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Spatial variability of soil micronutrients under paddy (*Oryza sativa*)-wheat (*Triticum aestivum*) cropping system in irrigated plains

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ABSTRACT

Soil properties vary spatially over short distances and sometimes prove detrimental to crop productivity in farmlands even after uniform application of balanced nutrients. In the present study, spatial variability of micronutrients was studied in Chakroi farm of Sher-e-Kashmir University of Agricultural Sciences and Technology of Jammu (SKUAST-Jammu) during 2016 and 2017. Results indicated that mean concentrations of micronutrients were in the order of Fe > Mn > Cu > Zn both in surface and sub-surface layers. Exponential model was the best fit for all micronutrients in surface soil layer. Linear model was best fit for Cu and Gaussian model for Mn in the sub-surface layer. Whereas for Zn and Fe, the best fit was defined by exponential model. All the four micronutrients showed strong spatial dependence in surface layer, whereas in sub-surface layer Mn and Zn showed strong spatial dependence as compared to Cu. More than 60% of the area in the surface layer had Cu in the range of 2.0–2.8 mg/kg of soil. A very small area was under high range on the eastern side of the farm while in the sub-surface layer, Cu was unevenly distributed. The soil maps of Zn showed that it is above the critical value in surface layer while in sub-surface layer nearly 40% of the area had Zn in the deficient range. Fe was unevenly distributed and in the sub-surface layer it was higher in the southern and north-western parts of the farm. Mn was above the critical limit in both surface and sub-surface soils of the farm.

Keywords: Irrigated plains, Paddy-wheat rotation, Soil maps, Soil micronutrients, Spatial variability

Micronutrient deficiency in soils may have detrimental impact on crop productivity. Micronutrient deficiencies such as those of zinc, copper, iron and manganese in soils around the world have been reported (Shukla *et al.* 2014). Micronutrient distribution vary spatially across management units (Mondal *et al.* 2007, Alaie *et al.* 2020, Wani *et al.* 2022) and their variability in Indian soils is high because of small land holdings and different practices adopted by individual farmers. These spatial variations over short distances can significantly impact the farm productivity under systems of uniform application of nutrients.

At the field, catchment and regional scales, geostatistical methods are effective for evaluating the spatial variability of soil characteristics (Tripathi *et al.* 2015). Geostatistics is a powerful tool for characterization and quantification of spatial variability. Semivariograms are a crucial tool for describing spatial patterns, and kriging is commonly adopted for predicting the values of soil properties in untested places. Numerous workers overtime have employed geostatistics as a tool for addressing spatial variability of soil properties (Shi *et al.* 2008, Sharma *et al.* 2017).

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From a field to a bigger area scale, soil characteristics change both geographically and temporally, as they are affected by both intrinsic and extrinsic factors (such as the cultural practices adopted by farmers). In apparently homogeneous soil, the soil variability can be significantly altered by past land use (Hussain *et al.* 2019, Wani *et al.* 2023). Even over short distances, there have been noticeable strong variances (Vasu *et al.* 2017). The Chakroi farm of Sher-e-Kashmir University of Agricultural Sciences and Technology of Jammu (SKUAST-J) has a history of predominantly paddy (*Oryza sativa*)-wheat (*Triticum aestivum* L.) cropping system. There are also some patches in the study area where waterlogging and hard pans have been encountered. Therefore, it is hypothesized that variations in soil micronutrients may exist. The present study under paddy-wheat cropping system of Jammu was carried out with the objective to measure the spatial variability of DTPA extractable copper, zinc, iron and manganese at farm level following ordinary kriging interpolation technique.

MATERIALS AND METHODS

The present study was carried out at Chakroi farm of Sher-e-Kashmir University of Agricultural Sciences and Technology of Jammu (SKUAST-Jammu) during year 2016 and 2017 for studying the spatial variability

of micronutrients. The farm lies between 32°32'9.29" N, 74°41'42.51" E and 32°31'38.28" N, 74°42'26.97" E having an area of 68 hectares. The dominant cropping system of the farm is paddy-wheat.

