Agropedology 2019, 29 (02), 119-127
doi.org/10.47114/j.agroped.2019.dec5

Characterization of Irrigation Water Quality Parameters Using Geo-Statistical Approach

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Abstract: The recent past has witnessed ever increasing importance of water in agricultural development that necessitates precise assessment of spatial variability in irrigation water quality of resources and its optimal utilization. Present study was aimed to characterize the variability in quality of irrigation water across the Rewa district of Madhya Pradesh using geo-statistical techniques. The results are compared with univariate interpolation algorithms such as ordinary kriging and inverse distance weighing. The comparisons were performed with cross validation at sampling locations and assessed based on mean and root means squared errors. The results revealed that all the physico-chemical parameters exist within the permissible limits as per the standards; hence quality of water is safe for irrigation purposes.

Keywords: *Variability maps, Co-Kriging, GIS, Geo-statistical approach, GPS, Correlation*

Introduction

Agriculture sector is facing scarcity of water in light of increasing demand for industrial and domestic purposes, which substantially reduces the share of available water resources for agriculture. Vagaries of monsoon and declining water-table due to over-use has resulted in shortage of fresh water supplies for agricultural purpose, which calls for an efficient utilization of water resources. Inventory on spatio-temporal variability in water quality in terms of physico-chemical properties and pollution level could aid in potential utilization of water resources (Topp 1980 and Murugesan *et al*. 2005). In light of these facts, present study was conducted across the Rewa district of Madhya Pradesh to characterize the spatial variability in water quality using geo-statistical approaches.

Materials and Methods

Study area

Rewa district is located in Madhya Pradesh having semi-arid and sub-tropical climate. The Bichiya River is the main drainage of the area. Upper Vindhyan rocks mainly limestone, sandstone and shale cover the area. Surface water samples were collected from fifty-five locations during the pre-monsoon in 2011 and sampling sites were geo-tagged using Global Positioning System (GPS). Location map is shown in fig.1.

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Results and Discussion

Physio-Chemical Parameters

The pH ranged from 7.5 to 8.8. pH provides an important information on geochemical equilibrium or solubility calculation (Shyamala *et al.* 2008). The temperature of the water samples ranged from 34.0 to 37.0^0 C (mean 35.2^o C). The water samples were colorless and odorless. The electrical conductivity of the sampled water varied from 303 to 2240 μ mho cm^{-1} with an average of 914 μ mho cm^{-1}.

Total dissolved salts (TDS) values indicate the general nature of water quality and are usually related to conductivity. Water containing more than 500 mg l^{-1} of TDS is not considered as desirable for irrigation water as per recommendation (WHO 2004). The total dissolved solids varied from 182.0 to 1483.6 mg l^{-1} (mean 589.5 mg l^{-1}) and was found within permissible limits. A high TDS level is not suitable for irrigation purposes as it may cause corrosion of delivery pipes and plumbing system.

Hardness (TH) is the property of water, which prevents the lather formation with soap and increases the boiling points of water (Trivedy and Goel 1984). The total hardness of the water in area varied from 118 mg l^{-1} to 1065 mg l^{-1}, with an average of 299.3 mg l^{-1}. The total hardness was above the permissible limit.

The bicarbonate concentration in water sample varied 76 to 567 mg l^{-1} with mean value of 252.8 mg l^{-1} while carbonate content was 5.3 mg l^{-1}. The chloride concentration varied from 7.0 to 230 mg l^{-1} with a mean value of 63.3 mg l^{-1} in water samples. Chloride usually occurs as NaCl, $CaCl_2$ and $MgCl_2$ in widely varying concentration, in all-natural waters. They enter water by solvent action of water on salts present in the soil, from polluting material like sewage and trade wastes (Shaikh and Mandre 2009).

The concentration of calcium in ground-water samples of area varies from 24 mg l^{-1} to 344 mg l^{-1} (mean 85.2 mg l^{-1}). The calcium content in ground-water largely depends on the solubility of calcium carbonates, sulphide and very rarely chloride.

