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Soil salinity assessment using directed soil sampling from a geophysical survey with electromagnetic technology: a case study

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Abstract

Spatial characterization of soil salinity is required for establishing salt control measurements in irrigated agriculture. For that, cost-effective, specific, rapid, and reliable methodologies for determining soil salinity *in-situ* and processing those data are required. This paper shows the usefulness of an integrated methodology involving a hand-held electromagnetic sensor (Geonics EM38), and the ESAP (Electrical conductivity or salinity, Sampling, Assessment and Prediction) software package to assess, predict and map soil salinity at field scale. The salinity of a 1.74 ha plot of a surface-irrigated field of Navarre, northern Spain, was analyzed by reading the bulk soil electrical conductivity (ECa) with the EM38 sensor at 180 locations. At 20 of those sites, soil core samples were taken at 0.3 m intervals to a depth of 0.9 m, and electrical conductivity of the saturation extract (ECe), saturation percentage (SP) and water content (WC) were measured. Salinity was the dominant factor influencing the EM38 readings. The multiple linear regression (MLR) calibration model predicted ECe from EM38 readings with R^2 ranging from 0.38 to 0.90 for the multiple-depth profile. The ESAP software also provided field range average estimates of soil salinity. Eighty-one percent of the field had ECe values above 4 dS m^{-1}. The obtained salinity map was helpful to display the spatial patterns of soil salinity and identify sources/causes of salt loading.

Additional key words: alfalfa, data-processing software, electromagnetic sensor, EM38, ESAP software, irrigation, salinity problems.

Resumen

Análisis de la salinidad edáfica mediante muestreo de suelos establecido a partir de un estudio geofísico con sensor electromagnético: un caso de estudio

La caracterización espacial de la salinidad edáfica es necesaria para establecer medidas correctoras de la salinidad en la agricultura de regadío. Ello requiere de metodologías específicas, fiables, rápidas y rentables para cuantificar la salinidad *in-situ* y para el procesamiento de dichos datos. Este artículo muestra la conveniencia de un paquete integrado que incluye un sensor electromagnético portátil (EM38 de Geonics) y el paquete estadístico ESAP (cuyas iniciales significan muestreo, evaluación y predicción de la conductividad eléctrica) para analizar, estimar y cartografiar la salinidad edáfica a nivel de parcela. La salinidad de una parcela de Navarra, NE de España, de 1,74 ha, regada por inundación, fue analizada midiendo la conductividad eléctrica aparente (CEa) con el EM38 en 180 puntos. En 20 de esos puntos se muestreó suelo a las profundidades 0-30, 30-60 y 60-90 cm, y en dichas muestras se midió la conductividad eléctrica del extracto de pasta saturada (CEe), el porcentaje de saturación (PS) y el contenido de humedad (CH) del suelo. La salinidad fue el factor más influyente en las lecturas del sensor. El modelo de calibración por regresión lineal múltiple (RLM) estimó la CEe para las diferentes profundidades y para el perfil medio a partir de las lecturas del sensor con coeficientes de determinación (R^2) de 0,38 a 0,90. El programa ESAP estimó además niveles medios de salinidad para el perfil medio. El 81% de la parcela presentaba valores de CEe superiores a 4 dS m^{-1}. El mapa de salinidad cartografiado identificó las áreas más salinas así como posibles fuentes/causas de su salinización.

Palabras clave adicionales: alfalfa, EM38, problemas de salinidad, programa ESAP, riego, sensor electromagnético, software de procesamiento de datos.

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Introduction

Salt accumulation in irrigated agricultural soils reduces the rates of plant growth, yields and in severe cases, leads to total crop failure, threatening the sustainability of agricultural production. Vast areas of irrigated land in the Central Valley of the Ebro River (Spain) are affected and threatened by salinization (Herrero and Aragüés, 1988; Herrero *et al.*, 1993). Mitigating and controlling this problem requires assessing and measuring soil salinity in the root zone in a quick, reliable and cost-effective manner.

