GEOSTATISTICAL ANALYSIS OF pH AND REDOX POTENTIAL (Eh) VARIABILITY OVER A RICE FIELD IN SUCCESSIVE CROP STAGES

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RESUMEN. *Se analizó la variabilidad espacial de pH y potencial redox (Eh) de un arrozal ácido en Corrientes, Argentina. Se muestrearon parcelas con tres dosis de encalado antes de la inundación y dos veces tras la inundación. Se tomaron 96 muestras por tratamiento de encalado y fecha de muestreo en una red de 11,9 x 20 m. Tras la inundación el pH aumentó, mientras que el Eh disminuyó. La variabilidad estadística del pH fue baja durante los tres muestreos, mientras que la del Eh fue baja en el primer muestreo y aumentó considerablemente durante el segundo. La dependencia espacial del pH fue acusada, mientras que la del Eh osciló entre moderada y fuerte, y ello durante los tres períodos muestreados y para los tres dosis de encalado. Se ajustaron semivariogramas de tipo esférico con efecto pepita bajo a moderado a los datos experimentales de las 18 series estudiadas. El krigeado mostró su utilidad para cartografiar los datos de pH y Eh, permitiendo identificar microrregiones con valores altos y bajos.*

ABSTRACT. *The spatial variability of pH and redox potential (Eh) on an acid paddy soil in Corrientes, Argentina was analyzed. Soil was sampled in plots with three liming treatments, first before flooding, and then two times after flooding. Ninety-six samples per lime treatment and sampling date were taken on a 11.9 x 20 m grid. Following flooding pH increased, whereas Eh decreased. The statistical variability of pH was rather low during the three sampling periods and those of Eh was initially low but it sharply increased during the second sampling date. The pH spatial dependence was rather strong and those of Eh was strong to moderate during the three study periods and for the three lime treatments. Spherical models with low to moderate nugget effect were adjusted to experimental semivariograms of the 18 data sets studied. Kriging was useful in mapping soil pH and Eh allowing identifying microrregions with contrasting values.*

1. INTRODUCTION

Soil spatial variability is a natural occurring and or management induced feature that is important for site-specific management practices such as variable rate fertilization. Since rice paddy fields are flooded and flat, apparently they should be homogeneous and, therefore, it had been thought that spatial variability both in yields and soil properties might be negligible. However, significant levels of variability in soil general properties, soil nutrients and rice yields (Trangmar et al., 1987: Iida et al., 1999, Yanay et al., 2001; Inamura et al., 2004, Roel and Plant, 2004) have been observed.

A paddy field is a flooded parcel of arable land used for growing rice. Therefore, rice fields require large quantities of water for irrigation. Flooding provides water, essential to maintain the growth of lowland rice. Water also provides a favorable environment for the rice strains being grown as well as discouraging the growth of many species of weeds. Paddy fields remain dry between successive rice crops. Changing from aerobic to anaerobic conditions in paddy fields leads to strong variations in pH, Eh and other related soil attributes such as available nutrients. In general, temporal changes in the spatial variability of soil properties or parameters have not been addressed on paddy soils (Morales, 2004).

Precision farming, otherwise known as site-specific crop management, has attracted interest in Argentina (Bongiovanni, 2007). Site-specific crop management can be viewed as a cyclical process of within field data collection, data analysis and optimum decision making, variable rate application, and evaluation. Yield, crop growth status, and soil properties are necessary data inputs to the system. As in other crops, in typical rice fields, describing spatial variability of within-field properties is a fundamental first step toward determining the size of management zones and the inter-relationships between limiting factors, for the development of management strategies. Site variables in interest are soil properties, crop growth status, and crop yield.

Geostatistics, based on the theory of regionalized variables, is the primary tool of spatial variability analysis. The results obtained from a geostatistical analysis are dependent on a number of variables, such as sampling frequency and number, sampling spacing and accuracy, and analysis parameter selection (Webster and Oliver, 1990; Vieira et al., 1997). Proper interpretation of the semivariogram and selection of appropriate models are very important to the analysis process (Vieira, 2000). Semivariogram models can then be used to produce maps of the investigated property by "kriging", an interpolation method that yields unbiased estimates with minimal estimation variance.

