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Spatial Analysis of Soil Properties and Site-Specific Management Zone Delineation for the South Hail Region, Saudi Arabia

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Abstract: Sustainable soil management with the appropriate understanding of soil characteristics is vital in maintaining and improving agriculture soil management. The objectives of the present study are to characterize the spatial variability of soil using the GIS technique and used agglomerative hierarchical clustering (AHC) for the delineation of management zones (MZs) for precision agriculture. A total of 111 soil samples were collected from 37 soil profiles in systematic depths (0–50, 50–100, and 100–150 cm) from the South Hail region, KSA. Samples were analyzed for pH, ECe, $CaCO_3$, available macro and micronutrients, and hydrological properties. The best fit models, using ArcGIS software, were J-Bessel for pH, Clay, bulk density (BD), and available water (AW); K-Bessel for EC and available N; Stable for $CaCO_3$, P, K, Fe, Zn, Sand, field capacity (FC) and saturated hydraulic conductivity (Ks); Spherical for Mn and Cu; Gaussian for saturation percentage (SP); whereas exponential for permanent wilting point (PWP). The principal component analysis (PCA) resulted in six principal components (PCs) explaining 79.75% of the total variance of soil properties. The PC1 was strongly influenced by soil BD, FC, clay, PWP, Ks, and sand. PC2 was dominated by N, ECe, and $CaCO_3$; PC3 was dominated by pH; PC4 was dominated primarily by K and P, PC5 was mainly dominated by Fe; Mn, and Cu, and PC6 was mainly dominated by SP and Zn. Based on AHC, four soil management zones (MZs) cover 77.94, 14.10, 7.11 and 0.85% of the studied area. Management zone 1 (MZ1) and Management zone 3 (MZ3) are classified as moderately saline while Management zone 2 (MZ2) is classified as highly saline soils, greater than the limiting critical value for the sensitive crops. The potential solutions to reduce salinization in the area include: reducing irrigation, moving to salt-tolerant crops or applying humic acids to fix anions and cations and eliminate them from the root zone of the plants. Treating the area with diluted sulfuric acid to remove salts and reduce ECe to less than 2 dSm^{-1}, to get maximum productivity. This finding is diagnostic for determining the amount of fertilizer and irrigation water to be applied to soils in different management zones. Its emphasis's the importance of site-specific management for long-term crop productivity and, as a result, reducing environmental hazards caused by uneven fertilizers and water applications.

Keywords: GIS; spatial variability; principal component analysis; management zone; agglomerative hierarchical clustering

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1. Introduction

Agricultural soils have a greater role in crop production, maintaining clean air and water, lowering greenhouse gas emissions, protecting natural biodiversity, and assuring the safety of food [1]. The hail region is one of the most important extents for crop production in the kingdom which has 225.4 km^2 of cultivation area [2]. This area has undergone extensive agriculture and unplanned resource use, which could cause land degradation. This is proved abundantly clear in the Modaihsh et al., [3] study, which observed that the degree of salinity-induced deterioration was typically correlated with certain physical soil features, irrigation water quality, and prior soil management activities. Furthermore, many studies stated that the groundwater in this region is exposed to non-point sources of pollution such as agricultural materials including fertilizers, heavy metals, and pesticides. At the same time, fertilizer consumption increased from 3.5 kg ha^{-1} in 1961 to 87.6 kg ha^{-1} in 2020. These indicate that more fertilizers losses to groundwater through the soil. So, it's necessary to manage the water and fertilizer according to soil properties [4,5]. The possibility of dividing the area under investigation into management sectors to reduce the loss of water and fertilizers and then prevent pollution, and soil degradation, and ensure sustainable agriculture.

In order to assess how the chemical, physical, and nutritional characteristics of soil vary with location and how to collect soil samples, spatial variability is necessary [6]. For site-specific management, it is vital to comprehend soil spatial variability [7–9] and can support the management of agricultural productivity by adjusting agricultural inputs to meet the spatial needs of soils and crops [10]. Geographic Information Systems (GIS) techniques have been used to examine the soil's physical, chemical, and nutrient properties and identify it spatially. It has been demonstrated to be a beneficial and effective tool for analyzing, mapping, processing, and presenting soil parameters and defining certain problems [11–17]. The maps of spatial distribution can identify and delineate problematic zones, making them powerful tools in site-specific management. The spatial distribution of soil characteristics provides a wealth of site information that can be used for environmental forecasting, precision agriculture, and natural resource management, among other things [18]. In comparison to interpolation techniques, geostatistics is a more appropriate approach for estimating soil parameters [19]. Kriging is a geostatistical technique that characterizes the values of variables close to the original sample locations, which have a statistically higher correlation with the observed value there than with values recorded elsewhere [20]. The projected values in this method are derived from the weighted mean's assessment of relationships in samples [20–22]. Furthermore, it was noted by Gupta et al. [20] that the weight of kriging is influenced by the overall spatial arrangement of the measured points and their individual values, in addition to the distances between the measured points and the predicted location. Kriging can be described as a trustworthy linear unbiased estimator that reflects this [23]. The best Kriging technique to utilize for producing an accurately predicted distribution map is ordinary kriging [20,24]. For sand, silt, and clay content, Gozukara et al. [25] found that the kriging interpolation method had a lower RMSE value in the soil profile. Moreover, for all maps of elemental concentrations and weathering indices, Gozukara [26] stated that the ordinary kriging interpolation methods with exponential semivariogram have the lowest RMSE.

Principal component analysis (PCA) is a multivariate statistical analysis used to create new uncorrelated variables called principal components (PCs) from the data set [27]. Since the PCs are linear combinations of soil attributes, they were used to define the MZs [28]. In correlation with the PCA model, GIS is described as a procedure that incorporates the preferences and concerns of decision-makers to produce an overall evaluation for selecting between agricultural activities and sites [29,30]. Additionally, enhance a crop management system to increase land productivity [31]. The AHC element GIS-based procedure integrates expert knowledge, combines qualitative and quantitative information, and provides an excellent framework for managing data and knowledge capture, storage, synthesis, measurement, and analysis, all of which are critical for the land management process [32,33]. Brevik et al. [34] reported that adoption of region-specific soil and crop management techniques at a reasonable cost using MZs created using geostatistical tools. Moreover, the cluster algorithm and kriging simulation can be used to define uniform soil attributes MZs with reduced sampling costs, and variance of estimation errors, and interpolate the data for unsampled places [35,36]. MZs delineated using deviations in soil properties have not only provided beneficial information for precise soil properties but also helped in detecting the areas of low, medium, and high productivity potential [37]. Additionally, Abdel-Fattah [38] used PCA to summarize soil properties and ArcGIS software to assess the spatial distribution outline of different soil properties. Similarly, used Agglomerative hierarchical clustering technique (AHC) to define MZs for the spatial variability of salt-affected soil properties and delineation of site-specific management zones.

The main objective of this study was to (a) assess the heterogeneity, distribution pattern, and spatial variability of soil properties using geostatistical analysis for defining the soil physical, chemical, and nutrients status of south Hail-KSA, (b) assess the correlation between measured soil properties, and (c) identify the potential MZs based on soil property status using principal component (PC) analysis and agglomerative hierarchical clustering (AHC).

2. Materials and Methods

2.1. Study Area

This study was conducted in the Hail province in northwestern Saudi Arabia. The total studied area is about 1253.76 km2 and is located between latitudes 27°7′37.261″ and 27°27′45.367″ N and longitudes 42°42′56.441″ and 43°23′47.137″ E (Figure 1). Generally, the soils are characterized by sand to sandy loam texture with a deep profile [5]. The ground water is the main irrigation source in the area. There is no drainage network due to the use of the new irrigation techniques (Drip and Sprinkler irrigation). The climate in Hail is mild during summer with air temperatures ranging between 30 to 38 °C (The warmest month with the highest average high temperature is August (38 °C). At the same time, soil surface temperature fluctuated between 41 to 52 °C. While it is cold during winter with air temperatures between 3 to 15 °C and can drop to even 0 °C (The coldest month with the lowest average low temperature in January (3 °C)). Simultaneously, the temperature of the soil surface fluctuated from 22 to 25 °C and can drop to 6 °C in the coldest month. This period accompanied by rain and precipitation with total rainfall in the year is 186 mm. Air humidity throughout the year ranged between 18 to 55%. The average wind speed in Hail is mild seasonal variation over the year. The windier part of the year, from 19 October to 27 May, with average wind speeds of more than 14.16 km per hour. The calmer time of year is from 27 May to 19 October. The calmest month of the year is September, with an average hourly wind speed of 20.45 km h^{-1} [39]. Date palm, barley, alfalfa, wheat, maize, and a few vegetables are cultivated in some of the areas under investigation.