Magnesium is one of the alkaline earth metals and also occurs in all types of water with calcium. The concentration of magnesium in water samples of the area varied from 4.4 mg l^{-1} to 55.3 mg l^{-1} with an average of 50.9 mg l^{-1}.

Sodium content in water samples varied from 12 mg l^{-1} to 117 mg l^{-1} (mean 42.1 mg l^{-1}). The concentration of potassium in water samples varied from 0.5 mg l^{-1} to 51 mg l^{-1} (mean 3.1 mg l^{-1}).

The concentration of sulphate in water samples of the area ranges from 2.0 to 610 mg l^{-1}, with an average of 68.1 mg l^{-1}. Nitrate concentration of the water samples ranges from 3.0 mg l^{-1} to 70 mg l^{-1} with an average of 20.5 mg l^{-1}.

The equivalent ratio of Cl/Na in the water is generally found as 1:1 but it can vary according to chemical composition which is mainly controlled by dissolution of evaporate minerals such as halite and also the polluted ground water reflect high ratios of Cl/Na. Water samples in area has Cl/Na ratios of 0.58 to 1.96, which indicates a significant anthropogenic input into ground-water systems.

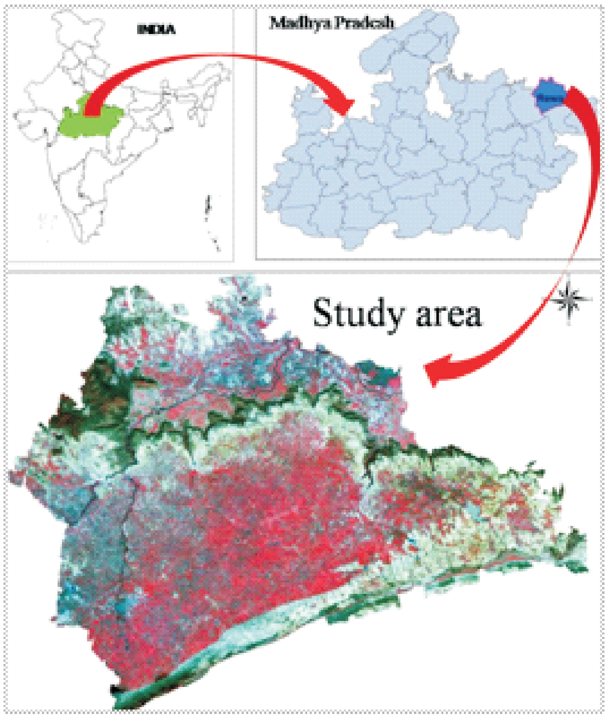

Fig. 1. Location map of area

Water sampling and analysis

Water samples were collected in cleaned plastic bottles and labeled it. The collected samples were analyzed for water quality parameters (temperature, pH, EC and total dissolved solids, hardness, calcium, magnesium, sodium, chloride, sulphates and nitrate) following standard procedure (APHA 2005). Statistical analysis (correlation coefficient and regression) had been carried out between various attributes of ground water quality.

Geo-statistical analysis

The expansion from point data to regions can be done through geo-statistical analysis, under the assumption that there is a continuous variation in soil properties from one point to its adjoining, as indicated by spatial auto-correlation between neighboring observations. The continuity of the spatial distribution of the measurements has been evaluated using geo-statistics (Vieira *et al.* 1991). All geo-statistical analysis is based on the assumption that measurements separated by small distances are more likely to be similar to each other than those farther apart, *i.e.* spatial auto-correlation exists. This assumption can be verified through examination of the semi-variograms for the attributes under investigation. The value of the experimental variogram for a separation distance of h (referred to as the lag) is half the average squared difference between the value at z (x_i) and the value at z (x_i+h).

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

Where: N (h) is the number of data pairs within a given class of distance and direction. If the values at z (x_i) and z (x_i+h) are auto correlated the result of Eq. (1) will be small, relative to an uncorrelated pair of points. From analysis of the experimental variogram, a suitable model is then fitted, usually by weighted least squares, and the parameters (*e.g.* range, nugget and sill) are then used in the kriging procedure.

