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Analysis of spatial interpolation for optimising management of a salinized field cultivated with lettuce

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Abstract

The lack of randomisation in irrigation experiments is usually a disadvantage. The introduction of spatial variable experimental design offers a convenient tool to help solving this problem. In order to understand the variation of some soil physical and chemical properties in an experimental block and its effect on lettuce (*Lactuca sativa* L.) production, graphical interpretation of those soil properties was done with the use of geostatistics in a geographic information system (GIS). In this work three techniques of geostatistics were used for the creation of several maps of soil properties in an experimental plot cultivated with lettuce. Lettuces were evaluated for individual weight and diameter at the end of the cropping season. The soil properties studied were: total mineral nitrogen, phosphorus, potassium, pH, electric conductivity and saturated soil hydraulic conductivity. The techniques used were: ordinary kriging, inverse distance and Thiessen polygon. Cross validation used to compare the prediction performances of the three geostatistical interpolation algorithms determined that kriging was the best technique for each soil property. Prior to the creation of the maps, semivariograms were produced for each soil property. The maps resulting from the interpolation techniques were introduced in a GIS and their values reclassified. After that, spatial modelling was used to develop a final overlay map from all the information of the analysed soil properties simulating a "lettuce production capability map". This final map was created with the objective to determine which areas in the plot had optimal conditions for lettuce development. It was concluded that the plot did not had an optimal area for lettuce production. Localized problems with soil properties were found that could be solved with simple geographically restricted amendment treatments. Final lettuce yield had high correlation ($r^2 = 0.83$) with the lettuce capability map derived.

Keywords: Geostatistics; Geographic information system; Salinity; Precision agriculture; Spatial variability

1. Introduction

Crops in the Mediterranean region are generally produced in fields that have a high degree of variability in soil type, topography, soil moisture and other major factors that affect crop production. Recent technological developments have paved the way for important and far-reaching changes in agricultural production practices. The geographical information systems (GIS), modelling and geostatistics are tools becoming progressively more suitable in fields of research like Agriculture (Ben-Asher et al., 1998; Gary et al., 1998; Bocchi et al., 2000; Basso et al., 2001). More specifically, these technologies can enable micro-management techniques on a site-specific basis to account for the natural and human induced variations that exist in agricultural fields such as variation in soil type, moisture, topography, chemistry, physical properties, and other factors. These technologies promise the possibility of optimising profit and reducing the adverse environmental impact of farming (Larson et al., 1997).

In recent years, major advancements have been made in the technologies required to implement precision farming practices (Yalouris et al., 1997). Traditional surveys of soil fertility, together with data from soil survey maps, can be used in combination with geostatistics by decision-makers to support management planning and to predict indicators related to soil quality as a measure of sustainability (Couto et al., 1997). Many authors used classical statistics and geostatistics to analyse the spatial variability of soil properties and crop yield (Sylla et al., 1995; Usowicz et al., 1996; Stevenson et al., 2001). Results obtained for a year can be used to suggest field specific improvements of management allowing a relatively high efficiency of natural resource-use also in years for which no statistical analysis were made (Casanova et al., 1999).

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Precision farming is an emerging technology and therefore limited research is available to practitioners who adapt precision agriculture for Mediterranean soils and crops. Christensen and Krause (1995) pointed out that computer literacy, GIS, global positioning system (GPS), expert systems, and remote sensing can provide knowledge-based management of agricultural production to reduce environmental impact.

While precision agriculture shows to be promising with respect to environmental quality, it also could increase profit margins. The variability within the field implies inefficient use of resources. Precision agriculture defines different management practices to be applied within single variable fields, potentially reducing costs and limiting adverse environmental side effects (Booltink et al., 2001).

Use of precision farming technologies requires better understanding of soil variability in physical, hydraulic and chemical properties. Some of that variation is natural and some is the result of the management history of the field (Sparovek and Schnug, 2001). Soils vary widely in their soil properties and in their ability to supply nutrients in quantities sufficient for optimal crop growth. Soils deficiency to supply nutrients to crops is aggravated by the fact that many modern cultivars of major crops are highly sensitive to low nutrient levels (White and Zasoski, 1999).

