcium carbonate ($CaCO_3$). Soil fertility/ quality standards according to the Soil and Water Testing Laboratory are given in (Table 1). These seven soil indicators were selected based on their sensitivity to soil quality assessment. These indicators are widely suggested by many researchers as they affect soil productiveness, nutrients supply, soil porosity, root development, soil structure, and soil aggregation stability (Dodd & Sharpley, 2015; Garnaik *et al*., 2020; Khasawneh *et al*., 1980; Nabiollahi *et al*., 2018; Ok *et al*., 2011; Rahmanipour *et al*., 2014). The soil samples were allowed to air dry and then were crushed. After sample grinding, the samples were passed through a 2mm sieve for physical and chemical examination (Table 1). These all indicators based on their sensitivity towards soil quality assessment were incorporated into TDS analysis. Particularly, it is crucial to check the soil pH levels as it reflects the plant growth condition, biological activity in the soil, and nutrient recycling. Besides the soil, EC merely tells you about plant growth yet it is useful in determining the salinity in soil and the availability of nutrients for the uptake of plants (Liebig *et al*., 2017; Thapa *et al*., 2018). Soil OM greatly influences the stability status of soil in terms of structure, pH, soil's reaction to fertilizer, and the availability of nutrients (Corwin & Yemoto, 2020). OM reduces the threat of erosion, improves the soil quality, fertility, cations exchange capacity, supply, and storage of nutrients (Kilmer, 2018). These selected indicators are deliberated as good gauges to determine the soil quality for crop and soil management practices (Liebig *et al*., 2017; Thapa *et al*., 2018). Therefore, for better characterization of the soil of the study area, these indicators were selected and TDS was employed on all the indicators.

Assessment and scoring the soil quality index: The Standard Scoring Function was used for assigning scores to indicators. According to soil quality indicator sensitivity, three types of functions that are associated with values i.e., high, low, and intermediate were applied. (i) More is better, (Andrews *et al*., 2002) (ii) Optimal range, and (iii) Less is better (Liebig *et al*., 2001). Indicator perimeter and their functions are described in Table 2. According to indicators, more is better function, was applied to organic matter, because soil organic matter plays a vital role in soil fertility, and fertility affects crop production. The greater amount of soil organic matter, increases crop production, soil fertility, and structural ability (Marzaioli *et al*., 2010). Function for the optimal range was applied to saturation percentage, electrical conductivity, potassium, phosphorus, and pH.

Table 1. Soil Fertility Standards.

Soil quality	Poor	Medium	Fertile
OM (%)	<0.86	0.87-1.29	>1.29
P (ppm)	<7.0	7-21	>21.0
K (ppm)	<80	80-180	>180
EC (dSm-1)	>16-8	8--4	<4
pH	>8.5-8.0	8.0-7.0	<7.0
SP (%)	<19	20-45	>45
$CaCO_3$ %	<0-2.0	2.0-4.0	>4.0

Table 2. Scoring the soil quality index.

Indicator	Function type	Lower limits	Upper limits
SP%	Optimal range	19	60
EC (dSm-1)	Optimal range	0.2	4
OM%	More is better	0.86	5
P (ppm)	Optimal range	7	21
K (ppm)	Optimal range	80	250
$CaCO_3$ %	Less is better	2	9.5
pH	Less is better	7.0	14

The optimal range is defined for the indicators, ranging between less is better, or more is better. Moreover, the electrical conductivity's optimal range is 0.2 to 2dSm^{-1}. The range for saturation percentage is 30 to 45, for phosphorus is 14 ppm, and for potassium is 180 ppm (Marzaioli *et al*., 2010). Since the soil in the studied area is calcareous in nature, so lower pH and $CaCO_3$ content are chosen as less is better because the lower values of both of these indicators are better for crop production and fertility (Bashir *et al*., 2019).