Soil sampling and processing: Grid based soil sampling procedure was followed for the entire study area and a square grid of 75 m × 75 m was adopted. To digitize the farm map ArcGIS 10.3 was used and soil sampling points were created on the map on square grid basis (75 m apart) by using the sampling tool. The soil samples were then collected at the depths of 0–15 cm (surface) and 15–30 cm (sub-surface) layers from the identified points by using stainless steel soil augers. A total of 258 samples were collected, i.e. 129 each from surface layer and sub-surface layers. The collected soil samples were air dried and processed.

Soil analysis: Basic properties such as soil *p*H, electrical conductivity (EC) and organic carbon (OC) level were measured by method given by Jackson (1973) while cation exchange capacity (CEC) and soil texture was determined following a method outlined by Piper (1966). The basic soil properties varied widely, i.e. *p*H, EC and OC varied from 5.71–9.93; 0.03–1.51 dS/m and 0.51–1.47% with mean values of 7.38, 0.24 dS/m and 0.99%, respectively. The CEC varied from 6.97–21.76 cmol (p^+)/kg with a mean of 13.71 cmol (p^+)/kg. The soil texture categories included silty clay loam, loam, silty clay, clay loam, clay and silt loam in the order of abundance.

Diethylene triaminepenta acetic acid (DTPA) was used to extract the available Zn, Cu, Mn, and Fe from soils (Lindsay and Norvell 1978). The samples were run in triplicates with a soil to solution ratio of 1:2 and were shaken for 2 hours before filtering with a whatman 42 filter paper. After extraction, the micronutrient cations were analyzed with an atomic absorption spectrophotometer.

Conventional statistical analysis: Descriptive statistics was worked out for the datasets that included mean, median, coefficients of variation (CV), minimum and maximum values, kurtosis, skewness, as well as standard error of mean using SPSS 13.5. Kormogorov-Shaprov test was carried out for testing normal distribution of data sets.

Geo-statistical analysis: After testing the data for normality, the non-normal data sets were log transformed to reduce the skewness before subjecting it to krigging. To assist in the kriging process, semivariograms of the soil attributes were constructed. Appropriate models were fitted to the semivariograms to attain different geo-statistical parameters.

Spatial dependence was quantified from nugget, range and sill obtained from a semi-variance analysis. Semivariogram were generated by following equation (Vieira *et al.* 1983):

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

Where, h is the lag distance; z(xi), the value of the variable Z at location xi and; N(h), the number of pairs of sample points [values $Z(x_i)$, $Z(x_i+h)$] separated by a vector h. These semi-variograms were generated in GS^+ for different soil properties. Semivariograms were fitted with appropriate models based on the lowest statistical error values.

Exponential model =

$$\gamma(h) = C_0 + C_1\left(1 - \exp\left(\frac{-3h}{a}\right)\right) 0 < h < d$$

where, *d,* the maximum distance at which the semivariogram is defined.

Gaussian model =

$$\gamma(h) = C_0 + C_1\left(1 - \exp\left(\frac{-h^2}{a^2}\right)\right)$$

Linear model =

$$\gamma\,(h) = C_0 + [h(C/A_0)]$$

Where, γ(h), semivariance for internal distance; C_0, nugget variance ≥ 0; h, lag interval; A_0, range parameter and; C, structural variance ≥ C_0. Once the best fit model was determined for each variable, interpolation was carried out. To categorise the degrees of spatial variability in each soil feature, a nugget/sill ratio was determined (Cambardella *et al.* 1994).

Prediction mapping: Prediction maps of the soil micronutrients were generated by Ordinary Kriging (OK). The kriging estimate is given as below:

$$Z(X_0) = \sum_{i=1}^{n} \lambda_i Z(X_i)$$

Where, n, the number of neighboring observations; $Z(X_o)$, the estimate of unknown true value and; λ_i, the weighted coefficient. The process of digitization and development of prediction maps was carried out in a GIS environment with the help of ArcGIS 10.3. The goodness of fit for various models was calculated in GS^+ and only the best models were selected. Cross validation indices of soil micronutrients were also determined to validate spatial analysis.