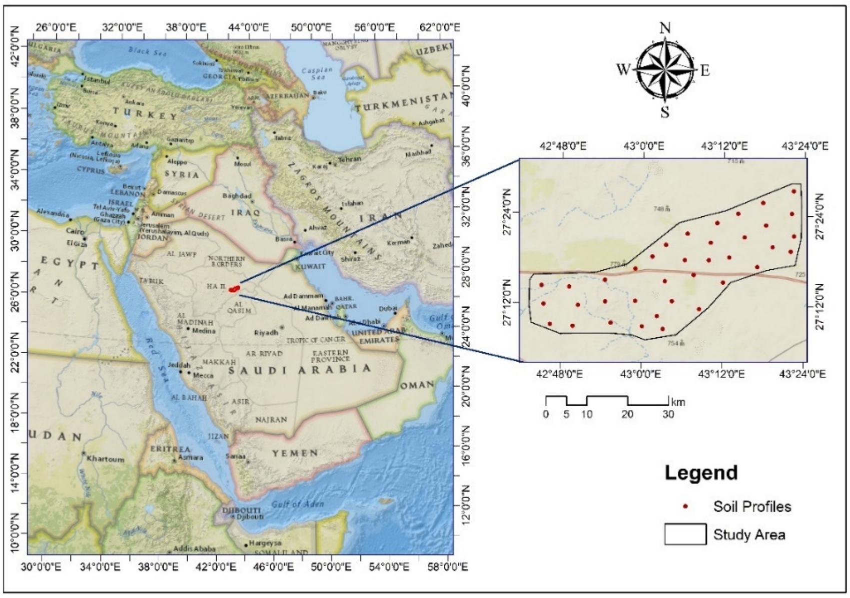

Figure 1. Location of the study area with sampling positions.

2.2. Fieldwork and Laboratory Analyses

The fieldwork aimed to characterize the soil properties by selecting sites according to surface soil characteristics. The total number of soil profiles was 37 in systematic depths (0–50, 50–100, and 100–150 cm) with 111 total soil samples. The soil profiles were located in UTM coordinate system by the GPS. The soil samples were air-dried and sieved through a 2 mm sieve to analyze the chemical, physical, and fertility characterization as follows:

2.2.1. Physical Properties

Soil particle size distribution was determined according to the hydrometer method [40]. Soil bulk density was determined from the volume-mass relationship for each core sample [41]. Saturated soil hydraulic conductivity was determined under a constant head [42]. Saturation percentage, field capacity, wilting point, and plant available water were determined using the method of [43].

2.2.2. Chemical Properties

Electrical conductivity (EC) was determined in the saturated soil paste extracted; soil reaction (pH) was determined in (1:2.5) soil water suspension [44]. Total calcium carbonate was determined volumetrically using Collin's calcimeter [45]. Available nitrogen in the soil was extracted in the 2.0 M KCl and determined by micro-Kjeldahl apparatus. Available phosphorus was extracted in 0.5 N $NaHCO_3$ solution (pH 8.5) and optical density was measured using a spectrophotometer. Available potassium was extracted in the 1.0 N ammonium acetate solution (pH 7) and measured using a flame photometer. Available N, P, and K were determined according to Page et al. [44]. Available Fe, Zn, Mn, and Cu were extracted by using DTPA and were assayed using an Inductively Coupled Plasma Atomic Emission Spectrometer (ICP-AES) (Thermo 7000) Thermo Scintific, Model iCAP7400 Duo [46].

2.2.3. Terrain Analysis

Was performed using Arc-GIS 10.8 software. Digital Elevation Model (DEM) derived using 38 $\times$ 38 m cell size thematic map. Slope and aspect were derived by spatial analyst extension using inverse distance weighting (IDW) interpolation techniques [47].

2.3. Statistical Analysis and Principal Component Analysis

Data were analyzed for descriptive measurements including minimum, maximum, arithmetic mean, median, range, variance, standard deviation, standard error, coefficient of variation, skewness, and kurtosis. The normality of variables was verified using the Shapiro-Wilk test before proceeding with the principal component analysis (PCA), and the correlation between different variables was measured by Pearson correlation. Furthermore, Bartlett's sphericity test as well as Kaiser-Meyer-Olkin (KMO). The measure of Sampling Adequacy was conducted to verify data dependence, where if the KMO result is larger than 0.5 and the p-Value of Bartlett's sphericity test is smaller than 0.05, this indicates the non-mutual independence of data and can be applied for PCA.

Soil properties were summarized using PCA. The PCA was performed using XLSTAT software version 2019.2.2.59614, Addinsoft, Boston, MA, USA [48]. PCA is a statistical procedure that uses an orthogonal transformation to convert a set of observations of possibly correlated variables (entities each of which takes on various numerical values) into a set of values of linearly uncorrelated variables called principal components (PCs). PCs having eigenvalues greater than one has been retained whereas PCs less than 1 were subtracted away [49].

2.4. Geostatistical Analysis

ArcGIS 10.8 software, 2019, Redlands, CA, USA was used to assess the spatial distribution pattern of different soil properties. Geostatistical and interpolation methods such as Ordinary Kriging was used to assess the spatial distribution of soil characteristics (Equation (1)) [50].

$$\hat{z}(x_0) = \sum_{i=1}^{n} \lambda_i \, z(x_i) \tag{1}$$

where $\hat{z}(x_0)$ is the value to be estimated at the location of x_0, $z(x_i)$ is the known value at the sampling site x_i and n is the number of sites surrounded by the search neighborhood used for the estimation.

The Semi-variogram models can be used with ordinary kriging (OK) for each soil property to represent the average rate of variation of soil property with distance. It is the basis for modeling the data set and for drawing a contour map [51].

The semi-variogram $\gamma(h)$ is defined as:

$$\gamma(h) = \frac{1}{2} Var[Z(x) - Z(x+h)] \tag{2}$$

where $Z(x)$ and $Z(x + h)$ are the values of a random function representing the soil property of interest z, at places x and $x + h$ separated by the vector h known as the lag or interval.

The accomplished semi-variogram values for each lag were fitted to one of the semi-variogram models (i.e., Stable, J-Bessel, K-Bessel, Hole Effect, Rational Quadratic, Gaussian, Exponential, Pentaspherical, Tetraspherical, Spherical, and Circular) using Arc GIS 10.8, 2019, Redlands, CA, USA. The selected model was evaluated based on criteria where the best fit model which has a mean error "ME", average standard error "ASE" and mean standardized error "MSE" values close to zero [52].

2.5. Site-Specific Management Zones

Agglomerative hierarchical clustering (AHC) was executed to define soil management zones. XLSTAT software version 2019.2.2.59614, Addinsoft, Boston, MA, USA was used to classify the data into different clusters having a common trait [48]. A one-way ANOVA test was performed for comparison between soil management zones and followed by a post hoc test using Duncan multiple range (DMR) test for comparisons between management zones.

3. Results and Discussion

3.1. Terrain Analysis

Digital Elevation Model analysis (DEM) indicated that the elevations varied from 698.6 to 813.7 m A.S.L. The lowest elevation part of the study area was located in the eastern. The prevailing elevation ranged from 700 to 760 m A.S.L. comprised 72.43% of the total area as shown in Figure 2. Soil surface slope is most important in terms of its effect on erosion. The soil depth increases with decreasing slope rate and decreases as the slope increases [53]. Using the Digital Elevation Model with GIS software gave the slope information data. The slope of the area ranged from 0 to 64.23% and the main slope class was from 0 to 9.57% which covered about 77.19% (96,777.42 ha) of the total area. This slope can classify as slightly inclined (Table 1). The slope indirectly restricts agricultural production by affecting soil properties negatively. It is noticeable that the directions of the area under investigation are in equal percentages in all direction classes as shown in Table 1, Alharbi and Aggag [54].

