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Spatial variability of agricultural soil parameters in southern Spain

Francisca López-Granados[1,3], Montserrat Jurado-Expósito[1], Silvia Atenciano[1], Alfonso García-Ferrer[2], Manuel Sánchez de la Orden[2] & Luis García-Torres[1]
[1]*Institute for Sustainable Agriculture/Spanish Council for Scientific Research (CSIC), Apdo 4084; 14080-Córdoba, Spain.* [2]*Dept. of Remote Sensing, University of Córdoba, Avda. Menéndez Pidal s/n, 14004-Córdoba, Spain*
[3]*Corresponding author**

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Abstract

Spatial patterns for seven soil chemical properties and textures were examined in two fields in southern Spain (Monclova and Caracol, province of Seville, Andalusia) in order to identify their spatial distribution for the implementation of a site-specific fertilization practice. Two sampling grids of 35×20 and 35×35 m were established in Caracol and Monclova, respectively. Fourteen and eight georeferenced soil samples per hectare were collected at two depths (0–0.1 and 0.25–0.35 m) in early November 1998 before fertilizing and planting the winter crop. Data were analyzed both statistically and geostatistically on the basis of the semivariogram. The spatial distribution model and spatial dependence level varied both between and within locations. Some of the soil properties showed lack of spatial dependence at both depths and at the chosen interval (lag h). Such was the case for clay, organic matter and NH_4 at Monclova; and clay and NH_4 at Caracol. Bray P and exchangeable K showed a strong patchy distribution at any field and depth. It is important to know the spatial dependence of soil parameters, as management parameters with strong spatial dependence (patchy distribution) will be more readily managed and an accurate site-specific fertilization scheme for precision farming more easily developed.

Introduction

Precision farming can be considered a new crop management system, in which inputs are limited to where they are needed. In recent years, many scientific efforts and economic resources have been spent on measuring the spatial variability of crop yield and for the distribution of weeds or soil nutrients, with the aim of minimizing pesticide use and optimizing crop yield (NRC, 1999). Developing accurate application maps for site-specific fertilization is critical in implementing precision farming technology and requires a profound and precise knowledge of the variable soil factors. Spatial variability drives precision agriculture because soil parameters with little or no spatial dependence will not be conducive to site-specific management and will be managed on the average (Pierce and Nowak, 1999).

Positioning technology is made possible by the use of global positioning systems (GPS). Further, spraying devices are available which inject nutrients near the nozzles, making it possible to vary the rate of application of nutrients over short distances (Tyler, 1993). Therefore, a variable application strategy could be based on a map showing soil chemical (pH, nitrogen, phosphorus, and potassium) properties, positioning devices and sprayer capable of varying the nutrient application in response to soil variability. This strategy will make it possible to reduce fertilizer use, costs and environmental pressure.

Geostatistics is concerned with detecting, estimating and mapping the spatial patterns of regional variables, and is centered on the modeling and interpretation of the semivariogram. This instrument distinguishes variation in measurements separated by given distances (Goovaerts, 1997; Isaaks and Srivastava, 1989; Journel and Huijbregts, 1978; Rossi et al., 1992). Semivariogram models provide the necessary information for kriging, which is a method for interpolating data at unsampled points.

To plan an optimal decision support scheme for site-specific farming, the semivariogram has proven

* E-mail: cs9logrf@uco.es

to be an excellent way of exploring the structure of spatial variation in agricultural soils (Cambardella and Karlen, 1999; Geypens et al., 1999; Webster and Oliver, 1992). McBratney and Pringle (1999) have used geostatistical techniques to estimate average and proportional semivariograms based on previously reported semivariograms. They discussed the possibility of managing an average semivariogram for different conditions and they warned us about the paradox of seeking a site-specific strategy with only minimal data acquisition.

Most soil spatial variability studies have been carried out in diverse temperate countries, e.g., UK (Blackmore et al., 1998), Belgium (Geypens et al., 1999), Denmark (Heisel et al., 1999), The Netherlands (Verhagen, 1997), Germany (Domsch and Wendroth, 1997), or at Iowa, USA (Cambardella and Karlen, 1999). Although these works provided very precise information for site-specific recommendations, similar information from soils under semiarid Mediterranean conditions was lacking and needed to be assessed. More precisely, it is necessary to consider the fact that spatial variability of soils depends on the specific soil studied. In other words, although the texture and the organic matter in the same field may be fairly static, soil mineral nitrogen may be highly variable over time as well as in space (Geypens et al., 1999).