The main rice zones of Argentina are in the provinces of Corrientes and Entre Ríos, which accounts 85% of the domestic production. There is a minor contribution of neighbouring areas in the Santa Fé, Chaco, Formosa and Misiones provinces (Morales, 2004). The general objective of this research was to describe the spatial-temporal variability of two physicochemical parameters, pH and Eh, present in a rice paddy field typical for Corrientes in the Argentinean Mesopotamia. Specific objectives were: (1) To asses the pattern of spatiotemporal variability of Eh and pH and (2) to map the studied soil properties.

2. MATERIAL AND METHODS

2.1. Experimental site, soil and sampling

The study site was a paddy field cropped with rice (*Oryza sativa* L.) of 5.1 ha in area, located in the Corrientes province, Argentina, with two consecutive years under irrigated rice. The climate is warm, subtropical and its main features are high temperatures and abundant rainfall the whole year round. According to the U.S. Soil taxonomy the study soil was classified a Typic Plintacualf. This soil was silty-loam textured with 4.8% clay, 67.0% silt and 28.2 % sand. Before lime addition soil pH was 3.7, organic matter content 2.14 %, cationic exchange capacity 21.7 $Cmol_c$ kg^{-1} and exchangeable aluminium 3.4 $Cmol_c$ kg^{-1}.

Field trials consisted of three different lime treatments: control with no lime addition and two applications of dolomite at rates of 625 and 1250 kg ha^{-1}. The dolomite amendment was applied two months before sowing. The three lime treatments were applied in adjacent plots separated by earth roads.

Soil was sampled at three different times along the rice vegetative period. The first time soil was collected when sowing, just prior to flooding, thus in aerobic conditions. Later on, during anaerobiosis soil samples were taken in two successive periods, four and eight weeks after flooding (i. e. 28 and 56 days) following bunch formation and flowering respectively. A systematic sampling scheme was used. In each of the three treatments and the three sampling dates, ninety-six soil samples were taken on a 20 x 11.9 m grid covering the 5.1 ha site. The used sampling scheme was intended to provide sufficient numbers of data pairs over a wide range of distances, thus allowing identification of short- and long- range variations. Site and soil description together with sampling grid have been thoroughly described elsewhere (Morales, 2004).

Prior to soil laboratory analysis, all samples were air-dried and sieved (2-mm mesh). The two study parameters, pH and Eh were determined by routine methods.

2.2. Statistical and Geostatistical Analysis

Exploratory statistical analysis included examination of mean values, coefficients of variation, maximum and minimum values. Proximity to the normal distribution was judged on the basis of Kolmogorov-Smirnov test

Spatial variability was assessed by means of semivariogram analysis. From models of spatial dependence between neighbouring data, the kriging approximation was used for interpolation at unsampled locations.

Geostatistical 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 autocorrelation exists). This assumption can be verified through examination of semivariograms for the attributes under investigation. The semivariogram is a statistical tool used to measure the between-sample autocorrelation. Thus, the first step of the geostatistical analysis was to calculate sample semivariograms. For each variable treatment and sampling data, a graph was obtained that showed the amount of variance between points as a function of distance. Following authorized recommendations (Vieira et al., 1997; Vieira, 2000) both visual inspection, by means of the traditional fitting-bye-eye method, and the cross-validation technique were used when modeling a semivariogram.

3. RESULTS AND DISCUSSION

Descriptive statistics pH and Eh for the three dolomite treatments and three sampling dates are shown in Table 1. Irrespective of lime dose, mean pH values increased, which is an expected result, due to the effects of flooding. So, mean pH ranged from 4.21 to 4.44 during the first sampling, 5.71 to 5.89 during the second sampling and 6.61 to 6.79 during the third sampling. Therefore, an increase of pH larger than two units was recorded along the rice growth period. Although mean pH values ranked as follows: control < 625 kg ha^{-1} dolomite, < 1250 kg ha^{-1} dolomite, differences between treatments were significant (P <0.01) only on the first sampling data, before flooding.

