Using Indicator Kriging Technique for Soil Salinity and Yield Management

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Abstract: This paper presents a practical method to manage soil salinity and yield in order to obtain maximum economic benefits. The method was applied to a study area located in the southeastern part of the Arkansas River Basin in Colorado where soil salinity is a problem in some areas. The following were the objectives of this study: (1) generate classified maps and the corresponding zones of uncertainty of expected yield potential for the main crops grown in the study area; (2) compare the expected potential productivity of different crops based on the soil salinity conditions; and (3) assess the expected net revenue of multiple crops under different soil salinity conditions. Four crops were selected to represent the dominant crops grown in the study area: alfalfa, corn, sorghum, and wheat. Six fields were selected to represent the range of soil salinity levels in the area. Soil salinity data were collected in the fields using an EM-38 and the location of each soil salinity sample point was determined using a global position system unit. Different scenarios of crops and salinity levels were evaluated. Indicator variograms were constructed for each scenario to represent the different classes of percent yield potential based on soil salinity thresholds of each crop. Indicator kriging (IK) was applied to each scenario to generate maps that show the expected percent yield potential areas and the corresponding zones of uncertainty for each of the different classes. Expected crop net revenue for each scenario was calculated and all the results were compared to determine the best scenarios. The results of this study show that IK can be used to generate guidance maps that divide each field into areas of expected percent yield potential based on soil salinity thresholds for different crops. Zones of uncertainty can be quantified by IK and used for risk assessment of the percent yield potential. Wheat and sorghum show the highest expected yield potential based on the different soil salinity conditions that were evaluated. Expected net revenue for alfalfa and corn are the highest under the different soil salinity conditions that were evaluated.

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Introduction

Soil salinity refers to the presence in the soil and water of various electrolytic mineral solutes in concentrations that can be harmful to many agricultural crops (Hillel 2000). Salts decrease the availability of water to plants due to increase osmotic potential and have direct adverse effects on the plant metabolism (Douaik et al. 2004; Greenway and Munns 1980). Increasing soil salinity is offsetting a good portion of the increased productivity achieved by expanding irrigation (Postel 1999). On average, 20% of the world's irrigated lands are affected by salts, but this figure increases to more than 30% in countries such as Egypt, Iran, and Argentina (Ghassemi et al. 1995). Crop yield reduction in fields in the Lower Arkansas Valley due to salinization is estimated to vary between 0 and 75% with a total revenue loss ranging from \$0 to \$750/ha based on 1999 crop prices (Gates et al. 2002).

Geostatistical methods have been used widely for sampling and mapping soil salinity. They provide means to study the heterogeneity of the spatial distribution of soil salinity (Pozdnyakova and Zhang 1999). Kriging is a collection of linear regression techniques that takes into account the stochastic dependence among data (Olea 1991). Kriging remains the best choice as a spatial estimation tool since it provides a single numerical value that is best in some local sense (Deutsch and Journel 1998). The results of spatial prediction generate reasonable estimates of soil salinity regardless of what interpolation method was used (Triantafilis et al. 2001). Kriging models estimate the values at unsampled locations by a weighted averaging of nearby samples where the correlations among neighboring values are modeled using variograms (Miller et al. 2007). Studies have shown that semivariograms of electrical conductivity (EC) can be a useful tool in determining the spacing between soil samples for laboratory EC determination (Utset et al. 1998). Samra and Gill (1993) used kriging results to assess the variation of pH and sodium adsorption ratios associated with tree growth on a sodium-contaminated soil.

The variogram is the key function in geostatistics as it is used to fit a model of the spatial correlation of the observed phenomenon and provides a unique spatial study. Given a collection of data, a variogram reveals the type of spatial structure inherent to a spatial phenomenon. In addition, the variogram reveals the amount of noise present in the data, known commonly as the nugget (Carr et al. 1985). Recent research shows that this noise can substantially mask prominent spatial autocorrelation and re-

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sult in what appears to be a purely random spatial process. When a variogram is used to describe the correlation of different variables, it is called a cross variogram. Cross variograms are used in cokriging. If the variable being analyzed is binary or represents classes of values, this is referred to as indicator variograms. Nonparametric geostatistical techniques such as indicator kriging (IK) offer immeasurable power for analysis of data quality (Journel 1983). A careful selection of thresholds in assigning an indicator function can yield an indicator variogram which reveals underlying spatial autocorrelation. Problems arise when dealing with highly variant phenomena where the data present long-tailed distributions with a coefficient of variation in the range of 2–5. Raw variograms become extremely sensitive to tail data, and are basically useless (Journel 1983). Indicator variograms are not affected by outliers, since they do not call for the data values themselves but rather for their rank order (indicator values) with regard to a given cutoff. Data are used through their rank order with regard to a given cutoff, allowing for a more comprehensive structural analysis, and are yet more robust with regard to outliers. The influence of outliers is removed from the distribution and data sensitivity to different thresholds can be uniquely studied. The indicator approach, whereby the data are used through their rank order, allows a nonparametric approach to study the bivariate distribution of the data (Journel 1983). This rich structural information allows a nonparametric risk-qualified analysis of the data as well as an estimation of local and global spatial distributions.

IK provides a nonparametric distribution estimated directly at fixed thresholds by considering indicator transforms of conditioning data in the form of cumulative distribution functions (Richmond 2002). The power of multivariable IK as a tool is that it is flexible and can be modified to fit specific management or research goals by modifying the critical threshold criteria (Smith et al. 1993). IK makes no assumptions on the underlying invariant distribution, and 0:1 indicator transformation of the data makes the predictor robust to outliers (Cressie 1993). At an unsampled location, the values estimated by IK represent a probability that the value is less than a specified threshold. That is, the expected value at the location derived from indicator data are equivalent to the cumulative distribution function of the variable (Smith et al. 1993). Mapping of uncertainty zones for individual phases is one advantage of using a geostatistical approach to characterize the morphology of quantitative variables (Soares 1992). Smoothing effects occurring around zero thickness investigation sites can be reduced significantly by the use of a combined ordinary-IK approach (Marinoni 2003). Solow (1986) used simple IK to estimate the conditional probability that a sample point belongs to one type or another. Their results show that simple IK performed well, and in some cases can be exact.

IK provides a way to use depth to water-table data to quantify the probability of saturation and evaluate the predicted spatial distributions of runoff generation risk (Lyon et al. 2006). Spatial principal component analysis and IK were used to estimate the geochemical distributions by using their statistical and spatial properties (Panahi et al. 2004). Indicator variables and multilevel thresholds were used to analyze the arsenic concentration probability in the coastal aquifer in Yun-Lin, Taiwan (Liu et al. 2004). Using this technique allowed them to solve the problem of data scarcity and provided multilevel thresholds in the probability estimation of contamination. IK geostatistics were also used successfully to identify the areas where mercury concentration was higher than the median in southern Portugal, and to produce an index that combines mercury contamination across trophic levels (Figueira et al. 2009). Mapping of uncertainty zones for individual phases is one advantage of using a geostatistical approach to characterize the morphology of quantitative variables (Soares 1992). Western et al. (1998) examined soil moisture patterns through indicator semivariograms and showed good spatial structure for high soil moisture conditions.

