Using Disjunctive Kriging as a Quantitative Approach to Manage Soil Salinity and Crop Yield

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Abstract: Disjunctive kriging (DK) is a nonlinear geostatistical model that provides unbiased estimates of the conditional probability (CP) that the true value of the property of interest does not exceed a defined threshold. It has important implications in aiding management decisions by providing growers with a quantitative input that can be used for evaluating the variability of the crop productivity at different zones in fields. The objectives of this study are (1) to identify the yield potential percentage (YP%) for several crops at different zones in fields under multiple soil salinity thresholds; (2) to evaluate the YP% of whole fields for several crops under multiple soil salinity thresholds; and (3) to provide guidelines to help growers decide which crops to grow. To achieve these objectives, the DK technique was applied to data from a project conducted in the southeastern part of the Arkansas River Basin in Colorado to generate CP maps. Two data sets of soil salinity (316 and 136 points) that were collected in two fields in 2004 and 2005 were used to generate the CP maps and to evaluate different scenarios of the expected YP% of several crops at multiple soil salinity thresholds. These data sets represented a wide range of soil salinity conditions to evaluate a wide variety of crops (i.e., a larger set of crops than those grown in the study area) in accordance with their soil salinity tolerance, The following crops were evaluated: the field crops, barley, sorghum, and corn; the fruit crops, pomegranate, apples, and strawberries; the vegetable crops, beets, tomatoes, and lettuce; and the forage crops, barley (i.e., hay), crested wheat grass, and alfalfa. This selection was set so that the three crops of each type represented high, moderate, and low soil salinity tolerances. Scenarios were created for each of the aforementioned crops and the DK technique was applied to each scenario to generate CP maps and to evaluate the expected YP%. The results of this study show that the CP maps generated by using the DK technique give an accurate characterization and quantification of the different zones of the fields. CP maps can be used to assess the expected YP% of whole fields for several crops under multiple soil salinity thresholds. On knowing the YP% of different areas, a management decision action can be undertaken to manage the productivity of a field in low productivity areas by selecting another crop or adjusting inputs such as fertilizer, seeding rates, and herbicides. **DOI: 10.1061/(ASCE)IR.1943-4774.0000392.** *© 2012 American Society of Civil Engineers.*

CE Database subject headings: Probability; Soil properties; Salinity; Crops.

Author keywords: Disjunctive kriging (DK); Conditional probability (CP); Salinity and crop yield management; Soil salinity thresholds; Yield potential percentage (YP%).

Introduction

Approximately 25 to 30% of the irrigated lands in the United States have crop yields that are negatively affected by high soil salinity levels (Tanji 1990; Postel 1989; Ghassemi et al. 1995; Wichelns 1999). Worldwide crop production losses associated with salinity on irrigated lands are an estimated US$11 billion annually and are increasing (Ghassemi et al. 1995). The Arkansas River is one of the most saline rivers in the United States (Tanji 1990; Miles 1977). The Arkansas River drains approximately 25% of the state and is the state's largest river basin. Soil salinity problems exist when the buildup of salts in a crop's root zone is significant enough that it results in a loss in crop yield. Soil salinity negatively affects crop growth by increasing the osmotic potential of the soil solution (Jones and Marshall 1992), which decreases a crop's ability to extract water. This suppresses plant growth and decreases yield. The development of saline soils is a dynamic phenomenon that needs to be monitored regularly to secure up-to-date knowledge of its extent, spatial distribution, nature, and magnitude (Ghassemi et al. 1995).

Linear kriging methods such as simple, ordinary, and universal kriging are well established for predicting soil variables at unsampled locations, and have been used widely in soil and water science. Eldeiry and Garcia (2008a, 2008b, 2010a) used different linear kriging techniques to estimate soil salinity by using remote sensing data. Burgess and Webster (1980) and Webster and Burgess (1980) demonstrated the use of block and universal kriging. Triantafilis et al. (2001) used ordinary kriging, regression kriging, three-dimensional kriging, and cokriging to predict soil salinity from electromagnetic induction data in irrigated cotton. However, correctly assessing prediction uncertainty (i.e., conditional probability) is as important as predicting a variable at unsampled locations. Nonlinear kriging methods provide estimates of the conditional distribution of a variable quantity. Two groups of nonlinear kriging techniques exists in which the conventional linear kriging estimators are applied to the data after a nonlinear transformation. The first group is the indicator method (Journal 1983) in which the nonlinear transform to data is a discrete (i.e., binary) indicator variable. These techniques have been widely

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Note. This manuscript was submitted on September 1, 2010; approved on June 23, 2011; published online on February 15, 2012. Discussion period open until August 1, 2012; separate discussions must be submitted for individual papers. This paper is part of the ***Journal of Irrigation and Drainage Engineering***, Vol. 138, No. 3, March 1, 2012. ©ASCE, ISSN 0733-9437/2012/3-211–224/$25.00.

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applied (e.g., Van Meirvenne and Governs 2001; Halvorson et al. 1995, Eldeiry and Garcia 2011). The second group of technique, which is discussed in this study, involves the nonlinear transformation of the data to a continuous (i.e., Gaussian) variable. This approach is exemplified by disjunctive kriging (DK) (Matheron 1976) and is widely used in soil science (e.g., Wood et al. 1990; von Steger et al. 1996).

DK, unlike other geostatistical methods such as ordinary kriging, can be used as a quantitative method for making management decisions if the conditional probability (CP) information is available. DK has several advantages over linear estimation methods. It provides a more accurate estimate of the property of interest and can generate an estimate of the CP for that property (Yates and Yates 1988). This CP can be used as an input to a management decision-making model and thereby provide a quantitative means of determining whether management actions are necessary (Yates and Yates 1988). An action should be taken whenever the value of a property in a region is larger than the cutoff level at a probability that is equal to or greater than the critical probability level. Such management decisions may often be based on the threshold values of a soil property. There may be threshold concentrations of contaminants specified by regulators that land managers are obliged to maintain. The management of soil nutrients may also be based on threshold values. For example, in accordance with the University of Nebraska recommendations (Ferguson et al. 2000), no phosphorus is needed if the concentration of available (Bray-1) phosphorus in the soil is larger than 15 $\mathrm{mg} \times \mathrm{kg}^{-1}$. Other examples exist in which the threshold values of other soil properties are important for management. In Scotland, if the concentration of cobalt in pasture soils is smaller than 0.25 $\mathrm{mg} \times \mathrm{kg}^{-1}$ then action should be taken to avoid cobalt deficiency in grazing livestock (Webster and Oliver 1989). Land use planning may also refer to threshold values of soil properties. Wood et al. (1990) used a DK technique to estimate and map the soil salinity in the Bet Shean Valley of Israel from measurements of electrical conductivity. Zirschky (1985), Zirschky and Harris (1986), and Zirschky et al. (1985) used geostatistics for determining reclamation strategies for the cleanup of hazardous waste sites. The kriged estimates of the concentrations of contaminants may be used to plan soil remediation. For example, estimates of the concentration of a nutrient may be used to plan spatially variable application of fertilizers (Schepers et al. 2000). Russo (1984a, b) described a method that used geostatistics to aid managing the soil salinity of a heterogeneous field.

In addition to kriging techniques, other authors have used delineation of management zones for soil salinity or for yield management. Fridgen et al. (2000) used elevation, soil salinity, and slope to create management zones for wheat. Fleming et al. (1999) used bare soil color, farmers' perception of yield, and field topography to classify fields into high, moderate, and low productivity zones. Fraisse et al. (1999) used cluster analysis to identify areas that have similar landscape attributes, soil properties, and plant parameters to quantify patterns of variability and to reduce the empirical nature of defined management zones. Stafford et al. (1998) used fuzzy clustering of combined yield monitor data to divide a field into potential management zones. Boydell and McBratney (1999) divided a field into management zones by using cotton yield estimates from satellite imagery.

