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Sub-basin scale spatial variability of soil properties in Central Iran

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Abstract Scientific information on the spatial variability of soil properties is essential for making sustainable soil and environmental management decisions. The spatial variation of soil electrical conductivity (EC), pH, carbonates, gypsum, gravel, clay, silt and sand in the Gavkhooni sub-basin, Central Iran was studied employing conventional statistics, geostatistics and a geographical information system (ArcGIS). By the method of random sampling within blocks, the study area was divided into 100 blocks of $6{\times}6\ km^2$ and in each block surface, samples (0–10 cm) were taken randomly. The EC content showed strong variation (CV>100%), pH and carbonates exhibited weak variation (CV<10%) and the other properties showed moderate variation. Soil parameters such as gravel, silt and gypsum were best fitted by a Gaussian model, sand and carbonates fitted best with a Spherical model and the remaining soil parameters were fitted to the Exponential model. Based on the models, the spatial correlation (range) of the soil properties greatly changed from 5.6 (sand) to 74.5 km (EC). Soil pH, EC, carbonates and clay had strong spatial dependence whereas the other properties had moderate spatial dependence. The spatial distribution maps were prepared using ordinary kriging interpolation. Comparison of the results using statistical methods indicated that kriging technique had satisfactory accuracy in characterizing the spatial variability.

Keywords Gavkhooni sub-basin · Geostatistics · Ordinary kriging · Soil properties · Spatial variability

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Introduction

Spatial variability in soils is governed naturally by exogenic and endogenic environmental factors. Natural variability of soil is the consequence of complex interactions among geology, topography, climate and land use (Quine and Zhang 2002). Additionally, variability can happen due to management practices and soil erosion–deposition factors. Accordingly, soils can display marked spatial variability at the macro and micro scales (Vieira and Paz-Gonzalez 2003; Brejda et al. 2000).

Among the soil variables, soil texture is one of the most important soil variables controlling most of the physical, chemical and hydrological soil variables. Variability in soil texture can be a factor in variation of nutrient availability and storage, water transport and retention as well as stability and binding of soil aggregates. It can directly or indirectly control many other soil functions and also soil threats such as soil erosion. Geostatistics has been widely applied for quantifying the spatial pattern of soil properties and kriging methods are proving sufficiently strong for estimating values at unsampled locations in most of the cases (Niemann and Edgell 1993; Crave and Gascuel-Odoux 1997). Soil pH is the other factor which is an indicator of the acidity or alkalinity of soil, and it is a reflection of the principal chemical and physical properties of soil quality (Nagy and Kónya 2007). Soil pH also has a significant influence on some other soil properties. Increase in alkalinity or acidity will alter the availability of nutrients and influence

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element imbalances in plants (Zhao et al. 2011). Geostatistics has been widely utilized for quantifying the spatial pattern of environmental variables (Webster and Oliver 2001; Goovaerts 1997). Kriging has been applied as a synonym for geostatistical interpolation for decades and has been confirmed as sufficiently strong for estimating values at unobserved locations based on the sampled data. The central theme of geostatistics is recognized as the regionalized variable theory and the complementary function is known as a semi-variogram (Burgess and Webster 1980). The regionalized variable theory allows us to consider the spatial variability of a soil property as a stochastic model. Kriging employs the semi-variogram to predict values at unsampled locations using minimization of errors (Krige 1966). These principles have been used in soil science for over two decades (Burgess and Webster 1980; Webster and Burgess 1980). Nael et al. (2004) utilized geostatistical techniques to study the variability of soil quality indices and their spatial variability in central Iran. Ayoubi et al. (2007) indicated that geostatistical techniques offer substitute methods to conventional statistics for the estimation of parameters and their associated variability at the field scale in Golestan Province, Iran.

For appropriate basin management planning, the maps of important properties of soil resources are needed. The use of traditional methods to study the variations in spatial structure of soil properties is expensive and time-consuming. On the other hand, classic statistics cannot consider spatial changes of variables. In addition, chemical and physical properties of soil resources change spatially and temporally. Hence, in this study, geostatistical methods are utilized to evaluate the spatial structure of soil properties in an extremely arid region. This study was conducted to assess the ability of kriging method to predict spatial variation of some chemical and physical soil properties such as texture, gravel, pH, EC, carbonates and gypsum at Gavkhooni sub-basin in Isfahan Province, Central Iran.