Distribution maps are prepared with different interpolation algorithms. Inverse distance weighting (IDW) map was developed to represent the simplest case and then an ordinary Kriging map has been used as the base scenario. Above two maps are then compared with maps produced by co-Kriging with auxiliary parameters. The accuracy of each interpolation method was then tested with cross validation, which is based on the principle of sequentially removing each known measurement point and using the rest of the points to predict its value *via* interpolation. The errors between measured and predicted levels are then reported to compare the performances of interpolation approaches. Mean error and root mean squared error are used in this comparison. The algorithms with lower errors were considered to perform better. A mean error near zero implies normally distributed errors around zero, and no systematic over-or under-prediction of parameters. The root mean squared error is indicative of the cumulative error and provides a better estimate of the overall performance of the approach.

Table 1. Descriptive statistics of quality of irrigation water (N=55)

Parameters	Min	Max	Range	Mean	Median	SD	Skew ness	β2	CV%	Permissible limit WHO (2004)
pH	7.5	8.8	1.3	8.2	8.2	0.3	-0.2	-0.5	3.74	6.5-8.5
EC (µ mho cm^{-1})	303.0	2240.0	1937.0	914.0	803.0	436.8	0.7	0.2	47.80	1000
Temperature (^{0}C)	34.0	37.0	3.0	35.2	35.0	0.8	-0.1	-0.9	2.24	
CO_3 (mg l^{-1})	0.0	24.0	24.0	5.3	0.0	6.4	0.9	-0.2	120.23	
HCO_3 (mg l^{-1})	76.0	567.0	491.0	252.8	252.0	111.3	0.4	-0.2	44.03	250
Cl (mg l^{-1})	7.0	230.0	223.0	63.3	56.8	46.9	1.3	2.0	74.04	250
SO_4 (mg l^{-1})	2.0	610.0	608.0	68.1	25.0	124.2	3.3	10.6	182.40	250
NO_3 (mg l^{-1})	3.0	70.0	67.0	20.5	16.0	14.9	1.7	2.9	72.73	50
F (mg l^{-1})	0.0	1.4	1.4	0.4	0.3	0.3	1.6	3.9	72.12	0.5-1.5
TH (mg l^{-1})	118.0	1065.0	947.0	299.3	260.0	174.0	2.4	7.4	58.14	-
Ca (mg l^{-1})	24.0	344.0	320.0	85.2	70.0	61.2	2.5	7.5	71.77	75
Mg (mg l^{-1})	4.4	55.3	50.9	21.5	19.0	11.7	1.1	0.8	54.44	50
Na (mg l^{-1})	12.0	117.0	105.0	42.1	37.0	23.6	1.3	1.3	56.05	50
K (mg l^{-1})	0.5	51.0	50.5	3.1	1.6	6.9	6.5	45.3	225.38	10
TDS (mg l^{-1})	182.0	1413.6	1231.6	589.5	526.0	276.2	0.6	0.1	46.86	500
SAR	1.7	16.5	14.8	6.0	5.7	3.1	1.4	2.2	51.67	-
SSP	9.1	136.8	127.7	44.2	39.5	24.3	1.4	3.1	55.05	-
RSC	0.1	3.9	3.8	1.5	1.5	0.8	0.6	0.0	56.03	-
ESP	19.4	70.7	51.4	44.1	45.5	11.5	0.2	-0.2	26.15	-
Mg/Ca	0.1	0.9	0.8	0.3	0.3	0.2	1.1	0.1	69.68	-
Cl/SO_4	0.0	17.0	17.0	2.8	2.2	3.2	2.4	7.1	112.53	-

Correlation matrix

Correlation matrix of water quality parameters (Table 2) clearly revealed that some parameters were highly correlated. Samples showing correlation coefficients $r > 0.7$ are considered to be strongly correlated, whereas the value in between the 0.5-0.7 shows moderate correlation.