Most of the previous studies that used geostatistical techniques were able to provide different approaches to assess soil salinity. However, most of these studies do not provide techniques that integrate soil salinity and crop yield to improve crop production. Geostatistical techniques have been used for the management of soil nutrients, land use, and reclamation (Ferguson et al. 2000; Webster and Oliver 1989; Wood et al. 1990, Zirschky 1985; Zirschky and Harris 1986; Zirschky et al. 1985; Schepers et al. 2000). Only a few studies have utilized geostatistical techniques to manage soil salinity (Eldeiry and Garcia 2011; Wood et al. 1990; Russo 1984a, and Russo 1984b). Eldeiry and Garcia (2011) used indicator kriging (IK), a non-linear technique, for soil salinity and yield management to maximize the economic benefits. They applied IK to different scenarios of crops and soil salinity thresholds to generate maps that show the expected percent yield potential areas and the corresponding zones of uncertainty. DK, a nonlinear technique, is used in this study to provide unbiased estimates of the conditional probability (CP) that the true value of the property of interest does not exceed a defined threshold. Even though two different techniques (i.e., DK and IK) have been used in the current study and the Eldeiry and Garcia (2011) study, both techniques provide management tools to maximize the crop productivity under the current soil salinity conditions. The main contributions of this study are (1) the evaluation of several crops under different soil salinity thresholds, which provide growers with a variety of crop selections; (2) the generation of CP maps that can be used to quantify the variability of YP% in different soil salinity zones of fields; and (3) the use of CP maps as management tools to increase crop productivity on the basis of the current soil salinity of different fields.

Data and Methodology

Study Area

The study area is located in the southeastern part of the Arkansas River Basin in Colorado near the cities of Rocky Ford and La Junta (Fig. 1). Farmers in this area are facing decreasing crop yields owing in part to high levels of salinity in their irrigation water. In some areas, land is removed from production because of unsustainable crop yields. This is partly the result of the fact that the Arkansas River is one of the most saline rivers in the United States (Tanji 1990; Miles 1977). Farmland along the lower Arkansas River Basin has been continuously irrigated since the 1870s and developed shallow, saline water tables by the beginning of the twentieth century (Miles 1977). Between 1969 and 1994, the average water table depths in this region have risen approximately 0.3 to 1.3 m toward the surface (Cain 1997). The increasing amounts of upflux of saline groundwater has only exacerbated the salinity problems. In a survey of the region, 68% of producers stated that high salinity levels

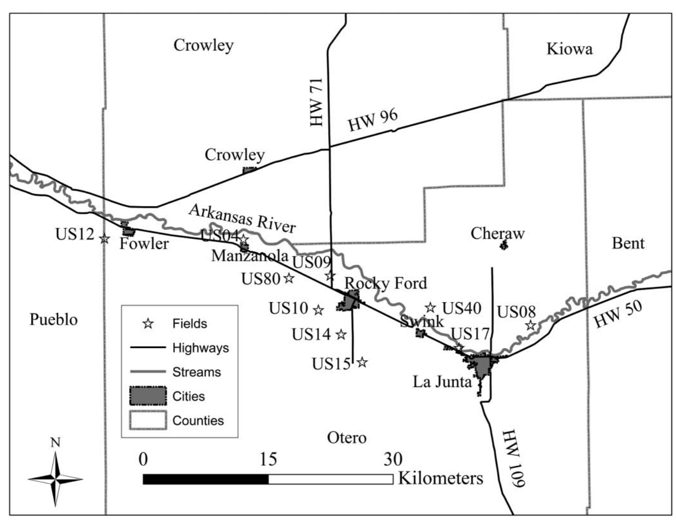

Fig. 1. The study area in the southeastern part of the Arkansas River Basin in Colorado

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were a significant concern (Frasier et al. 1999). Crop yield reduction because of salinity in fields in the Lower Arkansas Valley has been estimated to be between 0 and 75% with a total revenue loss ranging from \$0 to \$750/ha, using 1999 crop prices (Gates et al. 2002).

Selected Fields and Crops

Two data sets of soil salinity points (consisting of 316 and 136 points) were collected from two fields during the 2004 and 2005 growing seasons. These two data sets were selected to represent a high range of soil salinity, which allows evaluating a wide variety of crops with different soil salinity tolerances. The first data set consists of 316 points with a minimum soil salinity value of 2.38 dS/m, a maximum value of 41.23 dS/m, and a variance of 42.21 dS/m. The second data set consists of 136 points with a minimum soil salinity value of 3.04 dS/m, a maximum soil salinity value of 31.26 dS/m, and a variance of 31.38 dS/m. Soil salinity data were collected by using EM-38 electromagnetic probes. The location of the samples was determined by using global position system (GPS) units. The EM-38 electromagnetic probes provide vertical and horizontal readings, whereas the GPS units provide X and Y coordinates for each sample point. Wittler et al. (2006) developed a calibrated equation to convert the EM-38 electromagnetic probe readings to electrical conductivity (dS/m) for the study area. This equation was used in this study. Soil moisture content and soil temperature were used for the soil salinity calibration equation. Eldeiry and Garcia (2008a) and Elderiy et al. (2008) provide a detailed description of using EM-38 electromagnetic probes in combination with GPS in collecting soil salinity. The evaluated crops were selected to represent field, fruit, vegetable, and forage crops. Three crops of each category were selected to represent high, moderate, and low soil salinity tolerances. The following crops were evaluated in this study: for field crops barley, sorghum, and corn; for fruit crops, olive, apples, and strawberries; for vegetable crops, beets, tomatoes, and lettuce; and for forage crops, barley (i.e., hay), crested wheat grass, and alfalfa. Different scenarios that used each of these crops were created on the basis of the soil salinity thresholds for each crop. These scenarios provide growers with a wide selection of crops in accordance with the level of soil salinity in their fields. Other crops can be evaluated on the basis of their similarity in soil salinity tolerance to one of the crops evaluated in this study.

Table 1 shows the YP% and the corresponding soil salinity for the selected crops from field, fruit, vegetable, and forage crops. The YP% values on the basis of soil salinity levels were adapted from Ayers and Westcot (1976). They mentioned that during the germination and seedling stages, soil salinity for barley should not exceed 4 to 5 dS/m, except for certain semi-dwarf varieties. However, Storey and Jones (1978) mentioned that barley is most sensitive to salinity at the germination and young seedling stages, but it exhibits increased tolerance with age. Salinity tolerance at the germination and seedling stages determines the stand density in the field under saline conditions. Therefore, the effect of salinity on barley during the germination and seedling stages can be mitigated by increasing the seed density. Ayers and Westcot (1976) also mentioned that electrical conductivity should not exceed 3 dS/m for beets during germination. Many crops have little tolerance for salinity during the seed germination stage, but they have significant tolerance during later growth stages. Table 1 shows the significant effect of soil salinity on productivity. It also shows how some crops can reach high productivity, whereas others barely grow under the same conditions. For example, at a specific area of a field where soil salinity is 8.0 dS/m, the expected yield of barley is 100%, whereas the expected yield of apples would be between 50% and 0%.

DK Equations

The study provides a brief description of the basic equations of DK. A more comprehensive explanation can be found in Matheron (1976), Journel and Huijbregts (1978), Yates et al. (1986a, b), and Yates and Yates (1988).

To obtain the DK estimator, the original soil salinity data must be transformed into a new variable, $Y(x)$, with a standard normal distribution in which pairs of sample values are bivariate normal. The function $\phi[Y(x)]$ that describes this transformation is

$$\phi[Y(x)] = Z(x) = \sum_{k=0}^{\infty} C_k H_k[Y(x)] \tag{1}$$

where the values for $Y(x)$ are obtained by taking the inverse of the data, $Y(x) = \phi^{-1}[Z(x)]$, and where $H_k[Y(x)]$ is a Hermite

Table 1. Soil Salinity Threshold Values (dS/m) of Different YP% for Selected Crops

Crop		YP %				
Common name	Botanical name	100	100–90	90–75	75–50	50–0
				Soil salinity (dS/m)		
Barley	*Hordeum vulgare*	8.0	10.0	13.0	18.0	28.0
Sorghum	*Sorghum bicolor*	4.0	5.1	7.2	11.0	18.0
Corn	*Zea mays*	1.7	2.5	3.8	5.9	10.0
Fruit crops						
Olive	*Olea europaea*	2.7	3.8	5.5	8.4	14
Apples	*Pyrus malus*	1.7	2.3	3.3	4.8	8.0
Strawberries	*Fragaria spp.*	1.0	1.3	1.8	2.5	4.0
Vegetable crops						
Beets	*Beta vulgaris*	4.0	5.1	6.8	9.6	15
Tomatoes	*Lycopersicon esculentum*	2.5	3.5	5.0	7.6	12.5
Lettuce	*Lactuca sativa*	1.3	2.1	3.2	5.2	9.0
Forage Crops						
Barley (hay)	*Hordeum vulgare*	6.0	7.4	9.5	13.0	20.0
Crested wheat grass	*Agropyron desertorum*	3.5	6.0	9.8	16.0	28.5
Alfalfa	*Medicago sativa*	2.0	3.4	5.4	8.8	15.5

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polynomial of order k. The $C_k's$ are the Hermitian coefficients, which are determined by using the properties of orthogonality. They are generally determined by using numerical integration, as follows:

$$C_k = \frac{1}{k!\sqrt{(2\pi)}} \sum_{i=1}^{j} w_i \phi(v_i) H_k(v_i) \exp[-v_i^2/2] \quad (2)$$

where v_i and w_i are the abscissa and weight factors for Hermite integration (Hochstrasser 1965).