RESULTS AND DISCUSSION

DTPA extractable micronutrients in soil: The DTPA extractable Cu for surface soils varied from 1.10–4.42 mg/kg of soil, with mean value of 2.62 mg/kg of soil. Whereas, the values varied from 0.75–3.24 mg/kg of soil for sub-surface layers. The CV values were 22.03 and 27.44% and a negative skewness was observed for surface and sub-surface (-0.19 and -0.04) layers, respectively (Table 1). The DTPA extractable Zn varied from 0.33–1.90 mg/kg and 0.18–1.24 mg/kg of soil for surface and sub-surface layers having mean values of 0.93 and 0.62 mg/kg of soil, respectively. The CV value for surface layer was 35.59%, whereas it was 41.53% for sub-surface layers. The data for Fe varied from 18.78–76.22 mg/kg of soil for surface layers and 12.66–56.87 mg/kg of soil for sub-surface layers. The values of CV were 29.59 and 26.75%, with mean values of 50.51 and 34.61 mg/kg of soil for surface and sub-surface layers, respectively. The data was positively skewed, with values close to zero and kurtosis being -1.22 and -0.44 for surface and sub-surface layers. The values for DTPA

extractable Mn content varied from 11.60–46.20 mg/kg of soil and 7.58–36.54 mg/kg of soil for surface and sub-surface layers, respectively. The mean value was 26.60 mg/kg of soil and CV, 35.02% for surface layers, while mean for sub-surface layers was 18.88 mg/kg of soil and CV value was 37.85%. The data was positively skewed, with values being 0.20 and 0.53, and kurtosis being -0.94 and -0.44 for surface and sub-surface layers, respectively. Low, moderate, and high variability are indicated by CV values of 10%, 10–100%, and >100%, respectively. The micronutrient concentrations followed the order: Fe > Mn > Cu > Zn both in surface and sub-surface layers. DTPA extractable micronutrients, except Zn, were above the critical limit for sufficiency range. Variation in soil management were the main causes of the observed heterogeneity in the concentrations of accessible micronutrients (Li *et al.* 2008).

Spatial distribution of micronutrients: Geostatistics utilizes semivariogram to work out the geographic variation of a variable and outputs a set of parameters such as nugget, sill etc. These parameters are used as inputs for carrying out the spatial interpolation of variables using Kriging technique. However, an important criterion for kriging is that the data should be normal (Sepaskhah *et al.* 2005). This can be assessed from the skewness and kurtosis values. In the present study, the data was normal only for DTPA extractable Cu in surface layer, whereas in sub-surface it was normal for DTPA extractable Fe. Robinson and Metternicht (2006) has indicated that if the data has positive skewness of more than 0.5, transformation of data is required to reduce the skewness. Log transformed data was used for all other soil properties to make the semi-variograms. Typically, a theoretical model such as a spherical, linear, exponential, or Gaussian model is used to fit the experimental variograms. Using the deciding coefficient (R^2) and the least residual sums of squares (RSS), the ideal theoretical model is identified. The models supply data about the spatial organisation as well as the Kriging interpolation's input parameters (Wang *et al.* 2009). Exponential model was the best fit for micronutrients in surface soil. The type of model fitted depends upon the data structure. Shi *et al.* (2008) observed based on the geostatistical data that the exponential model was the best for Mn, Cu, Zn, and Mo, whereas spherical and linear model provided the best fit for Fe and B, respectively. Linear model was the best fit for DTPA extractable Cu, Gaussian model for DTPA extractable Mn in the sub-surface layer. For the other two micronutrients, exponential model was the best fit. Geo-statistical parameters were obtained from these models, viz. nugget, sill, partial sill and range of spatial dependence (Table 2). The range values indicated the maximum scale of spatial dependence. In surface soils, the least range of spatial dependence was for Zn (99.0 m). The values close to this in increasing order were Cu (102 m) followed by Mn (192 m). Whereas, in sub-surface layer, the highest range of spatial dependence was observed for DTPA extractable Fe (3267 m) followed by Cu (705.6 m) and Mn (128.1 m). When compared to characteristics with lower ranges, a broad range suggests that a soil characteristic is more likely to be affected by natural influences over greater distances (Sharma *et al.* 2017). In the present study, smaller range values for soil micronutrients could be the result of the management practices. While partial sill (C) represents the degree of variation that may be described by spatial correlation structure, nugget (C_0) describes the micro-scale variability and measurement error for the relevant soil characteristic. A nugget to sill ratio was obtained to classify the nature of spatial dependence. The nugget to sill ratio, two parameters derived from a semivariogram, is used to classify the spatial dependence of a soil property. When the nugget to sill ratio is equal to or lower than 0.25, the soil property is supposed to have strong spatial dependence (Cambardella *et al.* 1994). It is considered moderate for a ratio between 0.25 and 0.75 and weak if the ratio is greater than 0.75. Based upon this, all the four DTPA extractable micronutrients in surface layer showed strong spatial dependence, whereas in sub-surface layer DTPA extractable Cu showed weak spatial dependence while Zn and Mn showed strong spatial dependence.