MDS selection for data reduction: The evaluation of soil quality indicators was executed through the MDS. The soil quality parameters must be connected to the functions of soil. For the selection of MDS, the application of principle component analysis (PCA) was employed (Qi *et al*., 2009) to reduce the data (Minitab 18 software). Principal components axes are shortly called PCs showing eigenvalues >1 are measured in the indicator's selection; when less than three principal components axes had the eigenvalue >1, PCs, explaining >5% variation in the soil data. Variables received weight in each PC to represent their role in the alignment of the PC (Andrews *et al*., 2002; Rahmanipour *et al*., 2014). Each variable in a PC was assigned a weight showing its contribution to the formation of the principal component. The variables with an absolute weight value within the ten percent of the highest factor in each PC were retained to outline MDS. In the case of more than a single variable selection from each PC, the multivariate-correlation coefficient was executed to abolish the redundant variables in the minimal data sets.

Weight assignment for TDS/MDS: For TDS and MDS, Factor analysis (FA), (IBM SPSS 20 software), was employed to assign the values of the weights by considering the respective communality values (CV) of every selected parameter. CV considers the estimated factor model and represents the degree of variance explicated by each indicator. Its values lie between 0 to 1 and the indicator communality with higher values show the higher contribution of that indicator to illustrate the examined phenomenon. Here in the present study, weight values are the resultant of the ratio between every indicator's communality to the cumulative communalities of the indicators (Rahmanipour *et al*., 2014).

Soil quality index: For the index calculation, The Integrated Quality Index (IQI) was used for all indicators i.e., TDS and MDS methods, and all sample points scoring and weighting were applied (Doran, 1994). According to, Qi *et al*., (2009), the formula of IQI is,

$$\mathbf{IQI} = \sum_{i=1}^{n} \boldsymbol{W_i N_i} \quad (1)$$

Where,
IQI is the integrated quality index,
$\boldsymbol{n}$ is the number of indicators,
$\boldsymbol{W_i}$ is the weight of each indicator,
$\boldsymbol{N_i}$ is the score of each indicator

Soil quality classes: According to Jenk's optimization method, five classes were assigned to each indicator of soil quality. Data were organized into classes, and each class was minimized by the sum of variance. Quality grades were assigned to each indicator shown as follows: I (Very high), II (High), II (Moderate), IV (Low), V (Very low) soil quality in the study area.

The geo-statistical analysis was used (ArcGIS 10.7 software) to map the soil quality classes through spatial interpolation techniques to check the spatial distribution of these generated soil qualities. These methods are only valid for nonrandom or spatially dependent data. This method estimates the variable values from its neighbor values (Belkhiri & Narany, 2015; Xie *et al*., 2011). The geostatistical analysis is vital in the geo-visualization of soil quality classes because it has various interpolation methods that help in predicting the unknown values (at unsampled locations) through known (sampled locations) values (Rahmanipour *et al*., 2014). In this paper, we compared extensively used interpolation methods in soil investigations, *i.e.* Inverse Distance Weighting (IDW), Radial Basis Functions (RBFs), and Kriging (K). These methods estimate the respective model accuracy via cross-validation. This useful technique enables us to opt for an optimal model of variogram between different candidates and also lets us optimize the parameters (all required such as; range, sill, maximum, minimum neighbors) considered essential for achieving maximum possible accuracy. Cross-validation is quite helpful in accurately estimating the comportment of the analytical model. The cross-validation in multiple iterations presented the variograms in two sets that were used for building and validating the model (Huang *et al*., 2019; Rahmanipour *et al*., 2014; Robinson & Metternicht, 2006). Afterward, the variances between the predicted and measured (unknown vs known) data were tested through correlation coefficient (r) and Root Mean Square Error (RMSE). The methods showing the high r-value and less RMSE were kept. Accordingly, if the RMSE values were closer to 0 and the r-values tending to be 1, then the correctness of that interpolation method was considered higher (Rahmanipour *et al*., 2014; Robinson & Metternicht, 2006).