The DK estimator is calculated from a sum of unknown functions of the transformed sample values, $Y(x_i)$. Each unknown function, $f_i[Y(x_i)]$, must depend on only one transformed value, $Y(x_i)$. The DK estimator is calculated by using the following equation:

$$Z^*_{\mathrm{DK}}(x_o) = \sum_{i=1}^{n} f_i[Y(x_i)] = \sum_{i=1}^{n} \sum_{k=1}^{\infty} f_{ik} H_k[Y(x_i)] \quad (3)$$

where f_i is the unknown function with respect to the transformed variable and n is the number of samples.

An unbiased estimator with the minimum estimation variance can be obtained by using the following equations:

$$Z^*_{\mathrm{DK}}(x_o) = \sum_{k=0}^{K} C_k H^*_k[Y(x_o)] \quad (4)$$

where

$$H^*_k[Y(x_o)] = \sum_{i=1}^{n} b_{ik} H_k[Y(x_i)] \quad (5)$$

The series in Eq. (4) has been truncated to K terms and b_{ik} are the DK weights. The $H^*_k[Y(x_o)]$ represents the estimated value of the Kth Hermite polynomial at the estimation location. The sum of these estimates, multiplied by the coefficient C_k [which transforms $Y(x)$ into $Z(x)$], makes up the DK estimate at x_o. To obtain an estimated value for the Hermite polynomial, the DK weights, b_{ik}, must be determined by solving the linear kriging equation for each k, as follows:

$$\sum_{i=1}^{n} b_{ik}(\rho_{ij})^k = (\rho_{oj})^{k.} \qquad j = 1, 2, 3, \ldots, n \quad (6)$$

When $k = 0$, Eq. (6) represents the unbiased condition (i.e., the sum of the weights equals unity). The disjunctive kriging covariance can be calculated by using the following equation:

$$\sigma^2_{\mathrm{DK}} = \sum_{k=1}^{K} k! C_k^2 \left[1 - \sum_{i=1}^{n} b_{ik}(\rho_{oi})^k\right] \quad (7)$$

An advantage of the DK method is that an estimate of the CP can be calculated so that the value at an estimation site is greater than an arbitrary critical value, y_c. This CP is a useful means for determining the risk of various management alternatives. The CP is obtained by defining an indicator variable that is equal to unity if $Y(x_i) \geq y_c$, and is zero otherwise (Yates et al. 1986a, b). This allows the CP to be written by the conditional expectation and estimates the CP as

$$P^*_{\mathrm{DK}}(x_o) = 1 - G(y_c) + g(y_c) \sum_{k=1}^{K} H_{k-1}(y_c) H^*_k[Y(x_o)]/k! \quad (8)$$

where $G(y_c)$ and $g(y_c)$ are the cumulative and probability density functions, respectively, for a standard normal variable; $H^*_k[Y(x_o)]$ is determined by using Eq. (5). The estimated CP density function, $pdf^*_{\mathrm{DK}}(x_o)$, is determined by taking the derivative of Eq. (8) with respect to y_c and is

$$pdf^*_{\mathrm{DK}}(x_o) = g(u)\left\{1 + \sum_{k=1}^{K} H_k(u) H^*_K[Y(x_o)]/k!\right\} \quad (9)$$

Applying DK Technique on Soil Salinity Data Sets

Data Transformation

Data transformations should be performed before using DK. Transformations make the data normally distributed in which pairs of sample values are bivariate normal. Several transformation methods exist and the appropriate method should be chosen. For all transformations, the predictions are automatically back-transformed to the original values before a map is produced. Many forms of transformations exist such as the square-root transformation, which is a special case of the Box-Cox transformation and is usually used when data are counted; the log transformation, which is used for data with a skewed distribution; the arcsine transformation, which is used with data that is expressed proportions or percentages; and the normal score transformation, which is used with simple kringing, disjunctive kringing, and cokriging. DK ranks a data set from its lowest to highest values and matches these ranks to equivalent ranks from a normal distribution. This data of the study uses the normal score transformation because it is the best for the DK technique. Fig. 2 shows the histogram plots of the observed and transformed soil salinity data for the two data sets. Histograms can provide information about the mode and its frequency (which is an indication of the overall variation) and the shape of the distribution. Both data sets are transformed by using normal score transformations. When the first data set was transformed, the mode value was set to zero with a frequency of 60. The overall variation was between -3 and 3 dS/m and the distribution was normal. When the second data set was transformed, the mode value was set to zero with a frequency of 25. The overall variation was between -3 and 3 dS/m and the distribution was normal.

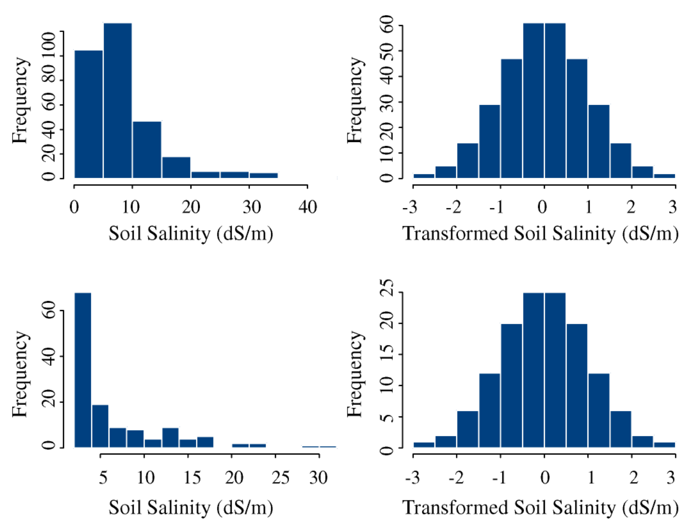

Fig. 2. Histograms of the collected and transformed soil salinity data for the two data sets

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Generating CP Maps

An advantage of DK is its ability to generate CP maps so that a value at an estimation site is greater than an arbitrary critical value. CP maps are generated by specifying a threshold as a condition of probability so that the values exceed (or do not exceed) the specified threshold. The level or quantity of the property that is being studied must be known in order to use DK effectively. This value is called the "cutoff level" or "critical level" and values of the property that are larger than this level represent the event under investigation. The probability level that spurs a management action must also be known. This is the critical probability level at which the levels of the property under investigation are no longer tolerated (Yates and Yates 1988). Maas and Hoffman (1977) concluded that crops will generally be unaffected by salinity up to a certain threshold, at which point the yield will begin to decrease linearly as the soil salinity levels increase. This study used this correlation between soil salinity and crop productivity to produce CP maps for YP% under different conditions of soil salinity thresholds. Each crop has different thresholds that can determine its YP% levels on the basis of its tolerance to soil salinity. For example, sorghum can produce 100, 100–90, 90–75, 75–50, and 50–0 YP% when soil salinity values do not exceed 4, 5.1, 7.2, 11, and 18 dS/m respectively; corn can produce 100–90, 90–75, 75–50, and 50–0 YP% when soil salinity values do not exceed 2.5, 3.8, 5.9, and 10 dS/m respectively. These soil salinity threshold values were the conditions used to produce CP maps for different YP% of the selected crops. For each condition, a CP map was generated from 0% to 100% probability with 20% intervals. Therefore, to generate a CP map of sorghum that reaches 90–75 YP%, the condition must be set so that the soil salinity values do not exceed 7.2 dS/m. To generate similar CP maps for corn, the condition should not exceed 3.8 dS/m. For soil salinity-sensitive crops such as strawberries, a higher CP cannot be produced because the condition requires a very low soil salinity. To produce a CP map for strawberries that has a 100% YP, the condition must be set so that soil salinity values do not exceed 1 dS/m.

