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Soil Quality Assessment in the Mashhad Plain, Northeast Iran: A Minimum Data Set and Spatial Analysis Approach

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ABSTRACT

Soil quality assessment is crucial for sustainable land management. Given the high cost and time required to measure all soil quality indicators, minimum data set (MDS) selection offers an efficient approach for accurate evaluation. This study identifies an optimal MDS and examines its spatial distribution in the Mashhad Plain. A total of 180 soil samples (0-10 cm depth) were analyzed for physical and chemical properties. The soil quality index (SQI) was computed using the weighted additive integrated quality index (IQIw) in four scenarios: total dataset-linear (IQIwL_TDS), total dataset-nonlinear (IQIwNL_TDS), minimum dataset-linear (IQIwL_MDS), and minimum dataset-nonlinear (IQIwNL_MDS). Among 11 physical and chemical properties, principal component analysis (PCA) identified sand, electrical conductivity (EC), pH, soil organic carbon (SOC), calcium carbonate equivalent (CCE), and nickel (Ni) as the MDS. IQIwL_MDS yielded the highest SQI, while IQIwNL_MDS produced the lowest. The nonlinear model (R^2 = 0.89) showed a stronger correlation between MDS and TDS than the linear model (R^2 = 0.76), underscoring the nonlinear model's predictive accuracy. Global Moran's I revealed a clustered spatial pattern, while Getis-Ord Gi* identified low-quality hotspots in the southern and southeastern regions, predominantly in barren lands. This study presents an innovative framework by integrating MDS selection and spatial analysis, offering a robust methodology for soil quality assessment in semi-arid regions. The findings provide valuable insights for sustainable soil management and conservation strategies in vulnerable landscapes.

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1. Introduction

In recent years, sustainable utilization of natural resources and establishing a balance between production levels and improving the quality of these resources have gained significant attention (Zhang *et al*., 2023). In this context, soil, as a critical component of ecosystem sustainability, plays a vital role, and its study is essential for achieving sustainable development and optimal utilization of natural resources. Among various approaches, soil quality has been recognized as a key method to assess soil status (Khormali *et al*., 2009; Ayoubi *et al*., 2014; Azizsoltani *et al*., 2019; Hemmati *et al*., 2019; Jian *et al*., 2020; Guillot *et al*., 2021).Soil quality is broadly defined as the capacity of soil to function within ecosystem boundaries and land uses, ensuring biological productivity, maintaining environmental quality, and promoting the health of plants and animals (Doran & Parkin, 1994; Muñoz-Rojas, 2018; Bhaduri *et al*., 2022; do Nascimento *et al*., 2023). Soil quality can be evaluated for agricultural ecosystems, where the primary service is productivity, and for natural ecosystems, where the primary objectives are maintaining environmental quality and preserving biodiversity (Bünemann *et al*., 2018; Orlandi *et al*., 2023; Maghami Moghim *et al*., 2024). The simultaneous use of remote sensing technology and GIS is a cost-effective and time-efficient method for data collection, which enhances the accuracy and reliability of results. This approach leads to effective monitoring, mapping, and identification of various soil characteristics, as well as the study of soil quality in arid and semi-arid regions (Alavipanah *et al*., 2016). Accordingly, in these regions, the Earth's surface temperature is also influenced by various environmental variables, including surface biophysical characteristics, topographic parameters, solar radiation, air temperature, wind intensity, soil moisture, as well as soil type and quality (Alavipanah *et al*., 2017). The assessment of soil quality provides comprehensive information to study soil conditions in response to management practices, to recommend appropriate management strategies for current land conditions, and to evaluate the future productive capacity of lands (Aziz *et al*., 2011). Moreover, it serves as a flexible approach for examining soil conditions under different management systems and estimating soil resilience against stresses caused by natural and human factors (Dhose *et al*., 2014; Maghami Moghim *et al*., 2024).

One of the key components in assessing soil quality is the soil quality index (SQI) (Bünemann *et al*., 2018), which refers to measurable soil properties that influence the soil's capacity to produce crops or perform environmental functions (Arshad *et al*., 2002; Bashtian *et al*., 2024). During the International Conference on Soil Quality Assessment and Monitoring, three fundamental components of the SQI were defined: (1) The soil’s ability to enhance crop production (productivity component); (2) The soil’s capacity to mitigate environmental pollutants, pathogens, and off-site damages (environmental component); and (3) The relationship between soil quality and the health of plants, animals, and humans (health component) (Arshad *et al*., 2002).

In studies aimed at assessing soil quality, numerous researchers have proposed a set of criteria for evaluating soil quality and have assessed it based on the total data set (TDS) method (Mahajan *et al*., 2020; Saygın *et al*., 2023; Perović *et al*., 2025). However, since measuring all soil properties for quality assessment is not cost-effective, and on the other hand, when a large number of variables are measured, certain scientific issues arise, and the number of relationships will also be far greater than expected (Yemefack *et al*., 2006). Therefore, alternative methods for selecting criteria, such as the minimum data set (MDS), can be used based on expert opinion or through mathematical or statistical methods like principal component analysis (PCA). The selection of this method can be effective in interpreting dynamic soil quality and subsequently in sustainable land management with minimal cost and time (Andrews *et al*., 2002; Bashtian, 2024; Maghami Moghim *et al*., 2024).

The most commonly used indices by researchers worldwide for assessing soil quality include the simple additive integrated quality index (IQI_s), the IQIw, and the Nemero quality index (NQI) (Zhang *et al*., 2022; Maghami Moghim *et al*., 2024). In the evaluation of soil quality in the eastern region of Tehran, two parameters, namely organic carbon (OC) and soluble sodium, were selected and reported as the MDS. It was reported that the SQI significantly differs across agricultural users, parks, urban green spaces, and barren lands, with the lowest soil quality found in barren lands (Nosrati & Majdi., 2018). Santos-Francés *et al*. (2019) compared the IQI and NQI indices using soil properties from both the TDS and MDS in agricultural lands in Spain. Their findings demonstrated that the IQI index provides a more accurate estimation of soil quality than the NQI index, with the IQI_{MDS} method offering a reliable assessment. Samie *et al*. (2022) determined the SQI (IQI) based on the MDS and both linear and non-linear scoring methods in the Si Dasht region of Gilan province. The results indicated that the SQI calculated using the non-linear scoring method better distinguishes the differences in soil quality classes among various land uses compared to the linear scoring method.

In environmental studies, spatial data are often interdependent due to their geographic arrangement, rendering conventional statistical methods unsuitable for analysis. Instead, spatial statistics, such as Global Moran’s I index and hot spot analysis, are widely employed for analyzing land surface temperature (Das & Angadi., 2020; Kowe *et al*., 2021), heavy metal distribution in soil (Chen *et al*., 2022; Liu *et al*., 2018), and soil properties (Pusch *et al*., 2021). In the context of soil quality assessment, spatial analysis provides valuable insights for identifying critical areas and optimizing management strategies. Integrating this approach with the MDS framework improves efficiency by selecting key soil indicators while accounting for spatial variability, leading to a more precise and resource-efficient evaluation.

The objective of the present study was to determine the most influential factors affecting soil quality in the Mashhad Plain and to investigate the spatial autocorrelation of soil quality data using the MDS approach and spatial analysis approach. The Mashhad Plain, particularly its southern regions, is considered a significant and primary area for agricultural production, with the economic livelihood of many people in this region depending on it. Over the past few decades, the cultivated area and yield (production per unit area) of these crops have increased significantly without considering management strategies to preserve and maintain soil health. This situation has created challenges for the sustainable development of the region. Therefore, the formulation of land management strategies and the development of digital soil quality maps for monitoring and optimizing land use in this plain are of great importance. Generally, this research introduces an integrated approach that combines MDS selection with spatial analysis techniques to assess soil quality in a semi-arid region. Unlike previous studies that primarily focus on either MDS selection or spatial analysis, this study bridges the gap between these methodologies by incorporating both PCA for indicator selection and spatial statistics for pattern detection. Additionally, the use of Getis-Ord Gi* alongside Moran’s I index provides a comprehensive spatial characterization of soil quality, which has not been extensively explored in similar studies.

Thus, this study was conducted with the following main objectives: (i) to use PCA and determine the contribution of each feature from factor analysis in two data sets: maximum and minimum data set for quantitative soil quality assessment, (ii) to calculate the Global Moran's I index for the soil quality indicator (IQIw) data and determine the spatial autocorrelation of soil quality, (iii) to identify and determine the boundaries and precise number of different soil quality classes and investigate their significance at the 90%, 95%, and 99% confidence levels using the Getis-Ord Gi* statistic and Z-Score values along with Kriging interpolation method in semi-arid regions.