IK has also been frequently applied to the pollution of soil by heavy metals. For example, Smith et al. (1993) and Oyedele et al. (1996) used multivariate IK to analyze the quality of soil; Lin et al. (2002) applied IK to delineate the variation and pollution sources of heavy metals in agricultural land; and Juang and Lee (1998), Castrignanò et al. (2000), and Van Meirvenne and Goovaerts (2001) adopted multilevel-threshold IK to estimate the probability distribution of heavy metal pollution in a field. Geostatistical indicator methods have also been applied in the lithological classification of rocks (McCord et al. 1997; Fogg et al. 1999) and in the estimation of probability of contamination in groundwater aquifers (Istok and Pautman 1996).

Several studies have been carried out using IK in soil science. Bierkens and Burrough (1993a) showed the application of IK to predict categorical soil data. Bierkens and Burrough (1993b) also applied IK to water-table mapping and land suitability assessment. Goovaerts (1994) compared the performance of cokriging, simple kriging, and multiple indicator kriging (MIK) in predicting soil quality indicators. Triantafilis et al. (2003) used MIK to produce conditional probability maps of deep drainage risk in an irrigated cotton field in the Lower Gwydir Valley in southeastern Australia. Triantafilis et. al (2004) used IK, MIK, and disjunctive kriging to assess the current status and potential threat of soil salinity using data from soil and water surveys in the Lower Namoi Valley of northern New South Wales, Australia.

The geostatistical approach presented in this paper uses IK to provide farmers with a tool to estimate the potential maximum economic benefit under the current conditions of their fields. Crops with different soil salinity tolerances have significantly different crop yield potential under the same soil salinity conditions. Therefore, depending on the soil salinity conditions of a field, some crops will have higher yields than others. A classified map of expected yield potential based on soil salinity thresholds of different crops can help in selecting the appropriate crop that maximizes the potential yield for a specific area. In this research, a set of scenarios generated from combinations of different crops and fields was analyzed using the soil salinity data for each field. Each field was classified into different thresholds to produce the following crop yield potentials: 100, 90, 75, 50, <50 and >0, and 0%. Indicator variograms were constructed for each of the scenarios and IK was applied to each scenario to generate maps that show the expected percent yield potential as well as zones of uncertainty for different parts of each field. Expected crop net economic revenue for each scenario was calculated. The expected yield potential maps can be used by farmers to determine which crop would maximize the yield and the economic benefits of their fields under the current soil salinity conditions.

Data and Methodology

Study Area and Data Collection

The study area is located in the southeastern part of the Arkansas River Basin in Colorado near the cities of Rocky Ford, Colorado and La Junta, Colo. (Fig. 1). Farmers in this area are facing decreasing crop yields due in part to high levels of salinity in their irrigation water. In some areas, land is being taken out of produc-

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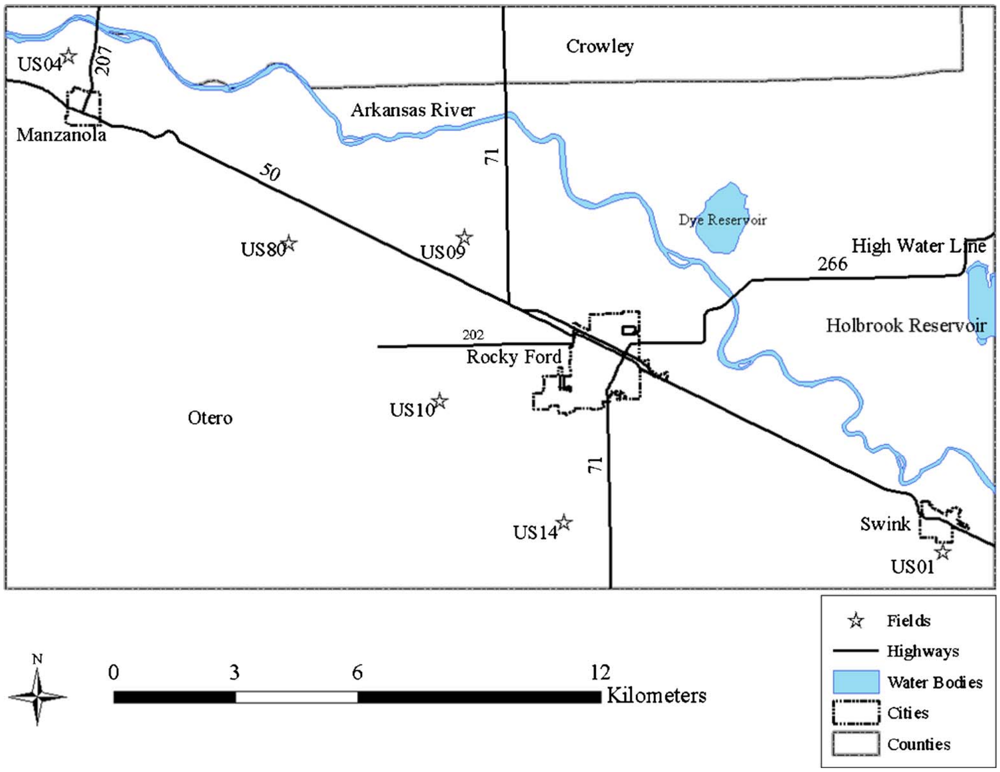

Fig. 1. Study area in the southeastern part of the Arkansas River Basin in Colorado

tion due to unsustainable crop yields. This is due in part to the fact that the Arkansas River is one of the most saline rivers in the United States (Tanji 1990; Miles 1977). In a survey of the region, 68% of producers stated that high salinity levels were a significant concern (Frasier et al. 1999). Farmland along the Lower Arkansas River Basin has been continuously irrigated since the 1870s and began to develop shallow, saline water tables by the beginning part of the 20th century (Miles 1977). Average water-table depths in this region have risen toward the surface approximately 0.3–1.22 m between 1969 and 1994 which has only exacerbated the salinity problems because of increasing amounts of upflux of saline groundwater.

Several fields were selected to carry out the soil salinity assessment in the study area. Soil salinity data were collected using EM-38 electromagnetic probes and the location of the samples was determined using global position system (GPS) units. The EM-38 electromagnetic probes provide vertical and horizontal readings while the GPS units provide X and Y coordinates for each sample point. A calibrated equation, which was developed for the study area by Wittler et al. (2006), was used to convert the EM-38 electromagnetic probe readings to EC (dS/m). Soil moisture content and soil temperature were used for the calibration equation. A detailed description of using the EM-38 electromagnetic probe in combination with GPS in collecting soil salinity can be found in Eldeiry and Garcia (2008) and Eldeiry et al. (2008). Six fields were selected to represent the different soil salinity ranges: low, moderate, and high.

Table 1 shows a description of the fields used in this study. The table contains the area, number of samples, minimum, maximum, and mean values of the soil salinity that were collected in each field. These fields were selected to represent different soil salinity ranges (low, medium, and high) since soil salinity is an important factor which can significantly affect crop yield. Table 1 shows that the selected fields represent a wide range of soil salinity levels from 1.57 to 41.23 dS/m.

