SJSS
SPANISH JOURNAL OF SOIL SCIENCE

Application of kriging techniques for assessing the salinity of irrigated soils: the case of El Ghrous perimeter, Biskra, Algeria

Aplicación de técnicas de kriging para estimar la salinidad de suelos bajo riego: el caso del perímetro de El Ghrous, Biskra, Algeria
Aplicação de técnicas de kriging para avaliar a salinidade de solos sujeitos a rega: o caso do perímetro de El Ghrous, Biskra, Argélia

AUTHORS

Abdennour M. A.[@,1]
ma.abdennour@univ-biskra.dz

Douaoui A. [2]

Bradai A. [3]

Bennacer A. [4]

Pulido Fernández M. [5]

[@] Corresponding Author

[1]Laboratory of ecosystem diversity and agricultural production system dynamics in arid zones (DEDSPAZA), Faculty of Natural Sciences and Life, Agronomy Department, University of Mohamed Khider of Biskra. Algeria.
[2]University Center of Morsli Abdellah, Tipaza 42000, Algeria. Laboratory of Crop Production and Sustainable Valorization of Natural Ressources, University of Djilali Bounaama-Khemis Miliana. Ain Defla 44225, Algeria.
[3]Laboratory of Water and Environment, Faculty of Natural Sciences and Life, Department of Water, Environment and Sustainable Development, University of Hassiba Benbouli. Chlef, Algeria.
[4]Laboratory of Valorization and Conservation of Biological Resources, Faculty of Sciences, University M'hamed Bougara of Boumerdes. Algeria.
[5]Geo-Environmental Research Group, University of Extremadura. Avenida de la Universidad s/n. 10071 Cáceres, Spain.

Received: 25.02.2019 | **Revised:** 16.05.2019 | **Accepted:** 04.06.2019

ABSTRACT

In semi-arid and arid areas, soil salinity has adverse effects both on the environment and agricultural production. The main causes of this salinization come from natural or anthropogenic processes, which is certainly an environmental problem that affects more than 20% of the world's land. This study was made in order to map the spatial distribution of soil salinity of the irrigated perimeter of El Ghrous in southeastern Algeria. These maps were performed based on data collected from 190 soil samples from 0 to 15 cm deep. We used ordinary kriging (OK) to analyze the spatial variability of soil salinity, while indicator kriging (IK) was used to analyze salinity versus threshold values. The salinity map predicted by the electrical conductivity (EC) values using the ordinary kriging (OK) method showed the different classes of salinity according to Durand's classification with moderately saline 3rd order dominance, while the unsalted soil (EC < 0.6 dS m^{-1}) represents a very low percentage (1.5%). The indicator kriging (IK) was carried out by four thresholds which correspond to the salinity class limits: EC > 0.6, EC > 1, EC > 2, EC > 3, and EC > 4 dS m^{-1}, for developing probability maps to determine risk areas. This study has shown the spatial trend of soil salinity by geolocation of different classes, and to carry out risk maps using geostatistical techniques.

RESUMEN

En zonas semiáridas y áridas, la salinidad del suelo tiene efectos adversos sobre el medio ambiente y la producción agrícola. La salinización es un proceso natural y/o inducido por el ser humano que afecta a más del 20% de la superficie mundial y que no para de crecer preocupantemente día tras día. El objetivo de este estudio fue elaborar mapas de distribución espacial de la salinidad en el perímetro irrigado de El Ghrous, en el sureste de Argelia. Estos mapas se realizaron a partir de datos recogidos de 190 muestras de suelo de 0 a 15 cm de profundidad. Se usó kriging ordinario (OK) para analizar la variabilidad espacial de la salinidad del suelo, mientras que el kriging indicador (IK) se utilizó para analizar la salinidad en función de sus valores umbrales. El mapa de salinidad usando valores de conductividad eléctrica (CE) obtenido por OK mostró las diferentes clases de salinidad establecidas por Durand, donde dominaron los valores de salinidad moderada de 3er orden, mientras que los suelos no salinos (CE < 0,6 dS m^{-1}) representaron un porcentaje muy bajo (1,5%). El IK fue usado con 4 valores umbrales que corresponden a los límites de salinidad utilizados para elaborar los mapas de riesgo: CE > 0,6, CE > 1, CE > 2, CE > 3 y CE > 4 dS m^{-1}. Este estudio ha mostrado la tendencia espacial de la salinidad del suelo localizando espacialmente sus diferentes clases y ha servido para producir mapas de riesgo mediante técnicas de geoestadística.

DOI: 10.3232/SJSS.2019.V9.N2.04

SJSS
SPANISH JOURNAL OF SOIL SCIENCE

RESUMO

Nas zonas semiáridas e áridas, a salinidade do solo tem efeitos adversos no ambiente e na produção agrícola. A salinização é um processo natural e/ou induzido pelo homem que afeta mais de 20% da superfície mundial e que não pára de crescer, constituindo um sério problema ambiental. O objectivo deste estudo foi elaborar mapas de distribução espacial da salinidade no perímetro de rega de El Ghrous no sueste da Argélia. Estes mapas foram realizados com base em dados de 190 amostras de solo de 0 a 15 cm de profundidade. A krigagem normal (OK) foi usada para analizar a variabilidade espacial da salinidade do solo, e a krigagem da indicatriz (IK) para analizar a salinidade segundo os seus valores limite. O mapa de salinidade, expresso em valores de condutividade elétrica (CE), obtido pela OK mostrou as diferentes classes de salinidade estabelecidas por Durand onde dominaram os valores de salinidade moderada de 3a ordem, enquanto os solos não salinos (CE < 0,6 dS m^{-1}) representaram uma percentagem muito baixa (1,5%). A IK foi utilizada com quatro valores limite que correspondem aos limites de classes de salinidade: CE > 0,6, CE > 1, CE > 2, CE > 3 e CE > 4 dS m^{-1} utilizados para elaborar mapas de probabilidade para delimitar áreas de risco. Este estudo mostrou o padrão espacial da salinidade do solo localizando espacialmente as suas diferentes classes e serviu para produzir mapas de risco mediante técnicas de geoestatística.

KEY WORDS
Electrical conductivity, geostatistic, soil maps, arid zone.

PALABRAS CLAVE
Conductividad eléctrica, geoestadística, mapas de suelos, zona árida.

PALAVRAS-CHAVE
Condutividade elétrica, geoestatística, mapas de solos, zona árida.

1. Introduction

Soil salinization is one of the forms of land degradation that causes difficulties for vegetation growth by influencing soil quality over time, leading to unsustainable agriculture and declining biodiversity and reducing water quality and agricultural production, resulting in sterile land due to excess salts easily dissolved in the surface soil of arid and semi-arid regions (Fan et al. 2011; Bui 2013; Aragüés et al. 2014; Cassel et al. 2015).

According to Gorji et al. (2015) the practice of ancient irrigation techniques as well as unconscious irrigation with salt-rich waters, clearing and the use of fertilizers rich in nitrogen and potassium salts are among the factors causing soil salinity, in addition to other natural factors such as parent material, soil structure, groundwater levels close to the surface, degradation of saline source rock and seawater. Water soluble salt accumulation increases electrolyte concentration in the soil solution and for most plants reduces their capacity to absorb water and growth (Alexandre et al. 2018).

Regular monitoring of land degradation processes, especially in arid and semi-arid zones, provides a precise estimate of the spatial variation in soil salinization on large areas and ensures effective soil and water management and the sustainability of agricultural land use (Afrasinei et al. 2017; Wang et al. 2018).

According to FAO and UNESCO reports, more than half of the world's irrigation systems are under the influence of secondary salinization due to the intensive exploitation of water resources (Rock et al. 1986). Fares and Philippe (2008) and Masoud and Koike (2006) estimated that millions of hectares of agricultural land were abandoned due to salinity accumulation. That endangers the national economy of some countries, such as Argentina, Egypt, India, Iraq, Pakistan, Syria and Iran (Rhoades 1990).

Geostatistics is considered as a reliable and efficient tool for studying and predicting the spatial structure, which is often used to map salinization of soils and water (Pozdnyakova and Zhang 1999; Douaik et al. 2005; Douaoui et al. 2006; Juan et al. 2011; Li et al. 2015a; Li et al. 2015b; Bradai et al. 2016; Boufekane and Saighi 2016; Bas Niñerola et al. 2017). Geoscientists often face interpolation and estimation problems when analyzing sparse data from field observation (Boufekane and Saighi 2016). Soil properties vary continuously in space and time, and are not easy to measure or record everywhere. To represent their spatial variations, the values of individual variables or class types at unsampled locations should be estimated from the data of these variables recorded at the sampling sites (Juan et al. 2011).

Kriging is the basis of the adopted digital cartography and is a geostatistical interpolation technique that has very different types: simple kriging, indicator kriging, ordinary kriging and co-kriging (Bradai et al. 2016). Several researchers have studied soil salinity through the application of different kriging techniques, of which ordinary kriging is the most common. Among these authors, Douaoui et al. (2006) used ordinary kriging (OK) to map soil salinity in the low Chellif plain, while Wang et al. (2018) used the same type of kriging to identify the change in spatial accumulation of soil salinity in an inland watershed in China. Bas Niñerola et al. (2017) demonstrated the benefit of using ordinary kriging for mapping soil properties.