Assessing Crop Productivity from CP Maps

The spatial analyst in ArcGIS software was used to reclassify the resulting CP raster maps into six classes for each crop scenario with each data set. These six classes of the CP maps represent data at 20% intervals from 0% to 100%. This was implemented in ArcGIS by using the manual classification and by setting the category values as 0, 0.2, 0.4, 0.6, 0.8, and 1. Contour maps were used for visual illustration and they were generated by using the ArcGIS surface analysis option of the spatial analyst. The "tabulated area" option in the ArcGIS toolbox was used to calculate the total area of each class (i.e., to quantify the CP maps). When a condition was set (e.g., soil salinity values that do not exceed 4 dS/m, which is a condition for sorghum to have 100 YP%), the resulting CP map has contour lines of probability from 0% to 100% with 20% intervals that represent the 100 YP% of sorghum. The area within the 100% contour lines represents the area of the field that has a 100% probability to produce 100% YP. Each threshold of a crop has one scenario that produces a specific CP map. For example, sorghum has five scenarios, whereas corn has only four scenarios on the basis of the soil salinity tolerance of each crop (i.e., corn is in the non-100 YP% class). The following is an example of how the areas of different contour lines are calculated for a CP map that has a condition set so that the soil salinity values do not exceed 7.2 dS/m. This is the condition needed for sorghum to have 90–75 YP%. The area within the 100% contour line represents the area of the field that has 100% probability to produce 90–75 YP%. The area within the 100% and 80% contour lines represents the area of the field that has a 80–100% probability to produce 90–75 YP%. The area within the 80% and 60% contour lines represents the area of the field that has a 60–80% probability to produce 90–75 YP%. After calculating the areas of the different classes, each class area was divided by the total area of the field to obtain the percentage of that class from the total area of the field. To obtain the cumulative probability for each scenario, the percentage of each class was multiplied by its probability and all cumulative probabilities were summed.

Model Evaluation

Cross-validation was used to evaluate the DK geostatistical model for the different scenarios of the selected crops at different thresholds. Cross-validation removes each data location one at a time, predicts the associated data value, and compares the measured and predicted values for all points. The statistics used in cross-validation serve as diagnostics to indicate whether the performance of the model is acceptable. The following statistical measures were set to guarantee that the prediction is unbiased and as close as possible to the measured value, and guarantee that the variability of the prediction is correctly assessed.

- The mean prediction error was used to check if the model is unbiased (i.e., centered on the measured values). These values should be near zero to guarantee that the model is unbiased.
- The mean prediction error depends on the scale of the data. Therefore, the mean standardized prediction error was also used to check whether the model is unbiased. These values should be close to zero to guarantee the model is unbiased.
- The root-mean-square prediction error was used to check whether the prediction is close to the measured values. The smaller the root-mean-square prediction error, the closer is the prediction to the measured value.
- The variability was assessed in the following two ways:
  1. By comparing the average standard error with the root-mean-square prediction error. If the values are similar, then the variability in the prediction is correctly assessed. If the average standard error is greater than the root-mean-square prediction error, then the variability of the predictions is overestimated. If the average standard error is less than the root-mean-square prediction error, then the variability of the predictions is underestimated.
  2. By evaluating the root-mean-square standardized error value. If it is close to 1, then the variability of the prediction is correctly assessed. If it is greater than 1, then the variability of the prediction is underestimated. If it is less than 1, then the variability of the prediction is overestimated.

Results

This section will discuss the use of the DK technique as a tool for the management of soil salinity and yield to achieve maximum productivity under existing soil salinity conditions. Through the DK technique, three examples of CP maps of YP% at different soil salinity thresholds are presented that represent a sensitive crop (strawberries), a moderate sensitive crop (corn), and a moderate tolerant crop (sorghum). These examples are discussed and evaluated later to demonstrate the variation in the probability of YP% within a field. The areas within the CP contours for all selected crops are tabulated to evaluate the quantity of variation in the probability of YP% at different zones. The cumulative probability of the whole field for each scenario is calculated to compare the probabilities to reach different YP% for all selected crops. Some recommendations and guidelines for growers are subsequently

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presented on the basis of outcomes of this study to help growers select specific crops or to use agrochemicals more efficiently in different zones in their fields.

Figs. 3–5 show three examples of CP maps of YP% at different soil salinity thresholds that use the first data set to represent a sensitive crop (strawberries) and a moderate sensitive crop (corn). The purpose of these three examples is to show the variation in the probability of YP% for different zones in fields when planting different crops with different soil salinity tolerances. Contour maps display the CP for which each line is labeled with its YP% value. The area within two contour lines represents the area of the field that has the range of probability of these two contours to reach a specific YP%. The first example (Fig. 3) shows the scenario of planting a sensitive crop (strawberries) with the highest probability of productivity of less than 75%. The soil salinity thresholds of ≤ 2.5 dS/m and ≤ 4 dS/m were used as conditions to produce probability maps of 75–50 of YP% and 50–0 of YP%, respectively, for strawberries. Fig. 3(a) shows that the contour lines with low probabilities cover most of the field; therefore, the probability that strawberries can reach 75–50 YP% are very limited with a condition of soil salinity ≤ 2.5 dS/m. The maximum probability that strawberries can reach 75–50 YP% is 71%, which is represented by a very small area at the bottom of the field. Fig. 3(b) shows a greater probability [than that in Fig. 3(a)] that strawberries can reach 50–0 YP% with a condition

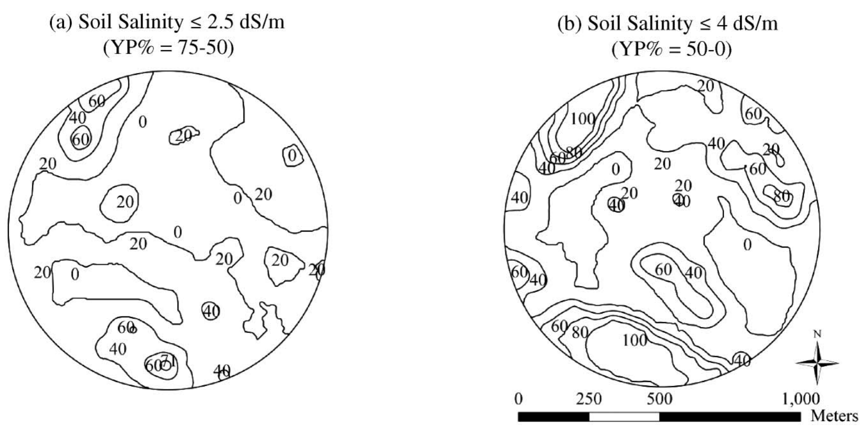

Fig. 3. CP maps of YP% of strawberries at different soil salinity thresholds, obtained by using the first data set

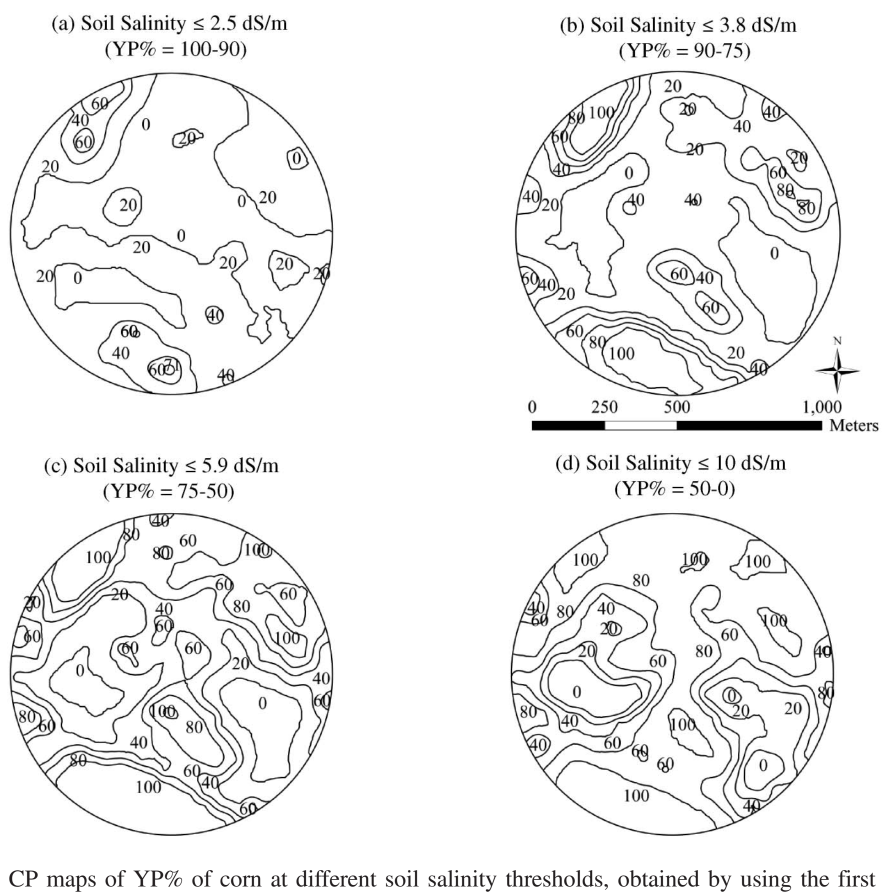

Fig. 4. CP maps of YP% of corn at different soil salinity thresholds, obtained by using the first data set