Cross-validation: Cross-validation is carried out to study the validity of the prediction models (Asa *et al.* 2012). Cross validation of observed values with predicted revealed a minor positive bias especially in case of Fe and Mn as observed from ME (mean error) values (Table 3). MSE

Table 1 Statistical summary of DTPA extractable micronutrients in surface (0–15 cm) and sub-surface layer (15–30 cm)

	Sub-surface (0–15 cm)				Sub-surface (15–30 cm)			
	Cu	Zn	Fe	Mn	Cu	Zn	Fe	Mn
	(mg/kg)				(mg/kg)			
Minimum	1.10	0.33	18.78	11.60	0.75	0.18	12.66	7.58
Maximum	4.42	1.90	76.22	46.20	3.24	1.24	56.87	36.54
Mean	2.62	0.93	50.51	26.60	1.89	0.62	34.61	18.88
Standard deviation	0.58	0.33	14.94	9.31	0.52	0.26	9.26	7.15
Standard error of mean	0.05	0.03	1.32	0.82	0.05	0.02	0.82	0.63
Coefficient of variation (%)	22.03	35.59	29.59	35.02	27.44	41.53	26.75	37.85
Skewness	-0.19	0.62	0.09	0.20	-0.04	0.52	0.12	0.53
Kurtosis	0.25	0.05	-1.22	-0.94	-0.16	-0.76	-0.44	-0.44

Table 2 Best fit models, data transformation and the obtained semivariogram parameters for the DTPA extractable micronutrients

Soil properties	Transformation	Model	R^2	Partial Sill (C1)	Range	Nugget (C0)	Sill (C0 + C1)	Nugget/Sill ratio	Spatial dependence
				Surface					
DTPA-Cu	None	Exponential	0.209	0.3045	102.0	0.0305	0.3350	0.09	Strong
DTPA-Zn	Log	Exponential	0.251	0.1217	99.0	0.0087	0.1304	0.07	Strong
DTPA-Fe	Log	Exponential	0.313	0.0886	195.0	0.0136	0.1022	0.13	Strong
DTPA-Mn	Log	Exponential	0.795	0.1303	192.0	0.0093	0.1396	0.07	Strong
				Sub-surface					
DTPA-Cu	Log	Linear	0.266	0.00	705.6	0.0959	0.0959	1.00	Weak
DTPA-Zn	Log	Exponential	0.312	0.1647	111.0	0.0137	0.1784	0.08	Strong
DTPA-Fe	None	Exponential	0.815	67.20	3267.0	67.10	134.30	0.50	Moderate
DTPA-Mn	Log	Gaussian	0.667	0.1372	128.1	0.0132	0.1504	0.09	Strong

DTPA, Diethylene triamine pentaacetic acid.