Another geostatistical variant, indicator kriging (IK), is a nonparametric approach based on a preliminary transformation of the studied variable into an indicator taking the value 0 and 1 according to selected thresholds of the variable (Walter et al. 2001; Douaoui 2005). Many authors have adopted this nonparametric geostatistical approach to assess the risk of soil and groundwater pollution (Eldeiry and García 2011; Arslan 2012; Bilgili 2013; Richa et al. 2015; Bradai et al. 2016). Eldeiry and García (2011) used this indicator kriging technique for the management of salinity and Bradai et al. (2016) adopted this type of kriging to improve the accuracy of groundwater salinity predictions in the Low Chellif (western of Algeria).

In Biskra, in the south-east of Algeria, large areas are affected by irrigation problems related to groundwater which causes soil salinization. The municipality of El Ghrous, which covers 3.2% of the irrigated area of the wilaya and represents 3.8% of the useful agricultural area (DSA Biskra 2013), is one of the areas that are affected by salinization. Soil salinity in the study area is caused by excessive use of irrigation water and inadequate or sometimes non-existent drainage systems, which become a threat to soil quality.

In the present study we applied two types of kriging: linear and non-linear, for a better prediction of soil salinity at the irrigated perimeter of El Ghrous using a combination of geostatistics and geographic information systems (GIS). The main purpose of this work is to make an evaluation of soil salinization in the studied perimeter and to estimate its risk using the geostatistical approach.

2. Materials and Methods

2.1. Study area

This study was conducted in the area of El Ghrous (34° 42' 19"N, 5° 17' 07" E) in the wilaya of Biskra, SE Algeria (**Figure 1**). The municipality of El Ghrous belongs to the zone of Zab Elgharbi, 47 km from the chief town of the wilaya of Biskra. It is bordered in the north by the municipality of Tolga, in the west by the municipality of Ech-Chaiba, in the east by the communes of Foghala and Bordj Benazouz and in the south by the communes of Doucen and Lioua. This municipality is characterized by a Saharan climate with an average annual rainfall of 138 mm. Mean annual temperature and relative humidity values are 22.3 °C and 42.9% respectively (ONM Biskra 2015).

The irrigated perimeter has an area of 9,324 ha and an altitude ranging from 130 m to 200 m. Soil salinization in this irrigated area has accelerated in recent years as a result of increased use of groundwater to meet irrigation water requirements.

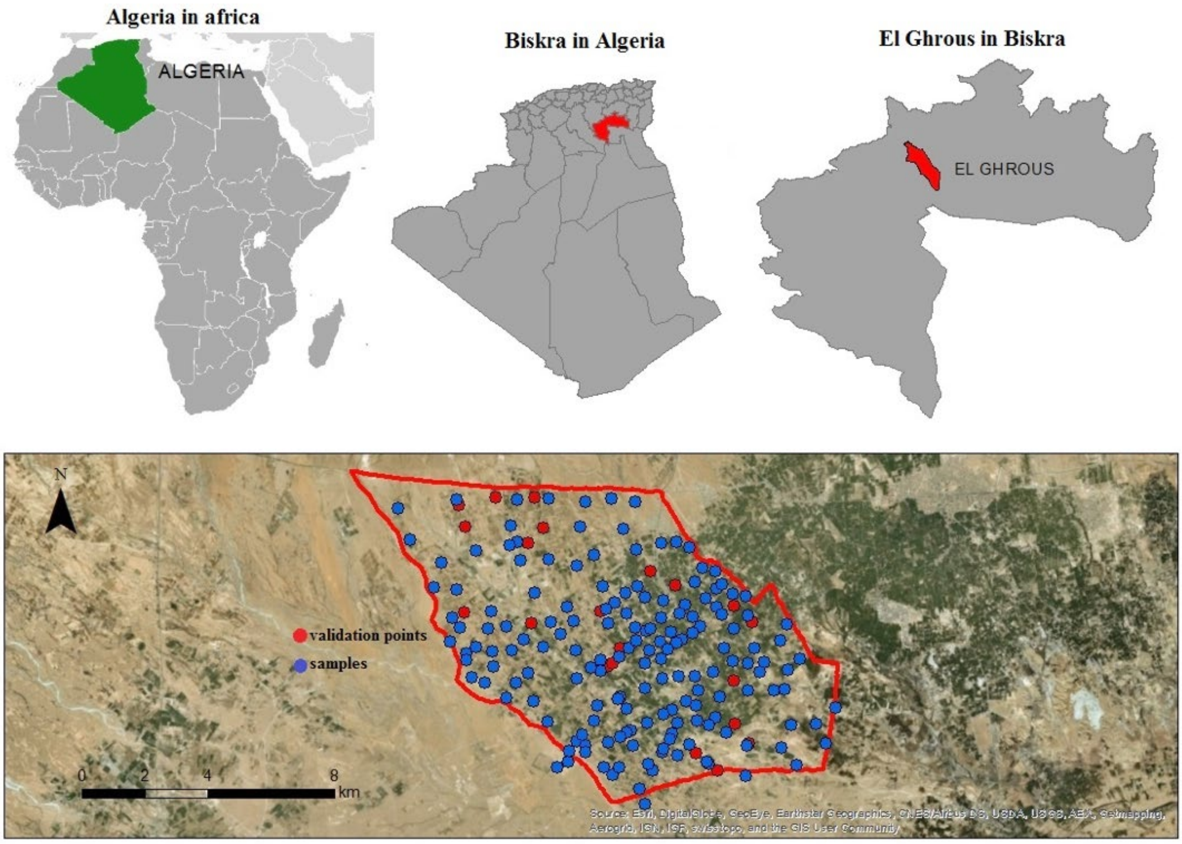

Figure 1. Maps of the geographical location of the study area.

The soils of the irrigated perimeter of El Ghrous are mainly alluvial soils and wind ablation soils (**Figure 2**). The dominant texture is sandy-silt, also in existence of fine silt and silty-sand texture and few soils that have a completely sandy texture.

Irrigation of agricultural land in the study area is provided by groundwater. El Ghrous region is famous for its dates and for its vegetables crops in greenhouses, where three production systems are dominant in this area: a date production system, vegetables crops system and a mixed system (dates and vegetables crops).

2.2. Soil sampling

The sampling was carried out in the period from October to November 2017 with 190 points to measure the electrical conductivity of the soil in the palm groves of El Ghrous. The exact position of the sampling points in latitude and longitude was determined by Global Positioning System with an accuracy of about 2 m (GPS model Garmin Foretrex 201). We adopted a semi-random sampling in the study area (**Figure 1**). Soil samples were taken at a depth of 0-15 cm, where salt accumulation was said to be high. Each sample was air dried, crushed, sieved with a 2 mm sieve and stored in a plastic bag until analysis. Next, we measured soil EC in the laboratory using the 1/5 diluted extract method (USSLS 1954).

2.3. Geostatistical analysis

Kriging, which is part of the geostatistical methods, allows the prediction by homogenizing the statistical characteristics of the real data (Safarbeiranvnd et al. 2018). According to Castrignano et al. (2002) one of the contributions of geostatistics is the possibility of creating error

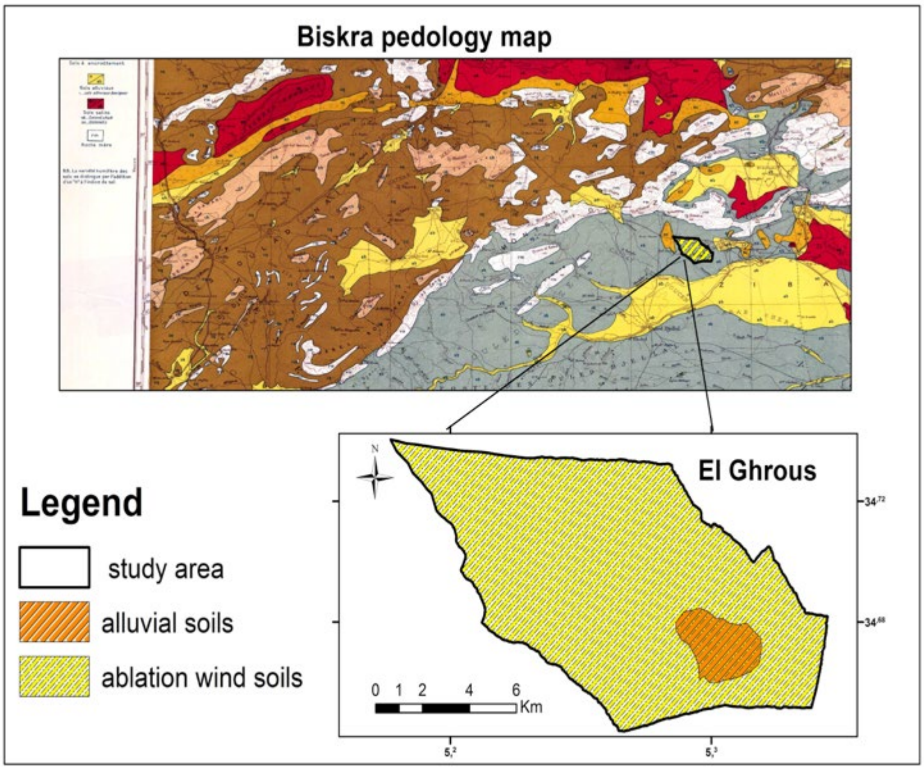

Figure 2. Soil map of El Ghrous.

maps and probability maps. Variography and kriging are the two key constituents for better geostatistical analysis.