The total dissolved solid showed significant positive correlation with electrical conductivity, chloride, hardness, calcium magnesium and sodium (0.98, 0.43, 0.69, 0.68, 0.33 and 0.47, respectively. It shows that amount of chloride a salt is higher than that of sulphate salts in the water samples. Chloride ion had significant positive correlation with Na and TDS (0.76 and 0.43). Sulphate showed high correlation with TH, TDS, calcium and moderate correlation with magnesium (0.85, 0.60, 0.87 and 0.35), respectively. The total hardness is showing high positive correlation with calcium and magnesium (0.97 and 0.53), respectively.

Mapping the distribution of the water quality parameters

Mapping the distribution of water quality parameters involves a number of difficulties associated with some uncertainties. Often, datasets with a wide data range and skewed distributions yield less accurate distribution maps as opposed to datasets that follow normal distribution. Under these conditions, the use of auxiliary variables helps to improve the overall performance of the distribution. The errors between measured and predicted levels are then reported to compare the performances of interpolation approaches. Mean error and root mean squared error are the two different error types used in this comparison. In general, the algorithms with lower errors were considered to perform better. The root mean squared error is indicative of the cumulative error and provides a better estimate of the overall performance of the approach. The results of the cross-validation tests of IDW and co-kriging algorithms are given in figure 2a and 2b.

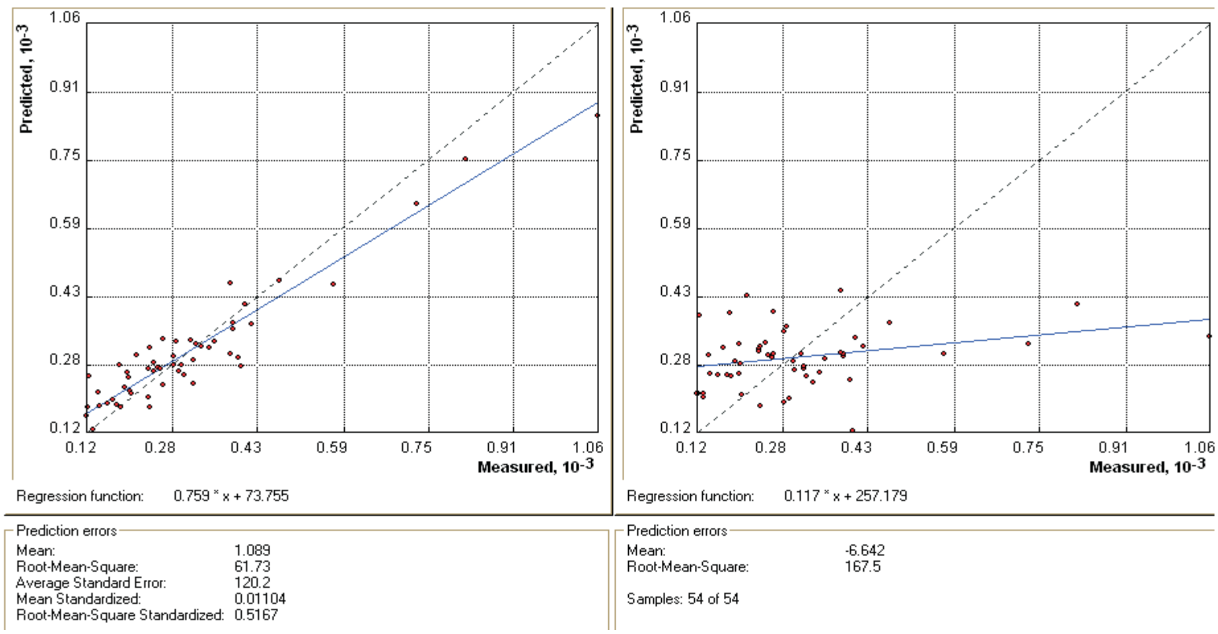

Fig. 2a. Total hardness prediction using Co-kriging versus IDW interpolation techniques