Materials and methods

Study area

The study was conducted in the Gavkhooni sub-basin (31°51′ to 32°45′ N, 52°31′ to 53°21′ E) within an area of 3616 km^2, which is located in Central Iran, southeast of Isfahan city. The wind-eroded sand dunes are located in the western part of the study area. Additionally, International Gavkhooni salt marsh, which is located at the terminal part of Zayandeh Roud River, has occupied approximately 472 km^2 of the study area (Fig. 1). The topography of the sub-basin is generally flat containing some undulating piedmonts with an altitude averaging of 1549 m a.s.l. The mean annual precipitation is 94.23 mm and the mean annual temperature is 16.9 °C. The soil temperature and moisture regimes are thermic and aridic, respectively, and soils are dominantly Aridisols (Soil Survey Staff 2014).

Sampling and soil analysis

As the study area was very vast, soil samples were collected by the method of random sampling within blocks. According to sampling area (3616 km^2), the Gavkhooni sub-basin was divided into 100 blocks of 6×6 km^2 and in each block surface samples (0–10 cm) were taken randomly (Fig. 1). The geographical position of the sampling points was recorded by using GPS. Soil samples were passed through a 2-mm sieve after being air-dried. The gravel percentage was determined by measuring the volume of gravels. Soil analysis included electrical conductivity (EC) (Rhoades 1982) and pH (Lean 1982) in saturated-paste extract, carbonates (Allison and Moodie 1965), gypsum (Artieda et al. 2006) and the clay, silt and sand contents (Gee and Bauder 1986).

Statistical analysis

Exploratory statistical analysis

Descriptive statistics and normality tests were carried out using IBM® SPSS® Statistics 23.0. For each soil parameter, the mean, maximum, minimum, standard deviation (SD), kurtosis, skewness as well as coefficient of variation (CV) were calculated to depict the central trend and spread of the soil parameters datasets. The analysis of exploratory data was done for outliers and normality tests. One-sample Kolmogorov–Smirnov Test was employed to determine the fit of the data in a normal distribution and, if they did not fit, a suitable transformation was utilized based on the distribution of the data before the calculation of semi-variance.

Geostatistical analysis

Geostatistics was utilized to determine spatial patterns and create the soil properties prediction maps. The data were examined for the presence of trend, before geostatistical analysis. Prior to application of ordinary kriging interpolation, the semivariogram analyses were carried out on the soil variables. It is because the semivariogram model determines the interpolation function. A semivariogram is assessed using the following equation (Goovaerts 1999):

$$\gamma(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} [Z(x_i + h) - Z(x_i)]^2$$

Where $\gamma(h)$ is the semivariance used for the interval class h, N(h) is the number of sample value pairs in the distance interval h and $Z(x_i)$ and $Z(x_i + h)$ are two sample values by the distance h. The variogram can then be fitted