According to Arslan (2012) and Bradai et al. (2016), the variogram (h) represents the semi-variance of the difference between attribute values for all points separated by distance. It usually follows **equation 1**:

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

where (h) = estimated or experimental semi-variance value for all pairs at an offset distance h; Z (x_i) = EC value of soils per point h; Z (x_i + h) = EC value (dS m^{-1}) of soils for other points separated by a discrete distance h; x_i = georeferenced positions where Z (x_i) values were measured; and N(h) then represents number of pairs of observations per distance h for the separated points (Delhomme1978).

In this study we applied two types of kriging, the first one is a parametric method–ordinary kriging (OK): this type was used to make predictive maps of salinity in non-sampled points from the other points already sampled, and the second one is non-parametric–indicator kriging (IK) for the purpose of mapping soil salinity probability maps in the El Ghrous perimeter.

2.4. Ordinary kriging

This method is one of the most common and powerful geostatistical techniques used to interpolate soil salinity (Akramkhanov et al. 2011; Triki Fourati et al. 2017). Ordinary kriging is a commonly used linear spatial interpolation method that provides estimates of variables at unsampled locations using information from neighboring points and assigning weights to these points as a function of their distance from the estimated point spatial variability structure (Bilgili 2013).

$$Z^*(x0)=\sum_{i=1}^{n}\lambda i\, Z(x_i) \qquad (2)$$

where Z *(x0) is the estimated value at the location x0, λi returns the weight attributed to the i observation, Z(xi) returns the known value at the sampling point x, and n is the number of sites in the neighborhood search for estimation and it is based on the size of the mobile window which is user-defined.

The weights are assigned to each sample so that the estimation variance is minimized and the estimates are unbiased (Webster and Olivier 2007).

2.5. Indicator kriging

Indicator kriging is a non-parametric geostatistical method for estimating the probability capability that the value of the attribute is not greater than a specific threshold, Z_c, at a given location U (Goovaerts 1997). In IK, the spatial variable Z(u) is transformed into an indicator variable with a binary response which is written as follows:

$$I(x_i; Z_c) = \begin{cases} 1 & if Z(x_i) \geq Z_c \\ 0 & if Z(x_i) < Z_c \end{cases} \quad (3)$$

where I (x_i; Zc) = value of the indicator at a location x_i; Z(x_i) = value measured at a location x_i; and Z_c= threshold. The expected value of I (x_i; Z_c), conditioned by n surrounding data, can be expressed as follows:

$$\text{E}\,[I(x_i; Z_c)] = \text{Prob}\,[Z(x) \leq Z_c]] = \text{F}(x_i; Z_c) \quad (4)$$

where F (x_i;Z_c) = conditional cumulative distribution function (CCDF). The function F represents the probability for an unknown value not exceeding a threshold Zc. CCDFs are modeled using a non-parametric approach (IK) (Eldeiry and García 2011).

2.6. Validation

For ordinary kriging, the validation step was performed using 22 samples (which represents 12% of the sampling frequency). From the 190 points sampled, we randomly selected 22 points to validate. These points are not included in the calculation of the variograms and kriging estimates, but they are estimated at their locations from other measured points, allowing the values of measured variables to be compared with the estimated one. For best prediction, the mean normalized error (MSE) should be close to 0 and the root mean squared error (RMSE) should be as low as possible (Triki Fourati et al. 2017; Arslan 2012). The mean error and the root mean squared error were estimated using the following formulas:

$$\text{ME} = \frac{1}{n}\sum_{i=1}^{n} Z^*(xi) - Z(xi) \quad (5)$$

$$\text{RMSE} = \sqrt{\sum_{i=1}^{n} \frac{1}{n}[Z^*(xi) - Z(xi)]^2} \quad (6)$$

where Z * (xi) = predicted value; Z (xi) = measured value; and n = number of validation points.

For indicator kriging, prediction performance was evaluated by cross-validation. As well as the average error and the mean squared error, three other criteria were retained for this validation step: Root mean square standardized which should be close to 1, mean standardized which must be close to 0 and the average standard should be as low as possible (Arslan 2012).

3. Results

3.1. Descriptive statistics on soil salinity

Soil EC ranges from 0.36 to 8.54 dS m^{-1}, with an average value of 1.89 dS m^{-1}. The variance is 1.24 and the standard deviation of 1.11 dS m^{-1}, which explains the spatial heterogeneity of the data used. **Table 1** shows descriptive statistics on soil salinity of El Ghrous.

Soil salinity values were interpolated using ordinary and indicator kriging in order to draw maps of spatial variability and probability of soil salinity distribution in the search area. Estimates OK and IK were obtained using the software ARCGIS model 10.5 with spatial Geostatistical Analyst.

Table 1. Descriptive statistics of soil salinity measured by electrical conductivity (EC)

Statistical parameters	EC (1/5 dS m^{-1})
Numbre of samples	190
Mean	1.89
Min	0.36
Max	8.54
SD	1.11
Coefficient of variation	58.83%
Variance	1.24
Skewness	2.38
Kurtosis	11.60
Transformation	Lognormal

3.2. Data distribution and soil classifications

A normality test (Kolmogorov-Smirnov) was performed to verify the normal distribution of soil EC data. The asymmetry and flattening (kurtosis) values were 2.38 and 11.6 respectively, which confirms the non-normal distribution of the data used. For this purpose, the values were transformed into logarithm before calculating the semi-variance.

We considered five salinity classes (Durand 1983): (C1) Non-saline: EC = 0-0.6 dS m^{-1}; (C2) Slightly saline: EC = 0.6^{-1} dS m^{-1}; (C3) Moderately saline: EC = 1-2 dS m^{-1}; (C4) Very saline: EC = 2-4 dS m^{-1}; (C5) Extremely saline soils: EC > 4 dS m^{-1}.

The frequency distribution of soil EC (**Table 2**) shows that the C3 class (moderately saline) is dominant with 112 samples (58.94%). Class C4 (very saline soil) represents 24.73% of the samples. The extremely saline C5 class represents 4.23%, the C1 and C2 classes (non-saline class and the slightly saline class) represent a small percentage in the study area. On the other hand, more than 88% of the points analyzed have an EC > 1 dS m^{-1}, which is the minimum level of salinity where it could pose real problems for soil management.

Table 2. The frequency distribution of the electrical conductivity of soils

Class	C1	C2	C3	C4	C5
Percentage %	3.15	8.94	58.94	24.73	4.23
Number	6	17	112	47	8

3.3. Ordinary kriging

In this study, the different models were tested and evaluated, the model we have chosen was selected as the best for this first type of kriging. The experimental omnidirectional EC variability of soils (**Figure 3**) indicates that the exponential model was more suitable for soil EC. The nugget effect (C0) was 0.023 (dS $m^{-1})^2$, the sill (C0 + C) was 0.298 (dS $m^{-1})^2$, and the range was 560 m.

According to Cambardella et al. (1994), Arslan (2012) and Bradai et al. (2016), the spatial dependence can be classified according to the ratio nugget / sill (%), with a ratio < 25% indicates a strong spatial dependence, a ratio of 25-75% signifying a moderate spatial dependence, and a ratio of > 75% for a weak spatial dependence. The quality of the spatial structure influences the accuracy of estimates using kriging models (Leenaers et al. 1990).

In our case, the value of the ratio was 7.7%, which indicates that the soil salinity in the El Ghrous region has a strong spatial dependence.

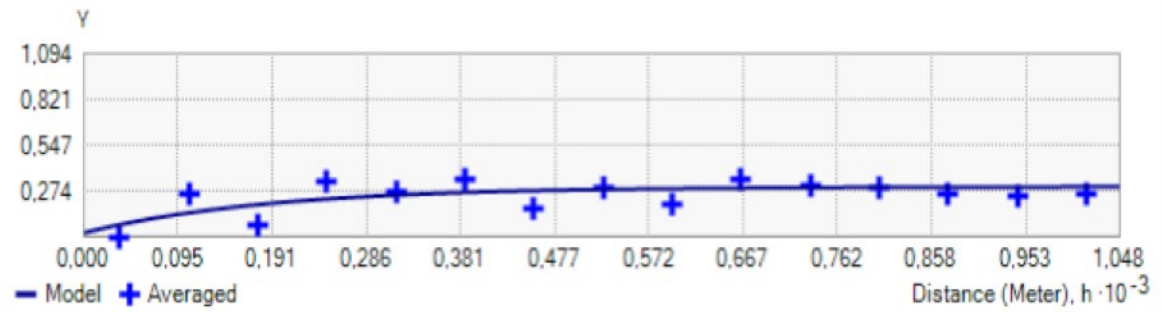

Figure 3. The experimental omnidirectional variogram of the electrical conductivity of soils.