2. Materials and Methods

2.1. Study Area

Mashhad Plain is a broad and relatively large valley situated between the Kopet-Dagh zone in the north and the Binalood zone in the south. The city of Mashhad is located in the southern part of the plain, at the foothills of the Binalood Mountains. The study area is located between the Binalood and Kopet-Dagh mountain ranges, extending from southern Mashhad to the city of Chenaran. It covers an approximate area of 1500 square kilometers and is situated between the latitudes 36°02' to 36°48' N and longitudes 59°06' to 59°58' E (Figure 1). The average annual precipitation in the Mashhad Plain is approximately 260 mm, with most rainfall occurring during the late autumn and winter months (November to March). The average annual temperature of this region is 13.7°C (IRIMO, 2017). Most of the soils in this region have naturally formed under the influence of various landforms, which differ in terms of elevation, topography, drainage, and soil types.

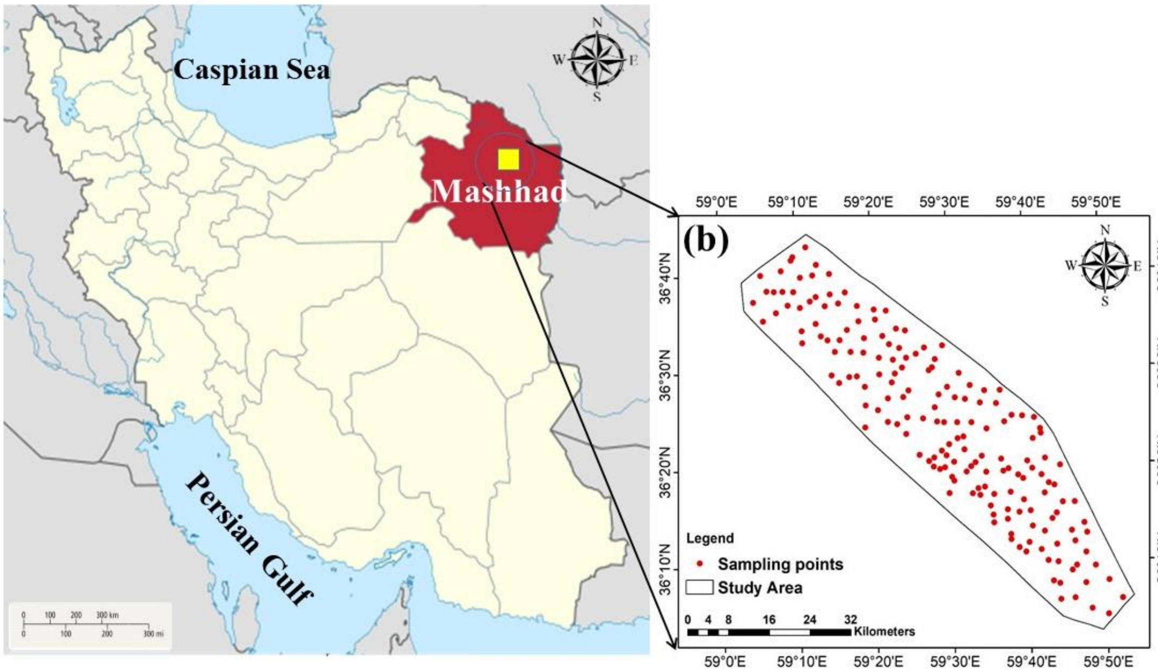

Fig 1. Location of the study area in Iran and the position of 180 sampling points within the study area

2.2. Research Methodology

The flowchart, general methodology, and steps of this study are shown in Figure 2. Each of these steps is described in detail in the following sections.

2.3. Soil Sampling in the Study Area

In this research, conducted in June 2019, a total of 180 surface soil samples (0-10 cm) were taken in grid cells of 3×3 km. In each grid, one composite sample was taken. To achieve this, five sub-samples were collected from each location, one from the center and four from the corners of a square with 50-meter sides.

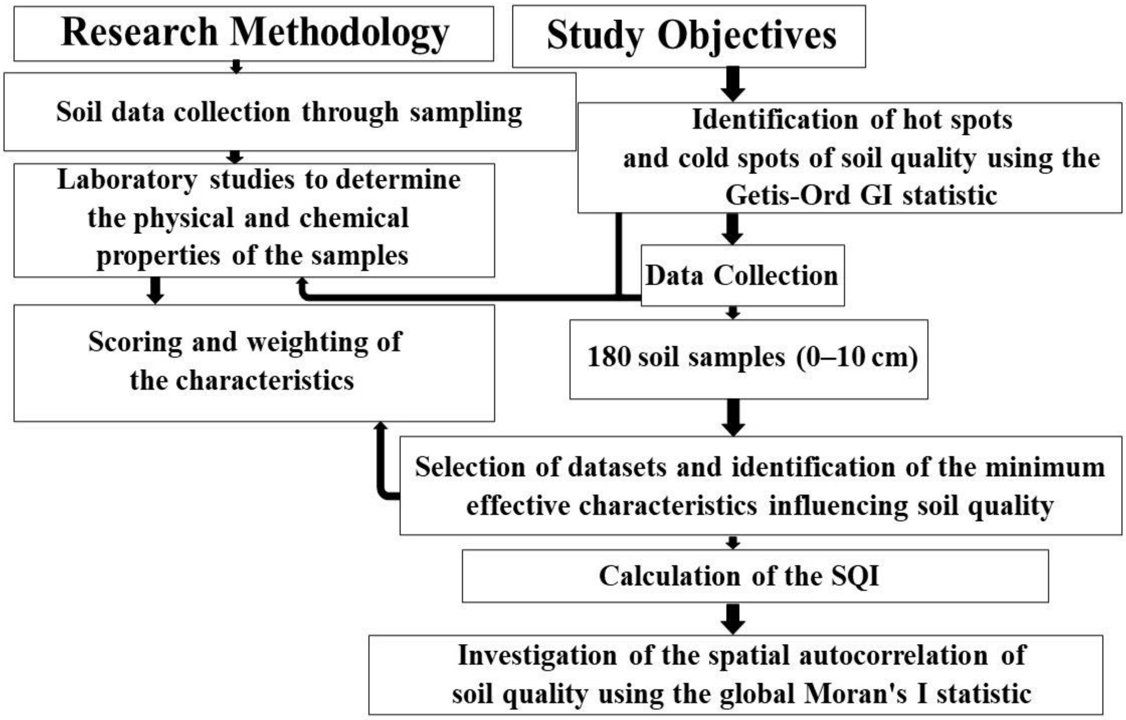

Fig 2. Flowchart illustrating the process of this research

2.4. Laboratory Studies

The soil samples were air-dried, passed through a 2-mm sieve, and subjected to physical and chemical analyses. Soil texture determined by the pipette method (Gee & Bauder,1986), Electrical conductivity (EC) and pH measured in a water–soil suspension (2:1) (Thomas, 1996), soil organic carbon (SOC) determined by the Walkley-Black method (Nelson & Sommers, 1982) calcium carbonate equivalent (CCE) measured by acid neutralization (Page *et al*., 1982), Gypsum was measured using the acetone method (USDA Soil Survey Staff, 1972). It is important to note that, given the agricultural land use in the study area, the application of various pesticides and fertilizers, as well as irrigation with wastewater-contaminated water, may lead to long-term soil contamination with heavy metals. Therefore, in this study, the total concentrations of lead (Pb), nickel (Ni), and zinc (Zn) were extracted using the aqua regia method (ISO/CD 11466, 1995) and measured by atomic absorption spectrometry (Shimadzu, AA-7000).

2.5. Soil quality calculation

2.5.1. Selection of Datasets

In this study, the weighted additive integrated SQI (IQIw) was used to evaluate soil quality. To calculate this index, it was first necessary to determine the datasets. In this step, all measured soil properties were considered as the TDS, while the second dataset included the most important properties influencing soil quality, referred to as the MDS (Qi *et al*., 2009). In this study, PCA was employed as an objective statistical method to identify the most influential soil quality indicators and reduce data dimensionality while preserving the most critical information. The PCA-based variable selection process was designed to identify an effective, stable, and representative set of indicators for soil quality assessment. The variable selection process followed a rigorous multi-step approach, ensuring that the MDS retained the most representative indicators of soil quality. Based on, to derive the MDS, the PCA method was employed (Doran & Parkin, 1994). After performing PCA, only those components with eigenvalues greater than 1 are retained to ensure that each component contributes significantly to explaining the total variance of the data. Subsequently, within each selected principal component, variables with factor loadings greater than 0.8 (in absolute value) are considered for inclusion in the MDS. This threshold ensures that only the most influential variables are selected, thereby preserving the maximum explanatory power of the reduced dataset. After analyzing the impact of each variable within the selected components, the key indicators for the MDS are chosen.

The data were categorized into several principal components (PCs) using SPSS software (version 26), and only those components with eigenvalues greater than one were selected (D'Hose *et al*., 2014). Within each component, properties with less than a 10% difference from the highest weight value for each property were chosen for the MDS.

2.5.2. Variable Scoring, Weighting, and SQI Calculation

Since the examined soil properties had different measurement units, standardization was necessary to integrate them into a comprehensive SQI. In this study, the selected variables were scored using standard scoring functions (SSF), which included both linear and nonlinear transformations.