3.2. Statistical Characterization of the Studied Soil

The soil is characterized as sand to sandy loam deep soil with low fertility content and low water holding capacity. Table 2 shows the descriptive statistical analysis which indicated that a wide variation in soil EC, pH, $CaCO_3$, available N, P, K, micronutrients Fe, Zn, Mn, Cu, and soil physical properties Sand, Clay, BD, SP, PWP, AW and Ks were recorded (Table 2). The distribution of variation in soil properties over space was highly skewed for all the properties except available phosphorus and B.D. Kurtosis in soil properties was also found to behave similarly.

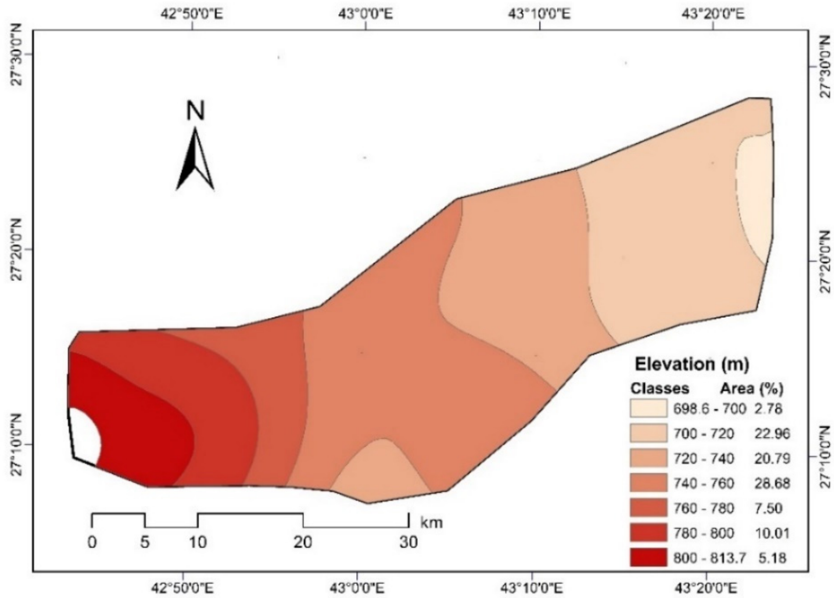

Figure 2. Digital Elevation Model for the area under study.

Table 1. Area percentage of DEM, slope, and direction classes for the study area.

Digital Elevation Model (DEM)		Slope Classes		Direction Classes	
Elevation Range, m	**Area, %**	**Slope Class, %**	**Area, %**	**Direction Class**	**Area, %**
698.6–700	2.78	0–3.78	25.26	Flat	1.55
700–720	22.96	3.79–6.55	28.96	North	11.16
720–740	20.79	6.56–9.57	22.97	North East	13.02
740–760	28.68	9.58–13.10	13.33	East	12.92
760–780	7.50	13.11–17.63	6.39	South East	12.48
780–800	10.02	17.64–24.94	2.58	South	12.62
800–813.7	7.27	24.95–64.23	0.51	South West	12.20
				West	12.14
				North West	11.91

Among soil properties, maximum variability was recorded for EC (1.04–18.94 dSm^{-1}) with mean, CV%, skewness, and kurtosis being 4.69, 93.4, 1.82, and 3.11, respectively (Figure 3b, Table 2). Higher EC was observed in the higher altitudes in the western area as reported by Alharbi and Aggag [54]. The soil pH was in the acidic range (7.52–8.24) with mean, standard deviation, and CV% being 7.92, 0.20, and 2.4, respectively (Table 2). The lower CV in pH is explained to be due to uniform conditions in the study area as indicated by the least skewness (−0.41). The alkaline reaction of soil is attributed to the alkaline parent material, climate, topography, and precipitation. Similar results have been reported in the area of Hail, KSA by Alharbi and Aggag [54]. $CaCO_3$ showed wide variability (0.9–17.2%) with the mean and CV being 6.4% and 61.6% (Figure 3m, Table 2). The clay content ranged from 10.0 to 25.9% with mean and standard deviation being 17.1% and 3.7. Abdel-Fattah [38] stated that the study area is categorized as moderate to high salinity soils, with ECe values varying from 0.87 to 20.33 dSm^{-1} with an average value of 5.30 ± 5.05 dSm^{-1}.

Wide variations in DTPA Fe, Zn, Mn, and Cu were recorded with respective mean values of 674.6, 235.2, 536.7, and 145.3 µg kg^{-1} (Table 2). This indicated a widespread deficiency of micronutrients in the area under investigation. The four micronutrients CV, ranging from 47.4 to 96.7 show high variability. The highest CV was observed for Fe (96.7%) followed by Cu (87.2%), Mn (53.8%), and Zn (47.4%). The spatial prevalence of four micronutrients reflected similar trends in skewness and kurtosis values ranging from 1.32 to 4.21 and 2.17 to 21.72, respectively (Table 2). The Kolmogorov-Smirnov and the

Shapiro-Wilk Tests result showed that the soil properties (ECe, K, Fe, Zn, Mn, Cu, sand, clay, SP, FC, PWP, AW, and Ks) are not normally distributed (p-Values < 0.05). Therefore, the data were transformed using the logarithmic transformation method before assuming the spatial distribution of soil properties using the ordinary kriging (OK) method [55]. While, pH, $CaCO_3$, available N, P, and BD are normally distributed (Table 2). Amer [56] found that all soil properties do not follow a normal distribution, where the value of p of the Shapiro-Wilk Test is less than 0.05 except for the CEC property. Furthermore, Gozukara [57] discovered that the EC, SOM, CaCO3, P, Zn, and Mn were not distributed normally. The parameters were then logarithmically transformed to achieve a normal distribution.

Table 2. Statistical characterization of soil properties.

Parameter	Min.	Max.	Mean	Variance	Std. Dev.	CV	Skewness	Kurtosis	Normality Test			
									Shapiro-Walk Test		Kolmogorov-Smirnov Test	
									W	Sig.	D	sig.
ECe (dSm^{-1})	1.04	18.91	4.69	19.13	4.38	93.38	1.82	3.11	0.77	<0.0001	0.24	0.024
pH (1:2.5 soil: water)	7.52	8.24	7.92	0.04	0.20	2.42	−0.41	−0.58	0.96	0.25	0.08	0.940
$CaCO_3$ (%)	0.85	17.23	6.35	15.27	3.91	61.62	0.74	0.28	0.94	0.06	0.10	0.831
Av. N (mg kg^{-1})	800.0	1350.0	1135.1	14,564.6	120.7	10.63	−0.47	−0.03	0.94	0.05	0.16	0.245
Av. P (mg kg^{-1})	8.00	40.90	22.96	85.51	9.25	40.28	0.22	−0.64	0.95	0.12	0.11	0.773
Av. K (mg kg^{-1})	12.00	220.5	100.7	3574.7	59.79	59.40	0.50	−0.93	0.93	0.02	0.16	0.289
DTPA Fe (µg kg^{-1})	141.64	3662.4	674.6	425,894.4	652.61	96.74	3.20	12.41	0.65	<0.0001	0.26	0.010
DTPA Zn (µg kg^{-1})	68.85	613.7	235.2	12,422.5	111.46	47.40	1.32	2.90	0.91	0.01	0.14	0.386
DTPA Mn (µg kg^{-1})	120.60	1438.8	536.7	83,336.9	288.69	53.79	1.33	2.17	0.90	0.00	0.16	0.248
DTPA Cu (µg kg^{-1})	36.84	809.8	145.3	16,048.8	126.69	87.20	4.21	21.72	0.57	<0.0001	0.20	0.101
Sand (%)	47.00	80.00	68.08	47.01	6.86	10.07	−1.16	2.01	0.92	0.01	0.14	0.433
Clay (%)	10.00	25.90	17.11	13.68	3.70	21.62	0.78	0.72	0.96	0.02	0.16	0.269
B.D. (Mg m^{-3})	1.41	1.58	1.49	0.00	0.04	2.39	−0.14	0.68	0.40	0.20	0.14	0.407
S.P. (%)	40.30	71.90	44.75	22.89	4.79	10.69	5.33	30.81	0.92	<0.0001	0.31	0.001
F.C. (%)	18.30	25.60	21.38	3.33	1.83	8.53	0.86	0.26	0.94	0.01	0.14	0.441
P.W.P. (%)	9.00	16.70	12.04	2.40	1.55	12.87	0.89	1.60	0.93	0.04	0.15	0.312
A.W. (mm m^{-1})	80.00	126.00	93.30	99.44	9.98	10.69	1.53	2.81	0.85	0.00	0.24	0.022
Ks (cm h^{-1})	0.36	2.78	1.12	0.24	0.49	43.88	1.41	3.05	0.90	0.00	0.20	0.097