Results obtained by OK show the salinity between 1 and 2 dS m^{-1} (class 3) is dominant. It occupies more than half of the perimeter (53%) which represents 5,025 ha, especially in the center and the south of the study area. In contrast, the northwest of the study area has an EC greater than 2 dS m^{-1} and less than 4 dS m^{-1} which represents class 4, the latter is also present in the center and south of the zone. The unsalted soil (EC < 0.6 dS m^{-1}) represents a very small percentage (1.5%) located in the northeast (**Figure 4**). Extremely saline soil (EC > 4 dS m^{-1}) represents a very low percentage of 1.3% as it is shown in **Table 3** below, this class is located southwest and a little to the south. They appear as spots. The spatial distribution of soil salinity is illustrated in **Figure 4** and the areas in **Table 3**.

Table 3. The area and percentage of each class are obtained after the OK

Classes	Area (ha)	Percentage %
C 1	139.2275	1.49
C 2	383.0224	4.10
C 3	5025.504	53.89
C 4	3659.274	39.24
C 5	117.6873	1.26
Sum	9324.7152	100.00

The validation was done by using 22 samples. We found that the soil salinity mean error was close to 0 (0.04) and the RMSE equal 1.24, which indicate an accuracy of predictions (Sun et al. 2009; Arslan 2012).

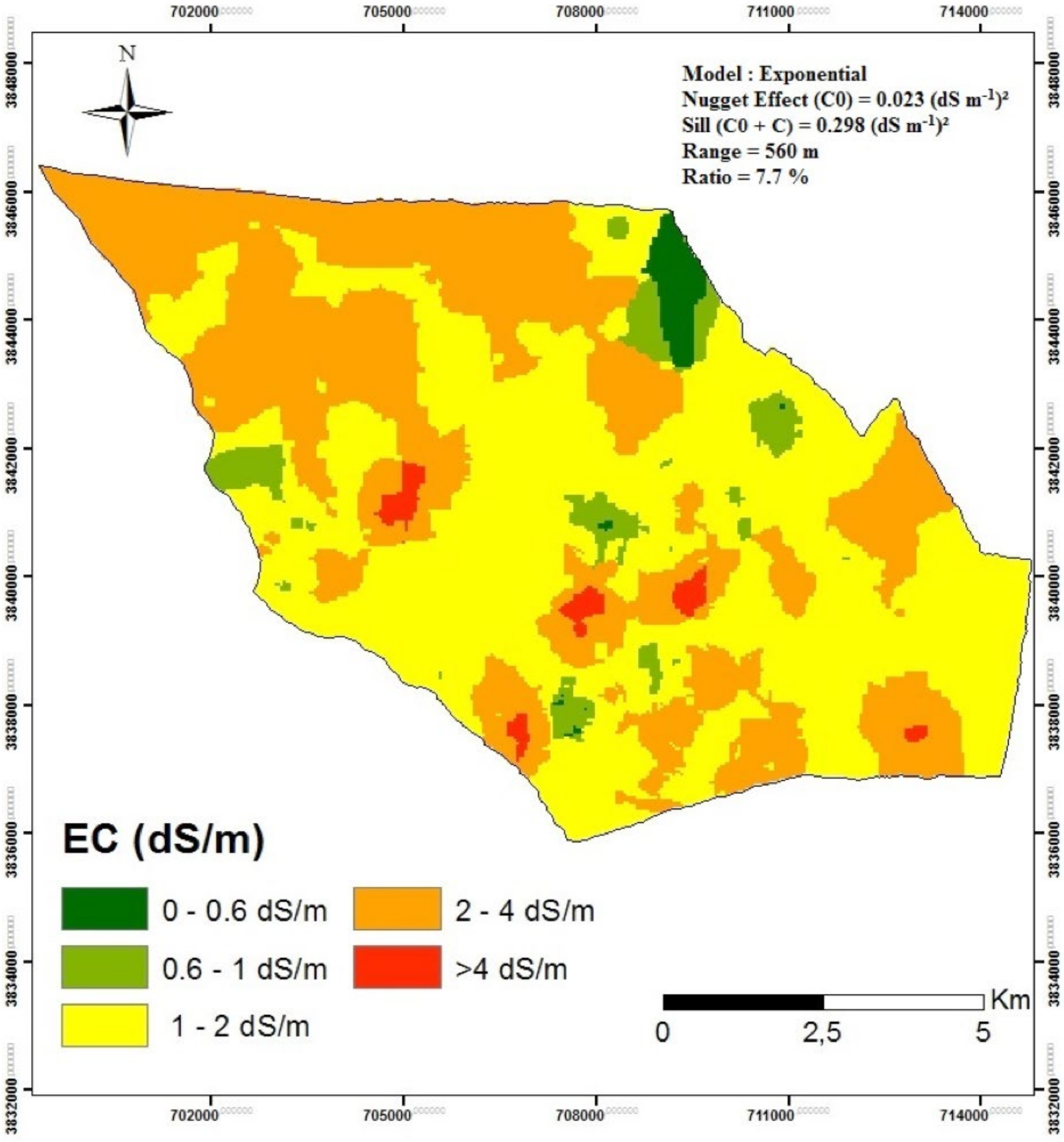

Figure 4. Prediction salinity map by applying OK.

The map of standard error of the salinity estimation obtained by OK shows a more heterogeneous spatial distribution and a higher sensitivity to sampling density (Figure 5). The northern part of the area where the sampling has very low density shows a lower estimation quality. In addition, where the sampling density is very high, the quality of the estimate is good.

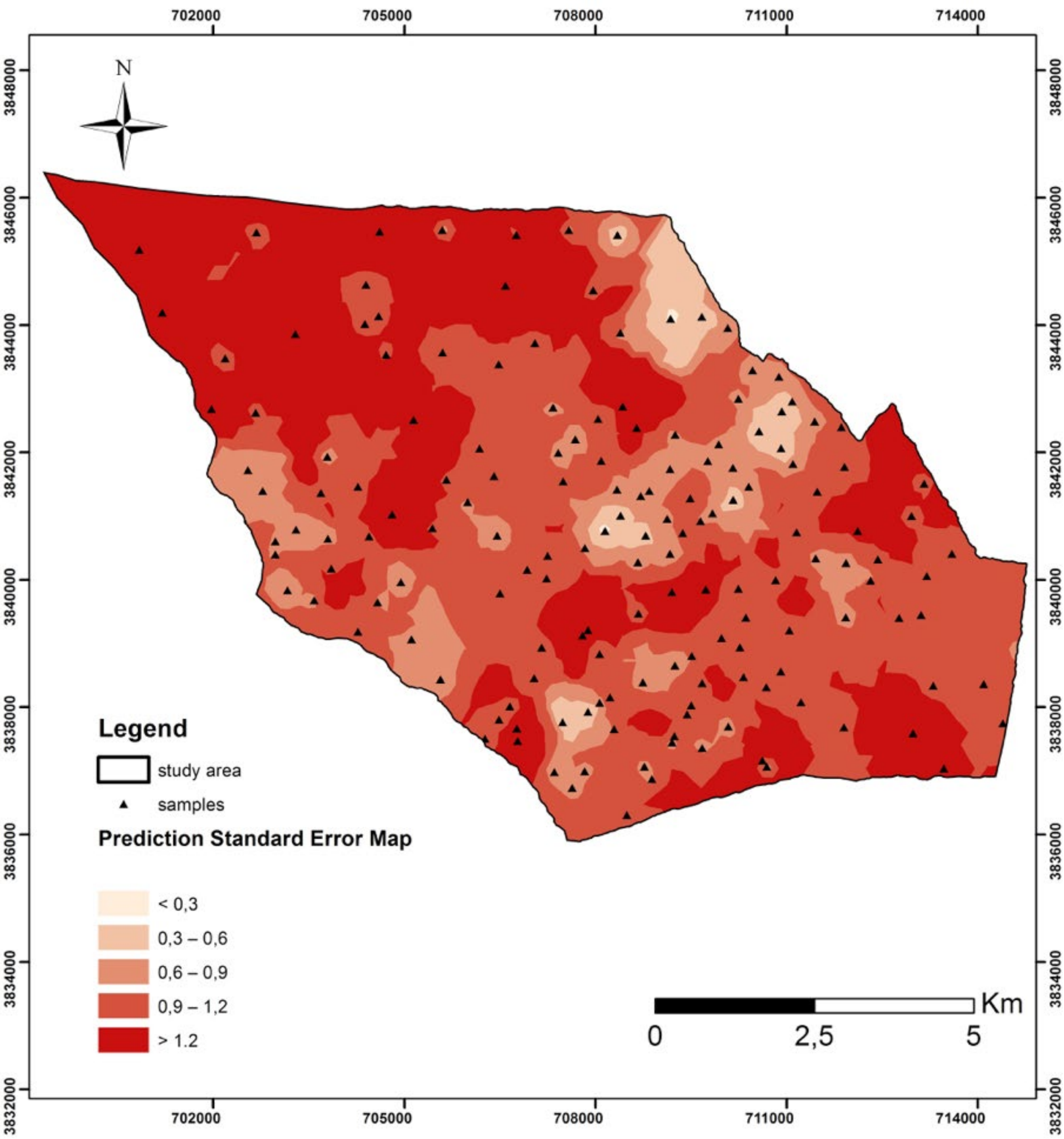

Figure 5. Map of the standard error for OK.