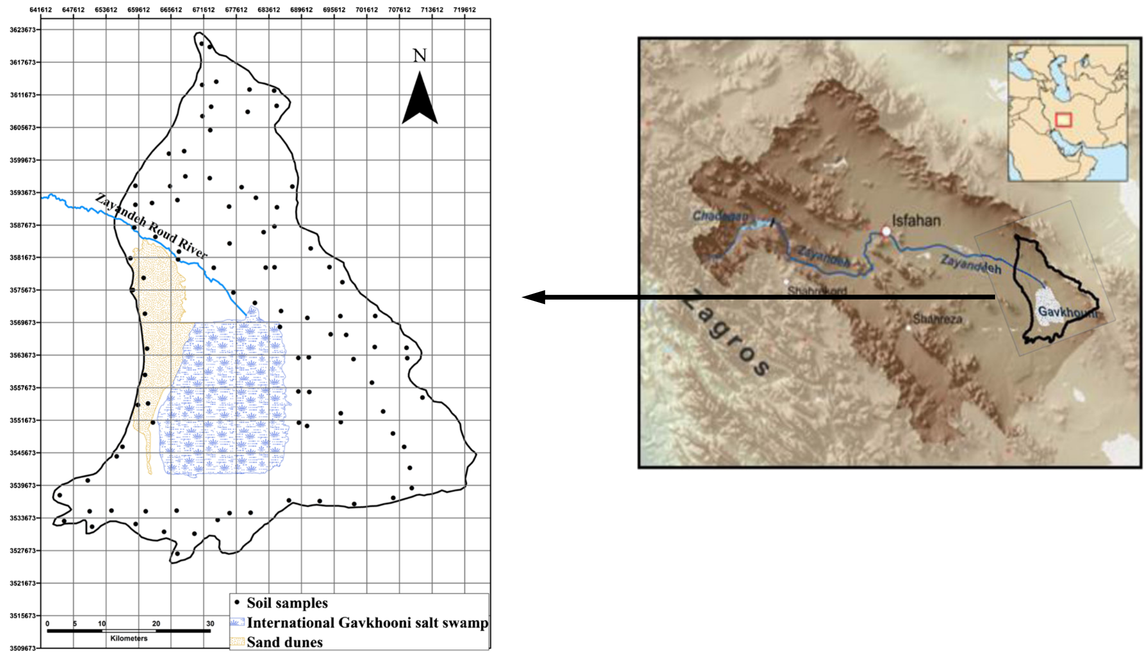

Fig. 1 Location of the study area and soil sampling points

using several models (Spherical, Exponential and Gaussian) (Webster and Oliver 2007).

A variogram is defined by permissible theoretical models and three parameters of nugget (the variance at zero distance), sill (the lag distance between measurements at which one value for a variable does not influence its neighbouring values) and range (the distance that values of one variable become spatially independent of another one). Several semivariogram models were evaluated to select the best fit with the data. Spherical, Exponential and Gaussian models were fitted to the empirical semivariograms.

To determine the degree of spatial dependence (DSD) for the soil parameters, the ratio between the nugget semivariance and the sill was employed. The variable was assessed strongly distributed in patches or having strong spatial dependence, if the ratio was less than 25%; the soil variable was regarded as having moderate spatial dependence, if the ratio was between 25% and 75%; the soil variable was considered to have weak spatial dependence if the ratio was greater than 75%; and ultimately the soil variable was assessed non-spatially correlated (pure nugget), if the ratio was 100% or the slope of the semivariogram was near to 0 (Francisca et al. 2002).

The cross-validation method was employed to select the appropriate semivariogram models for comparison of statistical values estimated from the actual values and semivariogram models. Differences between estimated and experimental values were summarized applying the cross-validation statistics which is mentioned below:

Root mean square error (RMSE) indicates how closely the model predicts the measured values and is calculated as follow:

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}\left[z^{*}(x)-z(x)\right]^{2}}{n}}$$

This value should be as small as possible.

The G-statistic (goodness-of-prediction (G) estimate) was used as a criteria to test the efficiency of the model fit compared to a mean model fit which could have been derived from using the sample average alone (Agterberg 1984) as follows:

$$G = \left(1-\left\{\sum_{i=1}^{n}\left[z(x)-z^{*}(x)\right]^{2} \Big/ \sum_{i=1}^{n}\left[z(x)-\bar{z}\right]^{2}\right\}\right)$$

A G value equal to 100% shows perfect prediction while negative values show that the predictions are less reliable than if sample average employed instead (Schloeder et al. 2001).

Where z(x) is a measured value, z*(x) is a predicted value, n is the number of observation and $\bar{z}$ is average of the observed values.

Ordinary kriging was chosen as the preferred method for soil variables spatial interpolation as it was more reliable than the other interpolation techniques according to the mean squared error which compares the predicted and measured values. Furthermore, due to the relatively low density of the soil sampling, ordinary kriging is the best impartial predictor at random unsampled locations (Cressie 1993). The other advantage of ordinary kriging is minimizing the influence of outliers (Triantafilis et al. 2001).