The research herein presented is part of a 3-year collaboration with pioneering programs on large farming operations to determine the profitability of precision management under Mediterranean conditions and to test if expectations for reducing fertilizer recommendation according to a site-specific strategy would be possible under such conditions.

Materials and methods

Study area, sampling design and laboratory analysis

Soil analyses were conducted on samples from two fields located at Monclova and Caracol (province of Seville), both within one of the most important and technologically advanced farming areas in Andalusia (southern Spain, 38°–36° N and 4°–6° W). According to the USDA soil series (1975), the soil at Monclova was classified as Alfisol, and that at Caracol as Vertic Xerochrep.

Sampling took place before winter crop fertilizing and planting. Each sampling area was 6 and 11.2 ha at Caracol and Monclova, respectively. Both were located within larger fields (of around 40 ha), and their borders were at least 50 m from the main borders of these fields. The farms were separated by around 100 km from each other, and management practices consisted in a 2-year wheat (*Triticum aestivum* L.)–sunflower *(Helianthus annuus* L.) rotation under conventional tillage (ploughing), weed control and fertilization practices.

Two systematic sampling grids were established, one at Caracol of 35×20 m and another at Monclova of 35×35 m. Soil samples were collected at two depths (0–0.1 m, topsoil, and 0.25–0.35 m, subsoil) at the grid intersection points to produce a total of 84 and 80 sampling points per depth at Caracol and Monclova, respectively. Each soil sample was collected as follows: four 500-g soil cores were taken within 2 m radius of each grid point and one more core right at the intersection point (node). The position of each node was geo-referenced using a DGPS (differential global positioning system). These five samples were mixed thoroughly to provide a bulked sample and to ensure that the sample was representative of the surrounding area. Just 500 g of the bulked sample were finally taken and kept at 4 °C for further laboratory analysis. Soil samples were air-dried overnight and passed through a 2-mm sieve. The texture (% sand, % silt and % clay) was measured using a Bouyoucos densimeter; organic matter content (%) was determined using Redox-Electrode (Methrom Titroprocesador), and pH was measured in a 0.1 mol KCl-solution. Bray extractable phosphorous concentrations (P, ppm) were measured by colorimetry using ascorbic acid–ammonium molybdate reagents, and exchangeable potassium (K, meq/100 g) was measured using atomic absorption spectrophotometry (AAS). NH_4(ppm), NO_3 (ppm) and NO_2 (ppm) were determined by colorimetry in SKALAR.

Statistical analyses

Exploratory statistical analysis

Data were analysed statistically. Classical descriptors were determined, such as mean, maximum, minimum, standard deviation and skewness of data distribution. The descriptive statistics of the soil data suggested that they were all normally distributed (skewness of between 1 and -2) and therefore no transformation was used for geostatistical analyses.

Geostatistical analysis

The soil properties data were analysed using geostatistics. A semivariogram was calculated for each soil property as follows (Isaaks and Srivastava, 1989; Journel and Huijbregts, 1978):

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

where $\gamma(h)$ is the experimental semivariogram value at distance interval h; $N(h)$ is number of sample value pairs within the distance interval h; $z(x_i)$, $z(x_i + h)$ is sample values at two points separated by the distance interval h. All pairs of points separated by distance h (lag h) were used to calculate the experimental semivariogram. Lag h varied between 15 and 30 m depending on soil property, depth and location. Several semivariogram functions were evaluated to choose the best fit with the data. Semivariograms were calculated both isotropically and anisotropically. The anisotropic calculations were performed in four directions (0, 45, 90 and 135 °) with a tolerance of 22.5 ° to determine whether semivariogram functions depended on sampling orientation and direction (i.e., they were anisotropic) or not (i.e., they were isotropic). Direction 0 ° corresponds to E–W and 90° to the N–S direction. The least-squares procedure in VARIOWIN software was used to fit various models to semivariograms. No nested semivariogram structures were used, as we were able to obtain adequate fits with a simple structure.

Spherical, exponential, Gaussian or pure nugget models were fitted to the empirical semivariograms. The parameters of the model: nugget semivariance, range, and sill or total semivariance were determined. Nugget semivariance is the variance at zero distance; sill is the lag distance between measurements at which one value for a variable does not influence neighboring values; and range is the distance at which values of one variable become spatially independent of another. To define different classes of spatial dependence for the soil variables, the ratio between the nugget semivariance and the total semivariance or sill was used (Cambardella et al., 1994). If the ratio was ≤25%, the variable was considered to be strongly spatially dependent, or strongly distributed in patches; if the ratio was between 26 and 75%, the soil variable was considered to be moderately spatially dependent; if the ratio was greater than 75%, the soil variable was considered weakly spatially dependent; if the ratio was 100%, or the slope of the semivariogram was close to zero, the soil variable was considered non-spatially correlated (pure nugget).