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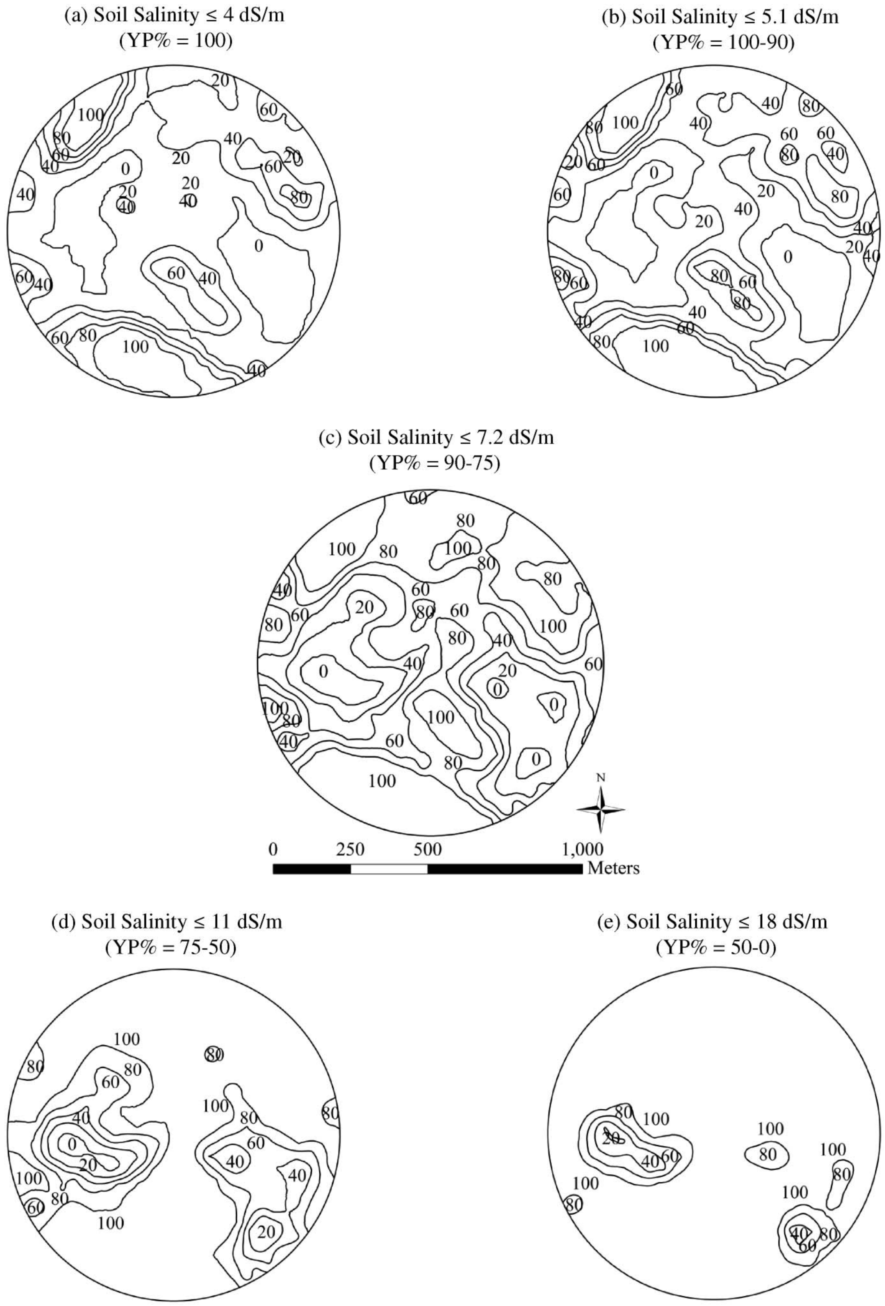

Fig. 5. CP maps of YP% of sorghum at different soil salinity thresholds, obtained by using the first data set

of soil salinity ≤ 4 dS/m. The contour lines with high probabilities cover significant areas of the field.

The second example (Fig. 4) shows the scenario of planting a moderate sensitive crop (corn) with the highest probability of productivity of less than 100%. The soil salinity threshold of ≤ 2.5, ≤ 3.8, ≤ 5.9, and ≤ 10 dS/m the conditions used to produce probability maps of 100–90, 90–75, 75–50, and 50–0 of YP% of corn, respectively. Fig. 4(a) is similar to Fig. 3(a), indicating that corn can reach 100–90 YP% under the same condition that strawberries can reach 75–50 YP%.

The third example (Fig. 5) shows the scenario of planting a moderate tolerant crop (sorghum) with the highest probability of productivity of 100%. The soil salinity threshold of ≤ 4.0, ≤ 5.1, ≤ 7.2, ≤ 11.0, and ≤ 18.0 dS/m were used as conditions to produce probability maps of 100, 100–90, 90–75, 75–50, and 50–0 of YP% of sorghum, respectively. Fig. 5 reflects the fact that sorghum is one of the moderate tolerant crops to salinity. There are significant areas representing the 100% of the YP%, which starts with a soil salinity threshold of ≤ 4.0 dS/m. The areas of high percentages continue to increase gradually with the increase of the soil salinity thresholds, whereas the areas of low productivity keep decreasing throughout the five parts of the figure. Fig. 5(a) is similar to Fig. 3(b), which means that under the condition of soil salinity ≤ 4.0 dS/m, sorghum can reach 100 YP%, whereas strawberries can reach 50 YP% at its maximum capacity. Figs. 5(d) and 5(e) show that under the conditions of soil salinity ≤ 11.0 and ≤ 18.0 dS/m, in which the productivity of the majority of crops is very low, sorghum can reach 75–50 and 50–0 YP% respectively. This is shown by the contour lines of high percentages (100% and 80%) that cover large areas of the field.

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Tables 2 and 3 show the areas with different CP that reach different YP% for all crop scenarios for both data sets. These tables provide a quantitative means of presenting the variation in the probability of YP%. Both tables show that the areas within the 100% CP contour lines increase, whereas the areas within the 0% CP contour lines decrease with decreasing YP%. This sequence of increase or decrease does not occur for the areas within contour lines between 100% and 0% of CP (i.e., 80%, 60%, 40%, and 20%). For the scenario of planting sorghum in Table 3 for the first data set, the areas within the contour lines of 100% CP increase (8, 11, 25, 62, and 88) as the YP% decrease (100, 100–90, 90–75, 75–50, and 50–0). For the same scenario, the areas within the contour lines of 0% CP decrease (16, 13, 4, 1, 0). However, the areas close to the 0% CP tend to decrease and the areas close to the 100% CP tend to increase. A transition zone exists among the areas that have a tendency to decrease and the areas that have a tendency to increase. This increase or decrease of the areas within contour lines with magnitudes between 100% and 0% CP depends on the values of the collected soil salinity data, the locations of the areas, and the soil salinity threshold of each scenario.