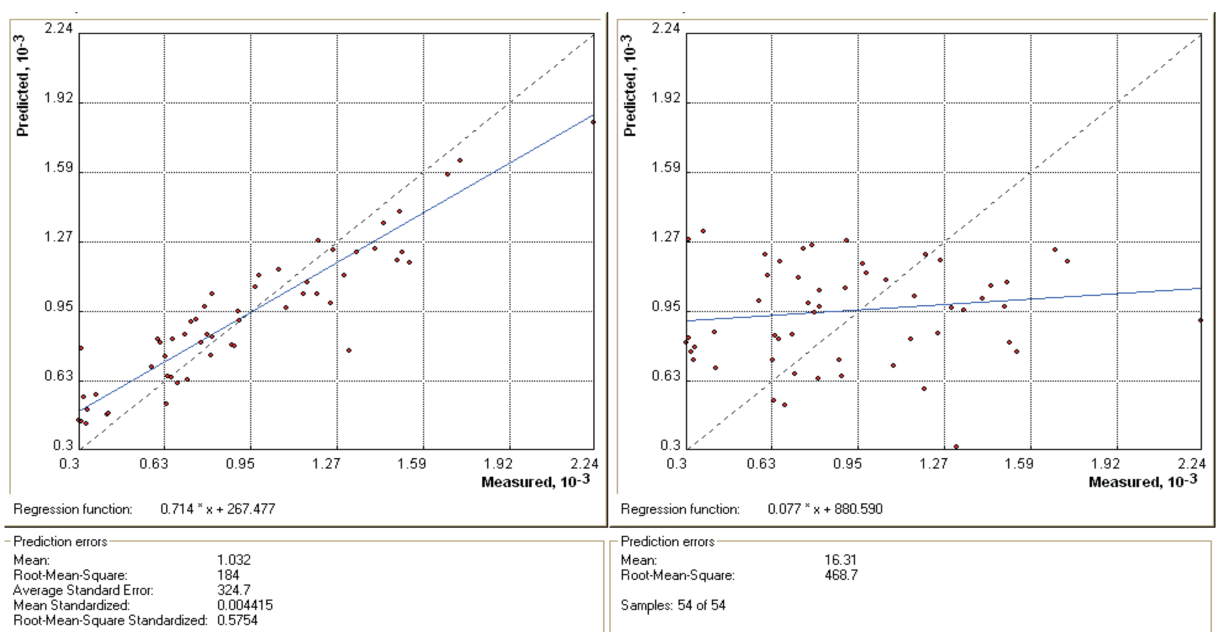

Fig. 2b. Electrical conductivity prediction using Co-kriging versus IDW interpolation techniques

Table 2. Correlation matrixes of irrigation water quality parameters

	pH	EC	HCO_3	Cl	SO_4	NO_3	F	TH	Ca	Mg	Na	K	TDS	SAR	SSP	RSC	ESP	Mg/Ca
EC	-0.107	1.000																
HCO_3	-.404**	**.381****	1.000															
Cl	0.030	**.451****	0.050	1.000														
SO_4	-.423**	**.610****	.283*	-0.036	1.000													
NO_3	-0.125	0.083	0.013	-0.038	0.121	1.000												
F	0.042	0.030	0.098	-0.162	-0.028	0.081	1.000											
TH	-.523**	**.712****	.654**	0.171	**.855****	0.126	-0.026	1.000										
Ca	-.506**	**.708****	.577**	0.154	**.873****	0.114	-0.092	**.972****	1.000									
Mg	-0.253	**.349****	.547**	0.151	**.351****	0.149	0.189	**.535****	.333*	1.000								
Na	-0.051	**.492****	.365**	**.762****	0.091	-0.093	0.044	0.265	0.247	0.186	1.000							
K	0.069	0.147	0.157	0.033	0.187	0.230	0.000	0.135	0.098	.461**	0.037	1.000						
TDS	-0.060	**.987****	**.358****	**.437****	**.602****	0.069	0.042	**.690****	**.689****	**.337***	**.473****	0.182	1.000					
SAR	0.188	0.243	0.137	.623**	-0.186	-0.096	0.110	-0.095	-0.108	0.001	**.905****	-0.032	0.234	1.000				
SSP	.359**	-0.005	-0.122	.390**	-.355**	-0.071	0.151	-.377**	-.378**	-0.191	.665**	-0.155	-0.009	.914**	1.000			
RSC	-0.074	-0.054	.792**	-0.063	-.316*	-0.089	0.163	0.064	-0.030	.330*	.272*	0.070	-0.066	.268*	0.160	1.000		
ESP	.285*	0.237	0.055	.651**	-0.197	-0.100	0.105	-0.131	-0.140	-0.020	.868**	-0.016	0.238	.957**	.874**	0.189	1.000	
Mg/Ca	0.208	-.276*	-0.170	-0.067	-0.239	-0.002	.278*	-.298*	-.470**	.497**	-0.114	0.223	-.277*	0.044	0.173	0.062	0.050	1.000
Cl/SO_4	0.207	0.077	0.048	.506**	-.334*	-0.120	0.047	-0.159	-0.147	-0.143	.485**	-0.129	0.069	.563**	.546**	0.200	.533**	0.055