2.5.3. Linear Scoring Method

In the linear method, soil properties were categorized into three groups:

(a) More is better: Applied to soil properties where an increase enhances soil quality (e.g., organic matter (OM), available nutrients).

(b) Less is better: Used for properties where an increase degrades soil quality (e.g., salinity, heavy metal content).

(c) Optimal range: Applied to properties where both excessive increase and decrease negatively affect soil quality, meaning there is an optimal threshold for maintaining soil health (e.g., soil pH) (Andrews *et al*., 2002).

Scoring for the "More is better" function was calculated using equation 1, while the "Less is better" function followed equation 2 (Askari & Holden, 2015).

$$S_L = \frac{x - \iota}{h - \iota} \tag{1}$$

$$S_L = 1 - (\frac{x - \iota}{h - \iota}) \tag{2}$$

where S_L score is a linear function with values ranging between zero and one, x represents the measured value of the soil property, ι is the minimum value, and h is the maximum value of the soil property.

For the optimal scoring function, an optimal range was defined for each soil property. Then, using "more is better" and "less is better" functions, the scoring of the properties was performed based on whether the measured value of the property was lower or higher than the optimal range. If the measured value of a soil property was equal to the optimal range, its score was considered as one (Qi *et al*., 2009).

2.5.4. Nonlinear Scoring Method

For the nonlinear scoring of the properties, a sigmoid function was used according to equation 3 (Askari & Holden, 2015), allowing for a more flexible representation of soil quality variations.

The S_{NL} score represents the nonlinear score for each soil property, ranging between zero and one, and is defined as follows:

$$S_{NL} = \frac{a}{(1+(\frac{x}{x_0})^b)} \quad (3)$$

where S_{NL} is a nonlinear score of the soil property, a represents the maximum score (set to 1 in this study), x is the measured value of the soil property, x_0 is the mean value of the soil property, and b is the slope parameter, set to -2.5 for the "More is better" function and +2.5 for the "Less is better" function.

In the next step, the weights of the variables were calculated through PCA and factor analysis (FA). In the PCA method, the weight of each variable is equal to the percentage of variance explained by each component. The weight values for the completely independent variables were assigned, and for the correlated variables, the weights were divided, ensuring that the total sum of the weights was standardized to one (Rahmanipour *et al*., 2014).

In the FA weighting method, the weight of each variable was calculated as the proportion of its contribution relative to the total contribution of all variables within each dataset. The weighting was performed for both TDS and the MDS. Finally, the IQI index was determined for both datasets using equation 4.

$$IQI = \sum_{i=1}^{n}(W_i \times S_i) \quad (4)$$

where IQI is a SQI, W_i represents the weight of the index, S_i is the linear score of the index, and n number of indices forming MDS and TDS.

2.6. Classification Method for Soil Quality Classes

The classification of soil quality classes in this study was based on the Integrated Quality Index (IQI) model, utilizing both TDS and MDS approaches. The classification was performed separately for linear and nonlinear scoring methods.

2.6.1. Classification Criteria

The classification was structured into five soil quality classes (I to V) based on the IQI values. Each class was defined using specific threshold values, with higher values indicating better soil quality. (1) Class I: Represents the highest soil quality; (2) Class II: Moderate to good soil quality; (3) Class III: Intermediate soil quality; (4) Class IV: Low soil quality; (5) Class V: Represents the poorest soil quality.

2.6.2. Classification Approach

The classification thresholds were defined based on statistical distribution of IQI values from both TDS and MDS datasets.

The higher thresholds in the MDS classification compared to the TDS indicate that the minimum dataset approach focuses on the most influential soil quality parameters, leading to a refined classification system.

The nonlinear scoring method accounts for more complex relationships between soil properties and their impact on soil quality, offering a more realistic and detailed classification compared to the linear method.

2.6.3. Significance of Classification

The classification system ensures a standardized assessment of soil quality across different locations.

It helps identify areas with poor soil quality (Classes IV and V) that require immediate attention for sustainable land management and soil conservation.

The use of both TDS and MDS approaches allows for comparison, demonstrating that the MDS approach can provide similar classification results with fewer soil properties, reducing analysis costs and time.

This methodology provides a scientific and systematic approach to assessing soil quality, supporting better land management and agricultural decision-making in semi-arid environments.

2.7. The Global Moran's I index

Global Moran’s I index examines spatial autocorrelation based on the spatial distribution of two values, analyzing the characteristic of the geographic phenomenon at that location. To calculate the Moran’s I statistic, the standardized Z score and p-value are first computed. In the next step, the significance of the statistic is evaluated. If the value of the global Moran's I index is greater than zero, the data show some form of spatial clustering. Conversely, if the value of the global Moran’s I index is less than zero, the studied phenomenon exhibits a dispersed pattern. In the context of global Moran’s I index, the null hypothesis states that there is no spatial clustering between the attribute values associated with the geographical features being studied. If the p-value is very small and the Z score is very large, the null hypothesis is rejected. The global Moran’s I index for soil quality data is calculated using the equation (5) (Getis & Ord *et al.*, 1992).

$$I = \frac{n}{S_0} \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} W_{i,j} Z_i Z_j}{\sum_{i=1}^{n} Z_i^2} \tag{5}$$

In this equation, Z_i represents the difference between the attribute value of feature i and its mean of $(x_i - \bar{x})$, W_{ij} is the spatial weight between features *i* and *j*, and *n* denotes the total number of geographic features in the layer being used are considered in this context. Additionally, S_0 represents the sum of all spatial weights, and Z_i is the standardized score, both of which are computed using equations (6) and (7), respectively.

$$S_0 = \sum_{i=1}^{n}\sum_{j=1}^{n} W_{i,j} \tag{6}$$

$$Z_i = \frac{I - E[I]}{\sqrt{V[I]}} ., E_I = -\frac{1}{n-1} ., V[I] = E[I]^2 - E[I]^2 \tag{7}$$

2.8. Identification of Hot Spot

After identifying the spatial pattern governing the soil quality data, the Getis-Ord Gi* statistic was applied using ArcMap 10.8.2 to detect hot spots and cold spots. This statistic examines each feature within the context of its neighboring features. A feature with high values may be important, but it does not necessarily constitute a statistically significant hot spot. For a feature to be considered a hot spot with statistical significance, both the feature itself and its neighboring features must have high values. In this analysis, the local sum of a feature and its neighbors is compared relatively to the overall sum of all features. The final Z-score output is obtained when the local sum is significantly higher than the expected local sum, to an extent that it cannot be attributed to random chance. A positive and statistically significant Z-score indicates that the higher values are highly clustered, forming a hot spot. The larger the Z-score, the stronger the clustering of high values. A negative and statistically significant Z-score indicates that lower values are highly clustered, forming a cold spot. The smaller the Z-score, the more intense the clustering of low values (Table 1). The Getis-Ord Gi* statistic was calculated using equation 8 (Das & Angadi., 2020).

Table 1. The Values of Z-score and P-value for Different Confidence Levels

Confidence level	Significance level (P-value)	Z-score
% 90	< 0.10	< -1.65 or > 1.65
% 95	< 0.05	< -1.96 or > 1.96
% 99	< 0.01	< -2.58 or > 2.58

After performing the hot spot analysis, interpolated maps were generated based on Z-score values using the kriging method. These maps were then classified according to the values presented in Table 1.

$$G_i^* = \frac{\sum_{i=1}^{n} W_{i.j} X_j - \bar{X} \sum_{j=1}^{n} W_{i.j}}{S_x \sqrt{\frac{\left[n \sum_{j=1}^{n} W_{i.j}{}^2 - \left(\sum_{j=1}^{n} W_{i.j} \right)^2 \right]}{n = 1}}} \tag{8}$$

In this equation:

X_j represents the attribute value of feature j, W_{ij} is the spatial weight between features i and j, n denotes the total number of features, S is a parameter that can be calculated using equation 9.

$$S = \sqrt{\frac{\sum_{j=1}^{n} X_j{}^2}{n}} - (\bar{X})^2., \bar{X} = \frac{\sum_{j=1}^{n} X_j}{n} \tag{9}$$

3. Results

The descriptive statistics of the physical and chemical properties of the studied soils are presented in Table 2. Based on the average sand (35.64%), silt (46.55%), and clay (17.81%) contents, most of the soil samples were classified as loam. EC in the study area varied from 0.12 to 3.03 dS/m, with an average of 0.76 dS/m, increasing from the upper to the lower parts of the Mashhad Plain (Mousavi *et al*., 2023). The soil pH in the study area ranged from 7.05 to 8.80, with an average of 7.84. The soil in the study area was categorized as normal based on its pH (ranging from 7.05 to 8.80) and EC (0.12–3.03 dS/m) (Scherer *et al*., 1996). The mean SOC content was 0.86%, indicating relatively low organic matter content. Additionally, the average CCE content was 19.15%. The average gypsum content in the studied soils was 6.99%, with maximum and minimum values of 31.41% and 0%, respectively. The presence of gypsum in soils of arid regions and sedimentary materials is expected and influences the geochemical characteristics of the soil. In dry environments, gypsum enters the soil through weathering processes and dust deposition, then moves within the soil through pedogenic processes. Among the studied variables, pH exhibited the lowest coefficient of variation (CV) at 3.47%, indicating minimal variability, while Ni had the highest coefficient of variation at 69.53%, reflecting significant spatial variability in soil across the region. Generally, the high CV values for EC, Ni, and gypsum in this study result from the interaction between natural soil formation processes and anthropogenic influences.