Recently new techniques and data-processing methodologies have been developed to assess and monitor soil salinity, overcoming the limitations of the traditional methodology. The electromagnetic (EM) induction sensor has become the first choice for measuring soil salinity in a geospatial context (Rhoades *et al.*, 1999; Corwin and Lesch, 2003). This technology measures *in-situ* the apparent bulk soil electrical conductivity (ECa), which is closely related to soil salinity (electrical conductivity of the soil saturation-extract, ECe). The portable electromagnetic sensor EM38 (Geonics Ltd, Canada) is designed to measure salinity in the agriculturally significant part of the soil (i.e., root zone), typically to a depth of 0.75-1.5 m depending on whether it is held in the horizontal or vertical mode of operation, respectively (Rhoades *et al.*, 1999). Measurements are taken quickly in the field, and the volume of measurement is large, perhaps 2-3 m^3, reducing local-scale variability. However, the ECa (EM) measurements can also be influenced by other soil variables such as texture and water content. Even though in saline soils salinity dominates the ECa measurements, it is necessary to know the other factors' influence on ECa to appropriately interpret the information conveyed by the ECa (EM) map. The simultaneous interaction among these properties must be first quantified before an accurate projection of the ECa-soil property correlation structure can be made (Lesch and Corwin, 2003).

The EM measurements need, however, to be calibrated (establishment of a direct ECe = f(EM) prediction equation) with classical sampling techniques for specific soil type and water-content conditions. It is necessary to establish an accurate ECe-EM relationship using a limited number of soil samples. Nevertheless, field and laboratory workload is much less than for the traditional methods. Several methods of calibration have been successfully developed (McKenzie *et al.*, 1989; Rhoades and Corwin, 1990; Díaz and Herrero, 1992; Lesch *et al.*, 1992, 1995a,b; Herrero *et al.*, 2003).

Proper data interpretation represents a critical component of any survey process. Correct data interpretation ultimately is the difference between simply collecting soil conductivity data and collecting assessment data which can be used to address soil and water management issues. To increase efficiency in collecting and interpreting soil conductivity data, the U.S. Salinity Laboratory Staff (ARS-USDA, Riverside, California) developed conductivity modeling software (Electrical conductivity Sampling Assessment and Prediction-ESAP; Lesch *et al.*, 1995a,b, 2000, 2002a,b). This user-friendly software allows (i) the generation of conductivity survey maps and directed soil sampling designs based on these maps, (ii) the calibration of conductivity signal data into soil salinity data, and (iii) the interpretation of the predicted spatial soil salinity data. The obtained information is useful for assessing various farm management practices.

The main objective of this paper is to show the usefulness of an integrated package including the hand-held EM38 sensor and the ESAP software programs for assessing and mapping soil salinity. The specific objectives include (i) determining the main factors influencing ECa readings and (ii) assessing, predicting and mapping the soil salinity of an irrigated plot.

Material and Methods

Study-site description

The 1.74-ha-plot (CAB1) is located in a low terrace of the Ebro river (Cabanillas-Navarre, Spain), between the river and the Tauste irrigation canal (Fig. 1A and B). This area corresponds to a flood plain. In this area, salinity accumulates in the depositional-fan of some gullies proceeding from the North East. These gullies deliver salts (gypsum and others) from the saliferous Miocene strata from which they are cut. The soil is classified as Xeric Torrifluvent (Gobierno de Navarra, 1987). The area frequently presents a shallow water table due to the rise of the Ebro river level. In order to enhance drainage and avoid salt accumulation, a drainage collector, parallel to the Ebro river, was built (Fig. 1A and B).

The study was conducted in October 2003. The plot was selected for the study because of the high salinity variability detected in a previous reconnaissance survey