When irrigation water contains a large concentration of soluble salts, it could affect crop production if not properly managed (Letey et al., 1985). The mechanism affecting crop yield reduction is due to the fact that at high salinity, the water content at wilting point is higher than at low salinity, resulting in an insufficient amount of available water and, therefore, a reduced yield (Beltrão and Ben-Asher, 1997). Generalized results from crop yield models with saline water were developed by Solomon (1985) and Warrick (1989) and Plaut (1997) and Beltrão et al. (1997) have obtained the production of horticultural crops under salinity stress. However, lack of randomisation is usually the main disadvantage of this kind of experiments.

Geostatistics provides descriptive tools such as semivariograms to characterize the spatial pattern of continuous and categorical soil properties (Goovaerts, 1999). Various interpolation techniques take advantage of the spatial correlation between observations to predict attribute values at unsampled locations using information related to one or several attributes. From them, Thiessen polygon creates a polygon of influence for each sample and assumes that all values inside the polygon are equal. The inverse distance interpolator assumes that each input point has a local influence that diminishes with distance. It weights the point closer to the processing cell greater than those farther away. It does not allow assumptions required for the data, but it is good to take a first look in the interpolated surface (Longman et al., 1995). The kriging interpolator assumes that the distance or direction between sample points reflects spatial correlation that can be used to explain variation in the surface (Chilès and Delfiner, 1999).

An important contribution of geostatistics is the assessment of the uncertainty about unsampled values, which usually takes the form of a map of the probability of exceeding critical values for soil quality (Castrignano et al., 2002). This uncertainty assessment can be combined with expert knowledge for decision making such as description of contaminated areas where amendment measures should be taken or areas of good soil quality where specific management plans can be developed (Kitanidis, 1997). Ordinary kriging appropriately estimates values in unsampled areas and identifies places where more intensive sampling is required because the method yield estimates of the errors associated with interpolation.

Establishing relationships between spatially variable attributes is very important and will allow the development of new understanding that can be used in precision farming. To establish those relationships the impact of spatial field parameters on spatial distribution of crop yield and yield potential was evaluated and quantified. The main aim of the present work was to use geostatistical techniques to quantify the spatial variation of soil attributes and to improve the estimates of lettuce yield in a field irrigated with saline water.

2. Materials and methods

Spatial soil and crop data was collected for soil and lettuce in an experimental field of 46 m × 48 m located in Gambelas Campus at the University of Algarve. Lettuces were transplanted in the field on the 12th August, with spacing between plants 2 m × 1 m. The lettuces were irrigated during summer with saline water (ECw of 8 dS/m) with a sprinkler line passing in the middle of the field. The salinity gradient of the plot was obtained according to the concepts of Hanks et al. (1976) and Magnusson and Bem Asher (1990). Seedbed and basic fertilization of N, P_2O_5 and K_2O were made according to conventional agrotechniques and soil fertility analysis. Weeds were controlled manually and the control of pests and diseases was not needed. At the 22th October lettuces were harvested and it was measured weight and individual diameter. Experiment was repeated twice.

A total of 25 soil samples were collected as suggested for small heterogeneous fields by, Webster and Oliver (1990) and Carter (1993). Soil sampling was carried out at the end of the crop in a grid scheme of 6 m × 6 m, starting 4 m from the plot borders and the sprinkler line. Individual soil samples of about 1 kg were collected from each sampling position at a depth of 10–30 cm. The mixture of soil and coarse fragments was air-dried, weighed and carefully sieved through a 2 mm screen without breaking up fragile fragments. The fraction passing through the 2 mm sieve was split with a stainless steel riffle and saved for analysis. This fraction was analyzed for physical properties (texture, coarse fragments, particle density, specific weight), pH, electrical conductivity, as well as, the main macronutrients (available phosphorus, total nitrogen and exchangeable potassium).