Semivariogram models were cross-validated (trial-and-error procedure) to check the validity of the models and to compare values estimated from the semivariogram model with actual values (Isaaks and Srivastava, 1989). Differences between estimated and experimental values are summarized using the following cross-validation statistics: mean estimation error (MEE), mean squared error (MSE) and standardized mean squared error (SMSE) (Hevesi et al., 1992; Isaaks and Srivastava, 1989).

Once cross-validated, the parameters of the semivariogram models described above were used in the construction of maps by kriging for each soil property determined for each field. Ordinary point kriging was performed on a regular grid of 7 m and produced unbiased estimates of each soil property value at unsampled points. Soil mapping of each single property was achieved by kriging. Thus, site-specific fertilizer application maps could be developed.

Geostatistical analysis, cross-validation and kriging were conducted on measured and calculated variables using VARIOWIN and GEOEAS software, and contour maps were generated using SURFER, contour mapping software based on GEOEAS kriged values showing the estimated soil properties and the standard deviation of the kriged estimates.

Results

Exploratory statistical analysis

The summary of the statistics for soil parameters are shown in Tables 1 and 2 (for Monclova and Caracol, respectively). The parameter values strongly varied both between and within fields. Low coefficients of variation (CV between 1 and 8%) for pH and organic matter content (OM), medium CV (from 16 to 49%) for texture, K and P, and high CV ($>$ 50%) for NO_3, NO_2 and NH_4 were found in general at each location. Comparing mean values, lower pH, OM and P were observed at Caracol than at Monclova, while mean values of NO_2 and NH_4 were similar for the two locations. In contrast, higher K and NO_3 values were found at Caracol.

Results from the two depths showed that, in general, the means of soil variables were similar regardless of sample depth, although trends indicated that soil parameters were slightly higher in the upper than in the lower layer.

Table 1. Descriptive statistics and geostatistical analysis of soil parameters in the topsoil (0–0.1 m depth) and subsoil (0.25–0.35 m depth) at Monclova (Seville, southern Spain)

Soil property	Depth (m)	Mean	Min	Max	CV (%)	SD	Skew	Range (m)	Nugget semivariance (#) Ratio (%)	Sill	(§) Spatial distribution, model	(*)MSE	r	(*)SMSE
Sand (%)	0–0.1	57.4	44	80	15	8.5	0.65	0	69 (100)	69	Pure Nugget	70.2	0.14	1
	0.25–0.35	55.6	36	76	14	7.8	–0.01	0	57 (82)	69	W, Exponential	51	0.39	1
Silt (%)	0–0.1	23	4	40	50	11.6	–0.31	29.4	2.8 (2.1)	133	S, Exponential	95	0.55	1
	0.25–0.35	22.4	4	48	50	11.2	–0.22	74.5	25 (20)	122	S, Spherical	91.5	0.55	1
Clay (%)	0–0.1	19.6	4	44	55	10.8	0.22	0	113 (100)	113	Pure Nugget	112.1	0.17	1
	0.25–0.35	22	4	44	46	10.2	0.30	0	102 (100)	102	Pure Nugget	96.8	0.31	1
pH	0–0.1	78.8	7.60	8.08	1	0.10	–0.61	66	0.003 (30)	0.01	M, Spherical	0	0.38	1.1
	0.25–0.35	78.8	7.54	8.04	1	0.09	–0.96	21.2	0 (0)	0.08	S, Exponential	0	0.24	1.1
O.M. (%)	0–0.1	1.6	1.3	2	6	0.1	0.47	0	0.02 (100)	0.02	Pure Nugget	0	0.1	1
	0.25–0.35	1.5	1.2	1.8	7	0.1	0.33	0	0.016 (100	0.016	Pure Nugget	0	0	1
P (ppm)	0–0.1	15.5	5	30	28	4.4	0.48	27.4	0.6 (3.1)	19.2	S, Exponential	17.8	0.31	1.1
	0.25–0.35	12.7	6	31	33	4.2	0.11	67.4	3.24 (18.5)	17.3	S, Spherical	13.6	0.45	1.1
K (meq/100 g)	0–0.1	1.2	0.6	2.1	25	0.3	0.24	34.5	0 (0)	0.1	S, Exponential	0	0.55	1.1
	0.25–0.35	1.1	0.6	2.1	27	0.3	0.61	32.4	0 (0)	0.1	S, Gaussian	0	0.55	2.2
NO_3(ppm)	0–0.1	7.1	0	44	75	5.3	0.39	0	27.2 (100)	27.2	Pure Nugget	26.7	0.31	1
	0.25–0.35	7.9	1	17	42	3.3	0.23	65.7	0.8 (7.5)	10.6	S, Spherical	8.1	0.55	1
NO_2 (ppm)	0–0.1	2	0.2	5	55	1.1	0.57	35.6	0.27 (24)	1.1	S, Gaussian	1.1	0.45	1.3
	0.25–0.35	1.9	0.2	5	58	1.1	0.72	0	1.2 (100)	1.2	Pure Nugget	1.2	0	1
NH_4(ppm)	0–0.1	1.9	0.4	3.6	42	0.8	0.10	0	0.53 (100)	0.53	Pure Nugget	0.6	0.14	1
	0.25–0.35	1.9	0.1	4.4	42	0.8	0.55	0	0.6 (100)	0.6	Pure Nugget	0.6	0	1