(mean standardized error) needs to be close to zero for better predictions while RMSSE (root mean square standardized error) values need to be close to 1 for accuracy. Our cross-validation data showed that MSE was close to zero for all parameters in surface as well as sub-surface samples. While RMSSE was closer to 1, except in case of Cu in sub-surface soils where the value was 0.867. Similarly, the root mean square error (RMSE) was on the lower side of the overall range of data for individual parameters indicating overall good predictions. Based on the error values, the overall predictions were found to be reliable.

About 66% of the area (44.7 ha; 65.7% of the area) in the surface layer had DTPA extractable Cu between 2.0–2.8 mg/kg of soil. A very small area (<1%) is under high range of 3.6–4.3 mg/kg of soil on the eastern side of the farm (Fig 1). In the sub-surface layer, the Cu was unevenly distributed. Overall, it was in the sufficiency range when considering 0.2 mg/kg as the critical limit.The soil maps of DTPA extractable Zn are presented in the (Fig 1). In the surface layer, the major portion of the farm (44.2 ha; 65%) was in the range of 0.6–1.0 mg/kg followed by 1.0–1.5 mg/kg (20.9 ha; 30.7%) of soil indicating that the soils have Zn

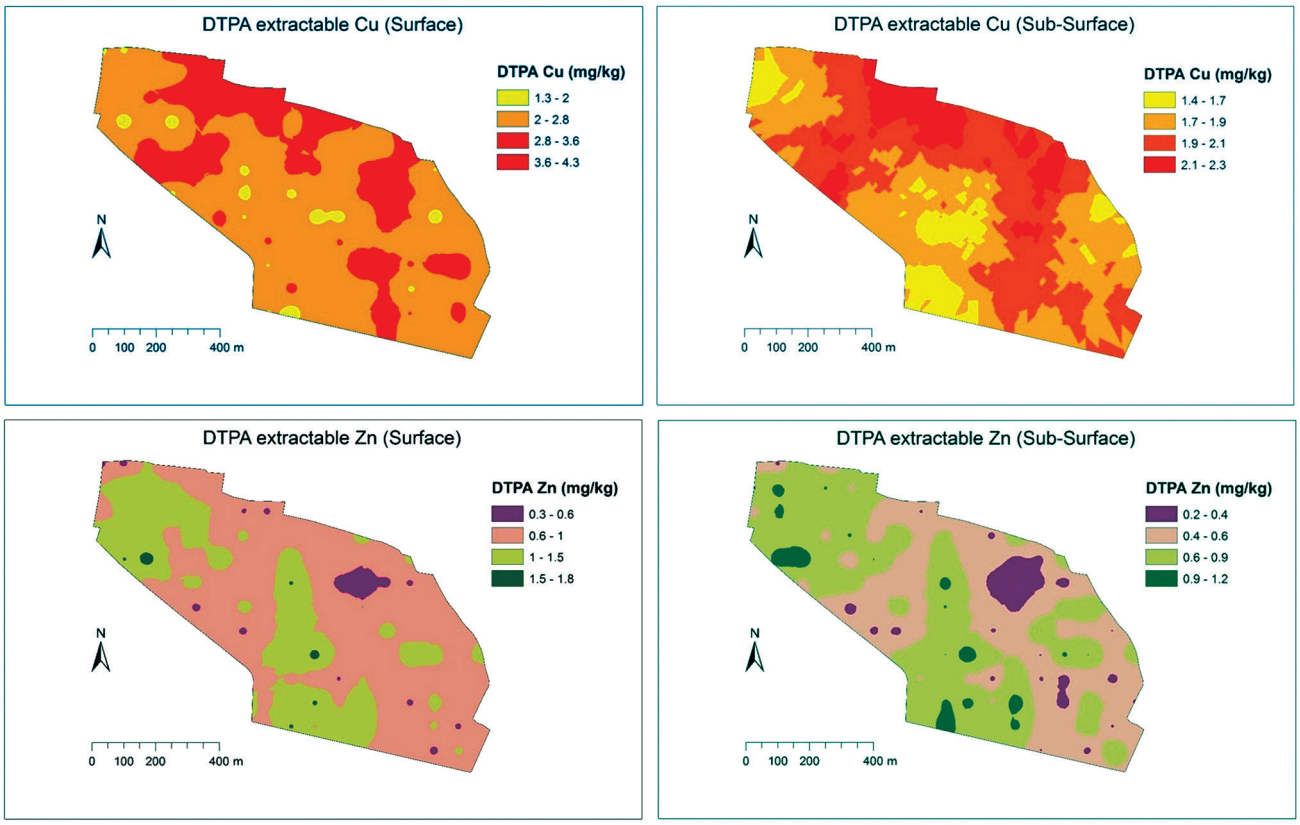

Fig 1 DTPA extractable Cu and Zn at surface and sub-surface soil depths of Chakroi farm.

