Electrical resistivity measurements for spatial soil moisture variability estimation

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Abstract: This experimental work empirically compares the results obtained in soil moisture spatial estimation performed with different interpolation techniques. Three algorithms were compared: Inverse Distance Weight (IDW), Ordinary Kriging (OK) and Co-Kriging (CoK). The data used were obtained through an *in-situ* sampling in a test site located in central Italy. The calibration and the validation data set contain respectively 40 and 133 point measurements of TDR soil moisture. The covariate used is a data set of 533 electrical resistivity (conductivity) point measurements. In terms of prediction accuracy results show no great differences between the performance of the IDW and the OK methods. Quite more accurate results were obtained incorporating the secondary variable information in the CoK algorithm.

Keywords: TDR, electrical resistivity, geostatistic, ordinary kriging, co-kriging.

1. Introduction

Being a key variable in many natural processes acting at different spatial/temporal scales, there is a great interest in the observation, estimation and interpretation of soil moisture (SM) patterns. Traditionally the in-situ measurements have been performed by using the thermo-gravimetric method and, most recently, Time Domain Reflectomery (TDR) and neutron probes. These methods can be very precise and accurate but they are invasive and carry information representative only for small areas and volumes. Emerging electrical resistivity (ER) method has been applied in a growing number of surveys. This technique is relatively less invasive, cost effective and gives information of a larger volume of soil. Our interest is on the investigation of SM spatial variability using different interpolation algorithms, both deterministic (Inverse Distance Weight, IDW) and geostatistical. Moreover, we would like to compare punctual soil moisture predictions obtained by Ordinary Kriging (OK) method, applied on the poor sampled SM variable, with those obtained through the Co-Kriging algorithm (CoK) incorporating the more dense information of the secondary variable (ER).

2. Materials and Methods

The study area is a 200m x 60m test site located in the Umbria region (central Italy). Simultaneous measurements of SM [% vol/vol] and ER [Ohm*m] were acquired on the nodes of a 5m sampling step regular grid. A mobile TDR probe with 15 cm wave-guide length (MiniTrase, Soil Moisture Equipment Corporation) was used for the SM measurements. A geo-resistivimeter Syscal Junior (IRIS Instrument) coupled with a Schlumberger 4-electrode device was used for the ER measurements at ~20cm of pseudo-depth.

The focus of this work was to compare different interpolation techniques in order to verify the advantages of using auxiliary variables for soil moisture patterns estimation. A strong under sampling of the SM variable was performed (Fig1) as often is in real cases. Through a completely random sampling, 10 calibration data sets (40 points each) and a validation data set (133 points) for each calibration data set were sub-sampled. We present here the results concerning one of the ten calibration data sets (Fig1).

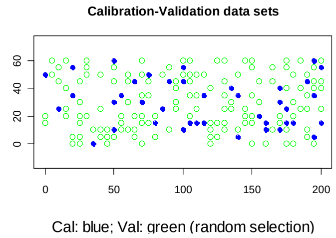

Figure 1: Relative positions of points used for the validation and one of the calibration data set.

Three different interpolation algorithms, IDW, OK and CoK (Govaerts, 1997; Hengl, 2007), were applied to obtain SM spatial predictions. All the interpolations and variogram models were performed on log transformed variables and then data were back-transformed for the validation of the results.

To fit a linear model of co-regionalization under the constrain of having positive definite partial sill matrices, we chose to use electrical conductivity, (EC= 1/ER), values [mS/m] because the experimental variogram looked more similar to the SM one.

Two validation steps were applied: first the difference between predicted and measured values (validation data set) was computed; then, a regression between predicted and measured values was conducted and residuals compared in terms of: mean prediction error (MPE), median, standard deviation (RMSE), mean absolute error (MAE), minimum and maximum value. Moreover, the Pearson correlation coefficients between predicted and measured values of SM for each interpolation algorithm were estimated.

3. Results

The summary statistics (Tab.1) show that SM variability (sd and CV) is broader for the validation than for the calibration dataset. The central values are slightly lower for the validation than for the calibration set. The log transformation of data was applied in order to obtain quasi-normal pdfs.

variable	unit	count	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	sd	CV	skewness
sm: calibration	% vol/vol	40	21,30	27,48	29,30	30,40	32,78	44,10	5,17	0,17	0,78
sm: validation	% vol/vol	133	17,60	26,40	28,90	29,83	34,10	45,90	5,26	0,18	0,31
electrical conductivity	mS/m	533	3,70	13,09	16,90	17,96	21,69	39,31	6,76	0,38	0,55

Table 1: Summary statistics of the different data sets.

The distributions of the EC, the SM validation and calibration sets are showed in Fig.2 along with a scatter plot of the logEC-logSM relation for the calibration sample.