Index validation: Previously, simple linear regression was used by many researchers for IQI_{MDS} (independent variable) versus IQI_{TDS} (dependant variable) (Zhou *et al*., 2020). We argue that such relationships should be represented geospatially as there are advanced methods available in spatial statistics to show such spatial heterogeneous associations. There are two main types of spatial multivariate linear regression methods. The first one is global linear regression (*e.g*., ordinary least squares (OLS)), which gives an overall statistical correlation between dependant and explanatory variables through a single equation. The second method is the local linear regression approach, (e.g., geographically weighted regression (GWR)), which is considered superior (evidently) to OLS. In the global regression method, the regression coefficients are considered as constants without regional or local disparity, which confuses the possible associations among significant local differences. However, GWR considers spatial heterogeneity and computes differentiated (local scale) estimations of regression parameters throughout the spatial locations. The GWR can be calculated through the following equation;

$$\text{TDS} = \boldsymbol{\beta_0}(\boldsymbol{X_i}, \boldsymbol{Y_i}) + \boldsymbol{\beta_1}(\boldsymbol{X_i}, \boldsymbol{Y_i})\ \text{MDS} + \boldsymbol{\varepsilon_i} \quad (2)$$

TDS is a dependant variable; i shows regions of the study area; (X_i, Y_i) represents the locations of ith observed region; $\beta_1(X_i, Y_i)$ shows regression parameter at the location of observation; MDS is an independent (explanatory) variable and ε_i is the error term (Ansong *et al*., 2015; Li *et al*., 2019). The GWR is used here for computing the possible relationships among TDS (dependant variable) and MDS (explanatory variable) at varied locations (locally).

Results

TDS method-based evaluation: Measured values of mean, standard deviation (±), coefficient of variation (CV) %, minimum, maximum, and range of the studied (seven) soil quality indicators (at each sampling point) are shown in (Table 3). pH values are higher than 8 to 8.5, and in some areas, they exceed from 9 to 9.5, indicating soil nature as alkaline and sodic. A very low soil electrical conductivity (EC) is found in the northwestern side of the study area, whereas the southeastern side contains very high EC. Overall EC values remained between 1.4 to 14.3. Moreover, high soil organic matter (OM) is found in the south and west of Toba Tek sigh's area, however, the north and east sides show lesser OM. Its overall variability lies between 0.41 to 1.14 in the study area. As a reference, more than 1% amount of OM in the soil refers to good soil quality.

The amount of phosphorus is very high on the southern side of the study area and moderate in (almost) the rest of the study area because Low phosphorus is covering only a small area. Phosphorus is less soluble, slowly available to plants, and remains in the soil for a long time. It is absorbed quickly into soil particles after its application in chemical fertilizer form. It becomes highly available in soils that have a pH below 7. Like other nutrients, phosphorus is also available in abundance in that soil which contains a high amount of organic matter.

Table 3. Measured values of samples.

Indicator	Mean values	Standard. Deviation	CV %	Min.	Max.	Range
pH	8.425104603	0.2377182	2.821546611	8	9.4	1.4
EC (dSm -1)	3.2145607	3.2697054	101.71547	1.4	14.3	12.9
OM %	0.76785774	0.169186	22.0315251	0.41	1.14	0.73
P (ppm)	9.654937	1.819218	18.84236	1.03	14.1	13.7
$CaCO_3$%	4.639121	1.10774	23.87822	2.9	7	4.1
K (ppm)	155.3138	36.08763	23.2353	70	360	290
SP%	35.88285	2.316111	6.454646	30	44	31

-pH (Soil Reaction), -EC (dSm $^{-1}$) (Deciemens per meter) (Electrical conductivity), -OM% (Organic Matter), -P (ppm), (Phosphorus, parts per million), -CaCO3% (Calcium carbonate), -K (ppm), (Potassium, parts per million), -SP% (Saturation percentage)

Table 4. Weight and communalities.