Table 1. Description of the Fields of the Study Area and the Collected Soil Salinity Samples

Field	Area (ha)	Number of soil salinity samples	Minimum	Maximum	Mean
U.S.01	16.20	318	2.38	7.19	3.32
U.S.04	93.19	316	2.38	41.23	8.41
U.S.09	28.92	369	1.57	3.49	2.30
U.S.10	4.19	132	3.04	31.26	6.82
U.S.14	12.73	254	2.66	11.26	4.45
U.S.80	11.26	178	2.86	12.33	4.21

Soil Salinity Classification

Table 2 shows the percent yield potential and the corresponding soil salinity EC (dS/m) for alfalfa, corn, sorghum, and wheat (adapted from Ayers and Westcot 1976). Ayers and Westcot carried out an experiment where soil salinity was measured based on the electrical conductivity of the saturated paste extract (ECe)

Table 2. Yield Potential and the Corresponding Soil Salinity (dS/m) for Selected Crops (Adapted from Ayers and Westcot 1976)

	Yield potential (%), Soil salinity (dS/m)				
Crop	100%	90%	75%	50%	0%
Corn	1.7	2.5	3.8	5.9	10.0
Alfalfa	2.0	3.4	5.4	8.8	16.0
Sorghum	4.0	5.1	7.2	11.0	18.0
Wheat	6.0	7.4	9.5	13.0	20.0

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taken from a root zone soil sample measured in dS/m. For barley and wheat, during the germination and seedling stages, ECe should not exceed 4 to 5 dS/m except for certain semidwarf varieties. For beets, during germination, ECe should not exceed to 3 dS/m. Many crops have little tolerance for salinity during seed germination, but significant tolerance during later growth stages. The crops shown in Table 2 were sorted based on their tolerance to soil salinity from low to high: corn, alfalfa, sorghum, and wheat. Table 2 shows that wheat can reach up to 100% of yield potential at a soil salinity of 6 dS/m while corn can only reach 50% of yield potential at a soil salinity of 5.9 dS/m.

Preparing the Data

The soil salinity data for each field were sorted and classified into different thresholds to produce the following crop yield potential classes: 100, 90, 75, 50, <50 and >0, and 0%. For each of these six fields, the classification was done for each of the four selected crops. For high soil salinity tolerant crops such as wheat or sorghum, in fields with low soil salinity levels such as U.S.09, there is no need for IK since the whole field has 100% expected yield potential. However, with the same crops in fields with moderate soil salinity levels, crops can reach a high yield potential from 75 to 100%, while classes with yield potential ranging from 0 to 100% can be present in fields with high soil salinity levels. For crops with moderate and low soil salinity tolerance such as alfalfa and corn, a wide range of yield potentials is represented in the selected fields for this study.

Constructing the Indicator Variograms

From the data combinations of crops and fields, 24 scenarios were created (combinations of four crops and six fields). For each scenario, data were analyzed using the S+statistical software package and the indicator variograms were decided based on the number of classes or thresholds of yield potential for each scenario. For example the scenario of planting alfalfa in field U.S.04 has five classes: 90, 75, 50, <50 and >0, and 0% of yield potential. The best model variogram among the exponential, Gaussian, and spherical was chosen based on the smallest Akaike information corrected criterion (AICC). AICC is a measure of the goodness of fit of an estimated statistical model. It is a tradeoff between bias and variance in model construction. It is not a test of the model in the sense of hypothesis testing; rather, it is a test between models (a tool for model selection). AICC was defined by McQuarrie and Tsai (1998) as

$$\mathrm{AICC} = \ln\frac{\mathrm{RSS}}{n} + \frac{n+k}{n-k-2} \tag{1}$$

where RSS=residual sum of squares; k=number of parameters; and n=number of samples.

Indicator variograms were constructed for each of the scenarios using the model with the smallest AICC value. Each phase of the variograms represents one class of percent yield potential. The indicator variograms contain six phases or less depending on the tolerance of the crop and the soil salinity in the field. The indicator variogram (Soares 1992) is defined as the probability that x and $x+h$ belong to different classes K_i

$$\gamma(h) = \tfrac{1}{2}E\left\{\sum_i [K_i(x) - K_i(x+h)]^2\right\} \tag{2}$$

where x and $x+h$ represent a pair of sample locations separated by distance h and i=number of k classes of soil salinity.

Applying IK

IK was applied to each scenario to generate classified maps that show the expected percent yield potential. The number of classes in each map depends on the number of phases of the indicator variograms of that scenario. One of the advantages of IK is that it has the power to quantify the zones of uncertainty for different parts of each field. Zones of uncertainty exist around the borders of classes and these areas have the probability of belonging to either of the classes. Assessing zones of uncertainty can be very beneficial for the accuracy of the generated maps since it can produce more information about the risk assessment. The essence of the indicator approach is the binomial coding of soil salinity data into either 1 or 0 depending upon its relationship to the thresholds of soil salinity for each crop. For a given value of $z(x)$

$$i(x{:}z_k) = \begin{cases} 1 & if\ \ z(x) \geq z_k \\ 0 & if\ \ z(x) < z_k \end{cases} \tag{3}$$

where z_k=salinity threshold for a specific crop (Lyon et al. 2006). More detailed description of IK can be found in Soares (1992).

Zones of Uncertainty

The indicator variable can be described as the probability of exceeding a given threshold. Therefore, the estimation of the indicator variable at unsampled locations produces probability maps (Reis et al. 2005b). Zones of uncertainty between soil salinity classes can be obtained by identifying locations with low probability, for a given threshold, of belonging to a specific soil salinity level. For example a zone of uncertainty can be defined as being the lowest 25% of the probabilities of belonging to a particular soil salinity level. To generate a map of uncertainty, the first thing to do is to obtain some information regarding the distribution of probabilities associated with each soil salinity class, such as identifying the threshold representing the lowest 25% of the probabilities.

Consider an attribute Z that must be conditionally simulated and the information available consists of z values at n locations x_i, $z(x_i)$, and $i=1,2,\ldots,n$. The uncertainty about the soil salinity value at an unsampled location x is modeled by the conditional cumulative distribution function (CCDF) of the random variable $Z(x)$

$$F(x,z) = \mathrm{Prob}\{Z(x) \leq z(x)\} \tag{4}$$

The function $F(.)$ represents the probability that the unknown soil salinity does not exceed a threshold z. The CCDFs are modeled using a nonparametric (IK) approach, which estimates the probability for a series of K threshold values z_k discretizing the range of variation of Z (Froideveux 1993; Saito and Goovaerts 2002; Reis et al. 2005a):

$$F(x,z_c) = \mathrm{Prob}\{Z(x)z_k|(n)\}, \quad k = 1,\ldots,K \tag{5}$$

where k=number of samples within a specific class K.

The calculated probabilities are recoded into 0 and 1 in order to obtain binary maps with two levels, the areas with uncertainty and the areas without uncertainty, while considering a confidence interval.

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Table 3. AICC of the Exponential, Gaussian, and Spherical Variogram Models for IK when Evaluating Alfalfa, Corn, Sorghum, and Wheat as Possible Crops

	Alfalfa			Corn		
Field	Spherical	Exponential	Gaussian	Spherical	Exponential	Gaussian
U.S.01	55.7	55.6	55.0	72.3	72.4	72.0
U.S.04	65.6	46.8	44.4	68.0	48.5	46.9
U.S.14	63.9	58.5	61.0	67.6	67.7	68.8
	Sorghum			Wheat		
U.S.01	61.5	61.5	54.5	N/A	N/A	N/A
U.S.04	64.0	60.3	60.3	84.0	84.2	84.0
U.S.14	62.5	62.4	63.3	64.5	64.6	64.5

Note: N/A=total area of the field has 100% yield potential.