Again as expected, mean Eh values decreased along the rice growth period due to increased anaerobiosis. On the three sampling dates, mean Eh ranked as follows: control > 625 kg ha^{-1} dolomite > 1250 kg ha^{-1}, contrasting with ranks for pH. Mean Eh oscillated between 554.4 and 532.4 mV during the first sampling, between -16.53 and -30.13 mV during the second sampling and between -186,2 and -210,3 during the third sampling. Differences between treatments were significant (P<0.01) only at the third sampling depth. Fig.2 shows the continuous decrease of mean Eh values along the growth period of rice, illustrating the large temporal variability of this parameter when compared with differences between treatments.

Also, the statistical variability between minima and maxima values of pH and Eh for a given treatment was rather important. The range of minima and maxima pH values within a plot was greater than 0.4 units at the first sampling date and even higher than 1 unit at the second sampling date. The range of minima and maxima Eh was between 40 and 75 mV at the first sampling date and increased at the successive samplings, so that in one of the study cases reached values higher than 150 mV (Table 1). Therefore, the range of Eh ranked as follows: first sampling < second sampling < third sampling.

During the first sampling coefficients of variation (CV) were low or very low, i.e. smaller than 2.1%, both for pH and Eh. In anaerobic conditions, i.e. at the second and the third sampling, CVs were still low or very low for pH and medium or high for Eh. Overall, CVs were much higher for Eh than for pH as they ranged from 1.58 % to 5.25 % for the former and from 1.34 % to 119.4 % for the later. Both pH and Eh exhibited the highest CV during the second sampling with values ranging from 4.11% to 4.82 % for pH and from 44.78 % to 119.4 %. Small coefficients of variation for pH than for other soil properties have been frequently reported both on rainfed soils (e.g. Paz González et al., 2000; Vieira and Paz González, 2003) and paddy soils (e.g. Tragmar et al., 1987; Yanay et al., 2001; Inamura et al., 2004). The sharp increase of the coefficient of variation for Eh during the second sampling period is an expected result, since the absolute values of this parameter were low, and both positive and negative values were recorded, which oscillates in a relatively narrow range around zero. Because of the different order of magnitude in mean values of Eh, in this particular case plot variability is better assessed by the range or difference between minima and maxima values than by CV.

The values of skewness were near 0, i.e. in the range of 0.5, in 12 out of 18 studied data sets, but frequency distributions were positive or negative skewed in the other 6 data sets. Moreover kurtosis was generally smaller that 3, so that 16 out 18 frequency distributions showed a platokurtic shape. These results suggest that frequency distributions for pH and Eh not always seem to be close to normal. However, the Kolmogorov-Smirnov tests showed that 17 out 18 data sets fitted a normal distribution, in spite of the more or less depart of skewness and kurtosis from standard values. The only exception was pH measured at the control plot during the third sampling. It is well established that kriging works best with normally distributed data (e.g. Vieira, 2000).

Table 1. Summary statistics for redox potential (Eh) and pH at three sampling dates, and on three lime treatments. (Data for Eh in mV).

	Treatment	Mean	Variance	C.V. (%)	Minimum	Maximum	Skewness	Kurtosis
				First sampling, before flooding				
Eh	**control**	554.4	54.92	1.34	538.0	577.0	0.323	0.278
	625 kg ha^{-1}	539.7	111.4	1.96	507.0	568.0	-0.182	0.959
	1250 kg ha^{-1}	532.4	113.2	2.00	487.0	553.0	-1.423	3.548
pH	**control**	4.21	0.0078	2.10	3.95	4.41	0.039	-0.206
	625 kg ha^{-1}	4.32	0.00	1.58	4.14	4.54	0.674	1.463
	1250 kg ha^{-1}	4.44	0.01	1.68	4.29	4.74	1.349	3.231
				Second sampling, 28 days alter flooding				
Eh	**control**	-16.53	389.6	119.4	-76.00	25.00	-0.570	0.464
	625 kg ha^{-1}	-25.81	240.1	60.03	-69.00	19.00	0.136	0.007
	1250 kg ha^{-1}	-30.13	182.0	44.78	-63.00	-6.00	-0.164	-0.652
pH	**control**	5.71	0.076	4.82	4.96	6.25	-0.087	-0.578
	625 kg ha^{-1}	5.79	0.093	5.25	4.92	6.35	-0.320	0.019
	1250 kg ha^{-1}	5.89	0.059	4.11	5.31	6.49	-0.062	-0.209
				Third sampling, 56 days alter flooding				
Eh	**control**	-186.2	1017.0	17.13	-262.0	-122.0	-0.131	-0.366
	625 kg ha^{-1}	-189.5	883.5	15.68	-286.0	-130.0	-0.663	0.487
	1250 kg ha^{-1}	-210.3	965.8	14.78	-275.0	-146.0	0.023	-0.739
pH	**control**	6.611	0.055	3.55	5.98	6.96	-0.872	-0.278
	625 kg ha^{-1}	6.711	0.048	3.28	6.12	7.13	-0.279	0.202
	1250 kg ha^{-1}	6.791	0.015	1.77	6.48	7.10	0.119	0.159