3.4. Indicator kriging

The four thresholds that were selected are the upper limits of the Durand (1983) classification for EC measurements (aqueous extract 1/5): 0.6, 1, 2 and 4 dS m^{-1}, IK has been applied to develop salinity probability maps for El Ghrous soils. The values of the EC measurements are converted into discrete indicator variables with a value of "1" or "0", the index "1" indicating a value greater than the selected threshold (Arslan 2012).

For the EC > 0.6 and CE > 4 dS m^{-1} the spherical model has been adjusted as the most suitable model for these two thresholds compared to the other different types of adjustment, whereas for CE > 1 and CE > 2 dS m^{-1} the exponential model adjusted better.

The ratios (ratio c0 / c0 + c) are illustrated in **Table 4** below: the spherical model in this study (for thresholds 0.6 and 4.0) has a strong spatial dependence (21.72% and 23.1% respectively) and the other models have a mean spatial dependence (40.6% and 42.22% for thresholds 1 and 2 respectively).

Table 4. Characteristic of semivariograms for the adopted IK thresholds

Sills	Model	Range(m)	Sills	Nugget effect	Ratio (%)
0.6	Spherical	415.93	0.0313	0.0068	21.72
1	Exponential	782.46	0.138	0.056	40.57
2	Exponential	1000	0.225	0.095	42.22
4	Spherical	550	0.039	0.009	23.07

According to the study conducted by Bradai et al. (2016), we chose the 50% probability as a degree of overflow significance: more than 99% of the study area exceeded the 0.6 dS m^{-1} threshold, 84% of the area had the highest probability (0.75-1.0) of exceeding 1 dS m^{-1}, the minimum threshold value for salinity and more than 10% of the area had a high probability (0.5-0.75) for the same threshold. Nearly a quarter of the area of this perimeter exceeds the threshold value of CE > 2 dS m^{-1}, mainly located in the northern part of the study area. On the other hand, a small percentage of the area (3%) exceeding the threshold corresponding to the EC value of 4 dS m^{-1} is located around the places where extreme higher values were measured. **Table 5** shows the areas of each probability interval of each threshold.

Table 5. Probability ranges of areas exceeded the EC thresholds obtained by IK

Probability range	EC > 0.6 dS m^{-1}		EC > 1 dS m^{-1}		EC > 2 dS m^{-1}		EC > 4 dS m^{-1}	
	Area (ha)	Area (%)	Area (ha)	Area (%)	Area (ha)	Area (%)	Area (ha)	Area (%)
0.00-0.25	1.17	0.01	51.69	0.55	4,070.69	43.65	8,616.04	92.40
0.25-0.50	39.75	0.42	453.90	4.86	2,939.05	31.51	447.64	4.80
0.50-0.75	279.23	2.99	980.85	10.51	1,910.41	20.48	242.62	2.60
0.75-1.00	9,004.55	96.56	7,838.51	84.05	404.56	04.33	18.40	0.19

The probability maps for the four thresholds are presented in **Figures 6, 7, 8 and 9**.

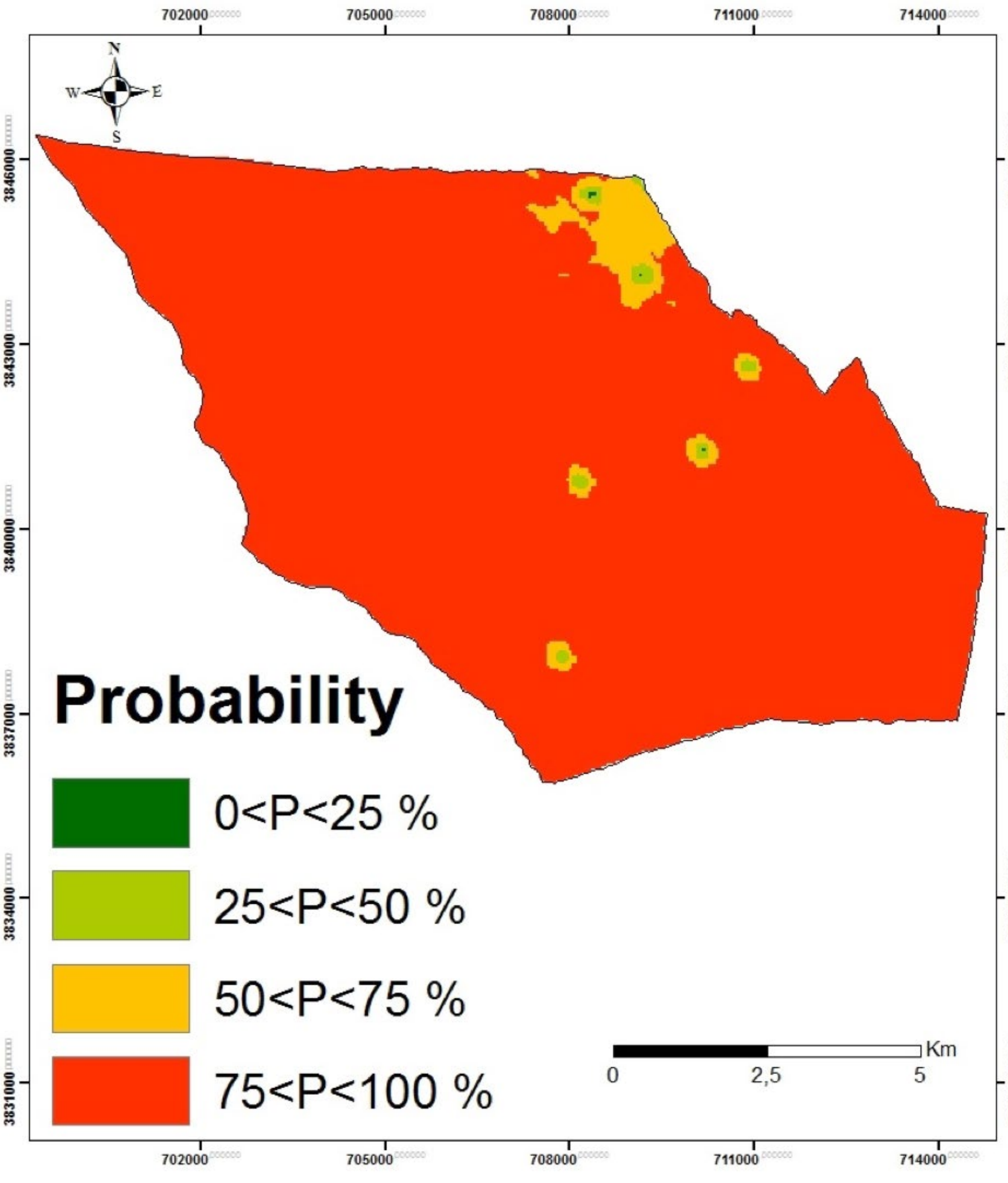

Figure 6. The probability map of soil salinity spatial distribution with EC > 0.6 dS m^{-1}.