Note. AW: available water; BD: bulk density; DTPA: diethylene-triamine-penta-acetic acid; EC: electrical conductivity; F.C.: field capacity; Ks: saturated hydraulic conductivity; PWP: permanent wilting point; S.P.: saturation percentage.

3.3. Distribution of Soil Properties

The measured salinity value ranged between 1.09 to 18.94 dSm^{-1}, indicating low, medium to high soil salinity as recorded by Richard [58]. About 8.43% (10,569.15 ha) of the study area has low salinity and is well suitable for agriculture, 59.35% (10,569.16 ha) area shows medium salinity, and 32.22% (40,395.98 ha) of the area show high salinity (Figure 3b). About 86.71% of the area (108,713.09 ha) has a pH between 7.52 to 8.00 (slightly alkaline), and 13.29% (16,662.40 ha) has a pH between 8.00 and 8.24 (alkaline) (Figure 3a) [59]. The $CaCO_3$% in the study area ranged between 0.9 and 17.2% and classified into low, (less than 5%) at about 51.61% of the area (64,706.30 ha), and medium (5 to 17%) 48.39% (60,669.20 ha) (Figure 3m). Most of the area is classified as medium nitrogen content (1000–1350 ppm) which covers 98.73% of the area (123,783.23 ha) and 1.27% of the area (1592.27 ha) classified as low N content (less than 1000 ppm) according to classification by Barthakur and Baruah [59]. Whereas 94.55% of the area (118,542.53 ha) was classified as medium potassium concentration (60–120 ppm K), 3.22% of the area (4037.09 ha) was classified as high K-concentration (greater than 120 ppm), and 2.23% of the area (2795.87 ha) has low K-concentration (less than 60 ppm). While 84.69% of the area (106,180.51 ha) was classified as medium phosphorus concentration (15–30 ppm P), and 15.31% of the area (19,182.45 ha) has high P-concentration (30–40.9 ppm), as classified by Barthakur and Baruah [59]. The investigated area has low micronutrients Fe, Zn, Mn, and Cu concentrations (Figure 3i–l); less than 4000, 600, 2000, and 200 µg/kg, respectively as mentioned by Reddy [60]. The available N ranges between 1.33 mg kg^{-1} and 61.6 mg kg^{-1}, indicating that the nitrogen content in the area is low. The available P content ranges from low 2.33 mg kg^{-1} to high 19.84 mg kg^{-1}, and available K ranges from 32.76 mg kg^{-1} to 734 mg kg^{-1}, which is classified as high [37]. Zn, Cu, Fe, and Mn levels varied greatly, with mean values of 0.28, 0.44, 8.51, and 8.59 mg kg^{-1}. Verma et al. [37] stated that micronutrient distribution varies due to parent material, climatic conditions, and anthropogenic activities.