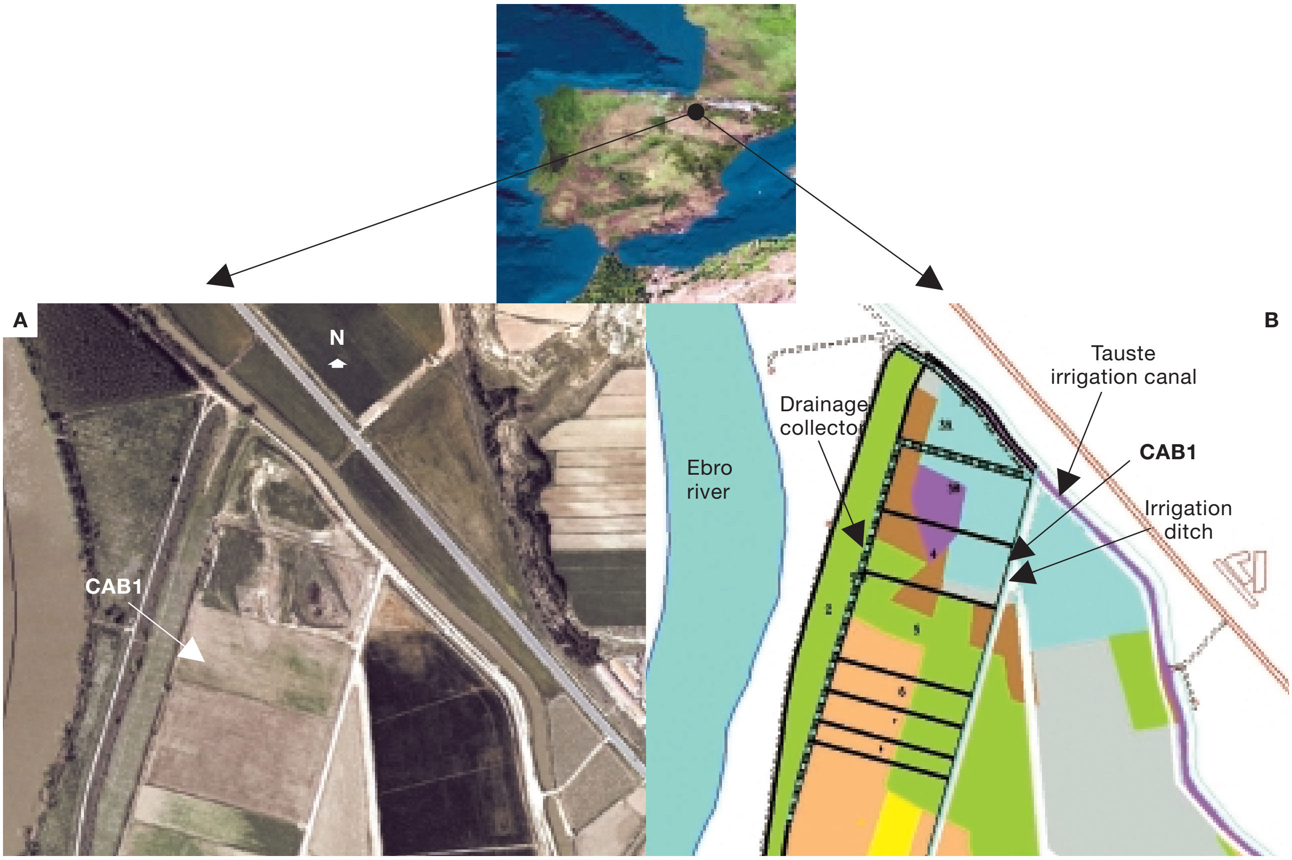

Figure 1. Location of the CAB1 plot: (A) aerial photograph and (B) map of the new plot after «land-consolidation» (black contour lines) overlapped on the map of classes of soil aptitude for agricultural use (the different colors represent different classes).

on June 10th. Since 2002, the plot included soils of different quality, as a result of the land-consolidation performed by the Government of Navarre (SEA, 2002). The field was left fallow one year, and in September 2003 the plot was leveled and alfalfa was sown and immediately surface-irrigated with a total amount of water of about 950 m^3 ha^{-1}. The electrical conductivity (EC) and the sodium adsorption ratio (SAR) of the irrigation water were 0.88 dS m^{-1} and 2.07 (mmol L^{-1})$^{0.5}$ respectively.

Field measurements

The EM38 readings (9 October 2003) were made in an orthogonal grid of 10 m × 10 m, in a total of 180 points (Fig. 2). At all survey points, two EM readings were made, one with the coil of the EM38 device positioned horizontally to the soil surface (EMh) and the second one with the device positioned vertically (EMv). These readings were performed a few days after an irrigation event and several rains, i.e., when the soil water content