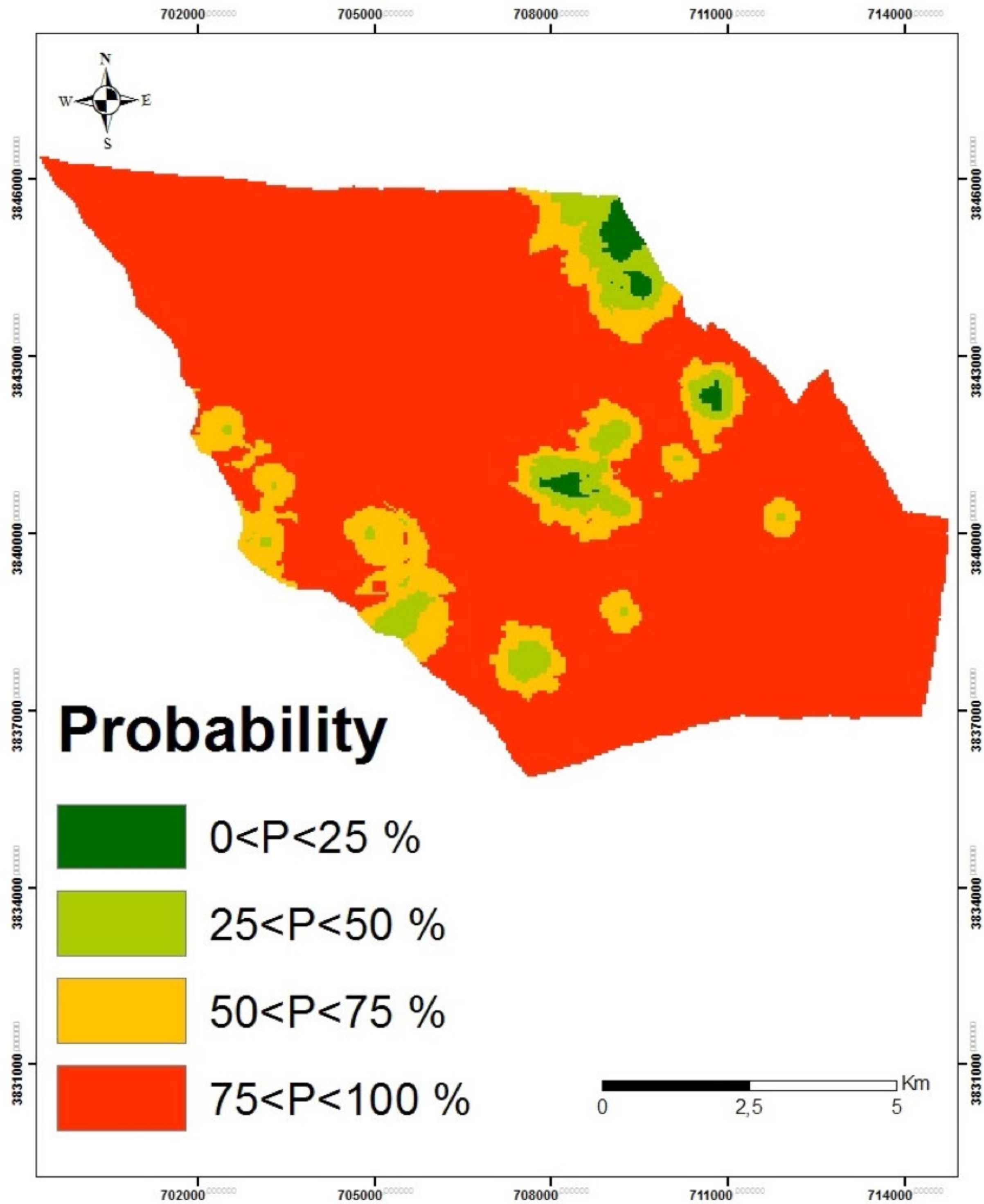

Figure 7. The probability map of soil salinity spatial distribution with EC > 1 dS m^{-1}.

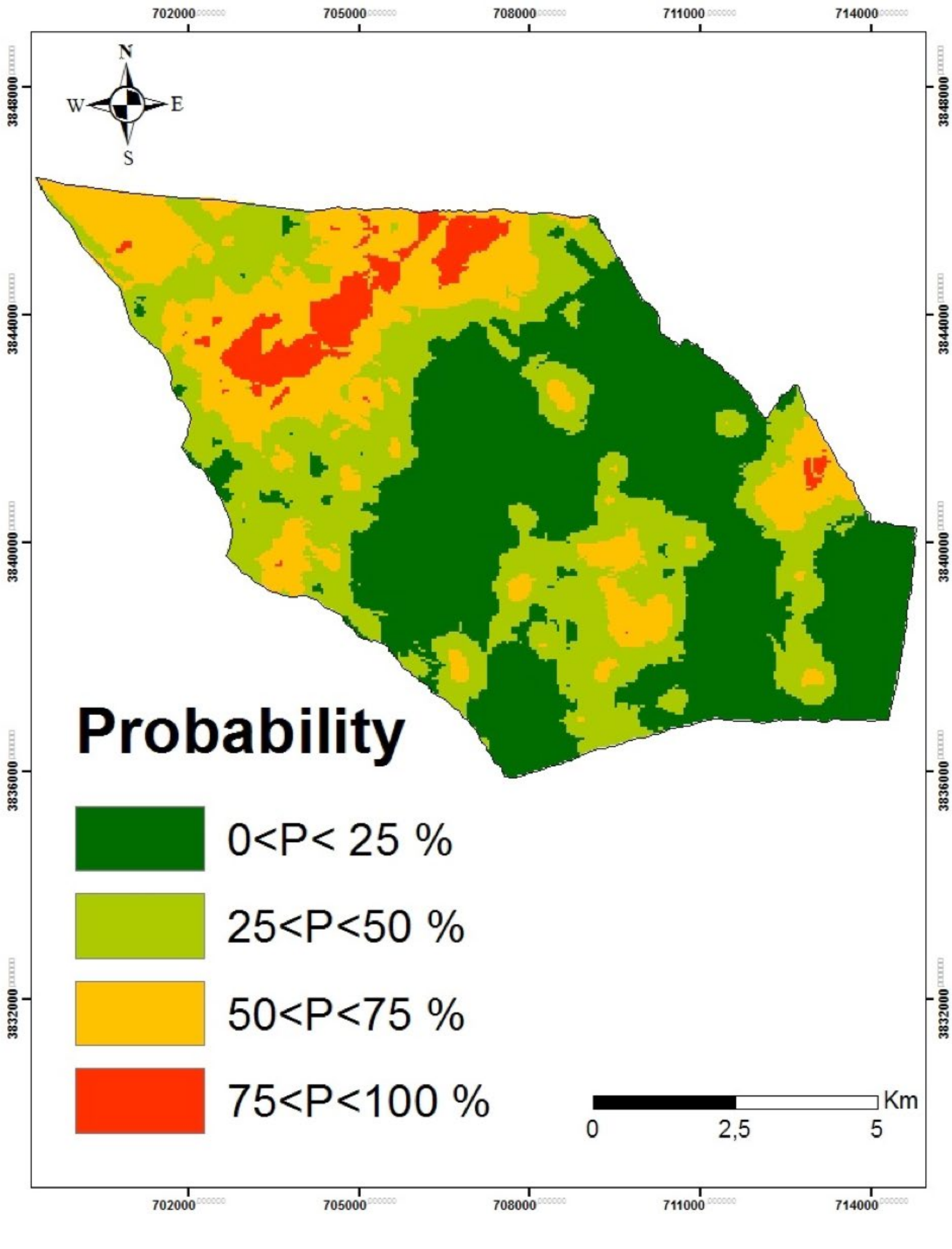

Figure 8. The probability map of soil salinity spatial distribution with EC > 2 dS m^{-1}.

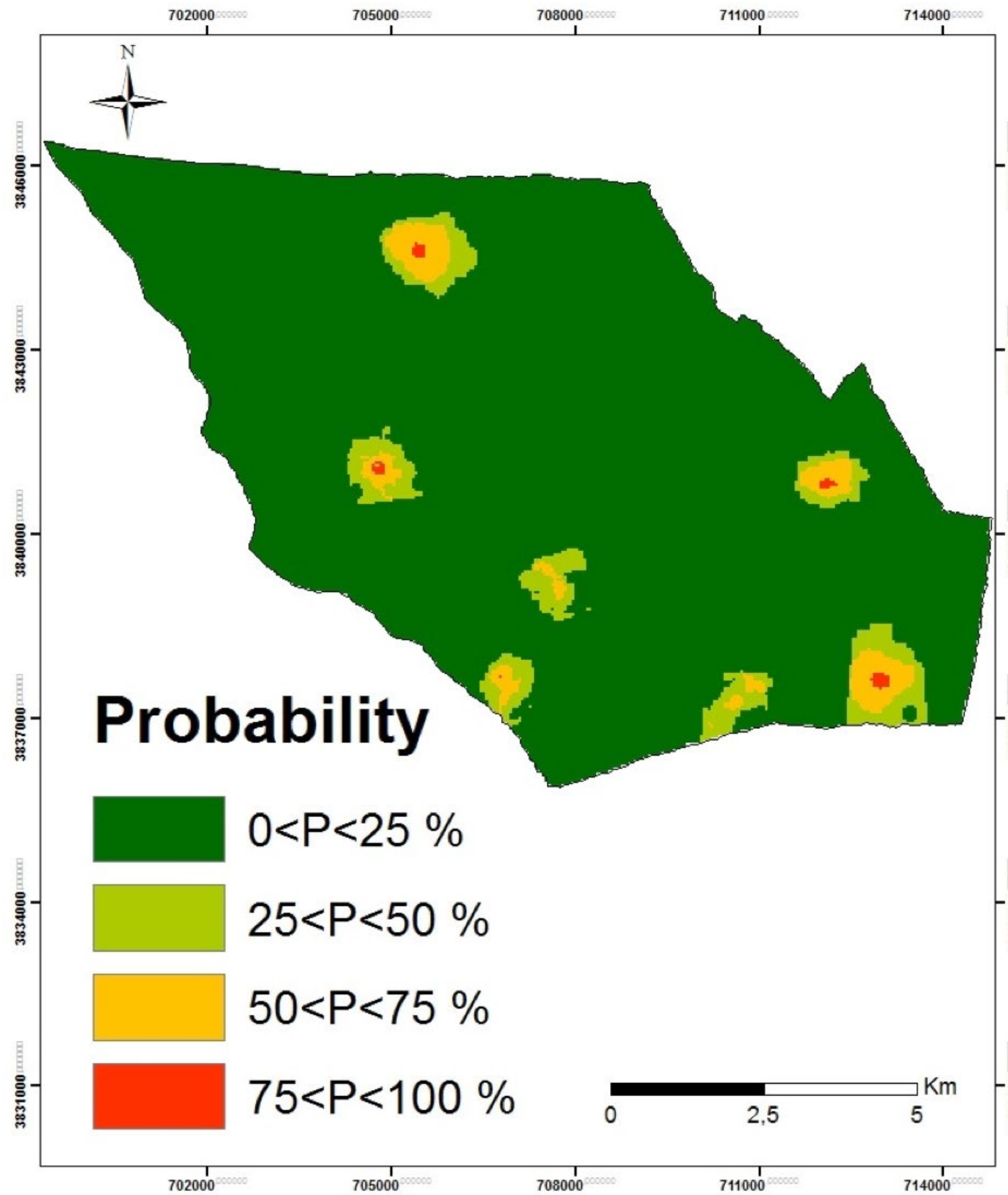

Figure 9. The probability map of soil salinity spatial distribution with EC > 4 dS m^{-1}.