While EC fluctuations are largely driven by irrigation and salt accumulation, Ni variability arises from both geological sources and industrial contamination. Gypsum distribution reflects geological heterogeneity but is also affected by agricultural practices. Based on, irrigation can alter gypsum distribution by dissolving and reprecipitating it over time, while land-use changes, such as converting natural areas into agricultural fields, also impact its content through soil disturbance and mixing. Also, irrigation with saline water, excessive groundwater extraction, chemical fertilizer application, and industrial wastewater discharge further exacerbate salinity fluctuations, leading to high CV values. In addition, the presence of Ni in soil is largely controlled by the geological composition of parent rocks, with ultramafic and sedimentary formations naturally containing high Ni levels. Moreover, due to their proximity to metal-processing industries and vehicular emissions, exhibit higher Ni concentrations, and ultimately leads to high CV values and the creation of pollution hotspots.

The average concentrations of heavy metals lead (Pb), nickel (Ni), and zinc (Zn) were 31.62, 61.42, and 74.10 mg/kg, respectively (Table 2). According to the study results (Karimi *et al*., 2017), the spatial distribution maps of Pb and Zn were largely similar, with the highest concentrations observed in the urban areas of Mashhad and Chenaran. The concentrations of these elements decreased with distance from the centers of these cities towards the suburban areas.

The spatial distribution of Ni indicated that the highest concentration of Ni was found in soils derived from ultramafic rocks, while the lowest concentration was observed in areas where the sediments originated from marl and loess, respectively. This distribution pattern suggests the release of Ni from ultramafic rocks and its dispersion across the study area (Karimi *et al*., 2017).

Table 2. Statistical Properties of the Studied Soil Characteristics

CV (%)	Kurtosis	Skewness	Standard deviation	75% quartile	Median	25% quartile	Mean	Max	Min	Parameters
42.30	0.20	0.40	15.09	46.55	34.40	23.58	35.64	90.30	5.60	Sand (%)
23.60	0.20	-0.60	10.99	54.53	47.70	38.95	46.55	65.70	8.60	Silt (%)
35.80	0.60	0.70	6.37	20.93	16.90	13.48	17.81	37.60	1.10	Clay (%)
66.93	1.56	1.31	0.51	0.98	0.58	0.39	0.76	3.03	0.12	EC (dSm^{-1})
3.47	0.80	0.13	0.27	8.04	7.82	7.67	7.84	8.80	7.05	pH
64.06	0.98	0.99	0.55	1.12	0.73	0.53	0.86	2.85	0.00	SOC (%)
56.14	-0.38	0.34	10.75	27.25	17.88	12.06	19.15	49.25	0.50	CCE (%)
56.48	8.97	1.71	3.94	7.85	7.85	4.71	6.99	31.41	0.00	Gypsum (%)
21.89	5.68	1.80	6.92	33.77	30.18	27.62	31.62	69.12	19.62	Pb (mg kg^{-1})
69.53	40.63	5.98	42.71	59.10	52.13	48.70	61.42	415.75	33.27	Ni (mg kg^{-1})
24.87	1.84	0.85	18.43	82.37	73.12	61.38	74.10	149.00	35.42	Zn (mg kg^{-1})

Min: minimum; Max: maximum.

3.1. Soil Quality Indicators

The selected indicators in the MDS for surface soil was assigned dimensionless scores ranging from 0 to 1 using the linear scoring method (Liebig *et al*., 2001). The type of other indicators is also presented in Table 3.

These indicators were classified into three categories based on their impact on soil quality: “More is better” (M), “Less is better” (L), and “Optimal range” (OL/OM). The classification ensures that each parameter is evaluated based on its contribution to soil functionality and productivity.

3.1.1. Soil Texture Components (Sand, Silt, and Clay)

The sand fraction significantly influences soil aeration, drainage, and root penetration. However, excessive sand content can reduce water-holding capacity, negatively impacting soil fertility. Given the wide range observed in the study area, some locations may exhibit sandy soils with lower water retention, while others may contain finer-textured soils. The optimal range scoring was applied, ensuring a balanced assessment of its role in soil quality.

Silt plays a crucial role in improving soil structure and nutrient retention. The recorded values indicate moderate variability across the study area. Since a higher silt percentage generally enhances soil fertility, this indicator was classified under the “More is better” (M) category.

Clay is essential for nutrient and moisture retention; however, excessive clay content can lead to poor drainage and compaction issues. The “Optimal range” (OM) scoring method was applied, ensuring that both excessively low and high values are appropriately weighted.

3.1.2. Soil Chemical Properties

EC is a critical indicator of soil salinity, influencing plant growth and microbial activity. Higher EC levels can lead to salinity stress, reducing agricultural productivity. Given its negative effects at higher concentrations, EC was classified under the “Less is better” (L) category.

The pH values in the study area indicate that most soils are slightly alkaline. While moderate alkalinity is suitable for plant growth, extreme pH values can affect nutrient availability. The optimal range scoring method was applied, considering its balanced influence on soil health. SOC is a key indicator of soil fertility, influencing nutrient cycling and microbial activity. The relatively low mean value suggests that soil organic matter (SOM) content is limited in the study area, potentially due to intensive land use or low biomass input. Since higher SOC levels generally improve soil health, it was categorized under the “More is better” (M) classification.

3.1.3. Soil Mineral and Heavy Metal Content

CCE reflects soil buffering capacity and affects nutrient availability. Excessive calcium carbonate may lead to nutrient deficiencies, particularly in phosphorus and micronutrients. Given its impact, CCE was classified under the “Less is better” (L) category.

Gypsum influences soil structure and drainage. Although moderate gypsum levels can improve soil permeability, excessive amounts may lead to soil degradation. Therefore, it was scored using the optimal range approach.

3.1.4. Heavy Metal Contamination

Lead accumulation in soil, particularly from industrial and agricultural sources, poses risks to both plant and human health. Given its toxic effects, Pb was classified under the “Less is better” (L) category.

Nickel concentrations varied widely, with some areas exhibiting significantly elevated levels, potentially due to lithogenic sources or anthropogenic pollution. Similar to Pb, Ni was categorized as “Less is better” (L) due to its potential toxicity.

Zinc is an essential micronutrient, but excessive levels can be harmful to plants. Since higher Zn concentrations can lead to toxicity, it was classified under the “Less is better” (L) category.

Generally, table 3 highlights the spatial and statistical variability of key soil properties, emphasizing the need for targeted soil management strategies. The classification of parameters into “More is better,” “Less is better,” and “Optimal range” categories allows for a refined assessment of soil quality. Notably, heavy metal contamination (Pb and Ni) and soil salinity

(EC) require closer monitoring due to their potential adverse effects on agricultural productivity. Meanwhile, efforts to enhance SOC levels could improve overall soil health and fertility. By integrating these indicators into soil quality assessment models, we can better understand spatial variability and implement site-specific management practices to ensure sustainable land use in the study area.

Table 3. Descriptive Statistics of the Indicators and the Corresponding Standard Scoring Function Types

Indicators	Min	Max	Mean ± Std	Type	Description of Type
Sand (%)	5.60	90.30	35.645 ± 15.09	OL	Optimal range (Less is better)
Silt (%)	8.60	65.70	46.539 ± 10.99	M	More is better
Clay (%)	1.10	37.60	17.816 ± 6.37	OM	Optimal range (More is better)
EC (dSm^{-1})	0.12	3.03	0.76 ± 0.51	L	Less is better
pH	7.05	8.80	7.84 ± 0.27	OL	Optimal range (Less is better)
SOC (%)	0.00	2.85	0.86 ± 0.55	M	More is better
CCE (%)	0.50	49.25	19.15 ± 10.75	L	Less is better
Gypsum (%)	0.00	31.41	6.99 ± 3.94	OL	Optimal range (Less is better)
Pb (mg kg^{-1})	19.62	69.12	31.62 ± 6.92	L	Less is better
Ni (mg kg^{-1})	33.27	415.75	61.42 ± 42.71	L	Less is better
Zn (mg kg^{-1})	35.42	149.00	74.10 ± 18.43	L	Less is better

Min: minimum; Max: maximum; Std: standard deviation.