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed)

Multivariate techniques had the highest root mean squared error values. The introduction of auxiliary variables in multivariate techniques is shown to improve the performance of interpolation; the highest improvement was achieved with TH as the secondary variable. Both performance criteria indicate that the improvement of EC concentration predictions, where the root means squared error in particular decreases significantly. The mean error value becomes less negative thereby implying less over prediction.

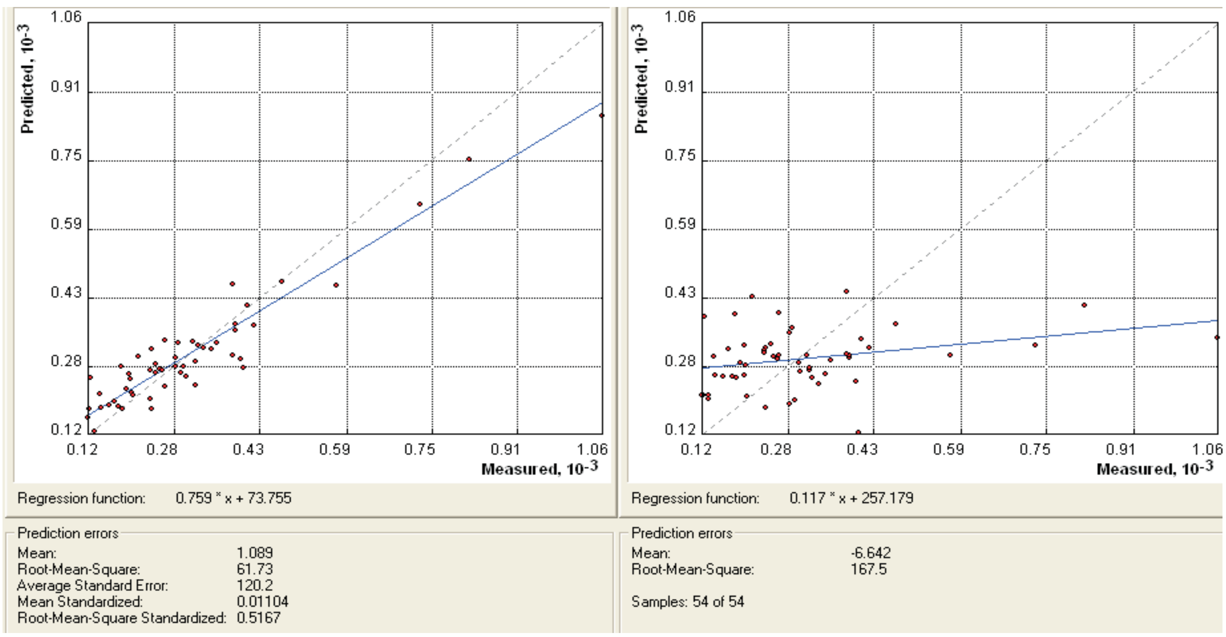

Fig. 2a. Total hardness prediction using Co-kriging versus IDW interpolation techniques