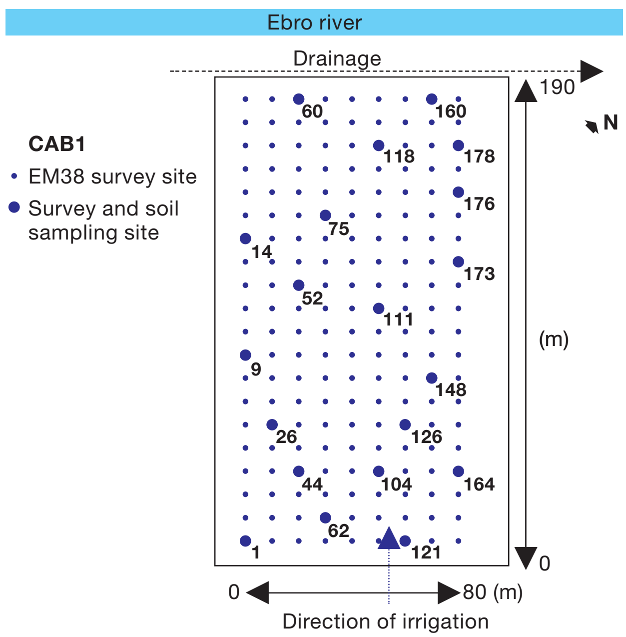

Figure 2. Locations of EM38 survey sites and soil sampling sites in the plot CAB1.

was close to field capacity. The soil temperature was measured at depths of 20 and 40 cm in order to convert EM38 readings to the reference temperature of 25°C. The EM38 readings were mapped with the ESAP-SaltMapper program (Lesch *et al.*, 2002b), which employs inverse-distance-squared (IDS) interpolation.

Soil sampling for EM38 calibration and laboratory analysis

Twenty of the 180 points, covering the full range of EM38 measurements and the entire study area, were chosen with the ESAP-Response Surface Sampling Design (ESAP-RSSD) software (Lesch *et al.*, 2002a) for soil sampling and EM38 calibration purposes (Fig. 2). This software uses the «response surface sampling design» statistical methodology to select a set of sample sites which optimizes the prediction model (Lesch *et al.*, 2002a). Automatic selection of calibration sites saves time and work for the researcher and optimizes the calibration model. The obtained sampling design had an optimization criteria value of 1.03, indicating an excellent uniformity (evenly spread across the field) of our sampling plan, according to Lesch *et al.* (2000).

Directly beneath the EM38, soil samples were collected by hand augering at 0.30 m intervals to a maximum depth of 0.90 m for laboratory analysis of ECe and saturation percentage (SP). The 60 soil samples were air-dried, ground and sieved (< 2 mm), and ECe and SP were measured by standard methods (USSL Staff, 1954). Additional soil samples were taken in small hermetic containers for determining gravimetric water content (WC). This was calculated from the mass lost after drying at 50ºC (because of the possible presence of gypsum) for one week. Calibration of EM measurements for prediction of EC by regression techniques considers soil texture and water content as influential variables (McKenzie *et al.*, 1989; Vaughan *et al.*, 1995). Therefore, SP (closely related to soil texture, Lesch *et al.*, 2000) and WC were determined to analyze their spatial variation within the field and their influence on ECa data.

Data analysis

EM38 readings, WC, SP and ECe values were analyzed with the ESAP software package (vs 2.01; Lesch *et al.*, 2000). Basic statistical parameters (mean, standard deviation, coefficient of variation-CV, and minimum-min and maximum-max values) and frequency histograms were examined.

Predominant soil properties influencing ECa measurements: Preliminary correlation analysis

In order to determine the predominant soil properties influencing the ECa (EM) measurement in our study area, a stochastic statistical approach («Dual Pathway Parallel Conductance-DPPC» correlation analysis) developed by Rhoades *et al.* (1989) and included in the ESAP-Calibrate program (Lesch *et al.*, 2000) was performed. Based on the soil samples' salinity (ECe), texture (SP) and WC values, a data set of 20 bulk average profile apparent soil conductivities were estimated by the DPPC model (calculated-calc ECa). Correlation analysis was established between (i) the calculated (calc ECa) and measured conductivity readings (EM38 readings or acquired ECa values), (ii) the measured conductivity readings (EM38 readings) and the measured soil variables (ECe, SP, WC), and (iii) the calculated readings (calc ECa) and the soil data (ECe, SP, WC). A complete description of the theoretical development of the DPPC model and its practical applications can be found in Rhoades *et al.* (1989), Corwin *et al.* (2003), and Lesch and Corwin (2003).

The correlation between estimated (calc ECa) and measured (EM38 data or acquired ECa) conductivity readings reflects the reliability and consistency of the survey data, serving as a survey data validation (Lesch and Corwin, 2003). The correlation between EM38 readings (acquired ECa values) and the soil data (ECe, SP, WC) allows determining the dominant factor influencing the ECa measurement within the study area (i.e., understanding how soil properties influence the acquired ECa data). It also helps interpreting the spatial distribution of soil salinity. The correlation between estimated conductivity readings (calc ECa) and the soil data (ECe, SP, WC) allows prediction of the expected correlation structure between ECa data and multiple soil properties.