4. Discussion

The PCA results revealed six PCs with eigenvalues greater than 1.0, explaining 83.19% of the total variability (Table 4). Indicators with a factor loading greater than 0.8 were considered strongly correlated and selected for the MDS, including Sand, Silt, SOC, Zn, EC, pH, Clay, CCE, Ni, Gypsum, and Pb. PC1 accounted for 27.93% of the total variance, with significant loadings on Sand and Silt content. This component has strong negative loadings on sand (-0.911) and positive loadings on silt (0.847), indicating that soil texture is a dominant factor influencing soil quality. The inverse relationship between sand and silt suggests that areas with higher sand content may experience reduced soil fertility due to lower water and nutrient retention. PC2 explained 20.22% of the variance, showing strong loadings for SOC content and Zn. This component is primarily influenced by SOC (0.841) and zinc (Zn) (0.702). SOC is a key determinant of soil fertility and biological activity, while Zn is an essential micronutrient for plant growth. The strong association suggests that organic matter content significantly affects micronutrient availability in the soil. EC and pH had significant loadings in PC3, which explained 10.84% of the variability. The dominant variables in this component are EC (-0.827) and pH (0.883). The high positive loading for pH indicates its substantial impact on soil chemistry, while the negative loading for EC highlights the role of salinity in influencing soil quality. The presence of these variables in the same component suggests that salinity and alkalinity variations are interrelated in the study area. PC4, which explained 8.93% of the total variability, showed high loadings for clay and CCE content. This component is primarily associated with clay (-0.847) and CCE (0.891). The inverse relationship between clay and CCE suggests that soils with high carbonate content may have lower clay fractions, which could affect soil structure and nutrient retention. The Ni contributed to PC5, accounting for 8.34% of the variability. This component is mainly influenced by Ni (-0.824), indicating that Ni concentrations significantly contribute to soil quality variability. The presence of Ni in a distinct principal component suggests potential lithogenic or anthropogenic sources of contamination. Lastly, PC6 explained 6.92% of the variability and had the highest factor loading for Pb (Table 4). This component is dominated by Pb (-0.804), highlighting its independent influence on soil quality. Pb is a heavy metal pollutant, and its strong loading suggests spatial variability, likely influenced by human activities such as industrial emissions and agricultural practices. The PCA results indicate that soil texture (sand and silt), salinity (EC), fertility indicators (SOC, pH, and CCE), and heavy metal contamination (Ni and Pb) are the primary factors influencing soil quality in the study area. The high cumulative variance explained by the first few components (PC1–PC3) suggests that soil texture, organic matter, and salinity management should be prioritized in soil quality assessment and land management strategies.

Table 4. Results of Principal Component Analysis (PCA)

Indicators	PC1	PC2	PC3	PC4	PC5	PC6
Sand (%)	**-0.911**	-0.278	-0.018	0.195	0.202	-0.044
Silt (%)	**0.847**	0.167	-0.094	-0.182	-0.201	0.011
Clay (%)	0.695	0.371	0.206	**-0.847**	-0.131	0.086
EC (dSm^{-1})	0.195	0.274	**-0.827**	0.177	0.019	0.160
pH	0.218	-0.536	**0.883**	-0.251	-0.050	-0.034
SOC (%)	0.108	**0.841**	0.090	0.398	0.063	0.013
CCE (%)	0.636	-0.084	0.212	**0.891**	0.180	-0.462
Gypsum (%)	0.400	-0.285	0.276	0.320	0.402	0.533
Pb (mg kg^{-1})	-0.255	0.698	0.307	-0.047	0.308	**-0.804**
Ni (mg kg^{-1})	-0.351	0.046	0.281	0.463	**-0.824**	0.130
Zn (mg kg^{-1})	-0.438	0.702	0.277	-0.278	0.011	0.229
Eigenvalue	6.480	3.850	2.630	1.550	1.430	1.220
Percentage of Variance	27.930	20.220	10.840	8.930	8.340	6.920
Cumulative Percentage of Variance	27.930	44.150	59.000	67.930	76.270	83.190

*Bolded values represent the highest factor loadings (>0.8) in each PC, which were identified as the most significant factors for selecting the MDS

The identification of a MDS based on PCA allows for an efficient and cost-effective approach to soil quality assessment, reducing the need for extensive soil sampling while maintaining accuracy in evaluating soil health. This approach provides valuable insights for sustainable soil management and helps prioritize areas requiring intervention to mitigate soil degradation and contamination.

Finally, six key indicators—Sand, EC, pH, SOC, CCE, and Ni were selected as the MDS variables for soil quality assessment.

In the assessment of the SQI in Nazarabad, located in the west of Alborz Province, the MDS was determined to include sand content, available phosphorus, bulk density (BD), porosity, SAR, and CCE (Mirkhani *et al*., 2020). Similarly, in the evaluation of soil quality in Neyshabur Plain, five key indicators—EC, OM, available phosphorus, available potassium (K), and total nitrogen—were identified as the most influential factors affecting soil quality (Maghami Moghim *et al*., 2022).

In a study, silt percentage, soil pH, CEC, OM, and available phosphorus were determined as the minimum set of parameters for assessing soil quality indicators in different land types within agricultural ecosystems in a region of Ethiopia (Mesfin *et al*., 2022). In another study, SOC, available potassium (K), Zn, magnesium (Mg), total potassium, and clay content were identified as the minimum factors affecting soil quality in a region of China (Liu *et al*., 2022). Therefore, in regions with varying climatic and management conditions, the minimum set of data may differ.

The contribution values of each feature derived from factor analysis in the TDS and MDS sets are presented in Table 5. These values highlight the relative importance of each indicator in assessing soil quality and forming the MDS for an efficient soil quality evaluation approach. Communality represents the proportion of variance in each variable that is explained by the extracted principal components. Higher communality values indicate that a variable is well-represented within the PCA model. The communality values for the TDS and MDS are reported as follows:

4.1. Highest communalities in the TDS

Sand (0.908): Soil texture plays a critical role in determining water retention, nutrient availability, and soil structure.

Silt (0.755) and Clay (0.663): The textural composition of soil significantly influences its physical and chemical behavior.

Zn (0.762): Zinc, an essential micronutrient, contributes to soil fertility and plant health.

4.2. Lowest communalities in the TDS

Ni (0.204): The relatively low communality suggests that Ni variability may be influenced by factors outside the primary soil quality components.

Gypsum (0.317): Gypsum content has limited influence on overall soil quality variability in the study area.

4.3. Highest communalities in the MDS

CCE (0.762): CCE strongly influences soil buffering capacity and nutrient availability.

SOC (0.738): SOC is a key indicator of soil fertility and microbial activity.

EC (0.708) and pH (0.710): Salinity and pH regulate soil chemical properties and plant nutrient uptake.

These results confirm that sand, SOC, EC, CCE, and pH are the most influential indicators in both the TDS and MDS models.

The weighting coefficients reflect the relative contribution of each soil property to the overall SQI calculations. The weights were assigned based on PCA-derived factor analysis, ensuring that the most influential variables receive greater emphasis in the soil quality model.

4.4. Highest weights in the TDS

Sand (0.058), CCE (0.056), EC (0.051), SOC (0.047): These parameters have the greatest impact on soil quality assessment.

4.5. Lowest weights in the TDS

Gypsum (0.032): Given its minimal influence, it was excluded from the MDS.

4.6. Highest weights in the MDS

CCE (0.181), Ni (0.178), SOC (0.152), EC (0.130), pH (0.128): These variables exhibit the strongest influence on soil quality variation and are critical for land management decisions.

Table 5. Shared variance of the examined properties with the extracted factor along with the weighting coefficient

Indicators	TDS		MDS	
	communality	weight	communality	weight
Sand (%)	0.908	**0.058**	0.732	0.144
Silt (%)	0.755	0.035	-	-
Clay (%)	0.663	0.043	-	-
EC (dSm^{-1})	0.642	**0.051**	0.708	0.130
pH	0.568	0.035	0.710	0.128
SOC (%)	0.569	**0.047**	0.738	0.152
CCE (%)	0.456	**0.056**	0.762	**0.181**
Gypsum (%)	0.317	0.032	-	-
Pb ($mg\ kg^{-1}$)	0.647	0.038	-	-
Ni ($mg\ kg^{-1}$)	0.204	0.042	0.712	**0.178**
Zn ($mg\ kg^{-1}$)	0.762	0.035	-	-

The results confirm that sand, salinity (EC), pH, SOC, CCE, and heavy metal pollution (Ni) are the dominant factors influencing soil quality in the study area. The higher weights assigned to CCE and Ni in the MDS indicate their significant impact on soil quality, justifying their inclusion in the reduced dataset.

Generally, using the MDS instead of the full TDS dataset offers several advantages: 1. Reduces data collection and analysis costs while maintaining accuracy; 2. Enhances efficiency in soil monitoring programs by focusing on the most critical parameters; 3. Facilitates targeted land management strategies by prioritizing key soil health indicators. Overall, Table 5 provides a statistically robust justification for the selection of MDS variables, ensuring a cost-effective and scientifically reliable approach to soil quality assessment.