The geostatistical analysis, fitting the best semivariogram model and related components for instance effective range, sill and nugget effect and also the construction of kriged maps were done using GIS software Arc Map (version 10.1).

Results and discussion

Exploratory data analysis

Table 1 provides the descriptive statistics of the soil properties (raw data) in the sub-basin study. In order to provide a base for further structural analysis, it is necessary to apply the normal data, so the abnormal data were transferred to normal data (Fig. 2). These processes reveal that the most distributions of soil properties vary significantly in the study sub-basin. Distinctions in soil properties may be associated with differences in geomorphic units, land use, vegetation cover and topographic effects and management practices, on the variability of soil erosion across the landscape of the area (Tesfahunegn et al. 2011). Soil properties may also be affected by variation in depositional erosion and or differences in pedogenic or hydrologic processes. These effects may cause data to depart from a normal distribution and cause positive or negative skewness (Momtaz et al. 2009).

The EC content showed strong variation with CV > 100% (Nielsen and Wendroth 2003). pH and carbonates exhibited weak variation with CV < 10% and the other properties such as gravel, sand, silt, clay and gypsum showed moderate variation with 10% < CV≤100% (Table 1). The strongest variation was observed by EC which is due to the existence of a salt marsh in the study area. The lowest CV was perceived for pH; because pH values are a log scale of H^+ concentrations in the soil solution. So, there would be much higher variability if soil acidity was expressed with regard to proton concentrations directly (Sun et al. 2003). Other researchers have also observed lower variance in soil pH compared to other soil properties (Mousavifard et al. 2012; Tesfahunegn et al. 2011). In general, employ of CV is a common method to evaluate variability in soil properties since it allows comparison among properties with different units of measurement. But, such classical statistics could not recognize the spatial variability of soil parameters in unsampled sites. The geostatistical procedure however allows the assessment of spatial dependence and variability of a specific soil property (Liu et al. 2006).

Geostatistical analysis results

Variograms and spatial dependence

Anisotropic semivariogram demonstrated higher differences in spatial dependence based on direction (angle) for all of soil properties (Table 2). The semivariogram analysis specified distinct spatial distribution models and spatial dependence classes for the eight soil properties (Table 2; Fig. 3). Soil parameters such as gravel, silt and gypsum were best fitted by a Gaussian model whereas carbonates and sand fitted best with a Spherical model. The remaining soil parameters were fitted to the Exponential model. In this study, the semivariograms indicated strong spatial dependence (DSD ≤ 25%) for soil properties such as pH, clay, EC and carbonates; and the rest of the soil properties showed moderate spatial dependence (25 < DSD ≤ 75%) (Table 2). The strong spatial dependence of soil properties may be as a result of natural factors, such as strong pedological and hydrological processes in the study sub-basin, soil type, the parent material, climate and soil-forming factors. However, moderate spatial dependence indicated that the anthropogenic factors changed the soil texture spatial correlation through farming, management practices, industrial production and other human activities (Yang et al. 2009).

The range values showed large variability among the soil parameters which can be a useful principle for mapping of soil parameters (Utset et al. 1998; Fu et al. 2010). Table 2 indicates that the soil properties spatial correlation (range) widely varied from 5.6 (sand) to 74.5 km (EC). The different ranges of the spatial dependence among the soil properties may be a result of differences in response to the land use–cover, erosion–deposition factors, parent

Table 1 Descriptive statistics of soil properties in the study area

Variable	Unit	Min	Max	Mean	SD	CV (%)	Skewness	Kurtosis	Distribution type
Gravel (2–20 mm)	%	1.00	40.00	16.24	9.08	55.88	0.71	0.10	Square root normal
Sand (0.05–2 mm)	%	46.67	96.00	75.74	11.24	14.84	−0.40	−0.31	Normal
Silt (0.05–0.002 mm)	%	2.00	38.33	11.86	7.35	61.97	0.97	1.13	Square root normal
Clay (<0.002 mm)	%	2.00	30.50	12.38	6.15	49.70	0.88	0.41	Square root normal
Carbonates	%	7.42	51.40	26.14	9.68	7.06	0.81	0.132	Log normal
Gypsum	%	0.03	12.10	1.31	2.32	177.3	3.41	11.95	Log normal
pH	–	6.70	8.93	8.01	0.54	6.74	−0.33	−0.62	Normal
EC	dS m^{-1}	1.01	389.2	40.21	85.66	213.01	2.95	8.18	$(\text{Log})^{1/2}$ normal