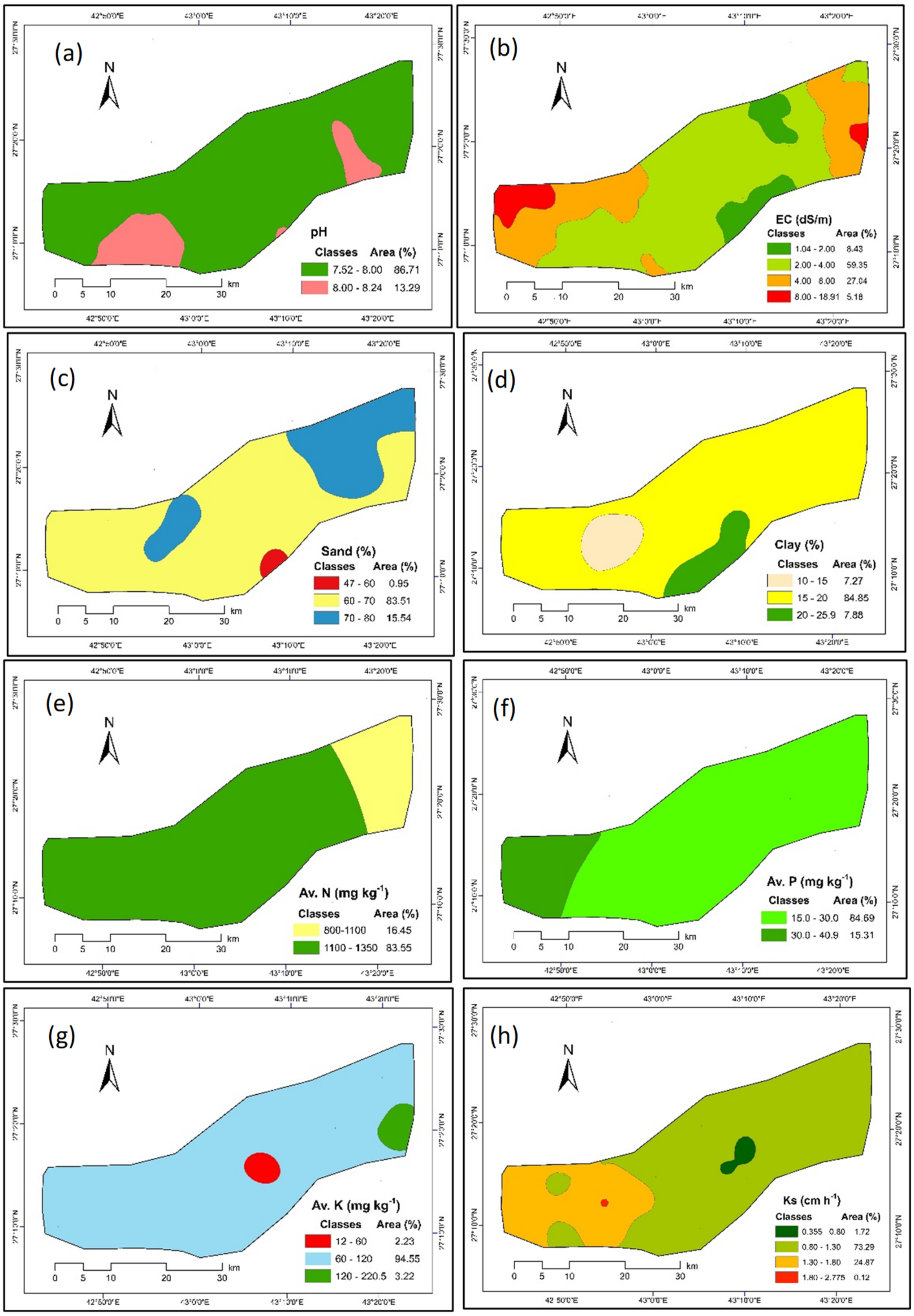

Figure 3. *Cont.*

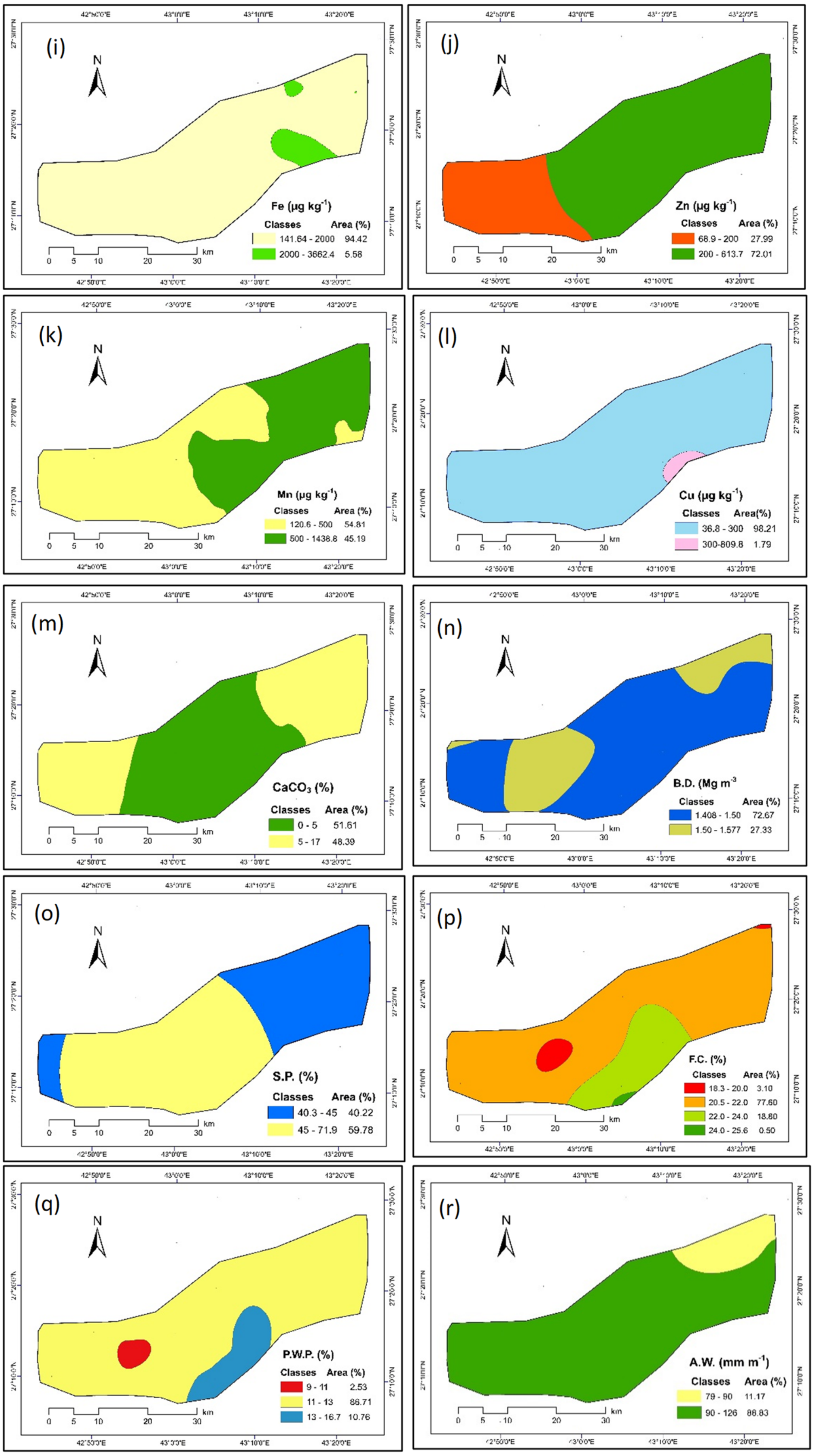

Figure 3. Spatial distribution (kriged) maps of soil pH (**a**), EC (**b**), Sand (**c**), clay (**d**), N (**e**), P (**f**), K (**g**), and Ks (**h**) in south Hail, KSA. Spatial distribution (kriged) maps of soil Fe (**i**), Zn (**j**), Mn (**k**), Cu (**l**), $CaCO_3$ (**m**), B.D. (**n**), S.P. (**o**), F.C. (**p**), P.W.P. (**q**), and A.W. (**r**) in south Hail, KSA.

The clay fraction range of less than 20% is classified as low and covers 92.12% (115,495.91 ha) of the study area and medium categories 20 to 26% clay covering 7.88% (9879.59 ha) of the study area (Figure 3d). Most of the area 72.67% (91,110.37 ha) has B.D. between 1.41 to 1.50 Mg m^{-3} and 27.33% (34,265.12 ha) have B.D. between 1.50 to 1.58 Mg m^{-3} (Figure 3n). The greatest of the area 96.89% (121476.32 ha) has medium FC between 20 to 25.6% and 3.11% (3899.17 ha) has less than 20% of FC (Figure 3p). A major of the area, 88.83% (111371.05 ha), has medium AW between 90 to 126 mm m^{-1} and 11.17% (14004.44 ha) has low AW, less than 90 mm m^{-1} (Figure 3r). These results were in agreement with those found by Brady et al. [61] and Abdel-Fattah [38].

3.4. Relationships between Soil Properties

A Pearson correlation test was running out to study the relationship between different soil properties as presented in Table 3. Some of the soil properties had significant correlations with each other. EC had a negative correlation with soil pH at P = 0.05 level. N and P were negatively correlated with Fe at P = 0.05. Whereas a positive correlation was found between each EC and K, N and P, and between Zn and Cu [62]. It was observed that there were positive strong significant correlations between clay and FC, and PWP while negative correlations were with BD and Ks. Correspondingly, negative correlation between sand and clay, FC, PWP, and AW; while positive correlation with BD.

Using a biplot (Figure 3), where the angles between the vectors show how traits correlate with one another, we can corroborate this from these correlations between the various variables. Variables have a positive correlation when they are near together and create a small angle. They are not likely to be associated if they intersect at a 90° angle. They are negatively correlated when they diverge and produce a significant angle that is nearly 180 degrees. Consequently, one or more major general components of these variables are present. According to the correlation between various soil properties, principal components analysis (PCA) was used to determine the principal sources of data variability. This is also supported by Bartlett's sphericity and KMO tests (Table 4), where small p-Values ($p < 0.05$) of the significance level indicate that a PCA may be useful with these data [63]. Table 3 contains the results of Bartlett's sphericity test. The observed p-Value is less than 0.001. Because the KMO values were greater than 0.586, a PCA may be useful for these data [64,65].

3.5. Geostatistical Analysis and Spatial Variability

The semivariogram-derived best-fit models for various soil parameters were presented in Table 5. Additionally, Figure 3 shows the spatial maps of soil properties. The best fit models were J-Bessel (pH, Clay, BD, and AW), K-Bessel for (EC and Av. N), Stable ($CaCO_3$, P, K, Fe, Zn, Sand, FC, and Ks), Spherical (Mn and Cu), Gaussian (SP), exponential (PWP). Gozukara et al. [25] reported that the exponential semivariogram model had the lowest prediction error with the lowest RMSE for sand and silt content on the soil surface, whereas the spherical semivariogram model had the lowest prediction error with the lowest RMSE. Similar best-fit models for various soil properties have also been reported by [66,67]. The models for the soil properties at various sites show how anthropogenic activities and the local environment have an impact on the spatial variability of soil properties.

The nugget is the measurement of the errors that sampling, measurement technique, and other sources contribute to overall variation. It denotes microvariability, and its values for various soil characteristics ranged from 0 to 50.72; the lowest values were for EC, FC, and BD, and the highest was for P, with the exception of Fe, which was extremely high and reached 14515.83. The nugget values of all the studied parameters were very small and varied from 0 to 1.23 [56]. Large nugget values indicated that ecological practices were affecting soil indicators on a small scale, and the chosen sampling distance could not adequately capture the spatial dependence [68].

Table 3. Matrix of Pearson's correlation coefficients between the soil properties used in this study.