Specifically, soil texture was determined with the Bouyoucos densimeter method (FAO, 1984). The pH and electric conductivity were measured in 1:2 slurry of soil and distilled water at 25 °C (Black, 1965). The Kjeldahl digestion method was used for nitrogen and the Olsen method by extraction with sodium bicarbonate at pH of 8.5 for the available phosphorus (Page, 1982). The exchangeable potassium was determined by atomic absorption using ammonium acetate extraction at pH 7 (Carter, 1993). Field-saturated hydraulic conductivity was determined

Table 1
Reclassification of field capability for lettuce production (adapted from Ware and McCollum, 1980; Kopp et al., 1989; Maroto, 2000)

Classification	Reclassification	EC (dS/m)	Ntotal (ppm)	P (ppm)	K (ppm)	Ks (cm/h)	pH
Limiting	1	>5	<10	<9	<45	<1	<5.5
Conditioning	2	2–5	10–50	10–40	45–120	1–3	5.5–6.5
Benefiting	3	<2	50–150	40–100	120–250	3–6	6.5–8

in situ with the Guelph permeameter method as described by Reynolds and Elrick (1985) and Carter (1993).

All data was entered into a field-scale GIS and interlayer data analytical tools was utilized to quantify spatially dependent relationships. A semivariogram was produced for each soil characteristic and several parameters that a semivariogram can provide were analysed. For the creation of prediction maps for the several soil properties, three interpolation methods were used: inverse square distance, Thiessen polygon and ordinary kriging.

The first two are simple deterministic interpolators that were used to have a first look at the exact values of the studied surface without the necessity to make decisions about assumptions required from the data. Ordinary kriging was used initially till to find if there was present trend or anisotropy in the data. After trend or anisotropy removal, kriging was used to create the final prediction map of all soil properties studied.

Cross validation was used to compare the prediction performances of the three geostatistical interpolation algorithms. Cross validation indicators and additional model parameters (nugget, sill, range) helped to choose the most appropriate model of the prediction maps for each soil property (Issaks and Srivastava, 1989).

After the creation of soil properties maps, the grids were reclassified using GIS software (Arcview spatial analyst). All maps were reclassified following the Table 1 reclassification. The reclassification was accomplished grouping the values of the maps in three classes: limiting production (1), conditioning production (2) and benefiting production (3). Von Liebig's law of the minimum was taken into consideration.

The reclassification maps where weighted and overlaid in Arcview model builder. The weighted overlay fertility map was produced combining the reclassified maps of nitrogen, phosphorus and potassium. Other factors like electric conductivity, pH and hydraulic conductivity were created, reclassified, weighted and overlaid to produce a final map (Fig. 1).

In the weighted overlay process each map was assigned with equal percentage influence. The cell values were multiplied by their percentages and then, added to create the output grid. Areas classified as limiting production were considered restricted areas by the model and therefore were not overlaid like the other non-restricted areas.

The superposed final map of fertility and the other soil properties was created to locate the optimal area for lettuce production. Also, it was superposed the graphical presentation of lettuce weight. The real lettuce weight was used to validate the prediction final map of lettuce production.

3. Results and discussion

A dataset of lettuce production and soil properties was created with their georeferenciated position in the field. Before creating surface diagrams, the distribution of data was analysed