(#) Percentage of the sill due to the nugget.
(§) Spatial distribution (S – Strong spatial dependence; M – Moderate spatial dependence; W – Weak spatial dependence; Pure Nugget – no spatial correlation), and spatial distribution model.
(*) MSE – Mean squared error expressed as percentage of the sample variance; SMSE – standardised mean squared error.

Geostatistical analysis

Anisotropic semivariograms did not show any differences in spatial dependence based on direction, for which reason isotropic semivariograms were chosen. The geostatistical analysis indicated different spatial distribution models and spatial dependence levels for the soil properties both between and within the locations. For example, at Monclova (Table 1) clay, OM and NH_4 at both depths; sand and NO_3 in the topsoil; and NO_2 in the subsoil did not follow a spatially correlated distribution (Figure 1a,b for OM, slope of semivariogram was close to zero or maximum, 100%, nugget semivariance/sill ratio). In contrast, silt, P and K at both depths; NO_2 in the top layer; and pH in the subsoil were strongly distributed in patches (Table 1, Figure 2a for P and Figure 2c for K). The remainder (pH in the top) was moderately spatially correlated. Exponential, spherical, pure nugget and Gaussian models were fitted to the soil characteristics.

At Caracol (Table 2) soil properties such as silt and pH in the topsoil (Figure 3a), clay in the subsoil, and NH_4 at both depths were not spatially correlated. Other parameters were strongly distributed in patches (P, NO_3 and NO_2 at the top layer; pH in the subsoil (Figure 3b); and OM and K at both depths), and the remainder (sand at both depths; clay at 0–0.1 m depth; and silt, P, NO_3 and NO_2 at 0.25–0.35 m depth) were moderately spatially correlated. Exponential, pure nugget and spherical models were fitted.

Exchangeable K and Bray's P exhibited a strong distribution in patches at any depth and location (Figure 2a–d at Monclova). Range values varied from 21.2 m (pH in the subsoil) to 74.5 m (silt in the subsoil) at Monclova (Table 1); and from 13.9 m (NO_2 in the topsoil) to 104 m (P at 0.25–0.35 m depth) at Caracol (Table 2).

Discussion

The spatial variation in soil parameters observed should not be surprising, since the values of the variables are usually the result of an intrinsic variation in soil properties and management practices as previously reported by Mallarino et al. (1999). Classical statistics did not show the strongly patchy distribution of some soil parameters and provided mean values that produced medium and large CV for all the soil prop-

Table 2. Descriptive statistics and geostatistical analysis of soil parameters in the topsoil (0–0.10 m depth) and subsoil (0.25–0.35 m depth) at Caracol (Seville, southern Spain)