Variables	EC	pH	N	P	K	Fe	Zn	Mn	Cu	$CaCO_3$	Sand	Clay	BD	SP	FC	PWP	AW	Ks
ECe (dSm^{-1})	**1**																	
pH (1:2.5 soil: water)	**−0.536 ***	**1**																
Av. N (mg kg^{-1})	0.033	−0.229	**1**															
Av. P (mg kg^{-1})	0.273	−0.156	**0.528 ***	**1**														
Av. K (mg kg^{-1})	**0.716 ***	−0.310	0.033	0.217	**1**													
DTPA Fe (μg kg^{-1})	0.007	0.094	**−0.434 ***	**−0.556 ***	0.174	**1**												
DTPA Zn (μg kg^{-1})	−0.084	−0.243	−0.131	−0.175	−0.002	0.187	**1**											
DTPA Mn (μg kg^{-1})	−0.154	0.095	0.016	−0.228	−0.170	0.296	0.103	**1**										
DTPA Cu (μg kg−1)	−0.140	0.015	−0.267	−0.236	−0.218	0.184	**0.596 ***	0.149	**1**									
$CaCO_3$ (%)	0.178	−0.137	−0.023	0.026	0.220	0.223	−0.052	0.059	−0.090	**1**								
Sand (%)	−0.090	−0.098	−0.205	−0.273	−0.038	0.094	−0.013	−0.144	−0.004	−0.058	**1**							
Clay (%)	−0.131	−0.269	0.368	0.189	−0.043	−0.128	0.172	0.066	0.116	0.113	**−0.441 ***	**1**						
B.D. (Mg m^{-3})	0.029	0.193	−0.261	−0.181	−0.054	0.078	−0.164	−0.074	−0.098	−0.161	**0.657 ***	**−0.895 ***	**1**					
S.P. (%)	−0.071	0.071	−0.120	0.074	−0.030	−0.123	−0.006	−0.081	−0.030	−0.080	−0.107	−0.032	0.054	**1**				
F.C. (%)	−0.023	−0.096	0.274	0.215	−0.012	−0.092	0.135	0.120	0.072	0.101	**−0.832 ***	**0.837 ***	**−0.915 ***	0.016	**1**			
P.W.P. (%)	−0.112	−0.300	0.265	0.136	−0.055	−0.129	0.188	0.053	0.068	0.175	**−0.448 ***	**0.948 ***	**−0.914 ***	−0.037	**0.833 ***	**1**		
A.W. (mm m^{-1})	0.119	0.232	0.126	0.213	0.052	−0.022	0.008	0.126	0.009	0.001	**−0.836 ***	0.082	−0.263	0.139	**0.544 ***	0.010	**1**	
Ks (cm h^{-1})	0.025	0.321	−0.135	−0.092	−0.066	0.008	−0.239	−0.115	−0.144	−0.241	0.232	**−0.779 ***	**0.815 ***	0.192	**−0.606 ***	**−0.836 ***	0.207	**1**

Note. AW: available water; BD: bulk density; CaCO3: calcium carbonate; DTPA: diethylene-triamine-penta-acetic acid; EC: electrical conductivity; F.C.: field capacity; Ks: saturated hydraulic conductivity; PWP: permanent wilting point; S.P.: saturation percentage. * Correlation is significant at a probability level of 0.05.

Table 4. Bartlett's Sphericity Test and KMO Measure of Sampling Adequacy.

KMO Measure of Sampling Adequacy	0.586
Bartlett's Sphericity Test	
Chi-square (Observed value)	568.457
Chi-square (Critical value)	196.609
DF	153
p-Value	<0.0001
alpha	0.01

Table 5. Semivariogram parameters of soil properties for the area under investigation.

Variables	Model	Nugget	Partial Sill	Sill	Nugget/Sill	Range (m)	MSE
ECe (dSm^{-1})	K-Bessel	0.00	0.681	0.68	0.00	21,238.42	4.399
pH	J-Bessel	0.03	0.012	0.04	0.68	17,359.25	0.196
$CaCO_3$ (%)	Stable	15.07	0.0	15.07	1.00	17,472.56	4.036
Av. N (mg kg^{-1})	K-Bessel	14,515.83	83.000	14,598.83	0.99	46,971.71	122.565
Av. P (mg kg^{-1})	Stable	50.72	27.934	78.65	0.64	17,359.25	8.231
Av. K (mg kg^{-1})	Stable	0.40	0.143	0.54	0.74	33,708.12	84.609
DTPA Fe (μg kg^{-1})	Stable	0.19	0.264	0.45	0.41	15,044.21	541.570
DTPA Zn (μg kg^{-1})	Stable	0.20	0.033	0.23	0.86	26,154.06	126.429
DTPA Mn (μg kg^{-1})	Spherical	0.22	0.085	0.30	0.72	11,080.77	367.920
DTPA Cu (μg kg^{-1})	Spherical	0.08	0.355	0.43	0.18	15,340.73	87.910
Sand (%)	Stable	0.01	0.007	0.01	0.48	37,650.31	6.847
Clay (%)	J-Bessel	0.03	0.02	0.05	0.67	20,425.33	3.748
B.D. (Mg m^{-3})	J-Bessel	0.00	0.00	0.00	0.57	21,798.39	0.034
S.P. (%)	Gaussian	0.01	0.00	0.02	0.44	23,877.11	4.131
F.C. (%)	Stable	0.00	0.00	0.01	0.53	16,586.41	1.650
P.W.P. (%)	Exponential	0.01	0.01	0.02	0.59	20,963.86	1.559
A.W. (mm m^{-1})	J-Bessel	0.01	0.01	0.01	0.79	39,149.09	9.221
Ks (cm h^{-1})	Stable	0.00	0.21	0.21	0.00	20,827.91	0.532

Note. AW: available water; BD: bulk density; DTPA: diethylene-triamine-penta-acetic acid; EC: electrical conductivity; F.C.: field capacity; Ks: saturated hydraulic conductivity PWP: permanent wilting point; S.P.: saturation percentage.

Sill is theoretically equal to the variance of the sampled population at a large separation distance if the data has no trend [69]. The highest sill was recorded for N (14598.83) followed by P (78.65) whereas BD, sand, FC, AW, PWP, SP, pH, and clay has the lowest recorded 0.0, 0.01, 0.01, 0.01, 0.02, 0.02 followed by 0.04 and 0.05, respectively. The sill ratio for remaining soil properties varied between 0.23 and 15.07.

If the value of the nugget-to-sill ratio was <0.25, 0.25–0.75, and >0.75, this exposes strong (attributable to intrinsic factors), moderate (attributable to both intrinsic and extrinsic factors) and weak (attributable to extrinsic factors) spatial dependence, respectively [70]. The nugget: sill ratio, which indicates the relationship between location and ratio, showed that the soil's EC, Cu, and Ks characteristics were strong, while pH, P, K, Fe, Mn, sand, clay, BD, SP, FC, and PWP were moderate and $CaCO_3$, N, Zn, and AW were weak (Table 4). Nugget-to-sill ratio values were less than 0.25 for all the studied soil properties except CEC [56].

Spatially dependent soil attributes are affected by parent material inherent to the soil, mineralogy, texture, farming techniques, and other anthropogenic activities. Variations in terrain, fertilizer application rates, nutrient management techniques, and diverse flora all affect how location and soil properties interact in different ways. The underlying mineralogy and parent material are ascribed to the high geographical dependency of soil characteristics [37]. Extrinsic factors such as soil management including tillage and fertilizer application influence moderate and weak spatial dependence of soil properties [24].

The semivariogram's range value can be interpreted as the farthest distance at which there is spatial dependency or autocorrelation. The range of soil property values was 11.08

for manganese to 46.97 km for nitrogen (Table 5). Beyond this point, autocorrelation is absent. Large-range values show that measured soil properties are impacted by natural and human-made causes over a wider area [24]. Kerry and Oliver [71] state that the delay between soil samples should be no more than half the semivariogram range value.

Kriged maps of pH, ECe, $CaCO_3$, available macro and micronutrients, and hydrological properties were created by ordinary kriging interpolation methods to evaluate the distribution of these nutrients (Figure 3a–r) which were successfully applied by many studies [72]. Future studies will use these maps as a knowledge resource. The maps can be used by individual farmers to adopt a variable rate of nutrient application in certain places. The maps will also serve as a foundation of knowledge for State authorities, decision-makers, and extension specialists as they build site-specific strategies for landscape management and application of balanced nutrients. Applications for computers and mobile devices that are based on these maps will provide farmers with more exact and balanced rates of nutrient application [37].