CV coefficient of variation, *EC* electrical conductivity, *Min* minimum, *Max* maximum, *SD* standard deviation

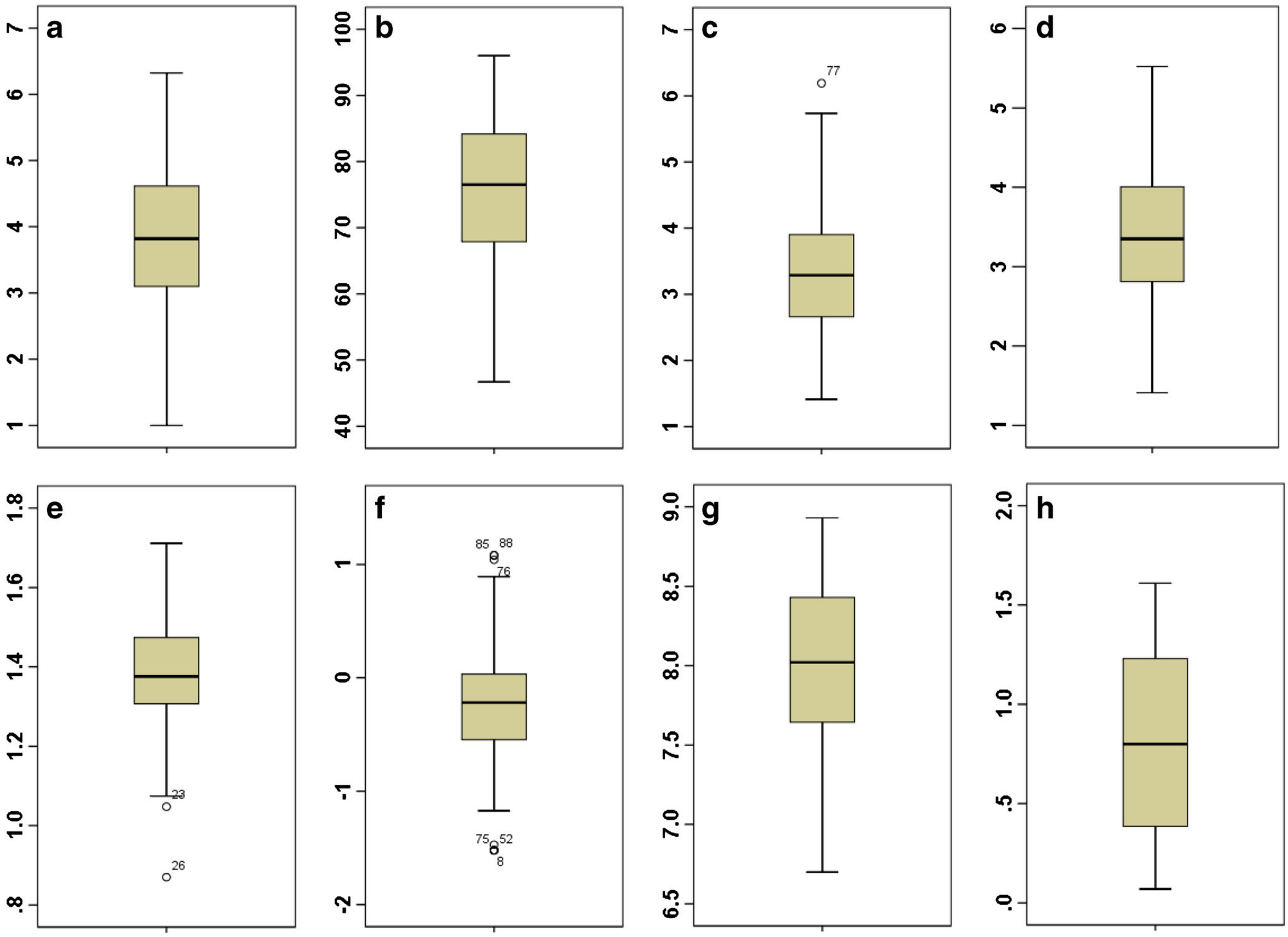

Fig. 2 Boxplots of trimmed soil properties. **a** gravel, **b** sand, **c** silt, **d** clay, **e** carbonates, **f** gypsum, **g** pH and **h** EC