Table 2 shows main results of semivariogram analysis, including fitted model type, model parameters (sill, nugget and range) and parameters from cross validation (mean error, EM, adimensional mean quadratic error, ECMA). All the experimental semivariogram display a steady increase in semivariance, with increasing lag distance, indicating a strong spatial dependence at small distances. A stable sill is reached suggesting there is no significant trend in all the 18 study data sets. All the pH and Eh experimental semivariograms were best fitted by spherical models with variable nugget effect, range of spatial dependence and sill values

In general, semivariograms or pH and Eh could be adjusted quite well, over the spatial scale of interest, by spherical models with a nugget component (C_0) plus a spatial component (C_1) with a correlation range between 47 and 78 m, approximately, for all the 18 data sets. The nugget variances were all below 54% of the sill value, and in 13 out of 18 study cases below 30% of that value, which indicates, in general, good spatial continuity at close distances between sampled points.

The range of spatial dependence was from 44.9 to 66.6 m for pH, whereas for Eh it was somewhat larger, ranging from 47.3 to 77.5 m. Following the criteria proposed by Cambardella et al., (1994) the spatial dependence is considered strong when the ratio $C_0/(C_0+C_1)$ is lower tan 25% and moderate for values of this ratio between 25% and 75%. It follows that pH exhibited a strong spatial dependence in 8 cases, whereas this dependence was moderate in 1 case. In contrast, the spatial dependence of Eh was strong for 3 data sets and moderate for 6 data sets. Therefore, the imposed sampling grid captured large proportions of the spatial variance both for Eh and pH, but it could be considered more adequate for characterising pH than Eh plot's spatial variability. Moreover, the grid density necessary to capture the spatial variability also rely on dolomite treatment and sampling date.

Spatial variability depend both on soil forming factors and management, which in paddy soils seem apparently uniform as before stated. Clearly climate, topography and water level are homogeneous on the experimental units. The parent material consisted of sedimentary rocks characterised by various particle size distributions, which could be a main cause of spatial variability.

Table 2. Best fitted model parameters and cross-validation parameters for Eh and pH at three sampling dates, and on three lime treatments. (C_0 = nugget effect; C_1 = sill; a = range; r^2 = correlation coefficient; ME = Mean Error, ECMA = Adimensional Mean Quadratic Error).

	Treatment	Model	C_0	C_1	a (m)	r^2	ME	ECMA
				First sampling, befote flooding				
Eh	**control**	spherical	6.16	52.27	47.33	0.878	-0.0054	1.133
	625 kg ha^{-1}	spherical	19.56	93.51	56.40	0.892	0.0067	0.959
	1250 kg ha^{-1}	spherical	9.28	113.75	68.31	0.888	-0.0022	1.246
pH	**control**	spherical	0.0023	0.0059	57.92	0.784	0.0173	0.839
	625 kg ha^{-1}	spherical	0.00017	0.00463	57.92	0.885	0.0111	1.264
	1250 kg ha^{-1}	spherical	0.00072	0.00504	59.10	0.903	-0.0133	0.845
				Second sampling, 28 days alter flooding				
Eh	**control**	spherical	118.69	300.40	61.67	0.856	0.0027	0.694
	625 kg ha^{-1}	spherical	117.23	136.97	63.28	0.916	0.0103	0.821
	1250 kg ha^{-1}	spherical	101.46	86.74	66.11	0.851	0.0240	0.940
pH	**control**	spherical	0.00372	0.0795	61.58	0.930	-0.0151	1.107
	625 kg ha^{-1}	spherical	0.00000	0.0974	44.93	0.869	-0.0246	1.017
	1250 kg ha^{-1}	spherical	0.028	0.031	51.76	0.661	-0.0347	0.919
				Third sampling, 56 days alter flooding				
Eh	**control**	spherical	451.61	635.82	60.12	0.769	-0.0021	0.759
	625 kg ha^{-1}	spherical	245.73	745.43	76.63	0.892	0.0014	0.495
	1250 kg ha^{-1}	spherical	458.80	584.95	77.48	0.858	-0.0069	0.974
pH	**control**	spherical	0.006	0.053	60.79	0.890	0.0009	1.008
	625 kg ha^{-1}	spherical	0.002	0.048	45.51	0.793	0.0041	1.031
	1250 kg ha^{-1}	spherical	0.003	0.012	45.84	0.938	-0.0083	1.091