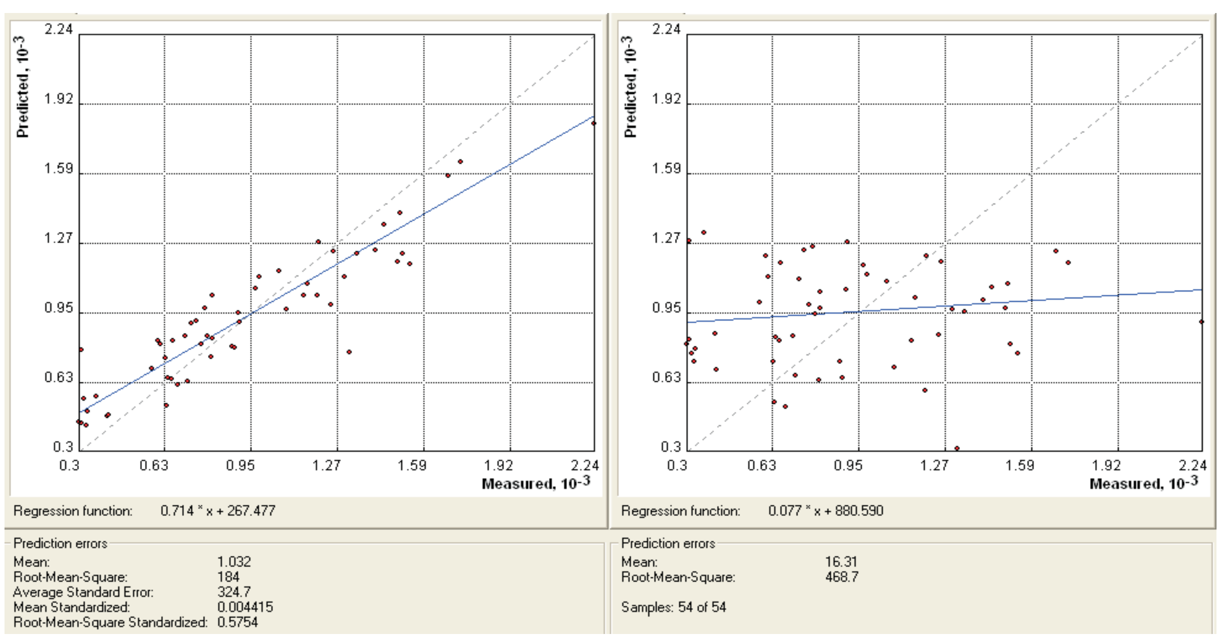

Fig. 2b. Electrical conductivity prediction using Co-kriging versus IDW interpolation techniques

Measured against interpolated EC concentrations are drawn for each approach used. A least square regression between these two values for each case revealed that methods with lower mean error such as IDW do not necessarily give the most accurate results. Thus, the deviation from the 1:1 line could be highest in a method where the mean error is lowest. Hence, root mean square error is a better estimator of the methods' performance. In this regard, co-kriging approach provided the best results and gave the closest fit to the 1:1 line. It should also be mentioned that when the extreme values are excluded from the entire dataset, better fits could be achieved. Thus, the method that could provide the best fit to the most extreme data could also to be considered to perform well since the overall aim of interpolation is to provide sophisticated way of predicting water quality in areas where no data exists and propose a more realistic estimate in areas of high gradient.

Conclusion

This study shows that all the physico-chemical parameters fall within the permissible limit as per standards. The quality of water is under safe limit. The measurement and exploitation of ground-water at optimum levels can be achieved on the basis of the assessment and continuous monitoring of ground-water resources. The results are compared with univariate interpolation algorithms such as ordinary kriging and inverse distance weighing. The comparisons were performed with cross validation at sampling locations and assessed based on mean and root means squared errors.

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