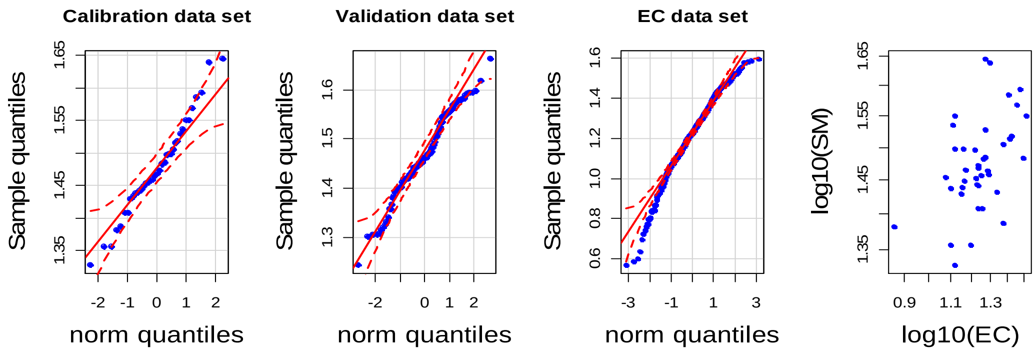

Figure 2: data set distributions and log(SM) vs log(EC) correlation.

After having modeled the SM variogram, the OK algorithm for spatial interpolation was applied and the results compared with those obtained through the IDW. The visual comparison of the two maps (not showed) highlighted no strong differences. The general large scale patterns are similarly reproduced. The OK map seemed to be smoother and with less artifacts. The statistics comparing the experimental errors were only slightly better for the OK than for the IDW algorithm (Tab.2).

(measured - predicted)	MPE	Median	RMSE	MAE	I quart	III quart	Min	Max	r
IDW	0,59	0,52	4,45	3,48	-2,10	4,45	-9,99	12,16	0,54
OK	0,56	0,64	4,43	3,47	-2,20	3,21	-9,86	10,70	0,55
CoK	0,38	-0,09	3,82	2,97	-1,74	2,66	-9,86	9,55	0,70

Table2: residual summaries between measured and predicted values.

Once the EC spatial structure and its covariance with SM were modeled (co-regionalization modeling) (Tab.3), a CoK map was produced. The map well reproduced the larger SM patterns and clearly showed better defined SM smaller scale details (Fig.3).

Moreover, the correlation between CoK predicted and validation data was sharply higher than that for OK and IDW (0.70 vs ~0.55) and the error statistics showed a better performance of the CoK in modeling the SM values (Tab.2).

	model	psill	range (m)
log(SM)	Nug	6,45E-04	
	Exp	3,57E-03	13
log(EC)	Nug	3,00E-03	
	Exp	2,98E-01	13
log(SM)log(EC)	Nug	3,17E-03	
	Exp	1,06E-02	13

Table 3: Model parameters of cross- and semi- variograms for the log-transformed variables

4. Concluding remarks

The comparison between different interpolation algorithms in modeling the spatial SM patterns was shown. The first comparison was done between OK and IDW algorithms, both accounting for the SM sampled data (40 points). These results were compared with that of the CoK algorithm that allowed us to incorporate the information of a more densely sampled covariate (530 data). The validation of the three interpolation methods applied was assessed using an independent validation data set (133 points).

The results of the validation procedure showed no marked differences between IDW and OK performances, with the latter being just slightly more accurate than the former. On the other hand, the comparison in term of SM estimation revealed the major accuracy of the CoK algorithm respect to the IDW and OK algorithms. This result confirm the relevance that secondary variables can have in spatial modeling. Further analysis of various issues need to be explored: how sample size and scheme affect the spatial predictions of the OK and CoK algorithms? And, how interpolation algorithms perform compared to simulations in modeling the spatial variability of the SM?

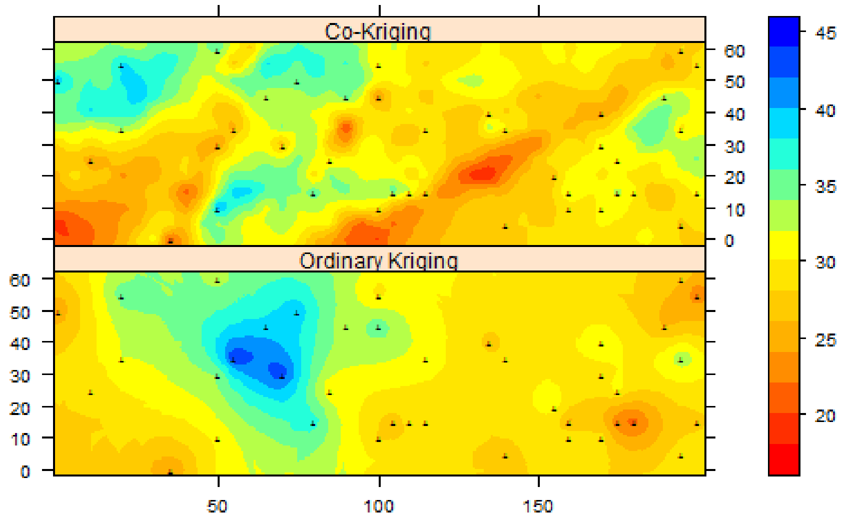

Figure 3: CoK map (top) compared with OK map (bottom) of the SM spatial pattern in the test site. Symbols on the map indicate the calibration sampling sites.

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