Dynamics of pH and Eh is considered to be complex and it is affected by numerous internal factors or soil properties such organic matter content, elemental composition or element speciation, which determine a number of chemical reactions and over a rice field are far from homogeneous. On the other hand, although all the experimental units were managed similarly uneven water application due to inaccuracies of the flooding system and/or microrelief features could be also a source of spatial variability. Therefore, texture, soil mineral and organic composition, uneven flooding and microtopographic irregularities are possible factors influencing pH and Eh variability.

Examples of kriging contour maps for pH and Eh that were drawn using the fitted semivariogram models are shown in Figure 1 and Figure 2, which correspond to the first and the third sampling, respectively. All the kriging maps present discrete patches or small zones with distinct pH and Eh values. Patterns of spatial variation clearly show disparities between the three dolomite treatments for a given sampling date. Moreover, kriging maps drawn for each liming treatment in successive dates also change, indicating a lack of temporal stability of pH and Eh at the studied plot scale. In general pH kriging contour maps show more patchiness than Eh maps. This trend is consistent with the somewhat higher nugget effect and larger range of Eh when compared with pH.

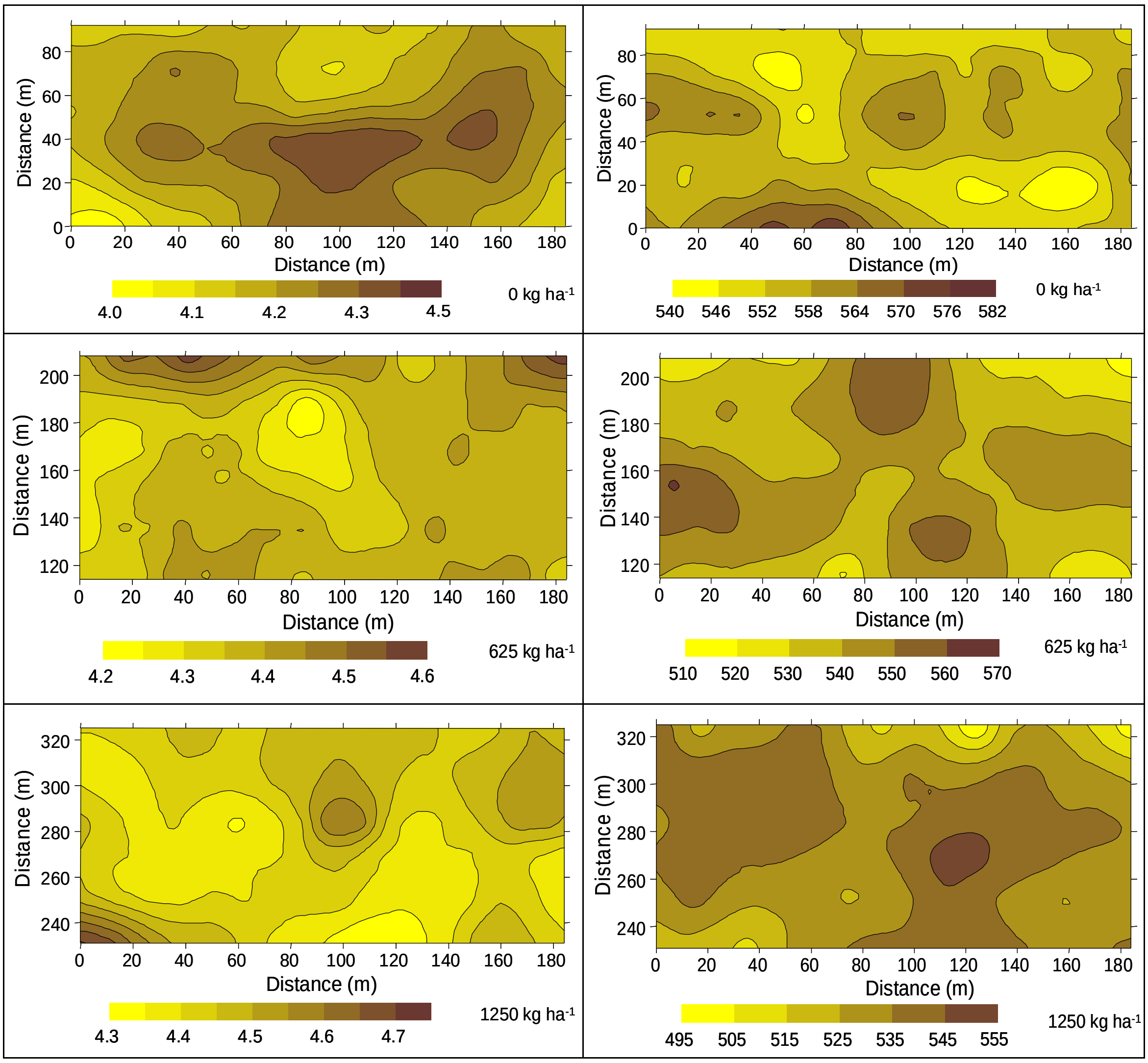

Figure 1. Kriging maps of pH (left) and Eh (right) for different dolomite doses during the first sampling date, in aerobic conditions.