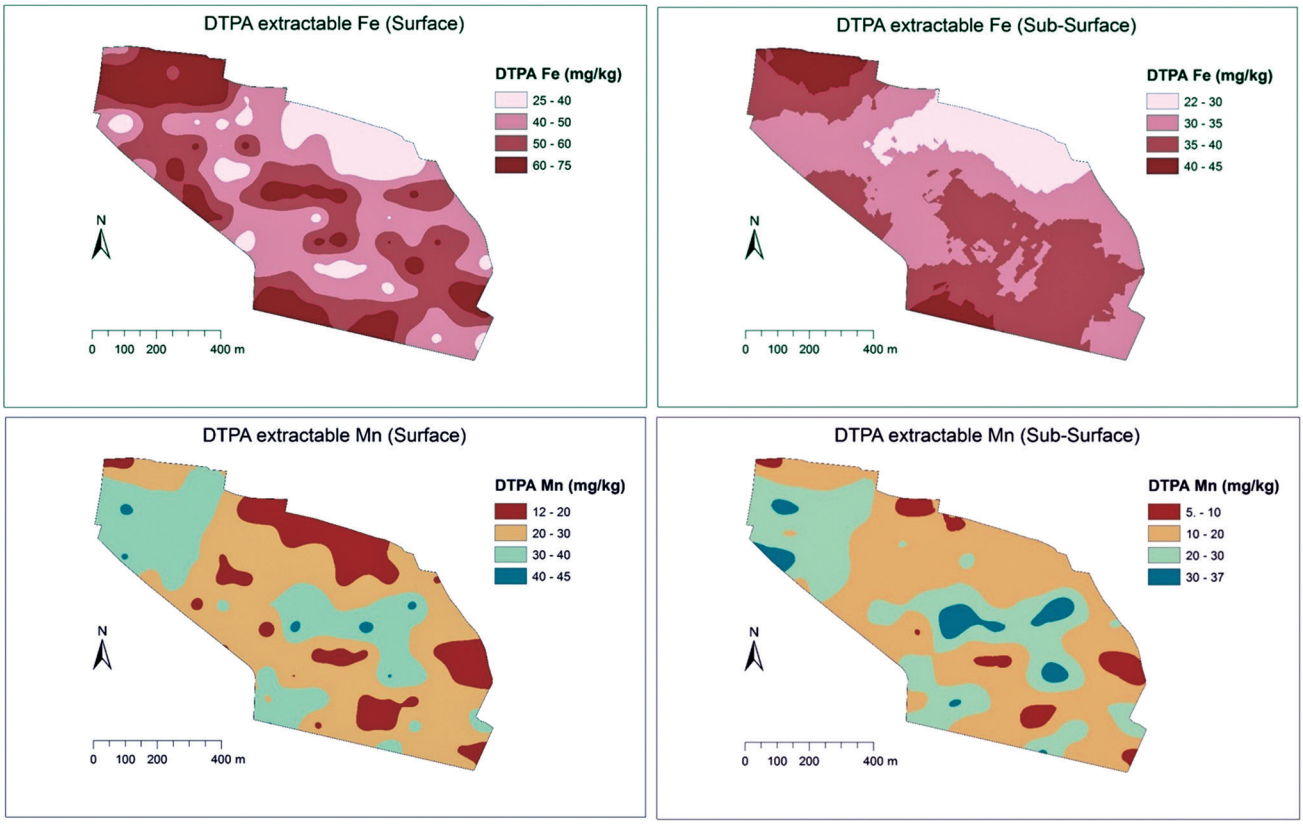

Fig 2 DTPA extractable Fe and Mn at surface and sub-surface soil depths of Chakroi farm.

Table 3 Errors generated through cross-validation of predicted and observed values

Parameter	ME	RMSE	MSE	RMSSE
Surface				
Zn	0.008	0.336	-0.015	0.946
Cu	0.001	0.565	0.001	0.981
Fe	0.239	13.84	0.001	0.935
Mn	0.244	8.168	0.016	0.908
Sub-surface				
Zn	0.005	0.266	-0.040	0.995
Cu	0.004	0.537	-0.010	0.867
Fe	0.077	8.544	0.008	0.972
Mn	0.126	6.562	-0.033	1.0361

ME, Mean error; RMSE, Root mean square error; MSE, Mean standardized error and; RMSSE, Root mean square standardized error.

above the critical value (0.6 mg/kg). However, in sub-surface layers nearly 40% had DTPA Zn in the deficient range. Zinc is an important nutrient especially with respect to rice crop. Low Zn content was associated with areas having high *p*H content and were sodic in nature. This is validated by significantly negative correlation (r = -0.224**) between *p*H and Zn observed in the present study as well as studies conducted by various other workers (Mühlbachová *et al.* 2011). DTPA extractable Fe was distributed unevenly with a range of 25–75 mg/kg of soil (Fig 2) which was well above the critical limit of 4.5 mg/kg. In the sub-surface layer, DTPA extractable Fe was higher in the southern and north-western parts of the farm. In the surface layer, the Mn was mainly between 20–30 mg/kg of soil (34.8 ha; 51% of the area), with some area (19.7 ha; 30% of the area) in the central and north-western side had range of 30–40 mg/kg of soil (Fig 2). In sub-surface layer, the Mn was mainly in the range of 10–20 mg/kg of soil. Overall, it was above the critical limit of 2 mg/kg.