Indicators	TDS		MDS	
	Communalities	Weight values	Communalities	Weight values
pH	0.616	0.138	0.544	0.354
EC	0.261	0.058	0.322	0.210
O.M	0.61	0.136	0.667	0.435
P	0.779	0.174		
K	0.718	0.16		
$CaCO_3$	0.789	0.176		
SP	0.687	0.154		

Most of the high amount of $CaCO_3$ was present on the north and western sides. Moreover, a moderate amount is available in (almost) the rest of the area, and a very low amount is available on the southern side of the study area. An only a small area on the southern side had a high amount of potassium because most of the area showed a moderate level of potassium, and a small area was covered by a lower amount of potassium. The higher amount of SP was located in northeastern and some of the western sides and the moderate SP level was in most of the areas but the lower amount of SP% was in the southern and middle of the study area. Based on estimated communality analysis, $CaCO_3$, SP, and OM showed considerable variability in the study area (Table 4). Moreover, P, pH, $CaCO_3$, SP, and OM contained the highest weights (176 to 136). K, OM, and EC had comparatively low weight values (0.16 to 0.058).

The Integrated Quality Index (IQI) for Total Data Set (TDS) is classified into five soil quality classes. The soil quality classes are defined as per Jenk's optimization method. The soil quality classes (TDS) are ranging from Very high > 0.696 to Very low <0.431 after IQI computation (Table 5).

RMSE and *r* were utilized for the comparison of different interpolation techniques as stated in previous methodological discussion. We identified RBFs as the most proper interpolation technique relative to other methods. Specifically, two RBFs were considered optimal for applying to IQI_{TDS} and IQI_{MDS}, i.e. CRS for TDS and Inverse multiquadric (IM) for MDS (Table 8). The resultant geostatistical maps (as presented in Fig. 4a & b) for soil quality showed that around 30% (446.9 km^2) of the study area has mainly very low quality (Grade V). An area of 48% lies as low (Grade IV) which covers an area of 727.1 km^2 (Table 5). 17% of the area showed Grade III, and only 3% area falls with Grade II (high) soil quality. Less than 1% of the total area was designated as Very High quality or Grade I soil.

MDS method-based evaluation: Principal component analysis (PCA) was used as a data reduction tool, for the selection of indicators of soil quality. Highly weighted indicators, which have the eigenvalues, ≥ 1 were selected for the minimum data set. Three indicators ranging from 1.3264 to 2.2585 were selected for the minimum data set (Table 6). Highly weighted variables from seven PCs were reflected. If >1 factor has a higher weight, a direct relationship was employed. The OM, EC, and pH factors were considered after communality analysis (Factor Analysis) because they showed high eigenvalues ≥ 1.

The IQI for MDS (Yu *et al.*, 2018) classified soils of the studied area into five quality classes. The soil quality classes were defined by "de Paz *et al.*, (2006)" as Jenk's optimization technique. The soil quality classes ranged from Very high > 0.665 to Very low <0.431 (Table 7).

Soil quality geospatial map of IQI_{MDS} indicated an almost similar pattern to the TDS method and exhibited that 30.6% of the studied area is of Grade V (Table 7 and Fig. 4b). On average, 29 % of the studied area accounted for moderate and low-quality soil (Grade IV and III). MDS analysis showed that 9.6 % of the area (143.5 km^2) is of Grade III and with a similar trend to TDS, less than 1% study area accounts for Very High-Grade soil (Grade I). The IQI_{MDS} displayed a reduction in soil quality from the south to the northwestern quadrant.

Table 5. TDS analysis for grading of soil quality.