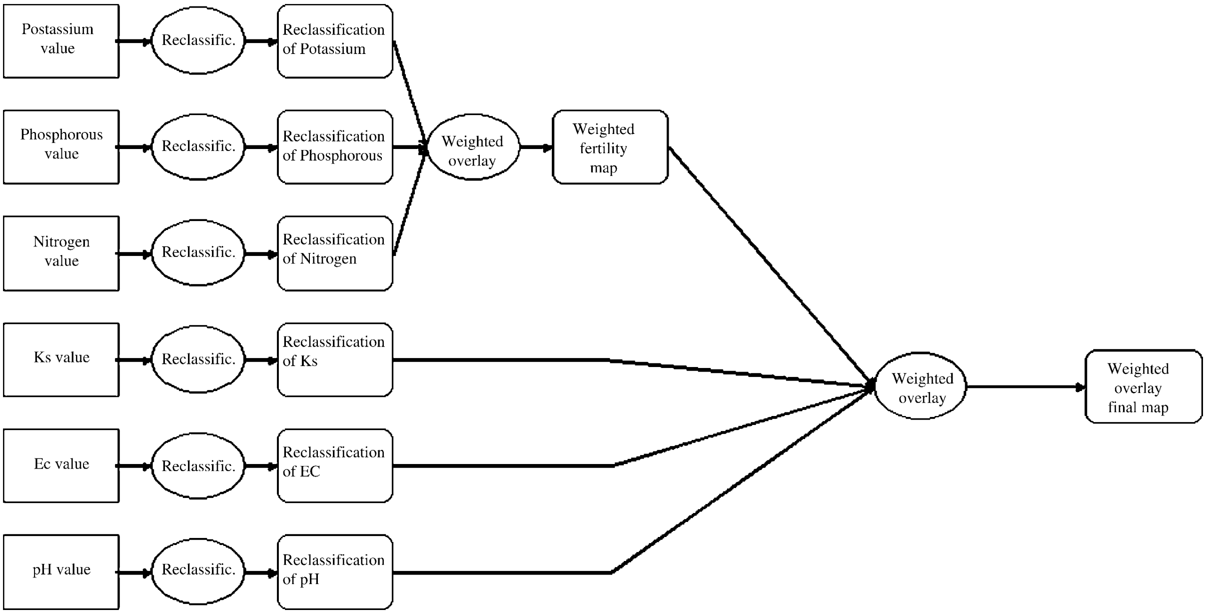

Fig. 1. Model used in Arcview model builder to overlay all the plant-producing factors after a reclassification of their values with objective to create a map showing the optimal location for lettuce production.

Fig. 2. Soil electrical conductivity (1:2) map of the field cultivated with lettuce and irrigated with saline water after ordinary kriging, showing a not perfect gradient around irrigation line.

to get a better understanding of trends, directional influences and obvious errors. In most of the cases the data was not normally distributed presenting large spread and no symmetry.

Differences between results of the three geostatistical interpolation algorithms were not significant. Kriging was offering the possibility of flexibility in assumptions required for the data to continue the study.

The field was irrigated with saline water from a line of sprinklers passing in its middle, thus an electric conductivity gradient was expected in the soil. Fig. 2 is showing the map of topsoil electrical conductivity after ordinary kriging, demonstrating a not expected irregular gradient around irrigation line. This was an indicator of a trend in the data that it could be caused from natural factors like wind direction during irrigation, slope, impermeable layer close to surface, soil texture, hydraulic conductivity and other soil properties or/and anthropogenic factors like years of tillage perpendicular to the isolines and consequent erosion.

With respect to the data that was not following normal distribution and presenting high number of extreme values, using Voronoi mapping was found that extreme values were not dissimilar to their surrounding neighbours, so they were not mistakes. The next step was to find if transformations and trend removal could help to justify an assumption of normality.

Kriging as a predictor does not require that the data have a normal distribution. Kriging relies on the assumption that all the random errors have zero mean and the covariance between any two random errors depends only on the distance and direction that separates them and not their exact locations (Goovaerts, 1997).

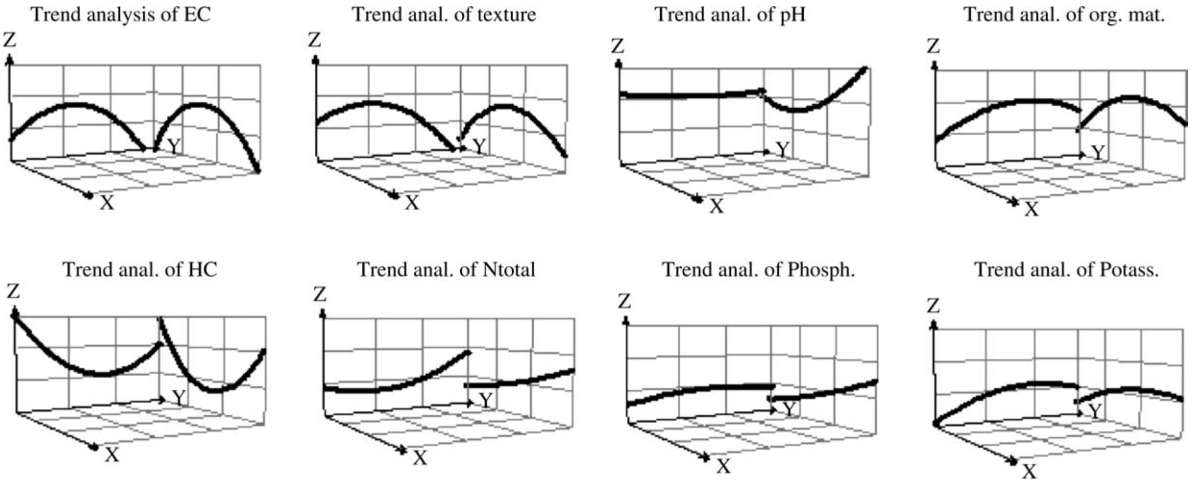
Trend analysis of EC
Trend anal. of texture
Trend anal. of pH
Trend anal. of org. mat.
Trend anal. of HC
Trend anal. of Ntotal
Trend anal. of Phosph.
Trend anal. of Potass.