3.6. Principle Components Analysis (PCA)

The principal component analysis (PCs) was used to sort through major soil properties to determine which can contribute the most to soil quality improvement and help priorities immediate management action. PCs with eigenvalues greater than or equal to 1.0 were chosen for this purpose; therefore, these PCs were used according to the method described by Kaiser [73] while PCs with eigenvalues less than 1 were subtracted. As a result, the first six PCs had eigenvalues greater or equal to 1.0 and a cumulative variability of 79.75%. (Table 6 and Figure 4). PC1, 2, 3, 4, 5, and 6 contributed 28.6%, 14.7%, 12.5%, 10.4%, 7.6%, and 5.9%, respectively. BD dominated the PC1 loading, followed by FC, clay, PWP, Ks, and sand. PC2 was dominated by N, ECe, and $CaCO_3$; PC3 was dominated by pH; PC4 was dominated primarily by K and P, PC5 was mainly dominated by Fe; Mn, and Cu, and PC6 was mainly dominated by SP and Zn. A biplot chart depicts the graphical representation of the variability contribution by PC1 and PC2, as well as the loadings for different soil properties (Figure 4). This will aid in decision making regarding the identification of properties for prioritization of physical, chemical, and nutrient management strategies in this area under investigation to improve agriculture production and reduce the effects of land degradation. Soil status of BD, FC, PWP, Ks, N, ECe, and $CaCO_3$ matters in that order may be used as criteria to decide priorities for improving water and salt and nutrient content based on variable loading of soil properties in different PCs and expert opinion.

3.7. Initiating Management Zones Using Soil Properties

A cluster analysis was applied to classify the four PCs into MZs. The XLSTAT was used based on the AHC technique to define the optimum number of MZs. This method allows us to differentiate different zones with a similar value of properties and higher differences between them [74]. To obtain the optimum number of MZs and plotted as shown in Figure 5, against the number of clusters (or MZs). In this study, four different management zones were finally identified as the optimum number of MZs, as shown in Figure 5. The four SMZs were distinctly different from each other and the percent areas were 77.94, 14.10, 7.11, and 0.85% for SMZ1, SMZ2, SMZ3, and SMZ4 respectively. Figure 6 shows the spatial distribution map of the four delineated MZs in the study area. In each delineated MZ, the measured soil properties present the lowest variance and highest degree of membership. Thus, in each zone, different management practices, such as agriculture management can be carried out to increase crop production while decreasing costs. Therefore, the one-way ANOVA was carried out to evaluate the effectiveness of the PCA and AHP combination to delineate MZs and also its spatial variability. There were significant differences ($p < 0.05$) between all soil and terrain attributes except for N, Zn, AW, and Ks among the four MZs, as shown in Table 7. The MZ1 and MZ3 which covers 85.05% of the area under investigation had a mean value of ECe as 3.03 and 4.52 dSm^{-1} and were classified as moderately salinized soils, greater than the limiting critical value for the sensitive crops. Whereas the MZ2 which covers 14.10% of the area has 7.23 dSm^{-1} of ECe and must be leached to remove salts from the soil and reduce ECe to less than 2 dSm^{-1} to get high productivity. When the total amount of salts accumulated in the root zone is high enough, negatively affects plant growth by reducing the plant's available water [75]. Only 0.85% of the area has low ECe, as shown in Table 7. In all MZs, the soil available nitrogen, zinc, available water content, and saturated hydraulic conductivity remains tight and did not show significant differences. The four MZs have low clay, available N, P, and lower micronutrient concentrations. Thus, these MZs have a great potential for environmental risk via nitrogen leaching through the soil profiles and also nitrogen load in soil surface run-off, especially with a high percentage of sand. This finding is diagnostic for determining the amount of fertilizer and irrigation water to be applied to soils in different management zones. Its emphasis's the importance of site-specific management for long-term crop productivity and, as a result, reducing environmental hazards caused by uneven fertilizers application. Moreover, all of the delineated MZs had low hydrological properties (SP, FC, PWP, and AW) and should be taken into account in agriculture management processes. According to several studies, analysis of variance is an effective method for determining the differences between delineation zones. [74,76–78].

Table 6. Principal component analysis of soil properties and loading coefficient for first six principal components.

	PC1	PC2	PC3	PC4	PC5	PC6
Eigenvalue	5.157	2.639	2.248	1.876	1.367	1.069
Variability (%)	28.648	14.661	12.488	10.423	7.595	5.936
Cumulative (%)	28.648	43.309	55.797	66.220	73.815	79.751
PC loading for each variable						
	PC1	PC2	PC3	PC4	PC5	PC6
ECe (dSm^{-1})	−0.019	0.601	−0.478	0.492	0.162	−0.065
pH	0.277	−0.275	0.685	0.047	−0.281	0.110
$CaCO_3$ (%)	−0.395	0.487	0.118	−0.349	−0.026	−0.465
Av. N (mg kg^{-1})	−0.312	0.711	0.135	−0.165	0.194	−0.115
Av. P (mg kg^{-1})	−0.049	0.502	−0.498	0.503	0.020	0.080
Av. K (mg kg^{-1})	0.172	−0.506	−0.277	0.564	−0.296	0.018
DTPA Fe (µg kg^{-1})	−0.191	−0.493	−0.273	0.138	0.622	−0.148
DTPA Zn (µg kg^{-1})	−0.100	−0.409	0.114	0.233	−0.274	−0.510
DTPA Mn (µg kg^{-1})	−0.081	−0.622	−0.088	0.117	0.553	−0.145
DTPA Cu (µg kg^{-1})	−0.180	0.056	−0.343	0.290	−0.469	0.154
Sand (%)	0.690	−0.120	−0.498	−0.453	−0.036	0.019
Clay (%)	−0.922	−0.128	−0.086	−0.209	−0.037	0.070
B.D. (Mg m^{-3})	0.965	0.100	0.021	−0.019	0.065	−0.100
S.P. (%)	0.044	0.075	0.306	0.061	0.316	0.656
F.C. (%)	−0.943	−0.049	0.224	0.168	−0.013	0.047
P.W.P. (%)	−0.922	−0.155	−0.147	−0.206	−0.081	0.149
A.W. (mm m^{-1})	−0.322	0.176	0.631	0.616	0.130	−0.123
Ks (cm h^{-1})	0.779	0.221	0.403	0.190	0.133	−0.068

Note. AW: available water; BD: bulk density; DTPA: diethylene-triamine-penta-acetic acid; EC: electrical conductivity; F.C.: field capacity; Ks: saturated hydraulic conductivity; PWP: permanent wilting point; S.P.: saturation percentage.

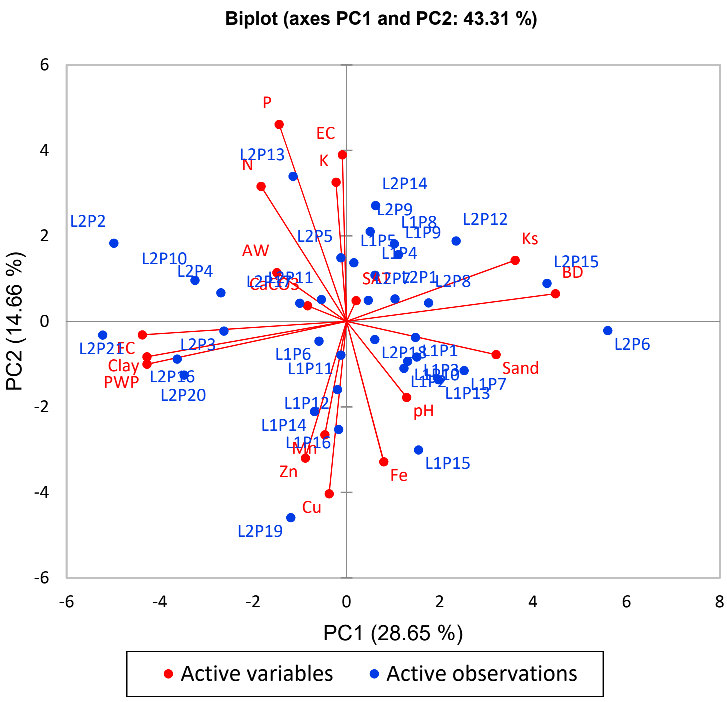

Figure 4. PCA biplot (PC1 vs. PC2) of soil properties in South Hail located in KSA.