Soil property	Depth (m)	Mean	Min	Max	CV (%)	SD	Skew	Range (m)	Nugget semivariance (#)Ratio (%)	Sill	(§)Spatial distribution, model	(*)MSE	r	(*)SMSE
Sand (%)	0–0.1	33.4	4	56	40	13.4	–0.86	84.8	85 (46)	184	M, Spherical	156.5	0.55	1.1
	0.25–0.35	34.4	4	60	32	11	–0.96	94.4	66 (57)	116	M, Spherical	142.6	0.31	1.2
Silt (%)	0–0.1	40.4	24	52	14	5.8	–0.05	0	32 (100)	32	Pure Nugget	33.2	0.39	1
	0.25–0.35	39.6	16	56	16	6.3	–0.55	14.5	26 (68)	38	M, Exponential	40.7	0.45	1.1
Clay (%)	0–0.1	26.3	8	56	46	12	0.92	29.9	61 (42)	145	M, Exponential	154.2	0.71	1
	0.25–0.35	26.4	12	52	37	9.7	0.95	0	87 (100)	87	Pure Nugget	103.8	0.77	1.1
pH	0–0.1	7.73	7	7.99	1	0.12	–1.17	0	0.01 (100)	0.01	Pure Nugget	0	0.63	1
	0.25–0.35	7.73	7.51	8.03	1	0.09	0.13	17.6	0 (0)	0.1	S, Exponential	0	0.55	0
O.M. (%)	0–0.1	1.3	1	1.8	8	0.1	0.99	44.8	0 (0)	0.02	S, Spherical	0	0.63	1.1
	0.25–0.35	1.3	1.1	1.7	8	0.1	0.71	24.1	0 (0)	0.01	S, Exponential	0	0.77	1.1
P (ppm)	0–0.1	11.3	3	31	49	5.6	0.95	28.3	0.7 (2)	34	S, Exponential	23.5	0.31	1
	0.25–0.35	10.2	3	23	46	4.7	0.49	104	9 (43)	21	M, Spherical	14.7	0.89	1
K (meq/100 g)	0–0.1	1.9	1.3	4	21	0.4	1.09	54.6	0 (0)	0.1	S, Spherical	0.3	0.31	1.12
	0.25–0.35	1.8	1.1	3	22	0.4	0.91	37.7	0.01 (10)	0.1	S, Exponential	0.2	0	0.9
NO_3 (ppm)	0–0.1	23.2	9	79	44	10.2	1.25	31.7	10 (10)	101	S, Exponential	110.8	0.45	1
	0.25–0.35	20.8	2	93	59	12.2	0.86	16.5	54 (40)	136	M, Exponential	173	0.63	1.13
NO_2 (ppm)	0–0.1	2	0.1	7.5	80	1.6	1.26	13.9	0 (0)	2	S, Exponential	3	0.77	1
	0.25–0.35	2	0.1	8	80	1.6	1.19	26.1	1.6 (64)	2.5	M, Exponential	2.6	0.71	1
NH_4 (ppm)	0–0.1	2	0.4	5	50	1	0.70	0	1 (100)	1	Pure Nugget	1	0.37	1
	0.25–0.35	2	0.1	8	55	1.1	1.09	0	1.3 (100)	1.3	Pure Nugget	1.3	0.36	1.1

(#) Percentage of the sill due to the nugget.
(§) Spatial distribution (S – Strong spatial dependence; M – Moderate spatial dependence; Pure nugget – no spatial correlation), and spatial distribution model.
(*) MSE– Mean squared error expressed as percentage of the sample variance; SMSE – standardised mean squared error.

erties except pH and OM. Cambardella and Karlen (1999) and Geypens et al. (1999) found similar general trends and reported CV in agreement with those report the one in this study.

With regard to the geostatistical analysis, the semivariogram function tests the null hypothesis that soil variable does not exhibit spatial dependence at the chosen lag h. The large nugget semivariance and the non-spatial dependence for some soil variables, e.g., clay at Monclova (Table 1), suggest that the lag h apparently did not characterize the spatial variation and that an additional sampling of these variables at smaller lag distances and in larger numbers might be needed to detect spatial dependence, if any is indeed present. However, under no research circumstances (which means in a commercial context) a larger sampling density usually is not feasible. It is necessary to consider if sampling costs could exceed the value of the resulting fertilizer savings and if a greater sampling density will result in a more accurate nutrient recommendation map (Birrell et al., 1996). At the moment other alternative techniques, including aerial photographs of bare soil to obtain the soil fertilization status, are being undertaken at the same locations.

In contrast, because the nugget semivariance of the semivariogram function for some soil parameters, e.g., NO_3 in the subsoil, and P and K at both depths at Monclova (Table 1), was very small and approached zero, the scale of lag h closely matched the spatial variation of them.

When the distribution of soil properties is strongly or moderately spatially correlated, the average extent of these patches is given by the range of the semivariogram. There were big differences between ranges of the different soil variables, as had been already reported in several other studies, e.g., it was 80 m for total organic N at an Iowa (USA) farm (Cambardella et al., 1994), for nitrate and ammonium it was 20 m at an old field community in Michigan (USA) (Robertson et al., 1997), and less than 2 m for nitrate in a southern Quebec (Canada) forest ecosystem (Lechowicz and Bell, 1991).