Fig. 3. Trend analysis demonstrating a North to South trend for electric conductivity (EC), texture (clay) and hydraulic conductivity (Ks) and an East to West trend for EC, texture, pH, Ks and organic matter.

Table 2
Values of model parameters used to find the best semivariogram to predict electric conductivity (ds/m)

Model	Nugget	Part. sill	Major range	Minor range	Direction	ME	RMSE	ASE	RMSSE
Circular	0.02	8.71	41.8	22.9	347	0.01	0.69	1.07	0.68
Spherical	0	8.39	43.7	26.2	346	0.02	0.69	1.08	0.67
Tetraspherical	0	8.49	43.1	29.4	345	0.02	0.69	1.08	0.68
Pentaspherical	0	8.42	43.1	32.3	344	0.02	0.71	1.09	0.68
Exponential	0	9.24	43.1			0.05	0.75	1.24	0.61
Gaussian	0.51	8.51	43.0	20.1	351	0.01	0.68	0.91	0.81
Rational quadr.	0.14	9.07	43.1			0.06	0.83	0.69	1.41
Hole effect	0.53	6.99	54.5	31.78	348	−0.01	0.73	0.91	0.86
K-Bessel	0.35	8.05	21.7			−0.01	0.74	1.04	0.77
J-Bessel	0.71	6.21	36.5			0.04	0.72	0.84	0.95
Stable	1.44	8.90	29.8			0.04	0.75	0.75	1.16

From the cross-validation of the models were used the mean error (ME), root-mean-square error (RMSE), average standard error (ASE) and root-mean-square standardized error (RMSSE).

Transformation and trend removal was done when necessary to create more accurate prediction maps. Fig. 3 is showing the results of trend analysis before to apply kriging. It was found to exist a trend for many of the parameters analysed indicating that trend removal was necessary to create more accurate prediction maps. Trend removal and logarithmic transformation helped to normalize data distribution.

Kriging after trend removal was done on the residual data of electric conductivity, texture (clay), hydraulic conductivity, organic matter, total nitrogen and pH. The prediction map of each factor was calculated and trend was added back to the output surface. Cross-validation and validation of the last map show that results were improved for electric conductivity, texture and pH but not for the other parameters. For the above production factors

Table 3
Results of the semivariogram chosen to create the prediction maps of the plant production factors studied

Plant production factor	Model	Nugget	Sill	Range	ME	RMSE	ASE	RMSSE	Nugget/sill
pH	Gaussian	0.20	0.49	17.1	0.02	0.47	0.67	0.86	0.41
EC (dS/m)	Gaussian	0.51	9.02	43.0	0.01	0.68	0.91	0.81	0.06
Nitrogen (ppm)	Exponential	2.80	11.42	43.4	0.01	2.32	2.88	0.91	0.25
Phosphorus (ppm)	Exponential	7.4	14.9	43.4	0.08	3.51	3.36	0.98	0.50
Potassium (ppm)	Exponential	22.9	35.3	43.4	0.86	11.34	16.53	0.94	0.65
Ks (cm/h)	Spherical	0.11	0.93	16.1	0.31	2.31	3.53	0.77	0.12
Texture (clay, %)	Gaussian	4	15	17.8	0.43	1.87	3.94	0.97	0.27
Lettuce weight (g)	Exponential	96	319	44.5	0.21	8.87	9.54	0.94	0.30
Lettuce diameter (cm)	Exponential	11	37	44	0.01	4.9	5.9	0.81	0.30

From the cross-validation of the models were used the mean error (ME), root-mean-square error (RMSE), average standard error (ASE) and root-mean-square standardized error (RMSSE).