Net Revenue

Expected crop net economic revenue for each scenario was calculated based on the Colorado State University Extension (Agriculture and Business Management) 2007 crop budget estimates. The total revenue includes the revenue of the crop without taking into account the costs. The costs include the operations associated with preharvest, harvest, property ownership and cost, and for some crops, a factor payment. Net revenue is the revenue after the costs are taken into account. The expected crop net economic revenue can be used as guidance for the growers to determine which crop would maximize the potential economic benefits from their fields under the current soil salinity conditions.

Each field is composed of a number of areas according to soil salinity classes. Each area produces a specific yield potential based on its soil salinity class for each crop. The total revenue, cost, and net revenue for alfalfa, corn, sorghum, and wheat are based on the Colorado State University Extension (Agriculture and Business Management) 2007 crop budget estimates. The crop budget takes the averages and does not take into account the distribution within each field. However, the actual net revenue of each field depends on how many soil salinity classes are present in each field and the yield potential percentage of each class for a particular crop being considered. Therefore, the following equation is used to adjust the net revenue of each field:

$$\text{Adjusted Net Revenue} = \frac{\sum_{i=1}^{n} \text{Net revenue} \times \text{Area of class} \times \% \text{ of class yield potential}}{\text{Area of the field}} \tag{6}$$

where n represents the number of different yield potential classes, i.e., n represents five classes when field U.S.04 is planted with alfalfa.

Model Validation

This study focused on three levels of soil salinity (low, moderate, and high) and each level was represented by two fields. Out of each set of two fields, one field was used to construct the indicator variogram while the other was used for validation of the indicator variogram. Four different scenarios of planting alfalfa, corn, sorghum, and wheat were evaluated for each field. Therefore, four different indicator variograms were constructed for each field, and then applied to the other field in the same soil salinity level (validation field). Fields U.S.01, U.S.14, and U.S.04 were used to construct the indicator variograms for low, moderate, and high soil salinity levels, respectively. Fields U.S.09, U.S.80, and U.S.10 were used for validation of the same levels of soil salinity, respectively. The criteria used for selecting a field for constructing the variogram or validating it was based on the range of soil salinity in each of the two fields. The field with the larger soil salinity range was chosen for constructing the indicator variogram while the other one was used for validation. Therefore, if the validation field has fewer classes for indicator variograms, the extra classes are removed.

Model Performance

IK performance with the different crops and fields is measured using the following criteria:

1. Model precision: the RMS error (RMSE) is used to measure the prediction precision (Triantafilis et al. 2001) and is defined as

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Z_i - Z_i^*)^2} \tag{6'}$$

where Z_i=observed value of the ith observation; Z_i^* is the predicted value of the ith observation; and n=number of points collected. The RMSE tends to place more emphases on larger errors and, therefore, gives a more conservative measure than the mean absolute error.

2. Smoothing effect: interpolation usually leads to a smoothing of the observations and thus to a loss of variance. To assess the ability of the interpolation method to preserve the vari-

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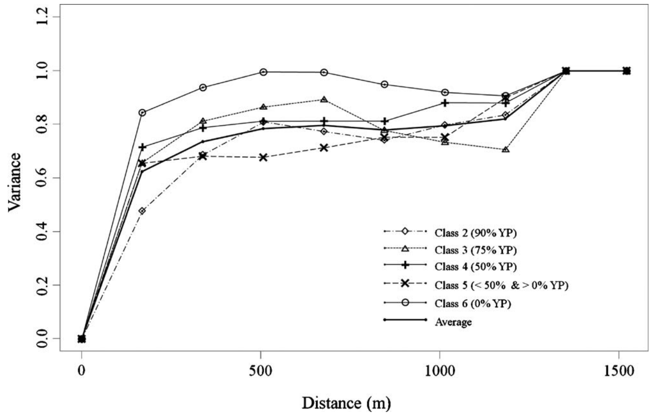

Fig. 2. Example of indicator variograms for field U.S.04 for alfalfa

ance, the ratio of the variance of the estimated values to the variance of the observed values is used (Haberlandt 2006):

$$\mathrm{RVar} = \frac{\mathrm{Var}[Z_i^*(u)]}{\mathrm{Var}[Z_i(u)]} \tag{7}$$

The closer RVar is to 1, the better the ability of the interpolation method to preserve the observed variance.

3. Model effectiveness: the effectiveness of the model was evaluated using a goodness-of-prediction statistic, G (Agterberg 1984; Kravchenko and Bullock 1999; Guisan and Zimmermann 2000; Schloeder et al. 2001). The G value measures how effective a prediction might be relative to that which could have been derived by using the sample mean (Agterberg 1984):

Table 4. Different Classes and Zones of Uncertainty for the Selected Fields Planted with Different Scenarios of Growing Alfalfa, Corn, Sorghum, and Wheat Were Evaluated

	U.S.01		U.S.04		U.S.09		U.S.10		U.S.14		U.S.80	
							Alfalfa					
YP (%)	A(ha)	Unc	A(ha)	Unc	A(ha)	Unc	A(ha)	Unc	A(ha)	Unc	A(ha)	Unc
100					3.83	0						
90	11.68	0.24	18.10	0.21	25.53	0.07	1.92	0.24	3.01	0.22	7.08	0.16
75	4.30	0.27	11.57	0.28			0.66	0.32	7.48	0.24	3.25	0.23
50	0.22	0.17	32.56	0.17			0.57	0.38	2.04	0.28	0.53	0.20
<50			20.54	0.17			0.72	0.23	0.20	0.32	0.40	0.25
0							0.33	0				
							Corn					
YP (%)	A(ha)	Unc	A(ha)	Unc	A(ha)	Unc	A(ha)	Unc	A(ha)	Unc	A(ha)	Unc
100					1.98	0.15						
90					16.89	0.17						
75	5.98	0.20	20.56	0.20	10.04	0.17	2.33	0.25	5.29	0.26	8.57	0.15
050	8.04	0.19	18.54	0.15			0.43	0.27	6.11	0.18	2.08	0.21
<50	2.18	0.18	29.74	0.19			0.43	0.27	1.34	0.13	0.61	0.22
0			24.34	0			1.00	0				
							Sorghum					
YP (%)	A(ha)	Unc	A(ha)	Unc	A(ha)	Unc	A(ha)	Unc	A(ha)	Unc	A(ha)	Unc
100	15.66	0.03	25.08	0.24	28.92	0	2.42	0.25	7.28	0.25	9.52	0.20
90	0.35	0.25	4.40	0.35			0.15	0.32	3.27	0.25	0.71	0.23
75	0.19	0.20	20.96	0.21			0.34	0.35	1.40	0.25	0.61	0.25
50			24.80	0.22			0.44	0.21	0.79	0.32	0.32	0.28
<50			10.85	0.18			0.72	0.24			0.09	0.29
0			7.09	0.24			0.11	0.30				
							Wheat					
YP (%)	A(ha)	Unc	A(ha)	Unc	A(ha)	Unc	A(ha)	Unc	A(ha)	Unc	A(ha)	Unc
100	16.20	0	40.66	0.29	28.92	0	2.87	0.23	12.28	0.18	10.98	0.21
90			12.48	0.25			0.11	0.24	0.01	0	0.15	0.19
75			13.32	0.26			0.11	0.16	0.34	0.26	0.13	0.18
50			11.84	0.25			0.54	0.22	0.11	0.23		
<50			9.06	0.28			0.56	0.24				
0			5.83	0.22								

Note: YP=yield potential and Unc=zone of uncertainty percentage.