Table 4 shows the cumulative probability of YP% for the whole field, which includes all zones of variable productivity. The CP% increases with the increase of the soil salinity threshold values (i.e., the decrease of YP%). For sorghum, the first data set shows that under the soil salinity thresholds of ≤ 4, ≤ 5.1, ≤ 7.2, ≤ 11, and ≤ 18 dS/m, the cumulative probability for the whole field can reach 34.7, 43.2, 64.1, 85.1, and 96.1 to achieve 100, 100–90,

Table 2. Areas of Different Zones with Different Conditional Probabilities for All Scenarios of Selected Crops under Different Soil Salinity Thresholds for the First Data Set

	Conditional probabilities					
YP (%)	100%	80%	60%	40%	20%	0%
Barley						
100	38.7	22.5	14.5	11.8	9.6	2.8
100–90	54.5	18.0	12.7	9.2	3.8	1.8
90–75	70.0	16.2	7.8	3.0	2.7	0.2
75–50	87.8	7.1	3.0	2.0	0.1	0.0
50–0	94.5	4.4	1.1	0.0	0.0	0.0
Corn						
100	0.0	0.0	0.0	0.0	0.0	0.0
100–90	0.0	0.1	2.1	7.5	47.0	43.3
90–75	7.1	5.1	8.8	21.4	40.9	16.8
75–50	14.4	15.8	22.2	20.4	17.7	9.5
50–0	54.5	18.0	12.7	9.2	3.8	1.8
Apples						
100	0.0	0.0	0.0	0.0	0.0	0.0
100–90	0.0	0.0	0.0	0.0	0.0	0.0
90–75	4.2	5.5	6.1	16.7	48.5	19.1
75–50	10.0	6.7	15.5	26.2	27.7	13.8
50–0	38.7	22.5	14.5	11.8	9.6	2.8
Beets						
100	7.8	5.3	10.0	22.6	38.2	16.2
100–90	10.8	8.1	17.6	26.0	24.6	12.9
90–75	21.2	23.1	20.4	14.9	14.7	5.7
75–50	51.9	18.9	12.7	10.1	4.4	2.0
50–0	78.0	13.7	4.0	2.8	1.4	0.0

Table 2. (*Continued.*)

	Conditional probabilities					
YP (%)	100%	80%	60%	40%	20%	0%
Lettuce						
100	0.0	0.0	0.0	0.0	0.0	0.0
100–90	0.0	0.0	0.0	0.0	0.0	0.0
90–75	3.4	5.6	5.7	15.2	49.9	20.1
75–50	11.3	8.6	18.2	25.9	23.5	12.4
50–0	49.3	19.8	13.0	10.6	5.2	2.2
Crested wheat grass						
100	5.2	5.2	6.8	18.2	46.3	18.3
100–90	15.0	17.2	22.3	19.4	16.9	9.2
90–75	54.5	18.0	12.7	9.2	3.8	1.8
75–50	81.0	11.9	3.4	2.8	0.9	0.0
50–0	95.0	4.1	0.8	0.0	0.0	0.0
Sorghum						
100	7.8	5.3	10.0	22.6	38.2	16.2
100–90	10.8	8.1	17.6	26.0	24.6	12.9
90–75	25.5	24.0	18.7	13.8	13.5	4.5
75–50	62.2	16.5	11.4	5.7	3.2	1.0
50–0	87.8	7.1	3.0	2.0	0.1	0.0
Pomegranate						
100	0.1	2.6	5.8	7.7	51.5	32.3
100–90	7.1	5.1	8.8	21.4	40.9	16.8
90–75	12.0	9.7	19.2	25.3	22.1	11.8
75–50	42.4	21.6	14.1	11.5	7.7	2.6
50–0	74.3	15.1	5.7	2.8	2.2	0.0
Strawberries						
100	0.0	0.0	0.0	0.0	0.0	0.0
100–90	0.0	0.0	0.0	0.0	0.0	0.0
90–75	0.0	0.0	0.0	0.0	0.0	0.0
75–50	0.0	0.1	2.1	7.5	47.0	43.3
50–0	7.8	5.3	10.0	22.6	38.2	16.2
Tomatoes						
100	0.0	0.1	2.1	7.5	47.0	43.3
100–90	5.2	5.2	6.8	18.2	46.3	18.3
90–75	10.5	7.5	16.9	26.1	25.8	13.2
75–50	30.8	23.9	16.9	12.7	12.3	3.3
50–0	68.5	16.4	8.7	3.2	2.9	0.3
Barley (Hay)						
100	15.0	17.2	22.3	19.4	16.9	9.2
100–90	29.4	23.8	17.5	13.0	12.7	3.6
90–75	51.4	19.1	12.8	10.2	4.6	2.1
75–50	70.0	16.2	7.8	3.0	2.7	0.2
50–0	90.4	5.4	3.2	1.0	0.0	0.0
Alfalfa						
100	0.0	0.0	0.0	0.0	0.0	0.0
100–90	4.8	5.3	6.4	17.6	47.2	18.6
90–75	12.0	9.7	19.2	25.3	22.1	11.8
75–50	45.2	20.9	13.8	11.0	6.6	2.4
50–0	80.9	11.8	3.4	2.8	0.9	0.0

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Table 3. Areas of Different Zones with Different Conditional Probabilities for All Scenarios of the Selected Crops under Different Soil Salinity Thresholds for the Second Data Set

	Conditional probabilities					
YP (%)	100%	80%	60%	40%	20%	0%
Barley						
100	62.0	11.2	7.8	7.5	6.4	5.2
100–90	71.5	8.5	7.2	3.9	6.1	2.8
90–75	82.7	5.8	3.4	4.1	4.0	0.0
75–50	91.6	4.6	2.7	1.1	0.0	0.0
50–0	97.3	2.6	0.1	0.0	0.0	0.0
Corn						
100	0.0	0.0	0.0	0.0	0.0	0.0
100–90	0.0	0.0	0.0	0.0	0.0	0.0
90–75	40.9	11.0	6.2	8.0	19.3	14.5
75–50	57.3	5.3	10.2	9.0	10.7	7.5
50–0	71.5	8.5	7.2	3.9	6.1	2.8
Apples						
100	0.0	0.0	0.0	0.0	0.0	0.0
100–90	0.0	0.0	0.0	0.0	0.0	0.0
90–75	20.5	15.1	10.1	7.5	21.9	25.0
75–50	49.7	8.2	5.8	10.3	15.4	10.6
50–0	62.0	11.2	7.8	7.5	6.4	5.2
Sugar beets						
100	42.7	10.6	5.7	8.7	18.9	13.5
100–90	51.8	6.8	7.0	10.0	14.4	10.0
90–75	59.8	9.7	8.7	7.2	8.4	6.2
75–50	69.5	8.9	7.2	4.9	6.0	3.5
50–0	85.9	3.8	3.6	4.8	2.0	0.0
Lettuce						
100	0.0	0.0	0.0	0.0	0.0	0.0
100–90	0.0	0.0	0.0	0.0	0.0	0.0
90–75	0.0	0.0	0.0	0.0	0.0	0.0
75–50	51.8	6.8	7.0	10.0	14.4	10.0
50–0	68.4	9.2	6.9	5.6	6.0	3.8
Crested wheat grass						
100	33.2	12.1	7.8	6.6	20.2	20.1
100–90	57.7	6.0	10.0	8.8	10.3	7.3
90–75	70.5	8.7	7.3	4.3	6.0	3.1
75–50	87.7	3.9	3.6	4.1	0.7	0.0
50–0	99.6	0.4	0.0	0.0	0.0	0.0
Sorghum						
100	42.7	42.7	42.7	42.7	42.7	42.7
100–90	51.8	51.8	51.8	51.8	51.8	51.8
90–75	60.2	60.2	60.2	60.2	60.2	60.2
75–50	75.1	75.1	75.1	75.1	75.1	75.1
50–0	91.6	91.6	91.6	91.6	91.6	91.6
Pomegranate						
100	0.0	0.0	0.0	0.0	0.0	0.0
100–90	40.9	40.9	40.9	40.9	40.9	40.9
90–75	53.9	53.9	53.9	53.9	53.9	53.9

Table 3. (*Continued.*)

	Conditional probabilities					
YP (%)	100%	80%	60%	40%	20%	0%
75–50	65.3	65.3	65.3	65.3	65.3	65.3
50–0	84.6	84.6	84.6	84.6	84.6	84.6
Strawberries						
100	0.0	0.0	0.0	0.0	0.0	0.0
100–90	0.0	0.0	0.0	0.0	0.0	0.0
90–75	0.0	0.0	0.0	0.0	0.0	0.0
75–50	0.0	0.0	0.0	0.0	0.0	0.0
50–0	42.7	42.7	42.7	42.7	42.7	42.7
Tomatoes						
100	0.0	0.0	0.0	0.0	0.0	0.0
100–90	33.2	33.2	33.2	33.2	33.2	33.2
90–75	50.6	50.6	50.6	50.6	50.6	50.6
75–50	60.7	60.7	60.7	60.7	60.7	60.7
50–0	77.1	77.1	77.1	77.1	77.1	77.1
Barley (Hay)						
100	57.7	57.7	57.7	57.7	57.7	57.7
100–90	60.7	60.7	60.7	60.7	60.7	60.7
90–75	68.4	68.4	68.4	68.4	68.4	68.4
75–50	82.7	82.7	82.7	82.7	82.7	82.7
50–0	91.6	91.6	91.6	91.6	91.6	91.6
Alfalfa						
100	0.0	0.0	0.0	0.0	0.0	0.0
100–90	26.1	26.1	26.1	26.1	26.1	26.1
90–75	51.8	51.8	51.8	51.8	51.8	51.8
75–50	66.9	66.9	66.9	66.9	66.9	66.9
50–0	87.6	87.6	87.6	87.6	87.6	87.6