The study concludes that not all data sets of soil properties and micronutrients show normal distribution and transformations must be carried out to make it suitable for krigging. Also, within farm level wide variations exist in micronutrients due to ecological conditions such as waterlogging and high *p*H as high as over 9.0 in this case. As such, a uniform dose may not be economically effective to produce the desired yield even at farm level. Zinc application is generally recommended here in these basmati producing soils. As far as other micronutrients (Fe, Mn and Cu) are concerned their values were much above the critical limits and hence are not recommended for the commonly followed rice-wheat system on the farm.

REFERENCES

Alaie T A, Gupta R and Sharma V. 2020. Spatial distribution of available micronutrient status under different land use systems of district Doda, Jammu and Kashmir. *Journal of Soil and Water Conservation* **19**: 317–21.

Asa E, Saafi M, Membah J and Billa A. 2012. Comparison of linear and nonlinear kriging methods for characterization

and interpolation of soil data. *Journal of Computing in Civil Engineering* **26**: 11–18.

Cambardella C A, Moorman T B, Novak J M, Parkin T B, Karlen D L, Turco R F and Konopka A E. 1994. Field scale variability of soil properties in central Iowa soils. *Soil Science Society of America Journal* **58**: 1501–11.

Hussain S, Sharma V, Arya V M, Sharma K R and Rao C S. 2019. Total organic and inorganic carbon in soils under different land use/land cover systems in the foothill Himalayas. *Catena* **182**: 104104.