Cross-validation (Table 6) revealed that the soil salinity mean error (ME) was close to 0 (between 0.0001 and 0.0054). The RMSE from 0.86 to 1.3181 was better for both 0.6 and 2 dS m^{-1} thresholds, as it is close to 1, which means a good estimate. RMSE for the EC threshold > 1 m^{-1} was 0.86 which it is lower than 1 indicating that there is an overestimation, but for threshold > 4 m^{-1} which is higher than 1 there is an underestimation (ESRI 2016). The standardized mean error values were close to zero, which means an accuracy of predictions (Sun et al. 2009; Arslan 2012).

Table 6. Cross-validation between measured and estimated values for soil salinity (IK)

Sills	Predicting errors				
	Mean	Root mean square	Average standard	Mean standardized	Root mean square standardized
0.6	0.0014	0.1881	0.1841	0.0085	1.0202
1	0.0001	0.3240	0.3840	0.0024	0.8657
2	0.0097	0.4764	0.4733	0.0172	1.0148
4	0.0054	0.2506	0.2254	0.0190	1.3181

4. Discussion

Since the 1990s, El Ghrous region has undergone a major agricultural change from traditional oasis agriculture to almost exclusive production of dates, followed by market gardening production throughout the year (Khiari 2002; Bouammar 2010). Irrigation by groundwater can either produce the mobility of the salts initially present in the soil, or to bring it to the soil, which will cause problems of soil management and conservation. This remarkable agricultural dynamic in the perimeter of El Ghrous will undoubtedly have negative repercussions on the soil by salinization and sodization with soil structure degradation.

The results obtained by the application of OK illustrated in Figure 4 showed that the area suffered from this phenomenon. If we take the value 1dS m^{-1} as a salinity threshold, more than 88% of the area of this perimeter is affected by salinity. The tolerance of cultures to salts varies from one culture to another.

The sensitivity of the crops to salt stress is reflected in a yield reduction and the tolerance threshold to salinity is specific to each crop. El Ghrous is famous for the date palm cultivation in the old perimeters and vegetable crops in greenhouses, especially in the north of the study area, which are affected badly by soil salinity (Daoudi and Lejars 2016). Vegetable crop culture gives a better yield in areas where the EC values (in aqueous extract 1/5) are less than 1 dS m^{-1} (Bulletin No 29 of FAO). Above this conductivity threshold, yield decreases steadily with increasing salinity and can lead to yield reductions of about 50% for several cultivars such as pepper, salad, potato for an EC threshold of 5 dS m^{-1} (Kotuby-Amacher et al. 2000). In order to obtain a better yield and quality, it is necessary to take into account the nature of the soil and its salinity level as well as the culture tolerance to salinity.

El Ghrous perimeter has large areas of palm cultivation. This plant has a salinity tolerance of water and soil, but for high rates, the date production is poor and of less quality, this salinity affects mainly the growth rate and the weight of the fruit (Girard 1961). In general the quality of the fruit is influenced by the type of cultivars and also by the environmental conditions (Amorós et al. 2014). The date palm can tolerate saline soils to a level of 6% soluble salts according to Arar (1975). This crop can adapt to extreme drought, heat and relatively high levels of soil salinity.

Ramoliya and Pandey (2003) screened particular varieties of date palms for their ability to adapt to salinity and found that some varieties could withstand a relatively high salinity of 12.8 dS m^{-1} with no visible effect on the species.

Another study conducted by Alrasbi et al. (2010) found that other varieties of date palms could tolerate up to 9 dS m^{-1} of soil salinity.

For a better production, cropping systems should use an adequate and effective strategy for a reasonable management of soil salinity. The map obtained by the ordinary kriging application can be used as an effective tool for managers to establish a management plan to minimize salinization of these soils, and for a salinity management and protection strategy of the cultures. A soil salinity map is necessary to assess and monitor salt accumulation and extension (Triki Fourati et al. 2017). This map also showed us the spatial variability of the salinity in the study area and its causes: increased use of groundwater irrigation coming from two different layers, the frequency and the technique of irrigation which is varied between the two systems of cultures (date palm and vegetable crops); and the lack of the drainage networks to drain the charged waters.

The variograms of the indicator functions showed a low nugget effect corresponding to the threshold > 0.6 dS m^{-1} and gradually increased towards the threshold > 2 dS m^{-1}. Soils of less salinity thus show less variability than soils with high salinity, with the exception of the threshold 4 ds m^{-1}, which has the lowest effect nugget, because the number of sample of this class represents just 4% of the soils analyzed as shown in **Table 2**, which explains this low variance value.

Probability maps developed by the application of IK will be useful for local authorities in the continuation of the agricultural land management strategy in the forthcoming PNDA (National Agricultural Development Plan) projects with the aim of creating new sub-areas in the irrigated perimeters and for the agricultural land management plan by identifying the areas at risk in this area. Illegal use of groundwater should be monitored (closure of unauthorized wells), and the introduction of economic irrigation schemes should be encouraged and subsidized.

These maps can be useful for the farmers choosing which crops to plant in their plots. These probability maps show the zones of greater salinity risks, and also takes into account the resistance of the selected crop. This allows for an improvement agricultural productivity and above all for better soil management and improved sustainability.

Our results on soil salinity are consistent with those obtained by Afrasinei et al. (2017) who applied remote sensing techniques for the assessment and monitoring of soil salinity and degradation, carried out in the wilaya of Biskra where the perimeter of El Ghrous is located. Their 2015 land-use maps from a supervised classification illustrated plots and areas within the irrigated perimeter of El Ghrous are classified as very saline, which confirm our results.

Salinization of soils in this area in addition to the nature of the soil, is mainly due to anthropogenic factors such as saline groundwater irrigation, unsuitable irrigation and intensification of agricultural practices, and by climatic factors that have a significant effect on soil salinization where evapotranspiration exceeds 1,200 mm per year with a temperature in summer that can reach peak values up to 45 °C. Salinization of the irrigated perimeter of El Ghrous has directly affected agricultural yield and soil and groundwater quality. This requires rapid intervention by local authorities for the rehabilitation of abandoned soils that are no longer profitable, for the realization of collective drainage networks, and to sensitize the players in the agricultural sector at the local level and accompany farmers by training them for better management of the natural resources.

According to Bas Niñerola et al. (2017), one of the best strategies for saline soil remediation is the proper selection of crops, not only for economic purposes, but also for the control of saline soil and water pollution. Cultures could extract salts and act as phytoremediators because of their ability to adapt to local saline environments.

For the managers in the perimeter, this study allowed us to have a clear view about the current state of soil salinization in this study area. Despite the development projects and efforts that have been made as part of the State's agricultural land concession, the irrigated area of El Ghrous requires the following perspectives that we considered useful: application of leaching rates to ensure that salts accumulate deeper in the soil, installation of drainage networks to keep the aquifer level below the critical salinization level, permanent monitoring and maintenance drains for the evacuation of contaminated water, crop selection based on salinity tolerance, and improvement of irrigation management taking into account the network and the techniques and frequencies that are used.

5. Conclusions

The choice of an interpolation method is very important for a spatial analysis of soil quality. The main objective of this study is to predict soil salinity at the irrigated perimeter of El Ghrous, for which we opted for two types of kriging: ordinary to map spatial variability and indicator kriging to map the probability of exceeding critical salinity thresholds for crop yield and soil degradation.

In the first place, ordinary kriging allowed us to distinguish the different salinity classes. The map resulting from this type of kriging gave predictions with a low RMSE (1.24 dS m^{-1}) and a ME close to zero (0.04 dS m^{-1}) and it has illustrated the advanced state of salinization of the soils in the study area where the moderately saline class occupies more than half of the area. This shows that the perimeter soils are very threatened by this salinity phenomenon, which will certainly lead to soil degradation and sterility.

Secondly, the indicator kriging application has shown that 88% of the study area exceeds the 1 dS m^{-1} value which represents the minimum threshold for soil salinity. This figure is very alarming, and requires follow-up and a rapid response plan to deal with this situation. This study showed the state of irrigated soils in El Ghrous region and their salinity problem, focused on the method of treatment and suggested better solutions to deal with this phenomenon.

6. Acknowledgements

The authors thank Mr. Aidat Toufik, PhD student at the University Mohamed Khider of Biskra, Algeria for his accompaniment in the sampling campaign. Also special thanks to Mr Boudhibi Samir, Miss Badache Sarah and Miss Kendri Samira, PhD students at the University Mohamed Khider of Biskra, Algeria, for their valuable help in the lab analysis.

REFERENCES

• Afrasinei GM, Melis MT, Buttau C, Bradd JM, Arras C, Ghiglieri G. 2017. Assessment of remote sensing-based classification methods for change detection of salt-affected areas (Biskra area, Algeria). Journal of Applied Remote Sensing Vol. 11:11-28.

• Akramkhanov A, Martius C, Park SJ, Hendrickx JMH. 2011. Environmental factors of spatial distribution of soil salinity on flat irrigated terrain. Geoderma 163:55-62.

• Alexandre C, Borralho T, Durao A. 2018. Evaluation of salinization and sodification in irrigated areas with limited soil data: case study in southern Portugal. Spanish Journal of Soil Science 8(1):102-120. Available from: htpps://doi.org/10.3232/SJSS.2018. V8.N1.07.