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$$G = \left(1 - \left\{ \sum_{i=1}^{n} [Z_i - Z_i^*]^2 \bigg/ \sum_{i=1}^{n} [Z_i - \bar{Z}]^2 \right\}\right) \quad (8)$$

$\bar{Z}$ is the sample mean. A G value equal to 1 indicates perfect prediction, a positive value indicates a more reliable model than if the sample mean had been used, a negative value indicates a less reliable model than if the sample mean had been used, and a value of zero indicates that the sample mean should be used.

Results

This section presents the process of selecting the indicator variograms of IK based on the AICC statistical parameter. Examples of IK maps for different scenarios of crops and fields are provided. Examples of zones of uncertainty are also presented to quantify the risk associated with each of these zones. Finally, an estimate of the net economic revenue for each of the scenarios is provided.

Table 3 shows the AICC values of the exponential, Gaussian, and spherical variogram models for the different combinations of crops and fields. The variogram model with the smallest AICC is considered the best. In most of the scenarios the Gaussian model performance is the best since the AICC values are the smallest. The performance of the spherical and exponential models is very similar. The average AICC values of the spherical, exponential, and Gaussian models for all the scenarios are: 66.3, 62.0, and 61.3, respectively. Fields U.S.01, U.S.04, and U.S.14 were used to construct variograms for the different crop scenarios while fields U.S.09, U10, and U.S.80 were used for validation.

Fig. 2 shows an example of the indicator variograms for field U.S.04 for a scenario of planting alfalfa. From the data presented in Table 3, the AICC value of the Gaussian model is the smallest; and therefore, it was used to construct the indicator variogram by sorting the collected soil salinity data for that field from low to high. Five classes were assigned to the sorted soil salinity data according to the percent yield potential of alfalfa to represent the following yield potentials: 90, 75, 50, $<50\sim>0$, and 0%.

Table 4 shows the yield potential areas of each class and the corresponding zones of uncertainty for all the scenarios of the selected crops and fields. In addition, Fig. 3 shows pie charts that summarize all scenarios of the different combinations of crops and fields. The same color scheme used with the maps was also used to produce the pie charts where colors go from light to dark to represent productivity from high to low. Both Table 4 and Fig. 3 show that fields with low soil salinity ranges (U.S.01 and U.S.09) can reach the maximum production for all crops. However, with moderate and high salinity fields, only sorghum and wheat start with 100% yield potential areas. Alfalfa has good production and in most scenarios, it starts with 90% yield potential areas. Corn has moderate production and in most cases, it starts with 75% yield potential areas.

Figs. 4–6 show three examples of IK maps for fields U.S.01, U.S.14, and U.S.04 which represent low, moderate, and high soil salinity ranges when alfalfa, corn, sorghum, and wheat are assumed to be grown. Fig. 4 shows the IK maps for field U.S.01, which has low soil salinity. The whole area of field U.S.01 can reach the maximum expected productivity (100% yield potential) for wheat, while the expected production of sorghum is quite high with the majority of the field having the potential to produce 100% of yield potential with small areas of 90 and 75% of yield potential. Alfalfa's expected production is high with most of the

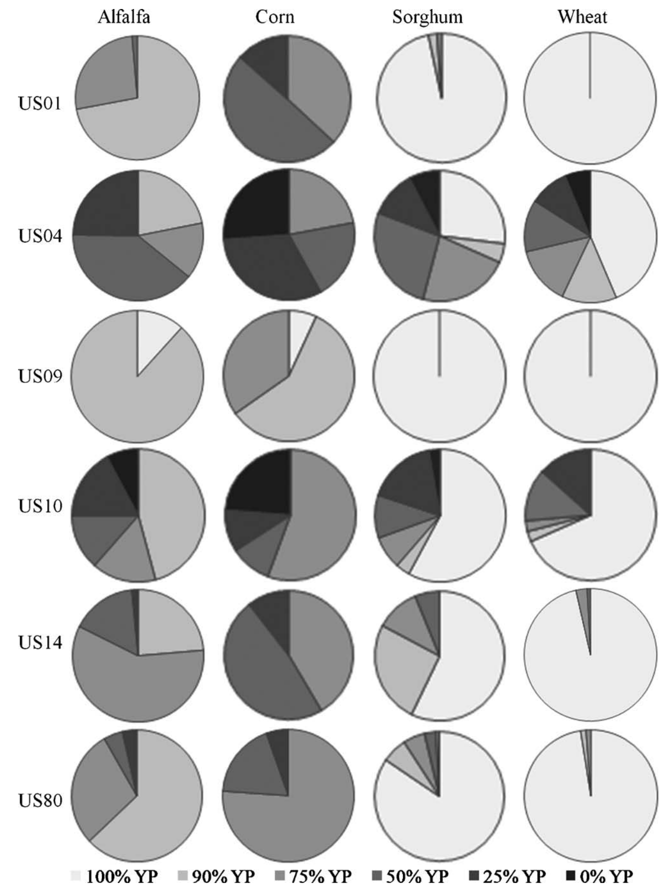

Fig. 3. Pie charts showing different categorical kriging areas for the different fields when different crops are evaluated

field expected to produce between 90 and 100% of yield potential and very small areas expected to produce 75% of yield potential. Corns' expected production is moderate where the production is between 90 and 50% of yield potential.

Fig. 5 shows IK maps for field U.S.14, with moderate soil salinity range when the scenarios of planting alfalfa, corn, sorghum, and wheat are applied. The wheat expected yield in field U.S.14 is high with large areas represented by 100% of yield potential and very small areas represented by 90 and 75% of yield potential. Alfalfas expected production is reasonably good where the expected yield production is between 90 and less than 50% of yield potential. Sorghum has moderate production where large areas in the field are represented by 100 and 90% of yield potential and some areas are represented by 75 and 50% of yield potential. Corn is moderate where the expected production is between 75 and less than 50% of yield potential.

Fig. 6 shows IK maps for field U.S.04, with high soil salinity range when the scenarios of planting alfalfa, corn, sorghum, and wheat are applied. Even though field U.S.04 has relatively high soil salinity, the expected production of wheat is relatively high with a large percent of the area represented by 100 and 90% of yield potential. The expected production for sorghum and alfalfa is moderate where the production of sorghum covers a range between 100 and 0% of yield potential, while alfalfa covers a range between 90 and 0% of yield potential. Corn's expected production is poor with a few areas represented by 75% of yield potential and the majority of the areas have 50% or less of yield potential.