The maps of pH obtained for the first sampling show distinct micro-regions with differences of about 0.4 units (Figure 1). Consistent with the statistical results, kriging contour maps even show the increase in pH spatial variability during the second sampling (data no shown) as indicated by small areas with differences ranging from about 0.8 to 1.2 units. During the third sampling, pH differences of the small patches within a plot are in the range of about 0.5 – 1 units (Figure 2). Taken into account all mapped data, pH before flooding was between 4.0 and 4.8, whereas after flooding it was between 6.1 and 7.1, with small differences regarding dolomite treatment.

The range of Eh differences between patches of a given plot was of about 40 to 55 mV during the first sampling (Figure 1), 55 to 75 mV during the second sampling (data no shown) and 90 to 130 mV during the third sampling (Figure 2). During the second sampling, at flowering, patches with maximum Eh values may be positive (treatments with 0 and 625 kg ha^{-1}), whereas those with minimum values are negative. Therefore at this stage aerobic and anaerobic areas are found on the same plot, which has consequences for rice development and production. This result indicates that variability in soil properties was not only present but was potentially of agronomic importance.

Kriging contour maps also show that there is no correspondence between patches with maximum or minimum values of pH and Eh. In some cases it can be observed that areas with maximum pH values show a trend to match those with minimum Eh and vice versa. This tendency is in accordance with the observed trend of a trend or even a small significant negative relationship between pH and Eh.