A larger range indicates that observed values of the soil variable are influenced by other values of this variable over greater distances than soil variables which have smaller ranges (Samper-Calvete and Carrera-Ramírez, 1996). Thus, sand had a range of more than 80 m at both depths at Caracol (Table 2). This indicates

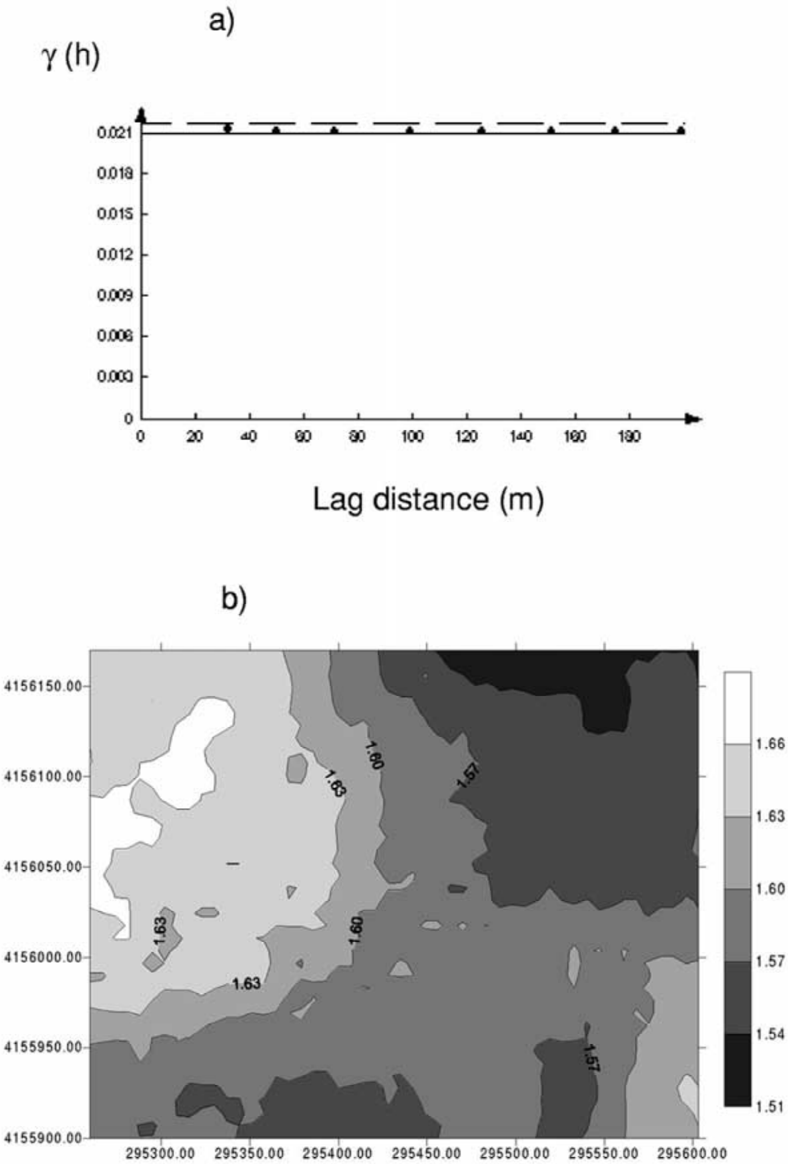

Figure 1. (a) Experimental (circles) and modelled semivariogram of the organic matter content (OM,%), and (b) Map of estimated OM, in the topsoil (0–0.1 m depth) at Monclova.

that sand values influenced neighboring values of sand over greater distances than other soil variable, e.g., NO_2, which had a range of less than 30 m at both depths.

Soil properties exhibited both a consistent and non-consistent spatial pattern regarding the sampling depth at both locations. There were soil properties, e.g., NO_3 and pH, following a different spatial distribution at each depth showed both no patchy distribution in the topsoil, and a strong spatial dependence in the subsoil (Table 1 and 2 for Monclova and Caracol, respectively). At the same time, there were soil characteristics that showed a similar trend at both sampling depths as well. Thus, texture (sand, silt and clay), OM, P, K and NH_4 at Monclova, and sand, OM, K and NH_4 at Caracol, followed the same spatial pattern at both depths (Table 1 and 2).