The degree of influence of each feature on soil quality models depends on the weight assigned to that feature. In other words, features with higher weights in the TDS and MDS sets have a greater impact on the soil quality model, and as their weight decreases, this influence diminishes (D'Hose *et al*., 2014). The results of calculating feature weights in the TDS set showed that the features of sand percentage, CCE, EC and SOC had higher weights, while Gypsum had the least impact on the soil quality of the studied area. In the MDS set, CCE and Ni also had higher weights (Table 5).

The classification of soil quality classes in the TDS and MDS sets is presented in Table 6, and the statistical parameters of the SQI using existing formulas for sampling points in both TDS and MDS sets are provided in Table 7. The classifications are provided for both the TDS and the MDS using linear and nonlinear scoring techniques. The results define five soil quality classes (I to V), ranging from the highest to the lowest soil quality. Based on, the classification thresholds for linear and nonlinear scoring methods are outlined separately for the TDS and MDS: Class I: Represents the highest soil quality, requiring an SQI above the specified percentage threshold; Class V: Represents the lowest soil quality, indicating severe degradation.

The results reveal that soil quality classes differ between the TDS and MDS, as well as between the linear and nonlinear scoring methods.

In the linear scoring approach, the SQI threshold for Class I in the MDS (≥80%) is higher than in the TDS (≥66%). This suggests that the MDS-based classification provides a more stringent evaluation of high-quality soils.

In the nonlinear scoring approach, the classification thresholds for high-quality soils are more similar, with Class I starting at 59% for MDS and 57% for TDS.

The MDS model assigns higher thresholds for each class compared to the TDS, reinforcing the effectiveness of the MDS approach in differentiating soil quality conditions with fewer indicators.

4.7. Linear Scoring

Assigns proportional weights to soil indicators without considering nonlinear responses.
Results in a wider distribution of soil quality scores, which may overestimate soil quality in some cases.

4.8. Nonlinear Scoring

Applies sigmoidal transformations, which better capture the actual impact of soil properties on quality.

Results in lower SQI values overall, as seen in the more conservative classification thresholds for Classes III–V.

Provides a better differentiation between soil quality levels, particularly for degraded soils.

The MDS-based classification maintains strong consistency with the TDS while offering a more efficient and cost-effective assessment.

The nonlinear approach provides a more precise differentiation of soil quality, especially in lower-quality classes.

The observed differences suggest that soil quality assessments should consider nonlinear relationships to enhance accuracy in decision-making.

The classification results can guide land management strategies, particularly in areas classified under Classes IV and V, where interventions such as organic matter restoration, salinity control, and heavy metal mitigation are necessary.

Generally, table 6 highlights the advantages of using an MDS-based approach for soil quality assessment, as it effectively distinguishes soil quality classes while reducing data complexity. The findings also emphasize the importance of nonlinear scoring methods in capturing soil quality variations more accurately. These results provide valuable insights for developing targeted soil conservation and management strategies to sustain agricultural productivity and environmental health.

The soil quality at the sampled points, based on the mean IQI_{TDS} and IQI_{MDS} in the linear state, was classified as grade II with values of 0.55 and grade II with values of 0.62, respectively. In the nonlinear state, based on the mean IQI_{TDS} and IQI_{MDS}, the soil quality was classified as grade II with values of 0.48 and 0.45, respectively. The highest SQI value (0.87) was obtained in the linear IQI_{MDS} state, while the lowest value (0.30) was observed in the nonlinear IQI_{MDS} state (Table 7).

Based on, table 7 presents the statistical parameters of the SQI calculated for both the TDS and the MDS using linear and nonlinear scoring methods. The table provides key statistical descriptors, including minimum, maximum, mean, standard deviation, variance, skewness, and kurtosis, allowing for a comprehensive evaluation of soil quality distribution across the study area.

The mean SQI values in the linear approach are 0.59 for TDS and 0.67 for MDS, indicating that the MDS model produces slightly higher SQI values compared to the full dataset. In the nonlinear approach, the mean values are 0.54 for TDS and 0.52 for MDS, showing that the nonlinear method assigns lower scores compared to the linear method, which aligns with its more conservative estimation of soil quality. The maximum SQI value is observed in the linear

MDS approach (0.87), while the lowest value is in the nonlinear MDS approach (0.30), reinforcing the notion that nonlinear scoring provides a more restrictive classification.

The standard deviation is higher in the nonlinear scoring method (0.094 for TDS, 0.097 for MDS) compared to the linear method (0.04 for TDS, 0.07 for MDS), indicating that nonlinear scoring results in greater variability in soil quality values.

Skewness values reveal that the distribution of SQI values is negatively skewed (-1.30 in linear TDS, -1.79 in nonlinear TDS), suggesting that most soils exhibit moderate to high quality, with fewer instances of severely degraded soils.

Kurtosis values indicate that the distribution of soil quality scores is relatively normal in MDS (-0.48 for linear, 0.47 for nonlinear), whereas the TDS shows more pronounced peaks (1.30 and 1.78 for linear and nonlinear, respectively). This suggests that the MDS-based approach provides a more balanced assessment of soil quality compared to the TDS, which exhibits a stronger clustering of values.

The higher mean SQI in MDS models supports the efficiency of the MDS approach, confirming that it can effectively replace the TDS with minimal loss of information.

The greater variability in nonlinear SQI values suggests that nonlinear scoring is better suited for differentiating soil quality classes, particularly in degraded areas where quality variations are more pronounced.

The negative skewness in both models indicates that a majority of the soils fall into moderate-to-good quality categories, with relatively fewer instances of severely degraded soil conditions.

The MDS approach provides similar statistical patterns to the TDS, reinforcing its validity as a cost-effective alternative for large-scale soil quality monitoring.

Generally, table 7 highlights the effectiveness of the MDS approach in capturing soil quality variations while reducing data collection efforts. The nonlinear scoring method demonstrates a more refined differentiation of soil quality, making it a preferred approach for assessing soil health in heterogeneous landscapes. The findings support the use of MDS-based nonlinear SQI models for accurate, cost-effective, and data-efficient soil quality assessment, ensuring improved decision-making in land management and conservation efforts.

The investigation of linear and nonlinear correlations between the SQI (IQI) and the TDS and MDS revealed that the nonlinear IQI index has a higher correlation coefficient compared to the linear IQI index (Figure 3). Given that this model assigns a weighting coefficient to each parameter, it provides greater accuracy in assessing the SQI (Page *et al*., 1982). The R^2 between the TDS and MDS sets was 0.76 in the linear state and 0.89 in the nonlinear state. These coefficients indicate that, with a confidence level of 0.76 in the linear state and 0.89 in the nonlinear state, the MDS set can be used as a substitute for the TDS set in the nonlinear state. In one study, the correlation coefficient R^2 between IQI_{TDS} and IQI_{MDS} was reported as 0.83 (Ghahramanpoor *et al*., 2019). Another study found a positive correlation ($R^2 = 0.87$) between the TDS and MDS methods (Shao *et al*., 2020). In yet another study, the R^2 between IQI_{MDS} and IQI was reported as 0.83, and it was concluded that a smaller number of carefully selected soil properties can adequately provide the necessary information for decision-making (Shakouri *et al*., 2021). Therefore, the use of the MDS set for studying soil quality is recommended, as this method utilizes fewer data, saves time, reduces costs in conducting studies, and yields results similar to those of the TDS method. In another study, the R^2 between the minimum and TDS was reported as 0.97. The results demonstrated that the MDS can be used instead of measuring all the properties, achieving the same results with a high level of confidence (Hematifard *et al*., 2019), which aligns with the findings of this study.

Table 6. Classification of Soil Quality Indices Based on the IQI Model in MDS and TDS Sets

Scoring	Method	Soil Quality Index (SQI)				
		I	II	III	IV	V
Linear	TDS	≥ 66%	0-57.66%	0-48.57%	0-39.48%	≤ 39%
	MDS	≥ 80%	0-68.80%	0-55.68%	0-42.55%	≤ 42%
Nonlinear	TDS	≥ 57%	0-50.57%	0-43.50%	0-36.43%	≤ 36%
	MDS	≥ 59%	0-49.59%	0-39.49%	0-29.39%	≤ 29%

Table 7. Statistical parameters of the calculated soil quality index (IQI) values in the TDS and MDS datasets

Parameters	IQI_{TDS}	IQI_{MDS}	IQI_{TDS}	IQI_{MDS}
	Linear		Non-linear	
Min	0.440	0.480	0.370	0.300
Max	0.710	0.870	0.510	0.620
Mean	0.590	0.670	0.540	0.520
Standard deviation	0.040	0.070	0.094	0.097
Variance	0.002	0.006	0.003	0.008
Skewness	-1.300	0.200	-1.790	-0.950
Kurtosis	1.300	-0.480	1.780	0.470