Index	Indicator method	Grades				
		I(Very high)	II(High)	III(Moderate)	IV(Low)	V(Very low)
IQI	TDS	>0.696	0.624–0.696	0.534–0.624	0.431-0.534	<0.431
	Area (km^2)	5.4	54.5	256.1	727.1	446.9

Table 6. Principal component analysis principal component analysis: pH, EC, O.M, P, K, CaCo3, SP eigen analysis of the correlation matrix.

Eigenvalue	2.0297	1.5672	1.3264	0.7865	0.5192	0.4443	0.3267
Proportion	0.290	0.224	0.189	0.112	0.074	0.063	0.047
Cumulative	0.290	0.514	0.703	0.816	0.890	0.953	1.000
Eigenvectors							
Variable	**PCs**						
	1	**2**	**3**	**4**	**5**	**6**	**7**
pH	-0.581	0.171	0.043	0.145	0.154	-0.623	-0.445
EC	-0.315	0.240	0.473	-0.592	-0.472	0.196	-0.082
O.M	0.615	0.004	0.039	0.027	-0.350	-0.160	-0.686
P	0.239	0.633	0.118	0.260	-0.290	-0.390	0.474
K	0.326	0.058	0.613	-0.237	0.660	-0.149	0.016
CaCo3	0.038	0.685	0.164	-0.154	-0.296	-0.543	0.311
SP	-0.140	0.201	0.596	0.693	-0.154	0.279	-0.054

Table 7. Soil quality grades for MDS.

Index	**Indicator method**	**Soil quality grades**				
		I	**II**	**III**	**IV**	**V**
IQI	MDS	>0.665	0.600–0.665	0.514–0.600	0.431-0.514	<0.431
	Area (km^2)	9.24	143.55	317.57	563.33	456.34

Table 8. Spatial interpolation for enhanced parameters.

Index	**Indicator method**	**Optimal Interpolation method**	**Parameter**	**Max. Neighbors**	**Min. Neighbors**	**RMSE**	**r**
IQI	TDS	CRS[b]-RBF[a]	1.0302	15	10	0.221	0.76^{**}
	MDS	IM[c]-RBF[a]	102.1960	15	10	0.196	0.78^{**}

[a] RBF = Radial basis functions; [b] CRS = Completely regularized spline; [c] IM = Inverse multiquadric
$^{**}p<0.01$