• Alrasbi SAR, Hussain N, Schmeisky H. 2010. Evaluation of the growth of date palm seedlings irrigated with saline water in the Sultanate of Oman. In: Proceedings of the IV International Date Palm Conference; 2010 Mar 13-17; Abu Dhabi; Vol. 882, p. 233-246.

• Amorós A, Rivera D, Larrosa E, Obón C. 2014. Physico-chemical and functional characteristics of date fruits from different Phoenix species (Arecaceae). Fruits 69:315-323.

• Aragüés R, Medina ET, Zribi W, Clavería I, Álvaro-Fuentes J, Faci J. 2014. Soil salinization as a threat to the sustainability of deficit irrigation under present and expected climate change scenarios. Irrigation Science 33:67-79.

• Arar A. 1975. Soils, irrigation and drainage of the date palm. 3rd FAO Technical Conference of Important Date Producers and Marketing. Paper No. A3.

• Arslan H. 2012. Spatial and temporal mapping of groundwater salinity using ordinary kriging and indicator kriging: The case of Bafra Plain, Turkey. Agricultural Water Management 113:57-63.

• Bas Niñerola V, Navarro Pedreño J, Lucs IG, Pastor IM, Vidal MMJ. 2017. Geostatistical assessment of soil salinity and cropping systems used as soil phytoremediation strategy. Journal of Geochemical Exploration 174:53-58.

• Bilgili AV. 2013. Spatial assessment of soil salinity in the Harran plain using multiple kriging techniques. Environmental Monitoring and Assessment 185(1):777-795.

• Bouammar B. 2010. Agricultural development in the Saharan regions. Case study of the region of Ouargla and Biskra region. PhD Thesis. Ouargla, Algeria: University Kasdi Merbah.

• Boufekane A, Saighi O. 2016. Kriging method of study of the groundwater quality used for irrigation-case of Wadi Djendjen plain (North-East Algeria). Journal of Fundamental and Applied Sciences 8(2):346-362.

• Bradai A, Douaoui A, Bettahar N, Yahiaoui I. 2016. Improving the prediction accuracy of groundwater salinity mapping using indicator kriging method. J Irrig Drain Eng. 142(7):04016023.

• Bui EN. 2013. Soil salinity: a neglected factor in plant ecology and biogeography. Journal of Arid Environments 92:14-25.

• Cambardella CA, Moorman TB, Novak JM, Parkin TB, Karlen DL, Turco RF, Konopka AE. 1994. Field-scale variability of soil properties in central Iowa soils. Soil Science Society of America Journal 58:1501-1511.

• Cassel F, Goorahoo D, Sharmasarkar S. 2015. Salinization and yield potential of a salt-laden Californian soil: an in situ geophysical analysis. Water, Air & Soil Pollution 226:422.

• Castrignano A, Maiorana M, Fornaro F, López N. 2002. 3D spatial variability of soils strength and its change over time in a durum wheat field in Southern Italy. Soil Tillage Research 65:95-108.

• Daoudi A, Lejars C. 2016. From oasis agriculture to Saharan agriculture in the Ziban region of Algeria: actors of dynamism and factors of uncertainty. New Medit 15:45-52.

• Delhomme JP. 1978. Kriging in the hydrosciences. Advances in Water Resources 1(5):251-266.

• Douaik A, Meirvenne MV, Tóth T. 2005. Soil salinity mapping using spatio-temporal kriging and Bayesian maximum entropy with interval soft data. Geoderma 128(3):234-248.

• Douaoui A. 2005. Spatial variability of salinity and its relation with some soil characteristics of the plain of lower Chellif. Contribution of geostatistics and remote sensing. Thesis Doctoral. INA Algiers. 119 p (in French).

• Douaoui AEK, Hervé N, Walter C. 2006. Detecting salinity hazards within a semiarid context by means of combining soil and remote sensing data. Geoderma 134(1-2):217-230.

• DSA Biskra. 2013. Rapport annuelle des activités agricoles. Biskra, Algérie: Direction Des Services Agricoles.

• Durand JH. 1983. Irrigable soils. Pedological study. Presses Universitaires of France. Agency of Cultural and Technical Cooperation. 338 p.

• Eldeiry AA, García LA. 2011. Using indicator kriging technique for soil salinity and yield management. Journal of Irrigation and Drainage Engineering 137(2):82-93.

• ESRI. 2016. ArcGis Desktop: Release 10.4. Redlands: Environmental Systems Research.

• Fan G, Qiang H, Xiaoyi SUN, Zhenglong YAN. 2011. Study on dynamic changes of the soil salinization in the upper stream of the Tarim River based on RS and GIS. Procedia Environmental Sciences 11:1135-1141.

• Fares MH, Philip CG. 2008. Characterization of salt-crust build-up and soil salinization in the United Arab Emirates by means of field and remote sensing techniques. In: Metternicht G, Zinck A, editors. Remote Sensing of Soil Salinization. Taylor & Francis Group, USA. p. 141-152.

• Girard M. 1961. News in the field of phoenicultural research. The days of the date. 3rd and 4th May 1990, Algiers.

• Goovaerts P. 1997. Geostatistics for Natural Resources Evaluation. New York: Oxford University Press. p. 259-368.

• Gorji T, Tanik A, Sertel E. 2015. Soil salinity prediction, monitoring and mapping using modern technologies. Procedia Earth and Planetary Science 15:507-512.

• Juan P, Mateu J, Jordán MM, Mataix-Solera J, Meléndez-Pastor I, Navarro-Pedreño J. 2011. Geostatistical methods to identify and map spatial variations of soil salinity. Journal of Geochemical Exploration 108(1):62-72.

• Khiari A. 2002. A pioneering region in the Algerian Sahara: El Ghrous. Mediterranean 99:27-30.

• Kotuby-Amacher J, Koenig R, Kitchen B. 2000. Salinity and Plant Tolerance. AG-SO-03. Utah State University Extension.

• Leenaers H, Okx JP, Burrough PA. 1990. Comparison of spatial prediction methods for mapping flood plain soil pollution. Catena 17:535-550.

• Li HY, Webster R, Shi Z. 2015a. Mapping soil salinity in the Yangtze delta: REML anduniversalkriging (E-BLUP) revisited. Geoderma 237:71-77.

• Li Y, Wang Y, Houghton RA, Tang L. 2015b. Hidden carbon sink beneath desert. Geophysical Research Letters 42:5880-5887.

• Masoud A, Koike K. 2006. Arid land salinization detected by remotely-sensed land-cover changes: a case study in the Siwa region, NW Egypt. Journal of Arid Environments 66(1):151-167.

• ONM Biskra 2015. National Meteorological Office Climate data for the Biskra region (2015).

• Pozdnyakova L, Zhang RD. 1999. Geostatistical analyses of soil salinity in a large field. Precision Agriculture 1:153-165.

• Ramoliya PJ, Pandey AN. 2003. Soil salinity and water status affect growth of Phoenix dactylifera seedlings. New Zealand Journal of Crop and Horticultural Science 4:345-353.

• Rhoades JD. 1990. Determining soil salinity from measurements of electrical conductivity. Communications in Soil Science and Plant Analysis 21(13-16):1887-1926.

• Richa A, Douaoui A, Bettahar N, Qiang Z, Mailhol J-C. 2015. Assessment and modeling the influence of nitrogen input in the soil on groundwater nitrate pollution: plain of Upper Cheliff (North Algeria). Global NEST Journal 17(4):744-755.

• Rock BN, Vogelmann JE, Williams DL, Voglemann AF, Hoshizaki T. 1986. Remote Detection of Forest Damage. Bioscience 36:439-440.

• Safarbeiranvnd M, Amanipoor H, Battaleb-Looie S, Ghanemi K, Ebrahimi B. 2018. Quality Evaluation of Groundwater Resources using Geostatistical Methods (Case Study: Central Lorestan Plain, Iran). Water Resources Management 32(11):3611-3628.

• Sun Y, Kang S, Li F. 2009. Comparison of interpolation methods for depth to groundwater and its temporal and spatial variations in the Minqin oasis of northwest China. Environmental Modelling & Software 24:1163-1170.

• Triki Fourati H, Bouaziz M, Benzina M, Bouaziz S. 2017. Detection of terrain indices related to soil salinity and mapping salt-affected soils using remote sensing and geostatistical techniques. Environmental Monitoring and Assessment 189(4):177-189.

• USSLS (United State Salinity Laboratory Staff). 1954. Diagnosis and improvement of saline and alkali soils. U.S. Department of Agriculture, Handbook n°60. Washington D.C.: U.S. Government Publising Office.

• Walter C, McBratney AB, Douaoui A, Minasny B. 2001. Spatial prediction of topsoil salinity in the Chelif valley, Algeria, using local kriging with local variograms versus local kriging with whole area variogram. Australian Journal of Soil Research 39:259-272.

• Wang YG, Deng CY, Liu Y, Niu ZR, Li Y. 2018. Identifying change in spatial accumulation of soil salinity in an inland river watershed, China. Science of the Total Environment 621:177-185.

• Webster R, Olivier MA. 2007. Geostatistics for Environmental Scientists. 2nd edition. Chichister: John Wiley & Sons.