90–75, 75–50, and 50–0% YP, respectively. However, for the second data set the cumulative probability for the whole field can reach 61.8, 68.4, 78, 88, and 97.4 to achieve the same YP%s. For corn, the first data set shows that under the soil salinity thresholds values of ≤ 2.5, ≤ 3.8, ≤ 5.9, ≤ 10 dS/m, the cumulative probability for the whole field can reach 13.7, 33.1, 52, and 80.9 to achieve 100–90, 90–75, 75–50, 50–0% YP, respectively. However, in the second data set the cumulative probability for the whole field can reach 0, 60.5, 73.4, 85.4 to achieve the same YP%s (i.e., no 100–90 YP% exists in the second data set).

Model Evaluation

Tables 5 and 6 show the cross-validation parameters used to evaluate the DK geostatistical model. The prediction errors of the mean, root-mean-square (RMS), average standard error (ASE), mean standardized (MS), and root-mean-square standardized (RMSS) were used as cross-validation parameters. These parameters were obtained for each scenario of the selected crops at multiple soil salinity thresholds. The mean and MS prediction errors were used to evaluate whether the model is unbiased or biased. Tables 5 and 6 show that the mean and the MS prediction errors are nearly zero for all scenarios in both data sets. This indicates that the DK model is unbiased (i.e., the prediction values are centered on the measured values for all scenarios.) The RMS prediction errors were used to check how close the predicted values were to the measured values. The smaller the error, the closer the predicted values were to the

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Table 4. Cumulative CP% of the Whole Field for the Two Data Sets at Different Levels of Soil Salinity Thresholds (Different YP%) for All Scenarios of the Selected Crops

YP (%)	CP% for the whole field: First data set	Second data set
Barley		
100	72.1	79.9
100–90	80.9	85.4
90–75	89.4	91.8
75–50	96.1	97.4
50–0	98.7	99.4
Corn		
100	0.0	0.0
100–90	13.7	0.0
90–75	33.1	60.5
75–50	52.0	73.4
50–0	80.9	85.4
Apples		
100	0.0	0.0
100–90	0.0	0.0
90–75	28.6	46.0
75–50	40.7	66.9
50–0	72.1	79.9
Beets		
100	34.7	61.8
100–90	43.2	68.4
90–75	60.8	77.3
75–50	79.5	84.1
50–0	92.8	93.3
Lettuce		
100	0.0	0.0
100–90	0.0	0.0
90–75	27.4	0.0
75–50	44.2	68.4
50–0	78.1	83.4
Crested wheat grass		
100	30.0	54.2
100–90	53.3	74.0
90–75	80.9	84.8
75–50	93.9	94.8
50–0	98.8	99.9
Sorghum		
100	34.7	34.7
100–90	43.2	43.2
90–75	64.1	64.1
75–50	85.1	85.1
50–0	96.1	96.1
Pomegranate		
100	19.0	19.0
100–90	33.1	33.1
90–75	45.8	45.8
75–50	74.3	74.3
50–0	91.3	91.3
Strawberries		
100	0.0	0.0
100–90	0.0	0.0
90–75	0.0	0.0
75–50	13.7	13.7
50–0	34.7	34.7
Tomatoes		
100	13.7	13.7
100–90	30.0	30.0
90–75	42.2	42.2
75–50	67.6	67.6
50–0	88.7	88.7
Barley (Hay)		
100	53.3	53.3
100–90	66.7	66.7
90–75	79.3	79.3
75–50	89.4	89.4
50–0	97.0	97.0
Alfalfa		
100	0.0	0.0
100–90	29.4	29.4
90–75	45.8	45.8
75–50	75.9	75.9
50–0	93.7	93.7

measured values. The values of the RMS prediction errors in both tables were small and close to zero, indicating that the DK model was successful in making the predicted values as close as possible to the observed values. However, the values in Table 6 for the second data set are slightly less than the corresponding values of the first data set, which indicates that the DK model was more successful when using the second data set, rather than the first data set. Two methods were used to assess whether the variability in the predictions is correct, overestimated, or underestimated. In the first method, the closer the values of the ASE that are to the values of the RMS prediction errors, the better the assessment of the variability in the predictions. This is clear for all scenarios. This indicates that the predictions correctly assessed the variability. In the second metohd, the values of the RMSS prediction errors should be 1 to correctly assess the variability. This is clear for most scenarios. Only in a few scenarios did the RMSS prediction errors exceed 1. This occurred for barley at YP% $< 75\%$, sorghum at YP% $< 50\%$, barley (hay) at YP% $< 50\%$, crested wheat grass at YP% $< 75\%$, and alfalfa at YP% is $< 75\%$. This indicates that the DK model underestimates the variability for these few scenarios.

Advantages and Disadvantages of DK

DK which is a nonlinear kriging technique has several advantages over linear estimation methods. The first advantage is that it provides a more accurate estimate of the property of interest and can generate an estimate of the CP for that property (Yates and Yates

Table 5. Cross-Validation Parameters for Selected Crops at Different Salinity Thresholds for the First Data Set

	Mean	RMS	ASE	MS	RMSS
Barley					
100	0.01	0.36	0.38	0.03	0.94
100–90	0.01	0.34	0.36	0.02	0.95
90–75	0.01	0.30	0.30	0.03	0.98
75–50	0.01	0.21	0.22	0.03	0.96
50–0	0.00	0.15	0.16	0.03	0.98
Corn					
100	—	—	—	—	—
100–90	0.00	0.19	0.19	0.02	1.01
90–75	0.00	0.32	0.34	0.01	0.92
75–50	0.00	0.39	0.39	0.01	1.00
50–0	0.01	0.33	0.35	0.02	0.95
Apple					
100	—	—	—	—	—
100–90	—	—	—	—	—
90–75	0.00	0.29	0.32	0.01	0.91
75–50	0.00	0.35	0.37	0.00	0.95
50–0	0.01	0.36	0.38	0.03	0.94
Beet					
100	0.00	0.33	0.35	−0.01	0.94
100–90	0.00	0.37	0.38	0.00	0.98
90–75	0.00	0.39	0.39	0.02	0.99
75–50	0.01	0.34	0.36	0.02	0.97
50–0	0.01	0.25	0.27	0.03	0.94
Lettuce					
100	—	—	—	—	—
100–90	—	—	—	—	—
90–75	0.00	0.28	0.31	0.01	0.91
75–50	0.00	0.37	0.38	0.00	0.98
50–0	0.01	0.35	0.37	0.02	0.95
Crested wheat grass					
100	0.01	0.29	0.33	−0.01	0.89
100–90	0.01	0.39	0.39	0.01	1.00
90–75	0.01	0.33	0.36	0.02	0.95
75–50	0.01	0.24	0.26	0.03	0.92
50–0	0.00	0.14	0.15	0.03	0.97
Sorghum					
100	0.00	0.33	0.35	−0.01	0.94
100–90	0.00	0.37	0.38	0.00	0.98
90–75	0.01	0.38	0.39	0.02	0.97
75–50	0.01	0.32	0.33	0.02	0.96
50–0	0.01	0.21	0.22	0.03	0.96
Pomegranate					
100	0.00	0.23	0.24	−0.01	0.91
100–90	0.00	0.32	0.34	0.01	0.92
90–75	0.00	0.38	0.38	0.00	0.98
75–50	0.01	0.35	0.38	0.02	0.93
50–0	0.01	0.28	0.29	0.03	0.99
Strawberry					
100	—	—	—	—	—
100–90	—	—	—	—	—
90–75	—	—	—	—	—
75–50	0.00	0.19	0.19	0.02	1.01
50–0	0.00	0.33	0.35	0.01	0.94
Tomato					
100	0.00	0.19	0.19	0.02	1.01
100–90	0.00	0.29	0.33	−0.01	0.87
90–75	0.00	0.36	0.38	0.00	0.96
75–50	0.01	0.37	0.39	0.02	0.96
50–0	0.01	0.30	0.31	0.02	0.97
Barley (Hay)					
100	0.01	0.39	0.39	0.01	1.00
100–90	0.01	0.38	0.39	0.02	0.96
90–75	0.01	0.35	0.36	0.02	0.96
75–50	0.01	0.30	0.30	0.03	0.98
50–0	0.00	0.19	0.21	0.03	0.93
Alfalfa					
100	—	—	—	—	—
100–90	0.00	0.30	0.32	0.01	0.91
90–75	0.00	0.38	0.38	0.00	0.98
75–50	0.01	0.35	0.37	0.02	0.94
50–0	0.01	0.24	0.26	0.03	0.92