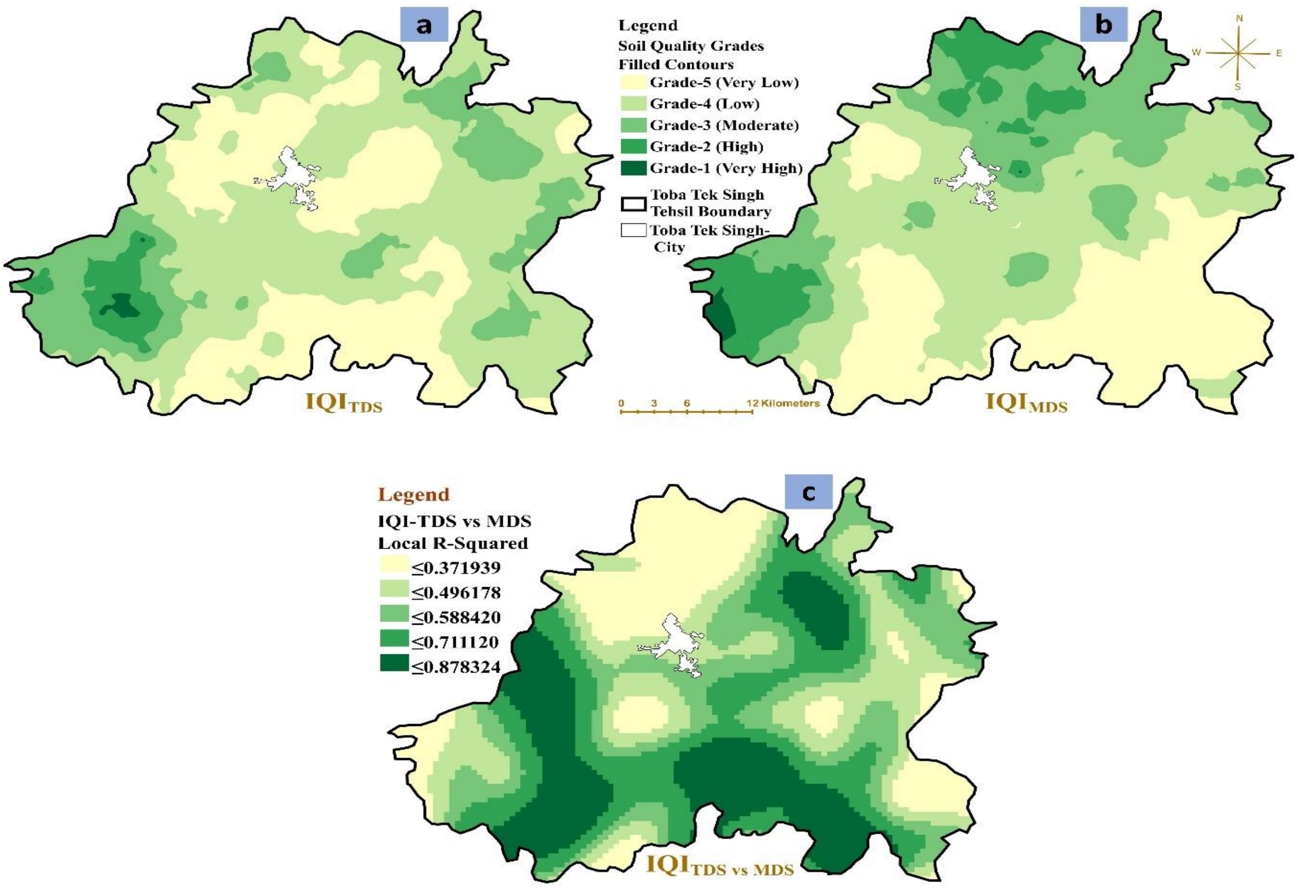

Fig. 4. (a & b) Final Geo-statistical maps showing the distribution of soil quality grades based on IQI $_{TDS}$ and IQI $_{MDS}$ indices in Tehsil Toba Tek Singh lands. (c) GWR analysis showing agreement between IQI_{TDS} and IQI_{MDS} via local R^2.

GWR presented a clear relationship between IQI $_{TDS}$ and IQI $_{MDS}$ (Fig. 4c and Table 9). This reveals that MDS can be used with high confidence to measure the soil quality because MDS variables strongly influence TDS variables and have local statistical significance. Overall model performance is significant with Adjusted local R^2 0.81. Mainly, in the top northwestern and extreme southeastern areas, the relationships are the least (R^2 0.37 and R^2 0.49) however nearby regions of these significances present higher to highest significances (R^2 0.58 to R^2 0.87). Both models are comparable and can be used alternatively however MDS is suggested here as an optimal option to evaluate the soil quality.

Table 9. Results from the GWR model for grid-based analysis.

Variable	Grid-based	
	Intercept	MDS
Mean of βs	0.471	0.488
SD of βs	0.072	0.080
Minimum	0.237	0.288
Maximum	0.698	0.732
Median	0.469	0.483
SE	0.023	0.047
Adjusted R2	0.81	

Discussion

Soils are classified as neutral, acidic, strong, or alkaline based upon their pH. The variation of EC values differentiates soils from no-saline to highly saline soils. Higher pH and EC values of soil in the study area represented the alkalinity and salinity of the soil. Another component of soil, organic matter is considered an essential characteristic of soil quality. OM provides essential nutrients to the soil, regulates the soil water availability, increases the infiltration of water in the soil, and affects the aggregate size, bulk density, and supply oxygen to the roots of plants. Soil organic matter increases soil fertility and crop production. A large amount of organic matter implies healthy soil, and the lower amount of soil organic matter in soil reflects poor soil quality (Rahmanipour *et al*., 2014). In the process of identification of soil quality, the soil organic matter is valuable; therefore it may be informative as a minimum data set that is used to assess the soils of the world. For the characterization of organic matter, a separate minimum data set is required for some salient functions such as biological activity, the structure of the soil, and storage of nutrients in the soil (Gregorich *et al*., 1994).