Fig. 4. Texture map of the field cultivated with lettuce and irrigated with saline water after ordinary kriging, showing the existence of a heavy textured area.

it was decided to not simplify data, to keep the models simple and trend removal was not taken into consideration because residual data presented too little variation.

Kriging cross-validation was used to estimate which of the semivariogram models could give the most accurate predictions of the unknown values of the field. Table 2 presents summarily the indicators which helped to choose the most appropriate model of semivariogram for the creation of the prediction map for electric conductivity.

The closer to 0 was the mean cross-validation error (ME) and the closer to 1 was the root-mean-square standardized error (RMSE) signified that the prediction values were closer to measured values (Wackernagel, 1995). When models presented similar values for ME and RMSE it was taken in consideration the lowest values of RMSE and average standard error (ASE). Table 2 was repeated for every parameter studied following the rules mentioned above and it was selected a semivariogram model for each one, in order to have an indication on how the samples were related to each other.

Table 3 presents the final semivariogram model chosen for the prediction map of each parameter analysed. From the several parameters that the semivariogram provided, the large nugget effect of some of them indicated a high variance at short distance as it is mentioned by Armstrong (1998). Also, exponential semivariograms for some factors was an indicator of high variance at short distance for those factors. All soil properties showed positive nugget, which can be explained by sampling error, short range variability, random and inherent variability. The variable is considered to have a strong spatial dependence if the ratio nugget-to-sill is less than 25%, and has a moderate spatial dependence if the ratio is between 25% and 75%; otherwise, the variable has a weak spatial dependence (Cambardella et al., 1994).

Fig. 4 is showing the map of texture derived from clay percentage data after ordinary kriging, demonstrating the existence

Fig. 5. Hydraulic conductivity map of the field cultivated with lettuce and irrigated with saline water after ordinary kriging, confirming the existence of a less permeable layer close to the surface.

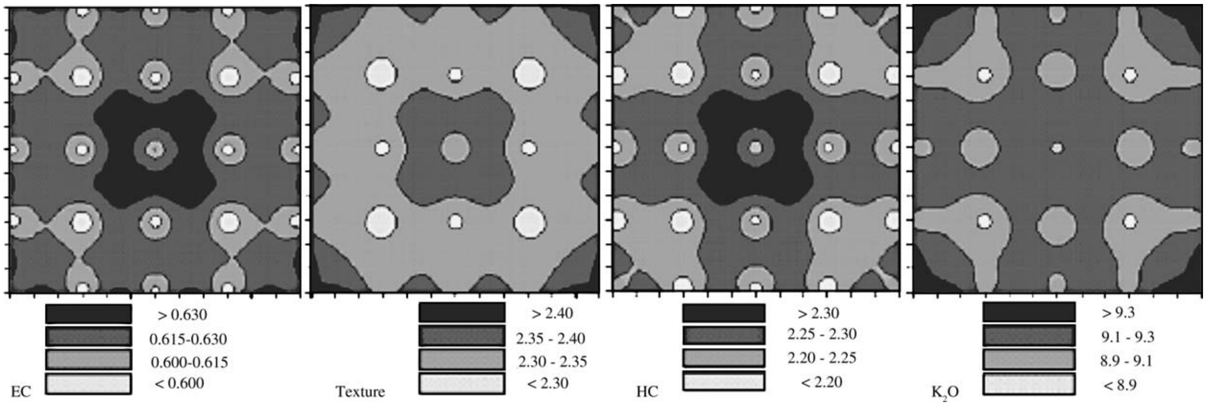

Fig. 6. Maps of standard deviation derived from kriging for electric conductivity (EC, ds/m), texture (clay, %), hydraulic conductivity (Ks, cm/h) and potassium (ppm).