1988). The second advantage is that DK produces CP maps that can be used as an input to a management decision-making model that provides a quantitative means of determining whether management actions are necessary (Yates and Yates 1988). The third advantage is that the DK technique provides important implications in aiding management decisions by providing growers with a quantitative input that can be used to evaluate the variability of crop productivity in different zones in fields. The fourth advantage is that DK performs better than IK because the continuous Hermite transform in DK retains all information from the original data, whereas the transform in other techniques such as IK uses discrete transformations that inevitably loses information. The only disadvantage in using DK is the increased computational time (Yates et al. 1986a).

Discussion

It has become imperative to explore the potential of increasing the food production from saline lands because of the increasing pressure from growing populations. Thus, combating land salinization problems through adopting salinity and crop management strategies is vital for food security. Plants vary widely in their salinity tolerance. A method to address the soil salinity problem is to select and plant salt-tolerant crops in saline soil areas. This paper introduces a technique to determine how to live with salinity in its current condition without leaching the soil salinity or performing other soil reclamation efforts. The critical or threshold soil salinity value is the value beyond which a crop's productivity is negatively affected. In this study, the threshold values were the input values (i.e., the conditional probability information) used in the DK technique to generate CP maps for YP% under different conditions

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Table 6. Cross-Validation Parameters for Selected Crops at Different Salinity Thresholds for the Second Data Set

	Mean	RMS	ASE	MS	RMSS
Barley					
100	0.01	0.22	0.27	0.02	0.81
100–90	0.01	0.20	0.25	0.02	0.80
90–75	0.01	0.19	0.21	0.04	0.89
75–50	0.00	0.21	0.14	0.02	1.47
50–0	0.00	0.13	0.09	0.01	1.50
Corn					
100	—	—	—	—	—
100–90	—	—	—	—	—
90–75	0.01	0.20	0.30	0.02	0.68
75–50	0.01	0.24	0.28	0.02	0.86
50–0	0.01	0.20	0.25	0.02	0.80
Apple					
100	—	—	—	—	—
100–90	—	—	—	—	—
90–75	0.00	0.30	0.28	0.00	1.05
75–50	0.00	0.19	0.29	0.01	0.65
50–0	0.01	0.22	0.27	0.02	0.81
Beet					
100	0.00	0.20	0.30	0.00	0.68
100–90	0.00	0.21	0.29	0.01	0.72
90–75	0.01	0.24	0.27	0.02	0.86
75–50	0.01	0.19	0.25	0.02	0.77
50–0	0.00	0.20	0.20	0.01	1.03
Lettuce					
100	—	—	—	—	—
100–90	—	—	—	—	—
90–75	−0.01	0.39	0.27	−0.03	1.47
75–50	0.00	0.21	0.29	0.01	0.72
50–0	0.01	0.18	0.26	0.02	0.71
Crested wheat grass					
100	0.00	0.26	0.29	−0.02	0.86
100–90	0.01	0.24	0.28	0.02	0.85
90–75	0.01	0.20	0.25	0.02	0.81
75–50	0.00	0.22	0.18	0.01	1.21
50–0	0.00	0.09	0.06	−0.01	1.51
Sorghum					
100	0.00	0.20	0.30	0.00	0.68
100–90	0.00	0.21	0.29	0.01	0.72
90–75	0.01	0.23	0.27	0.02	0.84
75–50	0.01	0.19	0.24	0.03	0.79
50–0	0.00	0.21	0.14	0.02	1.47
Pomegranate					
100	—	—	—	—	—
100–90	0.01	0.20	0.30	0.02	0.68
90–75	0.00	0.21	0.29	0.02	0.72
75–50	0.01	0.19	0.26	0.02	0.73
50–0	0.00	0.21	0.20	0.02	1.01

Table 6. (*Continued.*)

	Mean	RMS	ASE	MS	RMSS
Strawberry					
100	—	—	—	—	—
100–90	—	—	—	—	—
90–75	—	—	—	—	—
75–50	—	—	—	—	—
50–0	0.00	0.20	0.30	0.00	0.68
Tomato					
100	—	—	—	—	—
100–90	0.00	0.26	0.29	−0.02	0.86
90–75	0.00	0.20	0.29	0.01	0.69
75–50	0.01	0.23	0.27	0.02	0.83
50–0	0.00	0.20	0.23	0.03	0.88
Barley (Hay)					
100	0.01	0.24	0.28	0.02	0.85
100–90	0.01	0.23	0.27	0.02	0.83
90–75	0.01	0.18	0.26	0.02	0.71
75–50	0.01	0.19	0.21	0.04	0.89
50–0	0.00	0.21	0.14	0.02	1.47
Alfalfa					
100	−0.01	0.30	0.29	−0.02	1.03
100–90	0.00	0.21	0.29	0.01	0.72
90–75	0.01	0.18	0.26	0.02	0.69
75–50	0.00	0.22	0.18	0.01	1.21
50–0	0.00	0.22	0.18	0.01	1.21

of soil salinity thresholds. The CP maps can then be used as a quantitative method for making management decisions.

If the CP information is available, nonlinear kriging techniques can be used as a quantitative method for making management decisions for soil salinity and yield. Nonlinear kriging techniques include IK (which involves a nonlinear transformation of the data to a discrete variable) and DK (which involves a nonlinear transformation of the data to a continuous variable). Of the previous studies that used non-linear kriging techniques and targeted soil salinity and crop yield management, the findings of Eldeiry and Garcia (2011) are the closest to the findings of the current study, to the best of the authors' knowledge. Eldeiry and Garcia applied the IK technique by using indicator variograms to evaluate different scenarios of crops and salinity levels; From the variograms they generated maps showing the expected YP%. Their results show that IK can be used to generate guidance maps that divide fields into areas of expected YP% on the basis of soil salinity thresholds for different crops. In this paper, the DK technique provided unbiased estimates of the CP so that the true value of the property of interest does not exceed a defined threshold. The results of this study show that the CP maps generated by using the DK technique provide an accurate characterization and quantification of the different areas of a field. CP maps were used to assess the expected YP % of fields for several crops under multiple soil salinity thresholds. The methodologies used in the IK and DK techniques differ; however, both techniques can be used as management decision tools to manage the productivity under current soil salinity conditions. Both techniques provide knowledge of the YP% of different areas. By using the knowledge of YP% at different areas of a field, a decision can be made to manage the productivity of these areas by selecting another crop or adjusting inputs such as fertilizer, seeding rates, and herbicides.

Conclusions

Decisions are subject to error that are made on the basis of critical thresholds, which use estimates of variability. DK converts these errors to an estimated probability so that the true value exceeds a given threshold, thereby giving decision makers a means to judge the risk associated with a particular estimate. DK provides minimum variance estimates of properties from nonlinear combinations of spatially correlated sample data. It can also be used to estimate the conditional probability that a certain critical threshold is exceeded. This study used DK, a nonlinear kriging model, to provide an unbiased estimation of the conditional probability that a given variable exceeds a threshold. DK assists in management decisions by providing a quantitative input (i.e., CP maps) that can be used to evaluate the variability of different areas in a field. The results on the data show how the DK technique can generate valuable information for the growers to make decisions regarding which crops to select or the need to make the most efficient use of agrochemicals. Efficient use of agrochemicals is beneficial for farmers and for the environment. This study presented and discussed the visual information of the variation in probability of productivity in the different areas of a field, for different crop scenarios. This information enables growers to visualize the variability of the productivity in different areas of their fields. The information was tabulated and discussed to provide growers with quantitative information about the probability of the productivity of different areas in their fields. This information enables growers to quantify the variability of the productivity in different areas of their fields. This study shows that the DK technique provides a tool to achieve spatial optimization of farm management. This will increase productivity or reduce the amount of agro-chemicals applied.

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