In the present study, levels of phosphorous and potassium were recorded in a lesser amount. The soil phosphorus (P) after nitrogen is a very significant nutrient component that its shortage has restricted agricultural production in many regions like Australia and other parts of the world. Phosphorus decline in the soil dramatically affects the soil quality. Therefore monitoring of soil phosphorous is required to maintain a healthy balance of phosphorous. Excessive P is also dangerous as it leaks into the water and can make it contaminated. Larger P concentration in lakes and streams leads to algal growth, which may discharge destructive toxins (Corwin & Lesch, 2005). Islam *et al*., (2016) narrated that potassium is absorbed in large amounts by plants than other nutrients and it is the third major nutrient element. It is described that the presence of potassium in soil augmented crop production and grain yield, and improved the exchange of potassium and nitrogen from the stem. However, in Asia, farmers usually do not prefer potassium fertilizer application as compared to nitrogen and phosphorus. Many researchers reported the negative balance of K in rice soils. These days, 18.43% of soils lack K and due to insufficient K fertilizer application, this figure is increasing day by day. K erodability is also found to be responsible for the erosion of agricultural lands and soil degradation (Vaezi *et al*., 2008; Khormali *et al*., 2009).

The indices of IQI_{TDS} and IQI_{MDS} revealed that overall 17 and 21% of the total agricultural land area in Toba Tek Singh exhibited moderate level soil quality (Grades III). Whereas, less than 1% area showed high quality/ Grade I soil quality. Both MDS and TDS techniques showed that most of the study area has low-quality soil from Grade III, IV, and V. The EC recorded was also high in the study area. The reason can be explained as the area of Toba Tek Singh is one of the hot semi-arid climatic zones of Pakistan. Rainfalls mostly happen during the monsoon from July to August. Winters have (mostly) very little rain, thus the irrigation of crops relies on groundwater or canal system which leads to salinity and waterlogging problems (Karim & Hussain, 2012). The use of stored groundwater for irrigation in the cultivation areas can increase the salts concentration in the soil, therefore increasing the soil EC (Smedema & Shiati, 2002). The issue of soil salinity also increases due to the intensive farming practices in the area leading to a low level of OM and higher pH levels rendering poor soil quality. Low levels of OM, high levels of EC, and pH negatively affect the soil quality and ultimately the plant growth (Marzaioli *et al*., 2010).

The PCA technique has been applied in several other studies to reduce the datasets (Andrews *et al*., 2002; Qi *et al*., 2009; Rahmanipour *et al*., 2014). This is a useful tool that reduces data redundancy during soil indicator selection in addition to minimizing the cost and time of laboratory analysis. The latter feature of PCA is essentially important for developing countries like Pakistan and other Asian countries, which have a marginal infrastructure and low budgets to measure the indicators. For MDS analysis, organic matter, EC, and pH used in our study have been employed in other studies as MDS indicators to monitor the soil quality (Qi *et al*., 2009). Organic matter is also included in MDS and suggested as a good indicator for the evaluation of spatial changes in soils of urban and cropping areas of Province Tehran, Iran (Nosrati, 2013).