Cambardella and Karlen (1999) reported a similar consistent and non-consistent spatial distribution according to sampling depths, e.g., exchangeable K

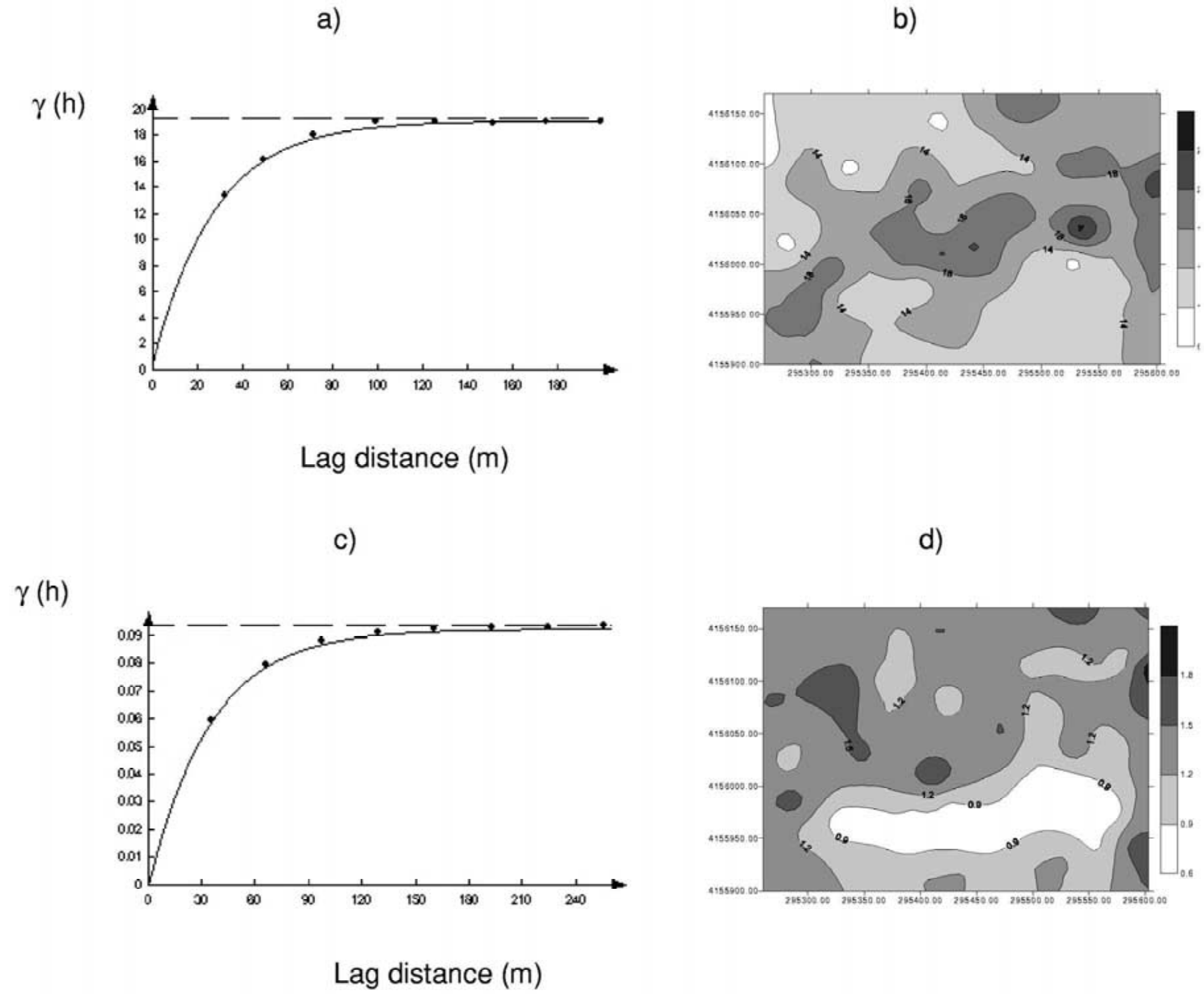

Figure 2. (a,c) Experimental (circles) and modelled semivariograms for phosphorus (ppm) and potassium (meq/100 g), (b,d) Maps of estimated phosphorus (ppm) and potassium (meq/100 g), in the topsoil (0–0.1 m depth) at Monclova.

exhibited three spatial patterns: strong spatial dependence at topsoil (0–0.05 m depth), moderate from 0.05 to 0.2 m depth, and no spatial correlation in the lower layer (0.2–0.3 m), while pH or OM showed a strong spatial dependence at all depths. They hypothesized that intrinsic variations, such as intensive tillage, may control the strongly spatially dependent soil variables.

Our study demonstrated that, even though the former agricultural management was similar, the spatial distribution and spatial dependence level of soil properties can be different. These results support one of the objectives of this paper concerning the importance of collecting information in every agricultural region to know how a site specific system should be undertaken. Long-term field management histories should be known since even the same farming practice clearly affected both spatial distribution and the level of spatial dependence.