Fig. 7 shows an example of zones of uncertainty for field U.S.14 when the scenario of planting alfalfa is applied. One of the

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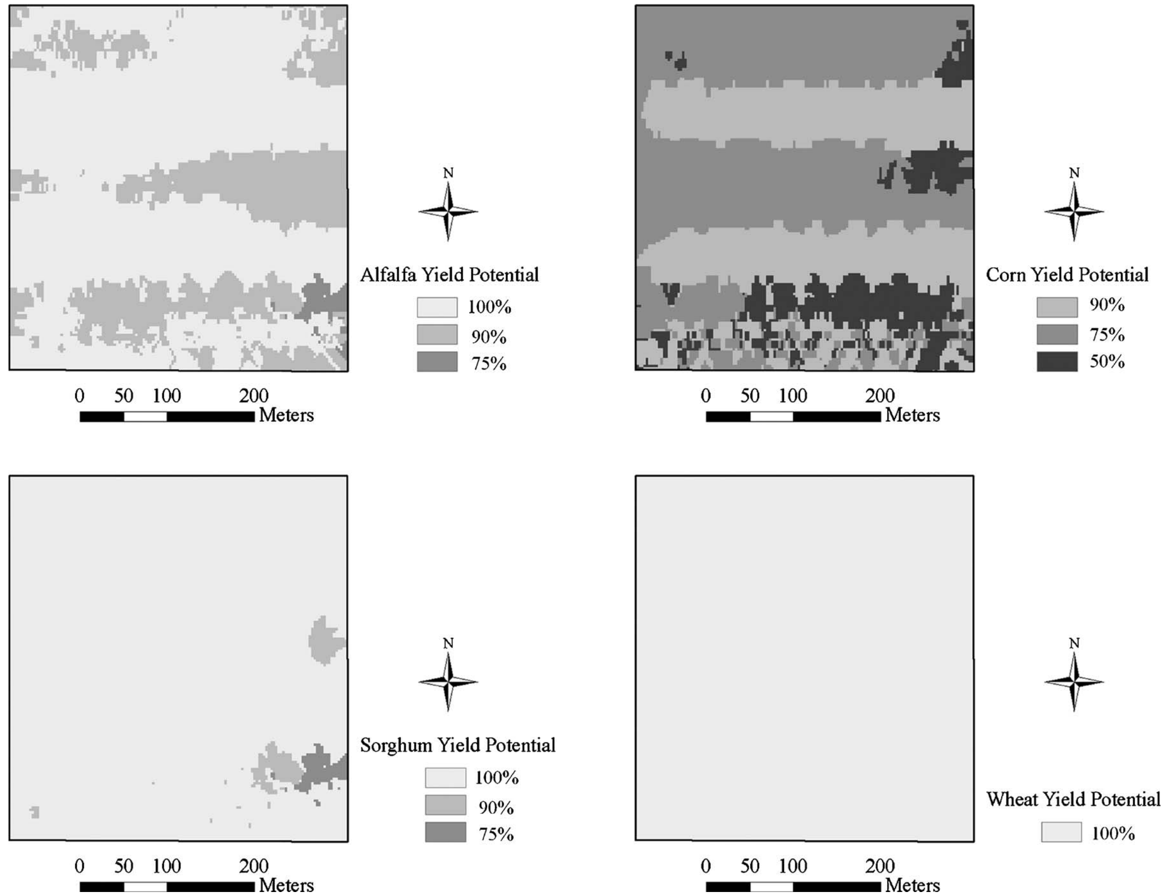

Fig. 4. IK maps for field U.S.01 (low soil salinity) when different crops are evaluated

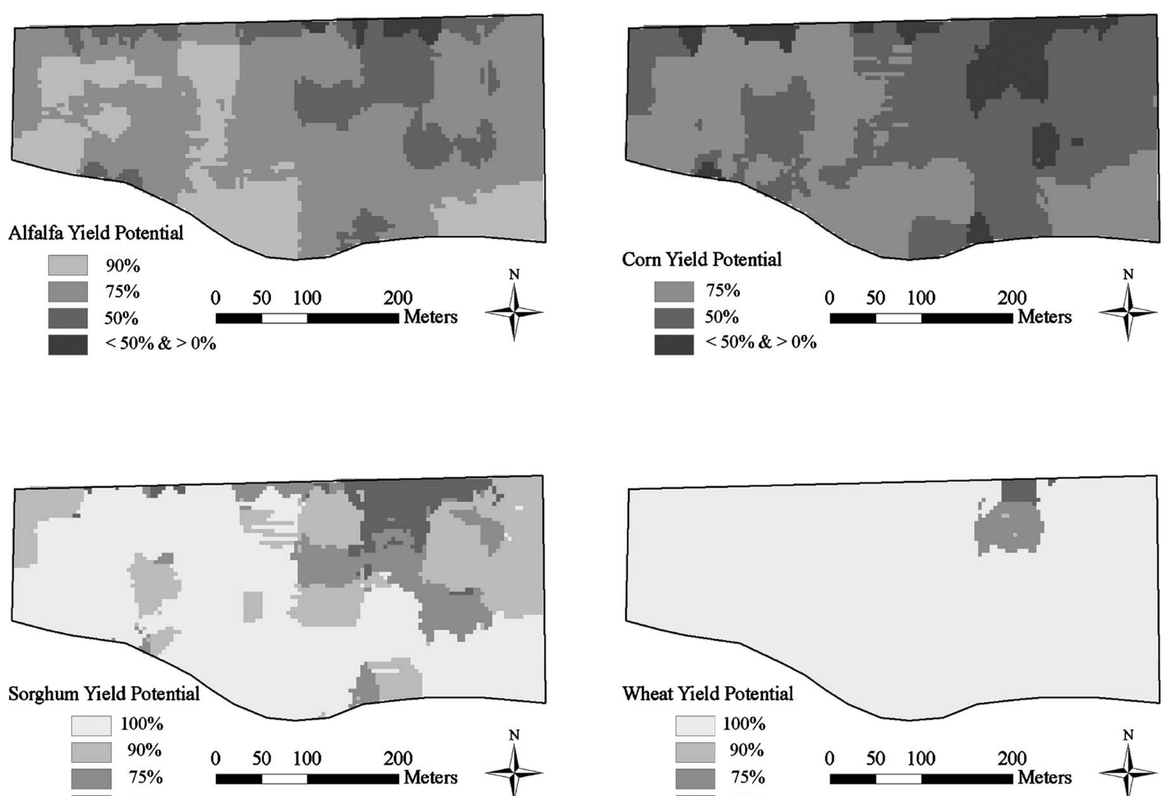

Fig. 5. IK maps for field U.S.14 (moderate soil salinity) when different crops are evaluated