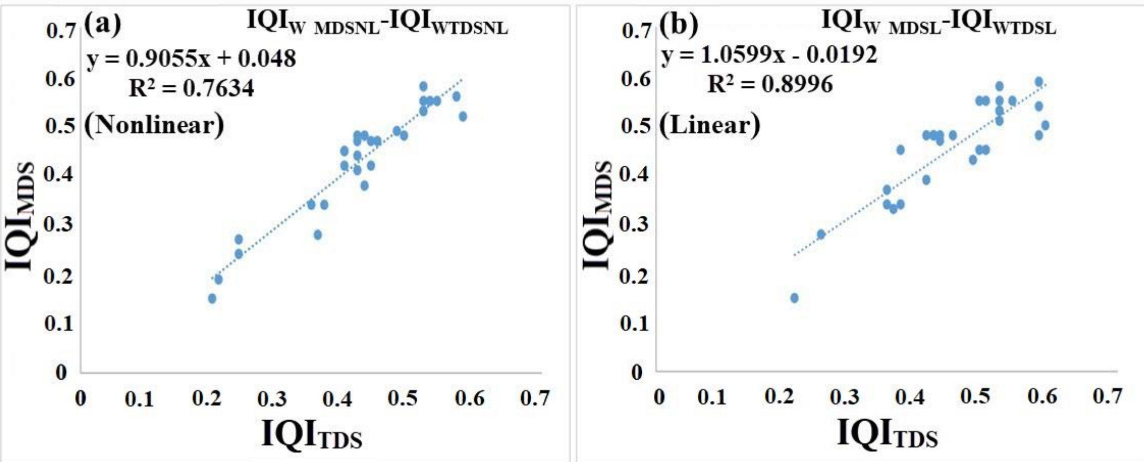

Fig 3. (a) Linear relationships of IQIwL_MDS - IQIwL_TDS, and (b) Nonlinear relationships of IQIwNL_MDS - IQIwNL_TDS

4.9. Spatial Pattern of the Parameters Based on the Global Moran's I Index

The Global Moran's I index values for the soil quality index (IQI) data in the total-linear (IQIwL_TDS), total-nonlinear (IQIwNL_TDS), minimum-linear (IQIwL_MDS), and minimum-nonlinear (IQIwNL_MDS) sets were calculated as 0.41, 0.38, 0.37, and 0.35, respectively. Given that the Global Moran's I index values are close to +1, and the p-value is very small while the z-value is very large (Figure 4), the null hypothesis of no spatial clustering among the soil quality data is rejected. This indicates that the soil quality data exhibit spatial autocorrelation at a 99%

confidence level (p-value = 0.01) and are distributed in clusters in space, meaning they are not independent of each other. Generally, based on Figure 4, the Global Moran’s I index values for these scenarios (0.41, 0.38, 0.37, and 0.35, respectively) confirm a strong spatial clustering of soil quality. The statistical significance of the results (p-value < 0.01) supports the rejection of the null hypothesis, indicating that soil quality data are not randomly distributed but rather form distinct clusters. Higher Moran’s I values in the total dataset scenarios suggest that incorporating a greater number of soil quality indicators increases spatial dependence, whereas the minimum dataset retains strong clustering while reducing data complexity. This spatial dependence highlights the influence of environmental and anthropogenic factors, such as land use, soil degradation, and localized management practices, on soil quality variation. In other words, high and low values of soil quality data tend to cluster spatially. In the investigation of the spatial distribution of soil properties, it was reported that significant spatial correlations exist for the distribution of soil particle size distribution (sand, silt, clay), but no significant spatial correlation was found for soil salinity (Liu *et al*., 2022). In another study aimed at the spatial analysis of soil EC, a Moran's index value of 0.45 was obtained, and a clustered distribution of soil salinity in western Iran was reported (Mir Mousavi *et al*., 2020).

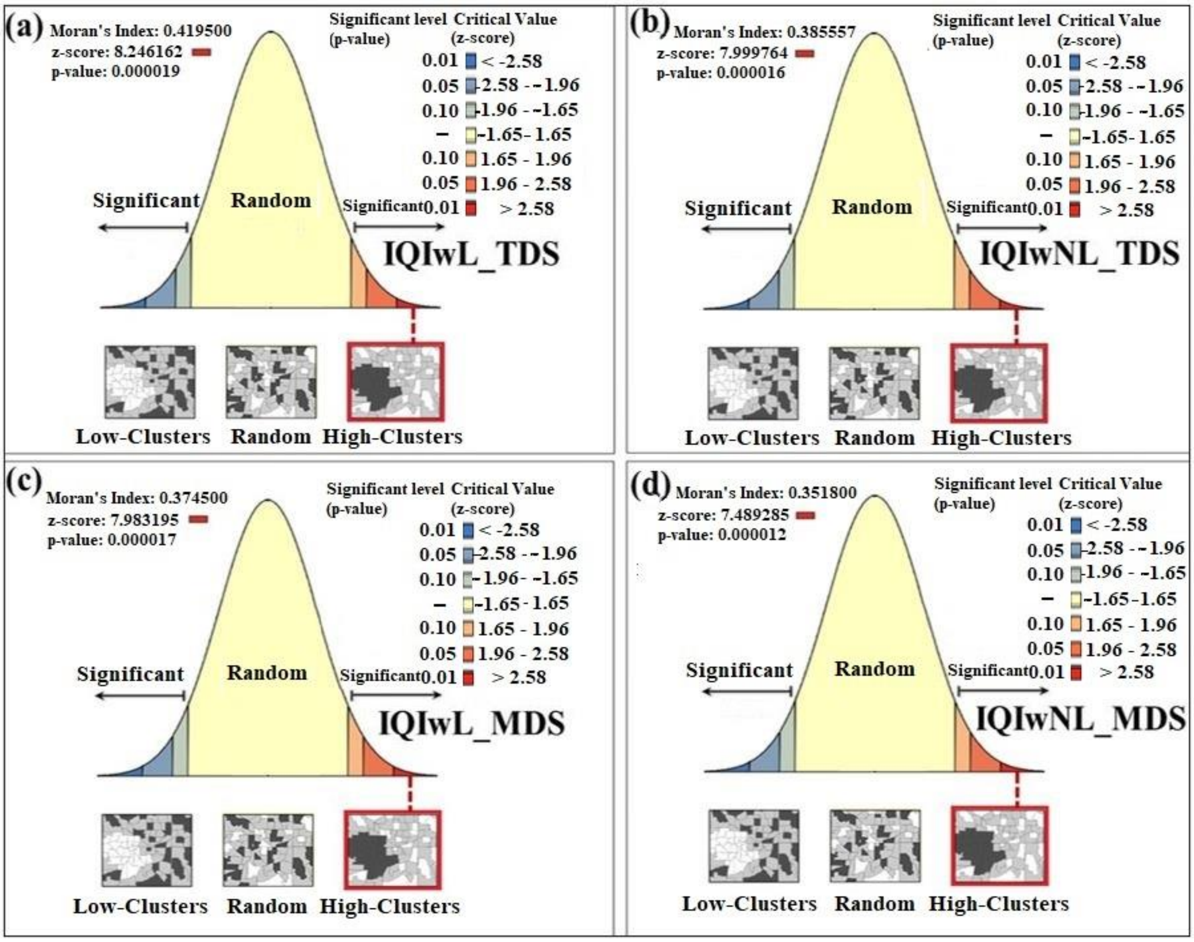

Fig 4. Results of the Global Moran's I index: (a) Total data set - linear (IQIwL_TDS), (b) Total data set - nonlinear (IQIwNL_TDS), (c) Minimum data set - linear (IQIwL_MDS), and (d) Minimum data set - nonlinear (IQIwNL_MDS)

4.10. Identification of Hot Spots Using the Getis-Ord Gi Statistic*

Figure 5 presents the spatial distribution of statistically significant hot and cold spots in soil quality based on the Getis-Ord Gi* analysis. The identified clusters include:

4.10.1. Hot spots (higher soil quality) at 90%, 95%, and 99% confidence levels

Predominantly located in the northern and northwestern parts of the study area, where agricultural activities are more intensive and soil management practices are optimized.

4.10.2. Cold spots (lower soil quality) at 90%, 95%, and 99% confidence levels

Concentrated in the southern and southeastern regions, particularly in barren lands with poor soil conditions.

The clustering of poor soil quality in the southern parts is attributed to factors such as excessive groundwater extraction, salinization, and lower organic matter content. Additionally, anthropogenic activities, including improper irrigation and overuse of chemical fertilizers, have likely contributed to the degradation of soil quality in these areas. The Getis-Ord Gi* results align with the Moran's I findings, reinforcing the conclusion that soil quality is spatially structured rather than randomly distributed. Based on the results of the Getis-Ord Gi* analysis, seven patterns were identified, including cold spots at the 90%, 95%, and 99% confidence levels, which lacked significant patterns, and hot spots at the 90%, 95%, and 99% confidence levels (Figure 5). The Getis-Ord Gi* statistic identified distinct spatial patterns of soil quality, revealing clusters of high and low soil quality, categorized as hot spots and cold spots at 90%, 95%, and 99% confidence levels. Cold spots, indicating low soil quality, were primarily located in the southern and southeastern regions, corresponding to barren lands with severe soil degradation. These areas were characterized by low SOC, high EC, and heavy metal contamination (Ni, Pb, Zn), likely resulting from unsustainable agricultural practices, overgrazing, and excessive irrigation with low-quality water. In contrast, hot spots, representing high soil quality, were concentrated in the northern and northwestern agricultural regions, where higher SOC levels, balanced pH, and lower salinity contributed to improved soil fertility. These areas benefited from better land management practices, such as controlled irrigation and organic amendments.