material and topography in the study area (Tesfahunegn et al. 2011). A large range shows that the observed values of the soil parameters are affected by other more distance values of this parameter compared to the soil parameters ranges are smaller (Lopez-Granados et al. 2002). Thus, a major range of 74.5 km for EC implies that EC values

Table 2 Semivariogram models, interpolation parameters and cross-validation statistics of selected soil properties in the study area

Variable	Model	Direction (angle)	Range (km)		Nugget	Sill	DSD (%)	Spatial dependence class	Cross-validation statistics	
			Major	Minor					RMSE	G (%)
Gravel[a]	Gaussian	45	8.5	5.7	0.35	1.26	27.98	Moderate	1.09	12.21
Sand	Spherical	90	5.6	5.4	42.23	84.43	50.03	Moderate	9.79	23.35
Silt[a]	Gaussian	91.23	29.9	16.3	0.62	1.02	60.4	Moderate	0.88	32
Clay[a]	Exponential	135	12.9	5.4	0	0.67	0	Strong	0.81	10.62
Carbonates[b]	Spherical	80.3	47.7	24.4	0.02	0.09	24.6	Strong	4.75	77
Gypsum[b]	Gaussian	150.3	56	28.8	1.17	1.98	59.1	Moderate	2.19	10.16
pH	Exponential	161.3	19.4	8.2	0	0.21	0	Strong	0.38	50
EC[c]	Exponential	145.9	74.5	40.1	0.04	0.27	14.27	Strong	0.33	52.52

DSD degree of spatial dependence, *EC* electrical conductivity, *G* goodness-of-prediction estimate, *RMSE* root mean square error

[a] Square root normal

[b] Log normal

[c] $(\text{Log})^{1/2}$ normal

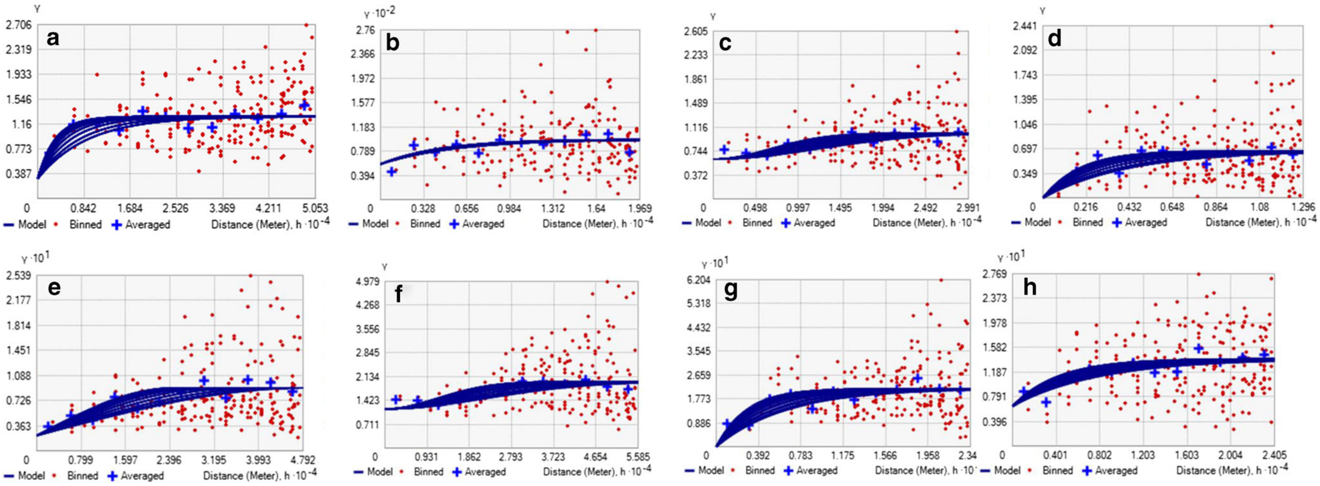

Fig. 3 Best-fitted semi-variogram models for **a** gravel, **b** sand, **c** silt, **d** clay, **e** carbonates, **f** gypsum, **g** pH and **h** EC