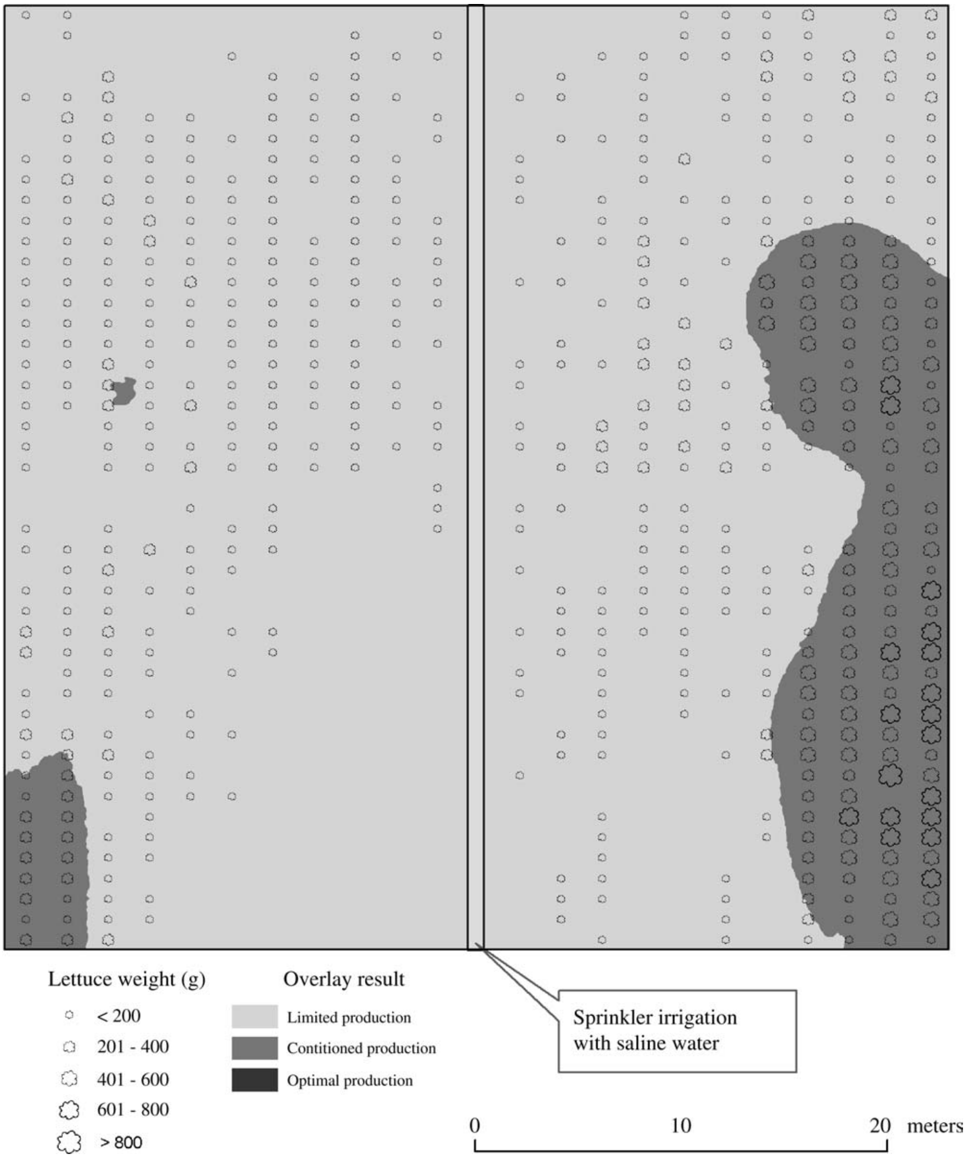

Fig. 7. Results of the overlay procedure of all soil properties in Arcview model builder after reclassification and weighting of the ordinary kriging values. Georeferenced, graphical presentation of lettuce weight corresponds to all lettuces produced in the field.

of a heavy textured area in the highest part of the field which could affect productivity of lettuce as well as soil salinity. This was due to continuous tillage and irrigation during years of experiments in that field which caused erosion, removing the surface sandy horizon and exposing an impermeable clay layer. Hydraulic conductivity map of the field after ordinary kriging (Fig. 5) confirmed partially the existence of the above impermeable layer. Also, it showed a less permeable layer around the line of sprinkler irrigation caused by high salinity.