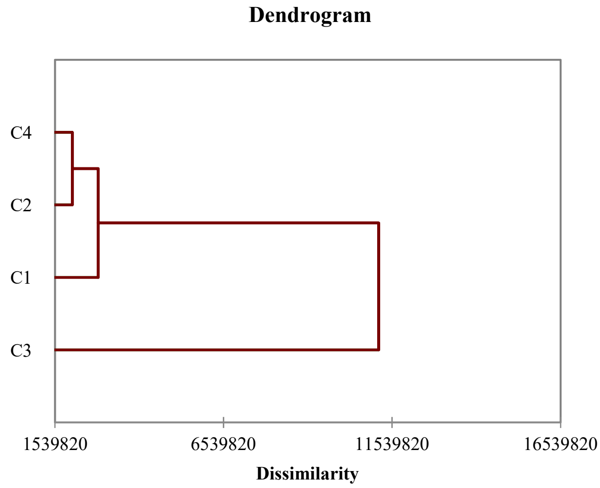

Figure 5. Dendrogram for Agglomerative hierarchical clustering.

Table 7. Mean values of soil properties in different management zones of South Hail located in KSA.

MZ	No.	EC	pH	N	P	K	Fe	Zn	Mn	Cu	$CaCO_3$	Sand	Clay	BD	S.P.	F.C.	P.W.P	A.W.	Ks
1	24	4.52 ab	7.91 b	1147.9 a	25.5 a	98.7 ab	432.4 b	233.5 bc	367.5 c	135.1 b	5.9 b	68.8 ab	16.9 b	1.49 a	45.1 a	21.2 b	12.0 b	92.6 bc	1.17 a
2	7	7.23 a	7.89 c	1078.6 ab	15.9 bc	120.1 a	1069.1 ab	244.1 ab	707.8 b	157.7 ab	7.9 a	67.2 b	15.9 b	1.49 a	43.7 b	21.1 b	11.6 b	94.4 ab	1.11 ab
3	2	3.03 b	8.02 a	1000.0 bc	8.1 c	140.3 a	2953.0 a	257.0 a	764.7 ab	216.2 a	8.7 a	71.1 a	17.5 b	1.49 a	44.0 b	21.3 b	12.0 b	89.5 c	0.98 bc
4	4	2.03 c	7.95 ab	1225.0 c	27.3 a	58.6 b	297.8 b	218.4 c	1138.1 a	149.1 b	4.9 b	63.7 c	20.2 a	1.47 b	45.0 a	22.8 a	13.1 a	97.3 a	0.85 c

Note. AW: available water; BD: bulk density; DTPA: diethylene-triamine-penta-acetic acid; EC: electrical conductivity; F.C.: field capacity; Ks: saturated hydraulic conductivity; No: number of profiles; PWP: permanent wilting point; S.P.: saturation percentage; a,b,c: Values not sharing similar letters are significantly different ($p > 0.05$).

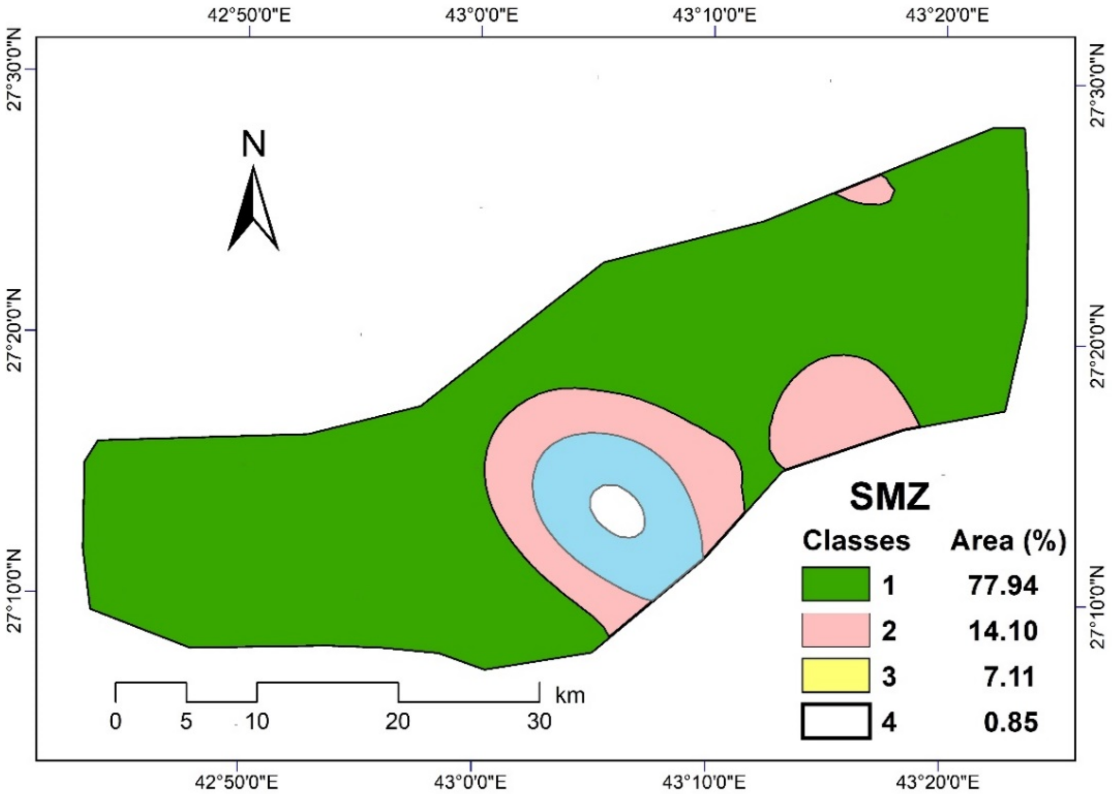

Figure 6. Management zones (MZs) kriged map of South Hail located in KSA.

4. Conclusions

A total of 111 soil samples were collected from 37 soil profiles in systematic depths (0–50, 50–100, and 100–150 cm) from the South Hail region, KSA. The samples were analyzed for pH, ECe, $CaCO_3$, and accessible macro and micronutrients and hydrological properties. A strong significant correlation was observed between most of the soil properties. The best fit models were J-Bessel for pH, Clay, BD, and AW; K-Bessel for EC and Av. N; Stable for $CaCO_3$, P, K, Fe, Zn, Sand, FC, and Ks; Spherical for Mn and Cu; Gaussian for SP; whereas exponential for PWP. The PCA resulted in six principal components (PCs) explaining 79.75% of the total variance of soil properties. The PC1 was strongly influenced by soil BD, FC, clay, PWP, Ks, and sand. PC2 was dominated by N, ECe, and $CaCO_3$; PC3 was dominated by pH; PC4 was dominated primarily by K and P, PC5 was mainly dominated by Fe; Mn, and Cu, and PC6 was mainly dominated by SP and Zn. Based on agglomerative hierarchical clustering, four soil management zones (MZs) cover 77.94, 14.10, 7.11 and 0.85% of studied area. MZ 1 and 3 classified as moderately saline while MZ 2 classified as highly saline soils. This area must be leached to remove salts and reduce ECe to less than 2 dSm^{-1}, to get maximum productivity. All MZs have a great potential for environmental risk via nutrients leaching through the soil profiles, especially with a high percentage of sand. This finding is diagnostic for determining the amount of fertilizer and irrigation water to be applied to soils in different management zones. Moreover, all of the delineated MZs had low hydrological properties (SP, FC, PWP, and AW) and should be taken into account in agriculture management processes.

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