influenced neighbouring values of EC over greater distances than other soil variables. The cross-validation statistics demonstrate how well soil properties can be estimated by application of the ordinary kriging method. Such test was checked with the RMSE values. The model with the lowest RMSE value was chosen as presented in Table 2. These low values are showing that kriging predictions of soil parameters are closer to measured values.

The G value was also employed to evaluate the accuracy of the kriged soil properties spatial maps (Table 2). The value of G parameter shows the prediction ability of the datasets employing kriging from the sample points as compared to sub-basin average values. The kriging model performed best for carbonates, EC and pH with G values of 77, 52.52 and 50, respectively, and moderately well for the other properties. However, kriging was more precise

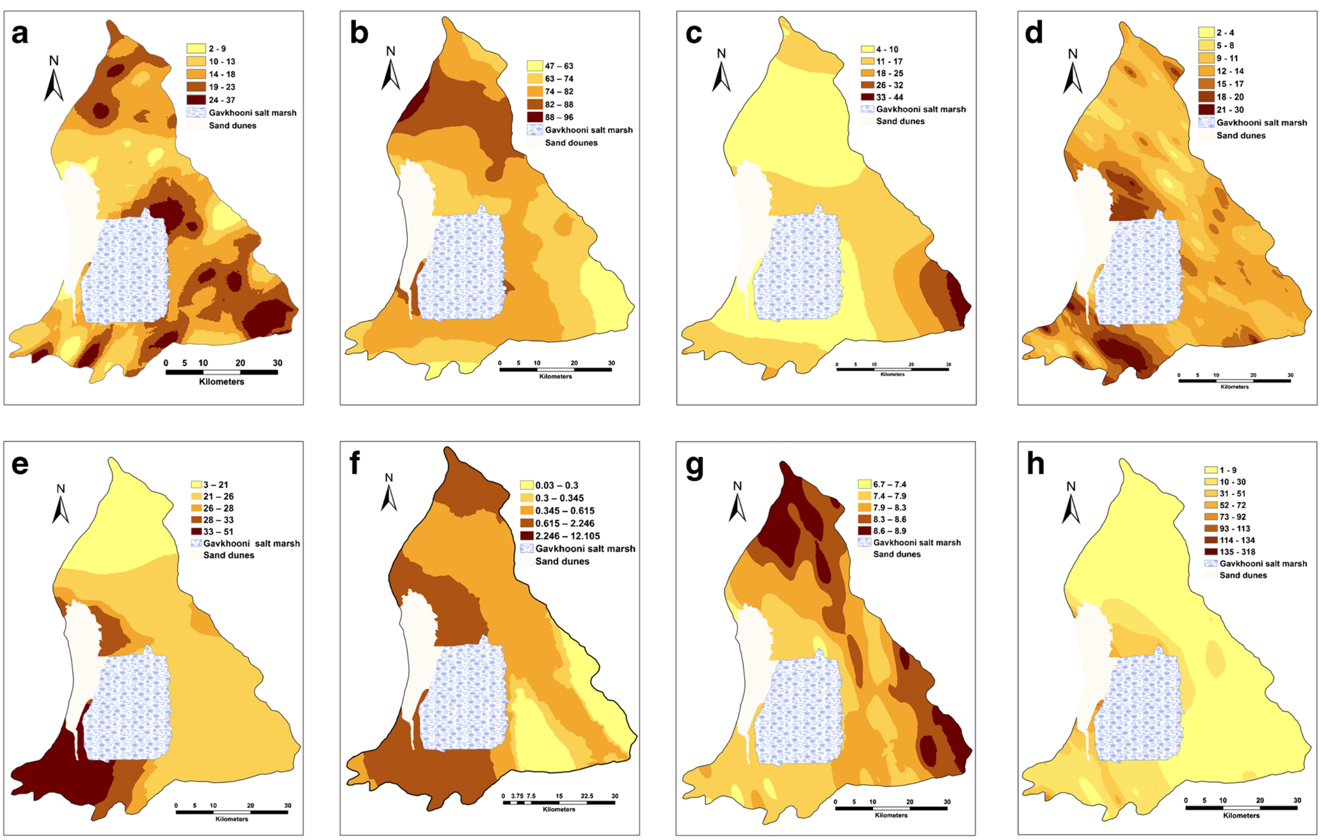

Fig. 4 Spatial distribution of selected soil properties interpolated by ordinary kriging for Gavkhooni sub-basin: **a** gravel, **b** sand, **c** silt, **d** clay, **e** carbonates, **f** gypsum, **g** pH and **h** EC

than the sub-basin scale average value; because the G values are more than zero. Consequently, the use of interpolation method was appropriate for developing the soil properties maps that can help to generate site-specific soil management strategies.

Spatial distribution of soil properties

Fig. 4 shows the interpolation maps of the soil properties. These maps could help to interpret the results. Additionally, the quantitative information achieved from these maps could be employed to facilitate management in the sub-basin study.

Wind is one of the most important factors in the transportation of salts and fine particles in the Gavkhooni region. The appearance of vast high sand dunes in the western parts of the Gavkhooni Marsh indicates the wind activity in this area. The high amounts of soluble salts, especially sodium, in the soil surfaces around the Gavkhooni salt marsh lead to dispersion of soil structure. Eventually, the coarser particle (sand) remains near the marsh (Fig. 4b); whereas, the finer particles (silt and clay) are transported to other parts of the sub-basin as a result of wind activity (Fig. 4c and d). In addition, the wind leads to spread sand dunes in wide area and consequently affected the soil structure. These factors are the reason for dominating the coarse texture in the study area. The gravel was also spread irregularly