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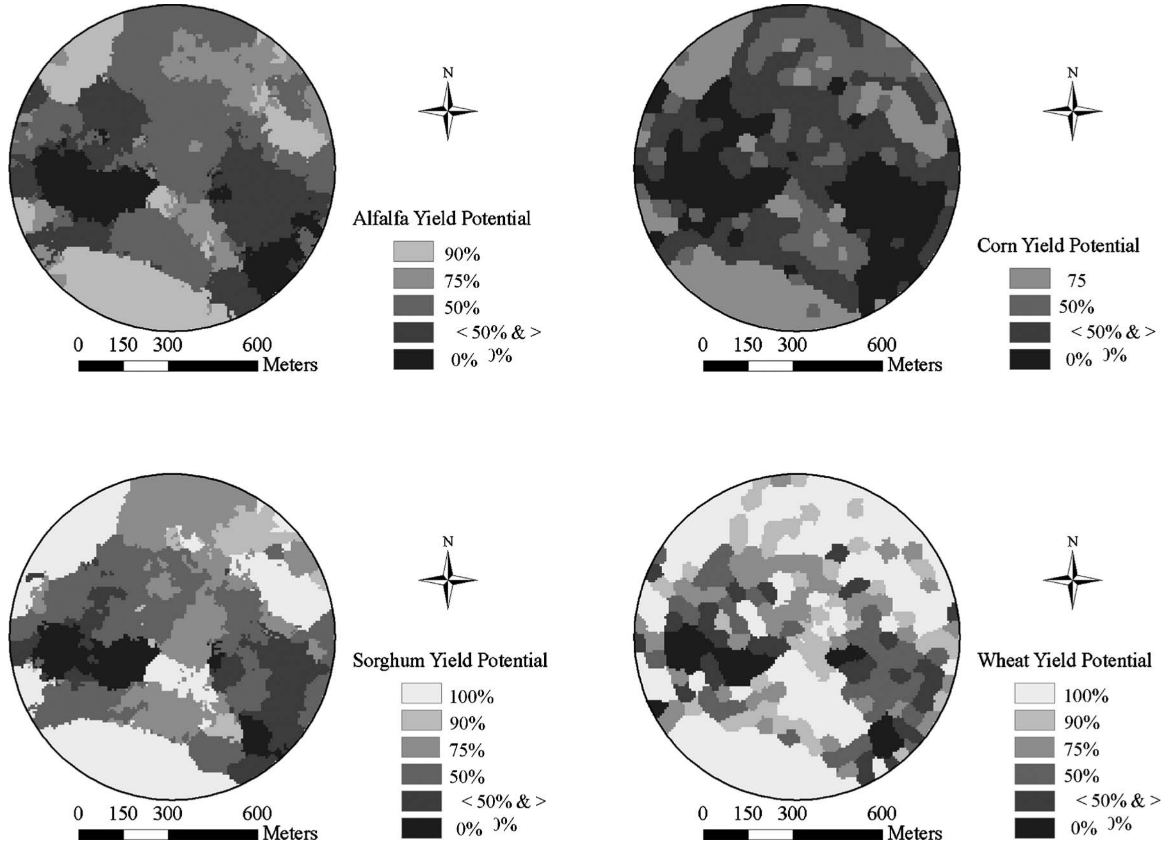

Fig. 6. IK maps for field U.S.04 (high soil salinity range) when different crops are evaluated

advantages of IK is that it can provide a risk-assessment tool for high-risk regions in a field. Fig. 7 as well as Table 4 show how these areas can be quantified. As shown in Table 4, the areas of the different zones of uncertainty vary between 0 and 35% of the class area.

Table 5 shows the total revenue, cost, and net revenue for alfalfa, corn, sorghum, and wheat based on the Colorado State University Extension (Agriculture and Business Management) 2007 crop budget estimates. The total revenue includes the final revenue of the crop without taking into account the costs. Net revenue is the revenue after the costs are taken into account. The net revenue and cost of alfalfa and corn are high while both are low for sorghum and wheat. For 1 ha of alfalfa, in order to gain a net revenue of $1,028, a grower needs to spend $751 while they only need to spend $161 for sorghum but they only gain a net revenue of $220.

Table 6 shows the adjusted net revenue with and without risk according to the IK maps of yield potential of each crop based on the soil salinity thresholds of each field. The net revenue of the different crops has the following order: alfalfa, corn, wheat, and sorghum. The net revenue of alfalfa and corn are highly affected by the soil salinity levels while sorghum and wheat are slightly affected. Table 5 shows that there is a slight difference between the net revenue of alfalfa and corn while Table 6 shows that there is a significant difference in the adjusted net revenue for alfalfa and corn among different fields due to the sensitivity of these crops to salinity and the salinity levels in each field. The difference between the net revenue of alfalfa and corn is significant in all fields except for field U.S.09. That is due to the fact that soil salinity in field U.S.09 allows for 100% of yield potential and there is a big portion of the field with 90% of yield potential while the salinity levels in other fields allows only for 75% or less of yield potential. Uncertainty zones sometimes have significant impact and sometimes marginal impact. Therefore, taking uncertainty zones into consideration provides farmers with more support when making a selection on the crop that has the potential to generate higher net revenue.

Table 7 shows the performance parameter values of IK when evaluating alfalfa, corn, sorghum, and wheat as possible crops under different soil salinity conditions. N/A means that the whole field can produce 100% of yield potential which applies to the crops with high tolerance to soil salinity when planted in the fields with low soil salinity levels. G values are positive for the fields with high and moderate soil salinity (U.S.04, U.S.10, U.S.14, and U.S.80) while it does not perform as well in fields with low soil salinity (U.S.01 and U.S.09). In some cases, the G value reaches 1 or close to 1 which means that the model is perfect, such as corn and wheat in U.S.04 and corn in U.S.09. The RVar values are closest to 1 in fields with a high range of soil salinity (U.S.04 and U.S.10). In cases where the RVar values are small such as wheat in U.S.14 and U.S.80, this means that the model was not able to overcome the smoothing effects problem. The RMSE values are reasonable in all fields since all values are equal or less than 1.

As previously mentioned, several studies have been carried out using IK applications in soil science. However, none of them used IK as a tool to manage soil salinity with crop productivity to maximize the benefit. As presented in the results above, IK was used to determine which crops to grow in order to maximize the potential net benefits taking into account the variability of soil salinity in the fields. In this study, different thresholds were made in the soil salinity databased on the salt tolerance of different

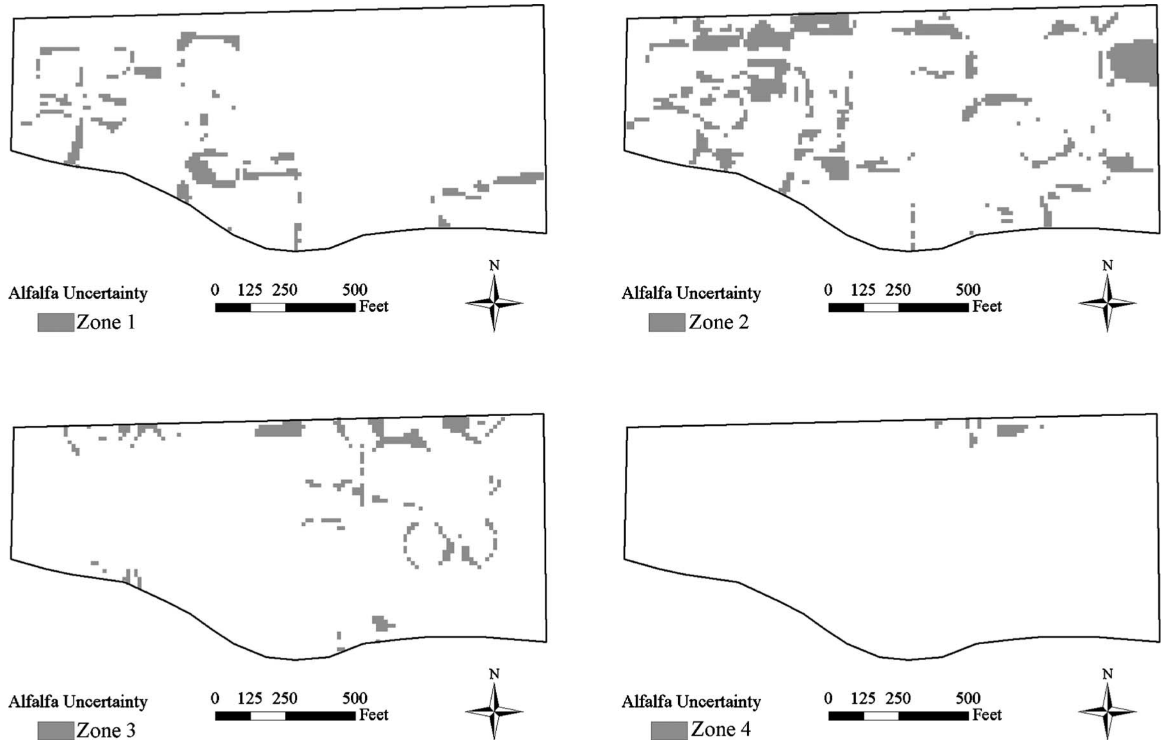

Fig. 7. Zones of uncertainty for field U.S.14 for alfalfa

crops. Therefore, instead of representing different soil salinity thresholds, the resulting indicator variograms represent different yield potentials. To improve the usability of the resulting maps, the different areas of yield potential as well as the corresponding zones of uncertainty of produced maps were quantified and evaluated. The yield potential and the uncertainty zones can provide a management tool for selecting the crops that have the potential to generate the highest yields. However, high yield of a specific crop is not guaranteed to provide the maximum net revenue due to the market price, therefore, the net revenue values were evaluated and adjusted to incorporate the variability in soil salinity in fields.