The clearly patchy distribution of P and K at both locations, together with the results reported by Pierce and Nowak (1999) regarding the low temporal component of variability that P and K usually show, indicated the feasibility of developing a strategy for a site-specific application of P and K at least under the most representative farming management practices of southern Spain.

We can conclude that prospects for precise management of P and K increase as the degree of spatial dependence of P and K increases. On the other hand, precision N management (including nitrate, nitrite and

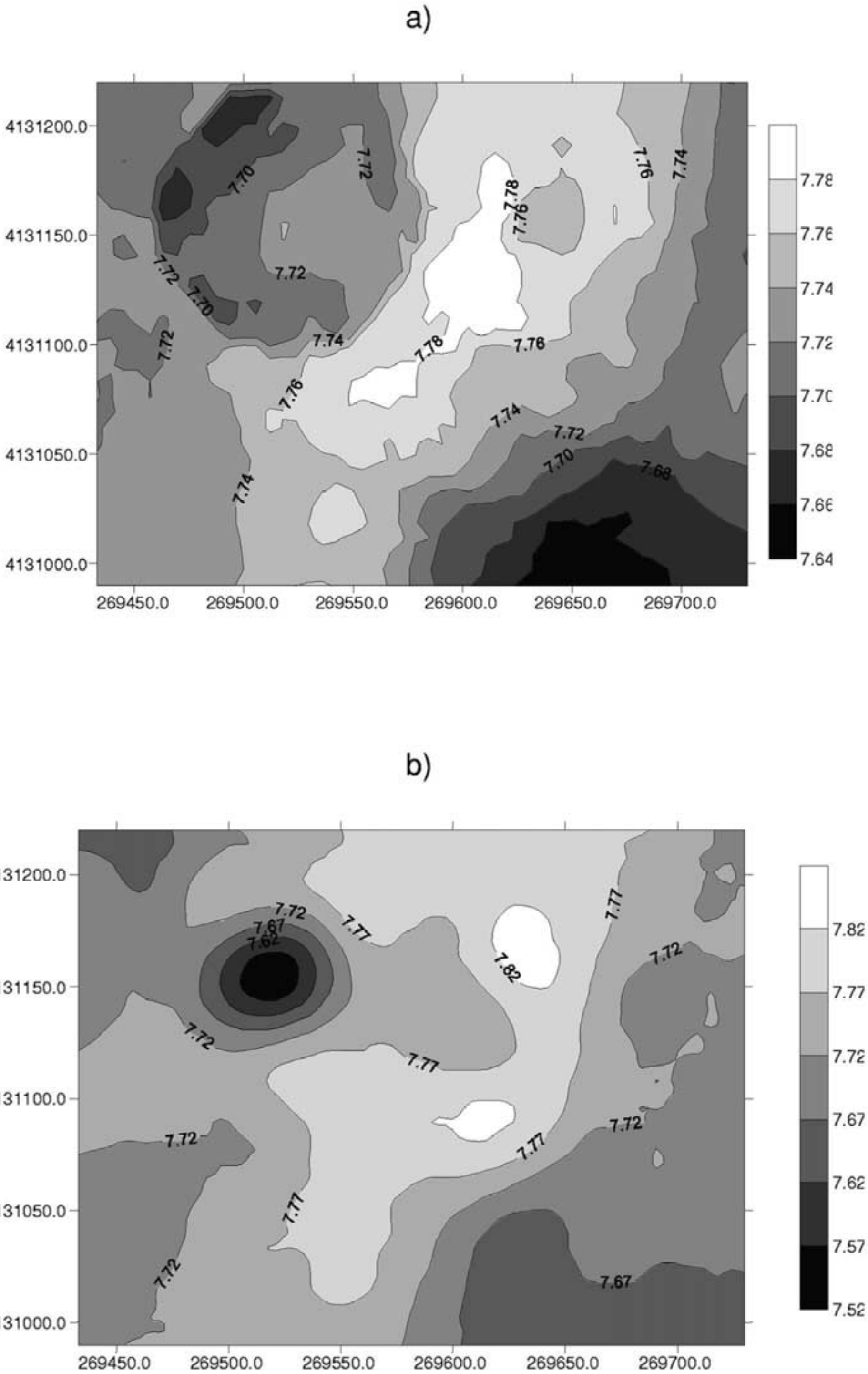

Figure 3. (a) Map of estimated pH in the topsoil (0–0.1 m depth), (b) map of estimated pH in the subsoil (0.25–0.35 m depth) at Caracol.

ammonium) would be more complex than precision management of P and K because the spatial distribution and spatial dependence of N varied between locations and depths.

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