Key soil parameters significantly influenced these spatial patterns. SOC was higher in hot spots, enhancing soil fertility, while lower SOC in cold spots indicated poor soil health and reduced microbial activity, often caused by erosion and lack of organic inputs. EC and salinity were elevated in cold spots, negatively impacting soil quality due to excessive irrigation and poor drainage, whereas hot spots had lower EC, supporting better plant growth. Soil pH, ranging from 7.05 to 8.80, influenced nutrient availability, with extreme values in some cold spots indicating chemical imbalances. Heavy metals (Ni, Pb, Zn) were more concentrated in cold spots, suggesting contamination from industrial activities, urban expansion, and irrigation with polluted water, leading to long-term agricultural and environmental risks.

These findings highlight the importance of identifying degraded areas (cold spots) for targeted soil restoration efforts, such as organic amendments, salinity management, and pollution control. The presence of hot spots demonstrates the effectiveness of sustainable land use practices, which should be promoted and expanded. The spatial clustering of soil quality reflects both natural processes and human-induced impacts, emphasizing the need for future studies integrating land use data, climate factors, and soil management history to refine these findings. Generally, the investigation of the distribution of cold spots, representing clusters with poor soil quality. Revealed that these clusters include the barren lands around the southern and southeastern parts of the study area. Other points did not show significant patterns, and a large portion of the agricultural lands located in the northern and northwestern parts of the study area form hot spots, representing clusters with high soil quality (Figure 5). The drought, caused by reduced rainfall, uncontrolled exploitation of groundwater resources, countless unregulated wells, and excessive extraction of groundwater for domestic, industrial, and agricultural purposes, are the main factors driving the severe depletion of water resources. Overall, the intensification of these factors in recent years has led to a decline in soil quality in these areas over time.

Based on the obtained results, if appropriate management measures are not taken to predict, control, and address hot spots areas with poor soil quality numerous environmental challenges and risks will arise in the coming years. These include the expansion of salt flats and salt plains, severe salt storms, extreme climate fluctuations, the loss of plant and animal species, the destruction of orchards and agricultural lands due to the displacement of salt by wind, and the deposition of these particles on fertile lands, rendering them unproductive. Consequently, the livelihoods of residents will be at risk.

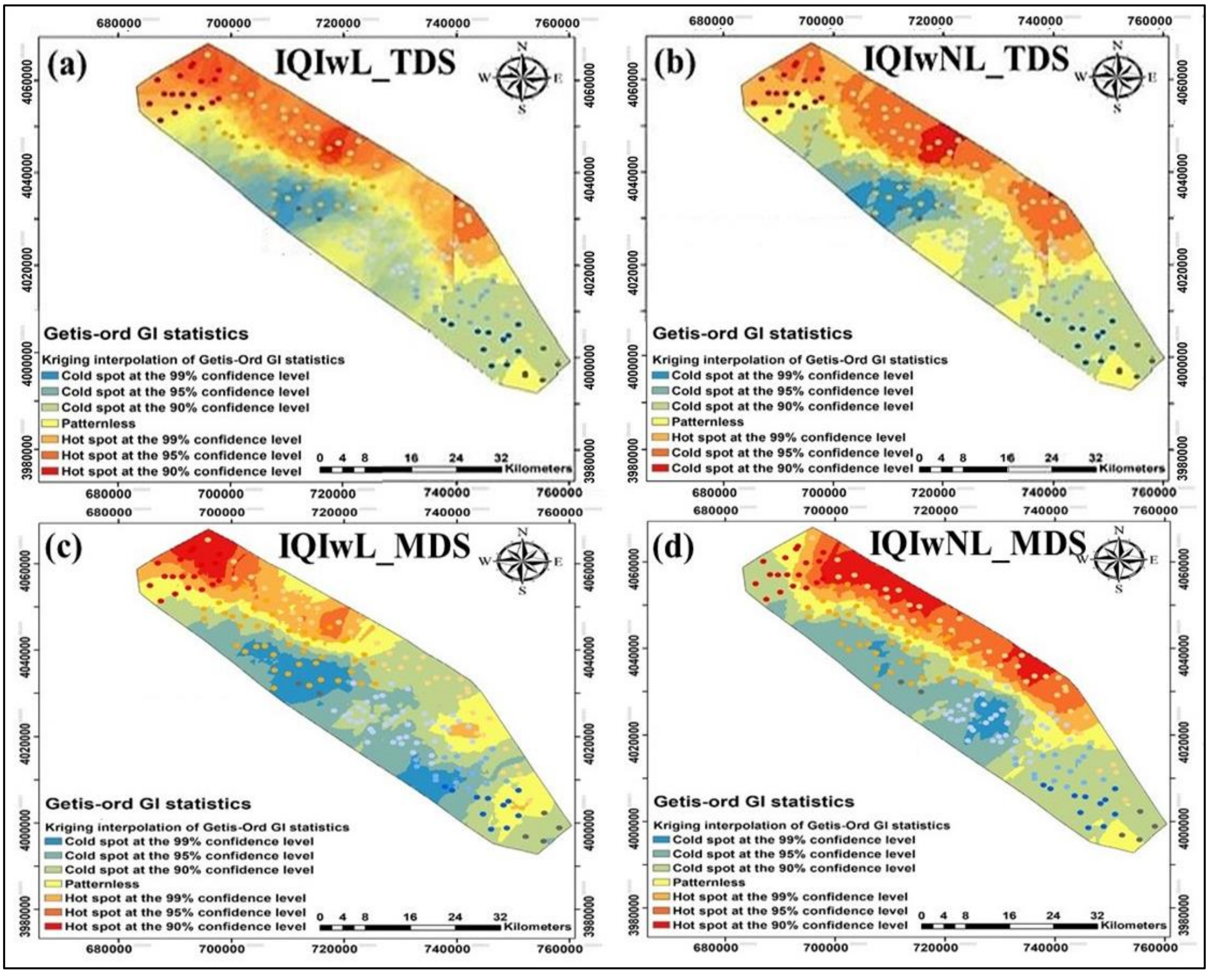

Fig 5. Results of the calculation and spatial mapping of the Getis-Ord Gi* statistic: (a) Total data set - linear (IQIwL_TDS), (b) Total data set - nonlinear (IQIwNL_TDS), (c) Minimum data set - linear (IQIwL_MDS), and (d) Minimum data set - nonlinear (IQIwNL_MDS)

5. Conclusion

Based on the results, the cumulative IQI proved to be highly effective for the quantitative assessment of soil quality. PCA and the determination of the contribution of each feature derived from factor analysis in both the TDS and MDS revealed that in the TDS, features such as sand, CCE, EC, and SOC had higher weights, while in the MDS, CCE and Ni were the most influential features in the studied area. The R^2 between the TDS and MDS was calculated as 0.76 in the linear state and 0.89 in the nonlinear state, confirming the efficiency of the MDS in evaluating soil quality. In maps generated through interpolation, the range and number of classes are user-defined, and only areas with high or low values can be identified. However, in this study, the use of the Getis-Ord Gi* statistic based on Z-scores, alongside interpolation methods, allowed for the precise determination of class boundaries and the number of classes with confidence in their spatial-statistical distribution. The study area, Mashhad Plain, was selected due to its agricultural significance and semi-arid climatic conditions, which are representative of many similar regions worldwide. While the results are specific to this area, they provide valuable insights into soil quality assessment in semi-arid agricultural landscapes, where similar environmental challenges such as low organic matter, salinity, and heavy metal contamination are common. Additionally, the study employed spatial analysis techniques (Global Moran's I and Getis-Ord Gi*) to assess soil quality clustering, which inherently accounts for spatial variations in land use and management practices across the study area. The identified hot and cold spots of soil quality correspond to regions with distinct land use types, highlighting the indirect influence of management factors. In other words, this method enabled the identification of different soil quality classes that are statistically significant. Accordingly, clusters with poor soil quality were identified in the barren lands around the southern and southeastern parts of the study area. It is recommended that future research investigate the relationship between soil quality and parameters such as land use, land surface temperature, soil moisture, and the spatial distribution of heavy and trace elements in the study area.

Author Contributions

All authors contributed to the study conception and design. AK and TS, prepared the samples and performed the experiments. AM and AsM analysed the data and conducted the modelling procedures. AM write the first draft of the manuscript with support of AK and SKA. AK and SKA provided critical feedback and contributed to the interpretation of the results. All authors substantially contributed to editing and reviewing the paper.

Data Availability Statement

The datasets in the study (generated or analyzed) are available from the corresponding author on request.

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Ethical considerations

The authors avoided from data fabrication and falsification.

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Conflict of interest
The authors have no conflicts of interest to declare that are relevant to the content of this article.

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