in the surface of study area due to water erosion and runoff which occurred in the past (Fig. 4a). The maps of carbonates, gypsum and EC contents of the surface soil in the study area (Fig. 4e, f and h) show that these parameters are higher in the west and southwest which could be rationalized as a result of natural effects such as parent material, since the area surrounding the west and southwest parts originated from limestone and marl. Additionally, the high level of groundwater around the Gavkhooni salt marsh and the high evaporation in this area lead to accumulation of soluble salts and evaporite minerals such as calcite, gypsum and halite in soil surfaces of these regions. However, the gypsum content seems less than other soluble salts and evaporite minerals in soil surface due to lower solubility. Because of the high concentration of electrolytes around the Gavkhooni salt marsh, salts prevent from hydrolysis and high alkalinity of soils. Accordingly, pH is not more than 8 in the west and southwestern parts of this area (Fig. 4g).

Conclusions

For understanding the behaviour of soil and, consequently, providing better soil managements, realizing the spatial variability of soil properties is essential. This study focused on assessing the ability of kriging method to predict spatial variation of some chemical and physical soil properties such as texture, gravel, pH, EC, carbonates and gypsum at Gavkhooni sub-basin, Central Iran. The EC parameter having larger CV showed stronger variability than the other studied soil properties. The semivariograms results showed that gravel, silt and gypsum were best fitted by a Gaussian model, sand and carbonates fitted best with a Spherical model and the remaining soil parameters were fitted to the Exponential model. Based on the models, the spatial correlation (range) of the soil properties greatly changed from 5.6 (sand) to 74.5 km (EC). Soil pH, EC, carbonates and clay had strong spatial dependence whereas the other properties had moderate spatial dependence. The spatial distribution maps based on ordinary kriging interpolation method were successfully applied for all the soil properties. Consequently, the results can be utilized as a source of information for performance of any land management as well as soil and water conservation plans in the study sub-basin. Additionally, geostatistics and GIS proved to be essential tools to study spatial variation of soil properties.

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