Jackson M L. 1973. *Soil Chemical Analysis: Advanced Course*, 2nd edn., Madison, Wisconsin, USA.

Li J, Richter D D, Mendoza A and Heine P. 2008. Four-decade responses of soil trace elements to an aggrading old-field forest: B, Mn, Zn, Cu, and Fe. *Ecology* **89**: 2911–23.

Lindsay W L and Norvell W A. 1978. Development of DTPA soil test for zinc, iron, manganese and copper. *Soil Science Society of America Journal* **42**: 421–28.

Mühlbachová G, Šimon T and Pechová M. 2011. The availability of Cd, Pb and Zn and their relationships with soil *p*H and microbial biomass in soils amended by natural clinoptilolite. *Plant, Soil and Environment* **51**: 26–33.

Mondal A K, Sharma V, Jalali V K, Arora S, Wali P and Kher D. 2007. Distribution and relationship of macro and micronutrients in soils of Chatha, the newly established location of SKUAST Jammu. *Journal of Research, SKUAST-J* **6**: 234–42.

Piper C S. 1966. *Soil and Plant Analysis.* Hans Publications, Bombay, India.

Robinson T P and Metternicht G. 2006. Testing the performance of spatial interpolation techniques for mapping soil properties. *Computers and Electronics in Agriculture* **50**: 97–108.

Sepaskhah A R, Ahmadi S H and Shahbazi A R N. 2005. Geostatistical analysis of absorptivity for a soil under tilled and no-tilled conditions. *Soil and Tillage Research* **83**: 237–45.

Sharma V, Arya V M and Sharma K R. 2017. Spatial variability of soil *p*H and electrical conductivity in the Jammu district of Jammu and Kashmir. *Journal of Soil and Water Conservation* **16**: 320–24.

Shi J, Xu J and Huang P. 2008. Spatial variability and evaluation of status of micronutrients in selected soils around Taihu Lake, China. *Journal of Soils and Sediments* **8**: 415–23.

Shukla A K, Tiwari P K and Prakash C. 2014. Micronutrients deficiencies *vis-a-vis* food and nutritional security of India. *Indian Journal of Fertilizers* **10**: 94–112.

Tripathi R, Nayak A K, Shahid M, Raja R, Panda B B, Mohanty S, Kumar A, Lal B, Gutam P and Sahoo R N. 2015. Characterizing spatial variability of soil properties in salt affected coastal India using geostatistics and kriging. *Arabian Journal of Geosciences* **8**: 10693–703.

Vasu D, Singh S K, Sahu N, Tiwary P, Chandran P, Duraisami V P, Ramamurthy V, Lalitha M and Kalaiselvi B. 2017. Assessment of spatial variability of soil properties using geospatial techniques for farm level nutrient management. *Soil and Tillage Research* **169**: 25–34.

Vieira S R, Hatfield J L, Nielsen D R and Biggar J W. 1983. Geostatistical theory and application to variability of some agronomical properties. *Hilgardia Berkeley* **51**: 1–75.

Wang Z, Zhang B, Song K, Liu D, Ren C, Zhang S, Hu L, Yang H and Liu Z. 2009. Landscape and land-use effects on the spatial variation of soil chemical properties. *Communications in Soil Science and Plant Analysis* **40**: 2389–412.

Wani O A, Sharma K R, Kumar S S, Sharma V, Kumar V V and Kumar S. 2022. Mapping of micronutrients in soils of Kishtwar District (Jammu and Kashmir)- A GIS Approach. *Current Journal of Applied Science and Technology* **41**: 26–38.

Wani O A, Sharma V, Kumar S S, Babu S, Sharma K R, Rathore S S, Marwaha S, Ganai N A, Dar S R, Yeasin M, Singh R and Tomar J. 2023. Climate plays a dominant role over land management in governing soil carbon dynamics in North Western Himalayas. *Journal of Environmental Management* **338**: 117740.