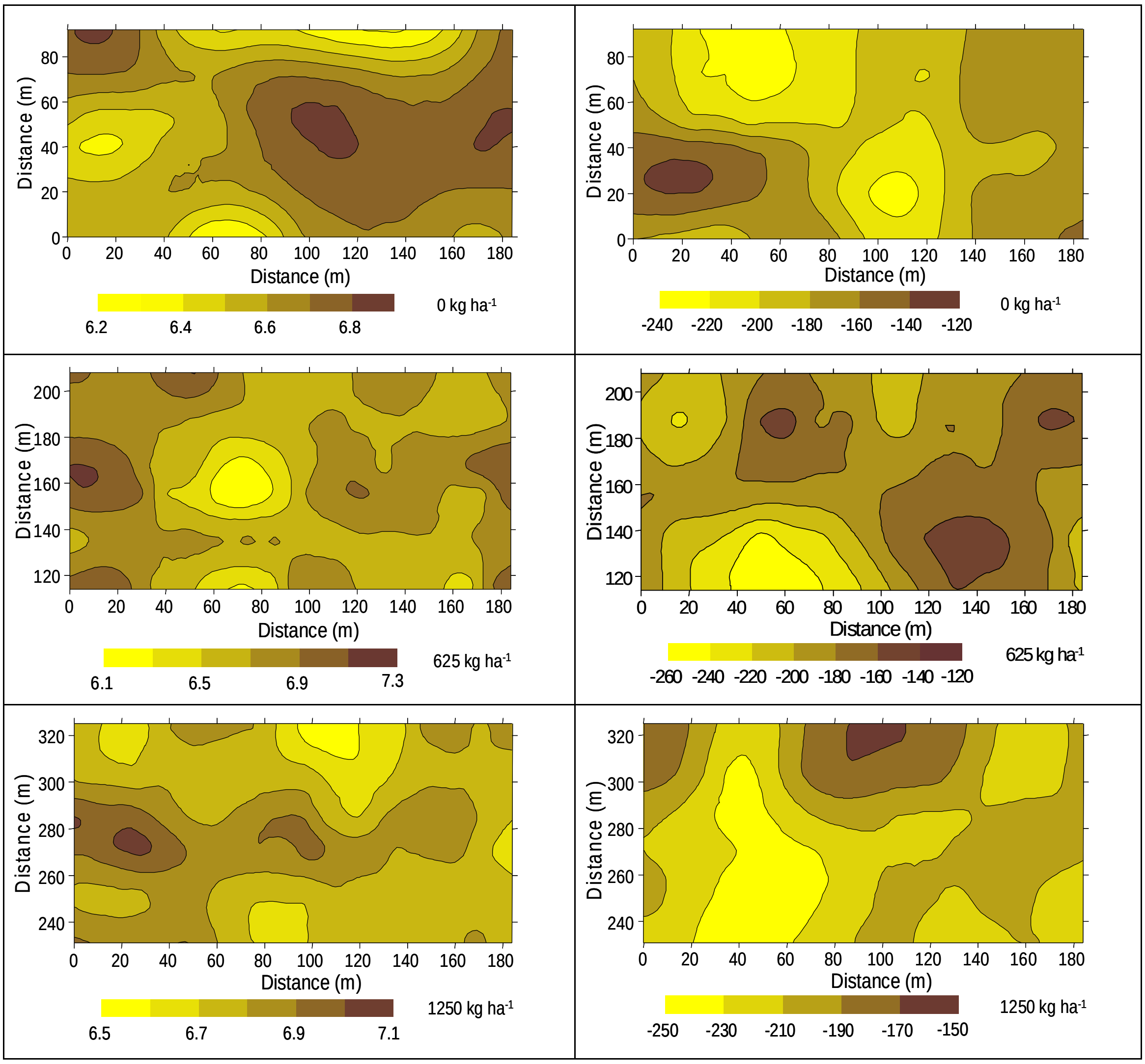

Figure 2. Kriging maps of pH (left) and Eh (right) for different dolomite doses during the third sampling date.

Measurement and management of the small scale variability in rice fields raises both, challenges and opportunities for precision agriculture. Small scale variability requires more careful consideration regarding both determination of design parameters and data processing issues. Precision agriculture strategies should be further investigated, depending on the feasibility of controlling spatiotemporal variability. The above results show that there is a great potential to apply site specific technologies and management strategies for rice production.

4. CONCLUSIONS

Spatial variability of pH and Eh on rice fields was far from negligible both on aerobic and on anaerobic conditions. So, the range of pH within a given plot was greater than 0.4 units and could even be higher than 1 unit. The range of Eh at the small plot scale was between 40 and 150 mV, approximately.

The pattern of spatial dependence of pH and Eh was described by spherical models with a nugget component. In general pH exhibited a stronger spatial dependence than Eh and also showed a tendency to present smaller ranges of spatial dependence.

Kriging maps clearly showed the presence of small scale variability for pH and Eh within each liming treatment and during each of the three sampling dates. Also the position of patches with maxima and minima values for pH and Eh changed between successive sampling dates illustrating the lack of temporal stability of the pattern of spatial distribution for pH and Eh. These findings indicate the potential for applying the principles of precision agriculture to control spatiotemporal variability in rice fields.

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