The IQI index employed in this study both for MDS and TDS is a method of choice as previously used by many researchers and offers an improved estimation of the soil quality. The usage of a few indicators for soil assessment is due to the lack of any data about Toba Tek Singh and generally for Pakistan. Our results with the use of a few indicators are in corroboration with previous studies in China and Iran (Qi *et al*., 2009;

Rahmanipour *et al*., 2014). Another study on soil assessment recommended that a small number of carefully selected indicators could effectively provide the assessment of soil quality (Andrews & Carroll, 2001). We here also suggest (for future inquiries) to further incorporate the toxic heavy metals in soil quality assessments because their presence affects plant growth which could lead towards loss of the agricultural productively in any crops (Mahalel *et al.,* 2021). Moreover, the effects of fertilizers should also be considered because the presence and variations of different fertilizers may alter the vital nutrients' composition and soil contents that affect plant root growth, overall yield, and quality of important crops (Zhang *et al.,* 2021).

Unlike conventional index validation procedures, we here employed GWR as a novel approach to check whether both of these models (IQI_{TDS} and IQI_{MDS}) have any degree of agreement with each other. To the best of our knowledge, this is the first attempt in such studies. This study has local and nationwide policy implications where soil degradation is a common cause of less agricultural productivity. We here strongly recommend that extensive national surveys for soil quality evaluation should be conducted as the evidence is reported in this alarming study. We also recommend working on farmers' education/knowledge, attitudes, and practices towards essential fundamentals. Finally, This study can also be adapted for other areas of the world for effective soil quality evaluation.

Conclusion

In this study, two sets of indicators, TDS, and MDS are compared under Integrated Quality Index (IQI), for the evaluation of soil quality in agricultural lands in Tehsil Toba Tek Singh. It is observed that the selected indicators were suitable for the evaluation of soil quality. TDS shows the soil quality results of all selected indicators including EC, pH, $CaCO_3$, OM, P, K, and SP. For the selection of MDS, the PCA was used and three indicators were selected for MDS *i.e.* pH, EC, and OM. For the quality indices from both approaches (IQI_{TDS} and IQI_{MDS}), Low and Moderate soil quality classes were recognized as leading grades (for soil quality) in the study area. The reason for low quality in the study area was identified as a low percentage of organic matter, a lower amount of $CaCO_3$, a high rate of pH and EC, and less amount of P and K in the soil of the study area. The results for TDS and MDS also appropriate to each other, soil quality is respectively low and moderate in these areas according to TDS and MDS results. Geostatistical interpolation helped in mapping the spatial distribution of soil quality grades. The best fit was the Radial Basis Function interpolation method (RBFs) for both IQI_{TDS} and IQI_{MDS}. Moreover, two of the sub-methods of RBFs were chosen after cross-validation including RBFs- Completely Regularized Spline (CRS) for TDS and RBFs- Inverse multiquadric (IM) for MDS. The IQI index was also validated as a whole based on spatial heterogeneity through the GWR technique, which is the first attempt in such studies. The GWR results clarify that IQI_{TDS} and IQI_{MDS} have a significant agreement with each other. However, we recommend MDS as an optimal option due to its time-saving and cost-effectiveness. The IQI_{MDS} approach might also be used as a helpful tool for the development of quantitative techniques to estimate soil quality. This kind of a research must be conducted from time to time for the monitoring of soil quality, and it could be helpful to identify areas where soil quality is low. This can be important information for better management practices to maintain the suitable amount of fertilizers in the soil. The MDS approach might be helpful to test the selected indicators in soil, and help to improve the soil quality, to keep a record of infertile areas. If the number of indicators reduces, then the sampling density could be increased to evaluate the soil quality in terms of a statistical point of view. The results are useful for practitioners, to improve soil fertility, better irrigation, land management practices, and appropriate use of fertilizers in the studied area. The mentioned research methods can be helpful for future researches in Pakistan. Because this sector is often neglected by governments (i.e., national and sub-national), there is an immediate need to reevaluate the soil quality in Pakistan at national and sub-national levels for better crop production and land management practices. To our knowledge, this manuscript is the first of its kind effort in the country towards the geospatial perspective of soil quality evaluation and we anticipate improvements in our methods - left for future studies.

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