In the cases that residual, spatially uncorrelated nugget was high, block-kriging was done to reduce it. An additional and powerful advantage of kriging is that the method yields estimates of the errors associated with interpolation. In Fig. 6 are shown the maps of standard deviation from kriging of electric conductivity (EC), texture (clay), hydraulic conductivity (Ks) and potassium.

Following the above described procedure, maps for the other soil properties based on ordinary kriging were produced. Various easy to identify important facts were taken into consideration, like areas of high and low nutrient concentration. Thus, those maps were important for the estimation of the optimal area of the field for lettuce cultivation and helped to predict which property was limiting lettuce production and where.

All maps of soil properties were reclassified, weighted and overlaid in Arcview model builder. A fertility map was produced first combining the maps for nitrogen, phosphorus and potassium. The superposed final map of all soil properties shows that with the existing soil conditions there were no optimal areas for lettuce production (Fig. 7). In the same figure it can be seen the confirmation of the above result with the graphical presentation of lettuce weight, after harvest. Empty areas in the field indicate no lettuce production.

The measured weight of lettuce was used to validate the results of the final soil property map. Lettuces of less than 200 g are not marketable according to the European Community norms

Fig. 8. Potassium map of the field cultivated with lettuce and irrigated with saline water after ordinary kriging, exhibiting a lower necessity of applying the nutrient in the right part of the field.

(CE No. 543/2001, of 27th July). It was found that 95% of the lettuces produced in the area estimated as the best area of this field had a weight over 200 g. In the area estimated as limited for lettuce production only 4% of lettuces had a weight over 200 g. Final lettuce yield had high correlation ($r^2 = 0.83$) with the lettuce capability map derived.

The understanding of the spatial distribution pattern of soil properties is important to determine soil limitations to plant growth and appropriate management of soil resources in cultivated areas. Localized problems in soil properties could be solved with simple geographically restricted amendment treatments. For example, the less permeable area located around the sprinklers line, should be treated with a deep tillage and soil washing; the heavy textured spot in the bottom of the field could be improved with sand addition. The saline area should be washed with clean water locally to not waste this valuable resource on the not salinized and highly permeable area of the field. The field could be managed better by shifting the irrigation positions to avoid the build up of strong trends.

The fertility of the field could be improved locally following the crop requirements for every nutrient, without spending money and damaging the environment with unnecessary fertilizing. For example, it can be visualised in Fig. 8 that the west part of the field had lower than 60 ppm of potassium and should be fertilised with 200 kg/ha of potassium, while most of the east part of the field had an estimated 100–140 ppm of the nutrient, suggesting fertilization with 80–100 kg/ha of potassium in that area.

4. Conclusions

This work shows that simple random sampling and the calculation of an average, usually used for the normal procedure of soil sampling in Agriculture, is not always the best answer.

Geostatistical methods describe the spatial variability and help to produce standard deviation maps, showing the confidence of the samples taken in an area.

Trend removal and direction of anisotropy of some soil properties was facilitated with kriging. However, when trend was not strong and justified from validation and cross-validation it was preferred to keep the models simple and with minimum data assumptions to decrease risk of error from simplicity of data and too little variation.

The absence of optimal area for lettuce production without amendment treatments was confirmed with the graphical presentation of lettuce weight. Final lettuce yield had high correlation ($r^2 = 0.83$) with predicted yield from the capability map derived.

The classification techniques of GIS used in the present work were sufficient to determine which areas were the most suitable for the crop and to localize problems with soil properties that could be solved with better management and simple geographically restricted amendment treatments. Geostatistics can be used as an inexpensive way to apply precision farming in integrated agriculture of small farms.

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