Crop Selection Recommendations

The following are practical recommendations for farmers and technicians to be used as guidelines for crop selection based on the variability of soil salinity:

- Case 1: low level of soil salinity where no significant impact on most crops. In this case, no restrictions for crop selection and high profit crops should be considered. Alfalfa would be strongly recommended as the first choice while corn would be recommended as the second choice. The expected net revenue from examples presented in this study for low levels of soil salinity can provide a net revenue for alfalfa of approximately $900/ha while the expected net revenue for corn is approximately $750/ha. Wheat and sorghum are not recommended since the net revenue for both of them is low compared to those of alfalfa and corn.
- Case 2: moderate level of soil salinity where the impact of soil salinity is slight on moderate sensitive crops such as alfalfa and corn and no impact on moderate tolerant crops such as wheat and sorghum. Alfalfa is strongly recommended as the best choice. The examples in this study for moderate level of soil salinity fields shows that the net revenue of alfalfa would be $800/ha while the net revenue of corn would be $660/ha.
- Case 3: high level of soil salinity where its impact on moderate sensitive crops is significant while the impact on moderate tolerant crops such as wheat and sorghum is slight. Even though the high level of soil salinity has significant impact on moderate sensitive crops, these crops still provide high net revenue. The examples presented for high soil salinity levels shows a net revenue of approximately $580/ha while the second choice would be corn with a net revenue of approximately $440/ha.

It is clear that the market price has greater impact on crop selection rather than soil salinity impact. As presented earlier, the expected yield of alfalfa and corn is less than the expected yield of wheat and sorghum. However, the market price of alfalfa and corn is higher than those of wheat and sorghum which makes alfalfa and corn better selections. There was a significant difference between the prices of alfalfa and corn versus wheat and sorghum in spite of the reduction in the productivity of alfalfa and corn due to the impact of soil salinity. To make the results of this study more general, the crops presented: alfalfa, corn, wheat, and sorghum can be replaced by crops with similar tolerance to soil salinity in order to accommodate other crop selections. Therefore, since alfalfa and corn are moderate sensitive to soil salinity, they can be replaced by some other crops that have the same tolerance to soil salinity such as broccoli, cabbage, celery, cucumbers, and

Table 5. Total Revenue, Cost, and Net Revenue per Hectare ($/ha) of Alfalfa, Corn, Sorghum, and Wheat

Crop	Alfalfa	Corn	Sorghum	Wheat
Total revenue ($/ha)	1,780	1,780	381	863
Cost ($/ha)	751	724	161	403
Net revenue ($/ha)	1,028	1,055	220	460

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Table 6. Adjusted Net Revenue ($/ha) with and without Risk of Alfalfa, Corn, Sorghum, and Wheat under the Different Conditions of Soil Salinity at the Selected Fields

	Alfalfa		Corn		Sorghum		Wheat	
	Net revenue ($/ha)		Net revenue ($/ha)		Net revenue ($/ha)		Net revenue ($/ha)	
Field ID	Without uncertainty	With uncertainty[a]	Without uncertainty[a]	With uncertainty	Without uncertainty[a]	With uncertainty	Without uncertainty[a]	With uncertainty
U.S.01	878	661	589	447	219	212	460	460
U.S.04	511	407	364	297	141	108	346	250
U.S.09	937	880	902	745	220	220	460	460
U.S.10	658	478	522	266	169	74	380	168
U.S.14	758	574	609	609	201	151	455	371
U.S.80	837	686	714	599	211	168	458	363

[a]With Uncertainty=net revenue was calculated using the percentage of the uncertainty zones.

tomatoes. Wheat and sorghum are moderate tolerant to soil salinity, therefore, they can be replaced by grapes, pineapples, squash, and sugar beets.

Conclusions

A geostatistical approach (IK), which makes no assumptions regarding the normality of the data set and is essentially a nonparametric model, was used in this study. IK uses the behavior and correlation structure of the transformed data instead of the data itself. It uses a series of threshold values between the smallest and largest data values in the data set. This advantage allows incorporating soil salinity with crop yield potential where soil salinity values were transformed into yield potential classes. Therefore, IK was successful in generating classified maps of expected yield potential of the main crops grown in the study area. In addition to generating the classified maps, the results show that IK has the power to generate the corresponding zones of uncertainty. Providing farmers with information regarding the uncertainty associated with each zone, which can help them in their decision making process. The fields used in this study were selected to represent different levels of soil salinity from low, to moderate, to high. Soil salinity values for some fields were homogeneous with small ranges such as field U.S.09 while others had high ranges such as U.S.04. The outcomes of this study show how to obtain the maximum productivity for a particular field under its current soil salinity conditions. However, to reach a high potential productivity may be a target; but to maximize the expected net revenue under different soil salinity conditions should be the optimal target. The results presented in this study show that wheat and sorghum provide the highest expected yield potential while alfalfa and corn provide the highest expected net revenue under the same conditions of soil salinity. Therefore, this study can be used to develop management strategy guidelines for crop selections in order to maximize the economic benefit based on the soil salinity of fields.

Table 7. Performance Parameters: RMSE, RVar, and *G* Values of IK when Evaluating Alfalfa, Corn, Sorghum, and Wheat as Possible Crops

	RMSE	RVar	*G*	RMSE	RVar	*G*
		U.S.01			U.S.04	
Alfalfa	0.59	0.95	−0.12	0.78	1.05	0.61
Corn	0.85	0.82	−0.49	0.06	1.00	1.00
Sorghum	0.46	0.54	0.02	1.00	1.04	0.57
Wheat	N/A	N/A	N/A	0.06	1.00	1.00
		U.S.09 (Validation)			U.S.10 (Validation)	
Alfalfa	0.60	0.40	−0.44	0.45	1.05	0.89
Corn	0.36	0.99	0.64	0.33	1.04	0.93
Sorghum	N/A	N/A	N/A	0.44	1.03	0.93
Wheat	N/A	N/A	N/A	0.61	1.06	0.84
		U.S.14			U.S.80 (Validation)	
Alfalfa	0.49	0.77	0.57	0.49	0.90	0.62
Corn	0.40	0.87	0.64	0.44	0.70	0.61
Sorghum	0.73	0.77	0.45	0.69	0.79	0.47
Wheat	0.63	0.42	0.02	0.46	0.25	0.38

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