In summary, the DPPC model has been used in a general-purpose validation procedure for survey data and for understanding how different soil properties influence the acquired ECa data.

Calibration of the EM38

The calibration equation for converting EM38 readings (EMh and EMv) into ECe data was estimated through the spatially referenced-depth specific-Multiple Linear Regression (MLR) model developed in the ESAP-Calibrate program (Lesch *et al.*, 2000), using log-transformed variables (lnEMh, lnEMv, lnECe). In the MLR modeling approach, the EM38 readings were combined with the trend surface parameters (spatial coordinates of each survey site; Lesch *et al.*, 2000). Thus, the prediction of the log soil salinity levels within a field from log transformed EM38 conductivity survey readings acquired across the field was performed using the following regression model:

$$\ln(ECe) = \\ = bo + b1(\ln \mathrm{EMh}) + b2(\ln \mathrm{EMv}) + b3(x) + b4(y) \quad [1]$$

where x and y represent the spatial coordinate locations of the EM38 survey data, and bo, $b1$, $b2$, $b3$, and $b4$ are the parameter estimates.

In practice, transformed and decorrelated signal data (i.e., the principal component scores) were used in place of the raw signal readings as predictor variables in the regression equation. The decorrelation procedure was pursued to eliminate colinearity between the EM readings, whereas the scaling techniques of the trend surface parameters were used to increase the prediction accuracy (Lesch *et al.*, 1995b).

Thus, the depth-specific MLR salinity prediction model was finally defined as:

$$\ln(\mathrm{ECe}) = bo + b1(z1) + b2(z2) + b3(u) + b4(v) \quad [2]$$

where $z1$ and $z2$ are the decorrelated signal readings (i.e., the principal component scores) and (u, v) represent the scaled spatial coordinates of each survey site.

The EMh and EMv readings were converted in $z1$ and $z2$ using:

$$z1 = a1\ [\ln\mathrm{EMv} - \mathrm{mean}\ (\ln\mathrm{EMv})] + \\ + a2\ [\ln\mathrm{EMh} - \mathrm{mean}\ (\ln\mathrm{EMh})], \quad [3a]$$

$$z2 = a3\ [\ln\mathrm{EMv} - \mathrm{mean}\ (\ln\mathrm{EMv})] - \\ - a4\ [\ln\mathrm{EMh} - \mathrm{mean}\ (\ln\mathrm{EMh})], \quad [3b]$$

where $a1, a2, a3$ and $a4$ are determined by the principal component algorithm.

The first principal component score ($z1$) represents an approximate average of the two EM readings at each survey site, whereas the second principal component score ($z2$) represents weighted linear contrasts between these same sensor readings (Lesch *et al.*, 1995a).

The spatial coordinate locations of the EM38 survey data were centered and scaled as:

$$u = (x\text{-}\min[x])/k;\ v = (y\text{-}\min[y])/k; \quad [4]$$

where k = the greater of ($\max[x]$-$\min[x]$) or ($\max[y]$-$\min[y]$).

The best calibration model for all of the depths, i.e., the one with (i) all the estimated parameters statistically significant ($P < 0.05$), and (ii) the lowest sum of squares of the jack-knifed prediction errors was selected. The jack-knifed prediction errors represent the difference between predicted and true values, being the predicted values those estimated by the model after temporarily removing each data point from the data set and using the remaining data points to predict them at the removed sites.

The selected model was then computed for the three increasing sampling depths and for the bulk average sample values (bulk profile) and the coefficients of the calibration equations were estimated.

Residuals from the adjusted models were tested using the standard residual diagnostic plots/tests of the ESAP-Calibrate program (Lesch *et al.*, 2000). The assumption of spatial independence was tested by the Moran autocorrelation test (Lesch *et al.*, 1995a); the normal distribution of residues was verified using the quantile-quantile plot and the homogeneity of variance through the residual *versus* prediction plot.

A realistic assessment of the prediction accuracy of the calibration models was established by comparing the observed and predicted soil salinity. The predicted salinity levels were expressed as «jack-knifed» predictions, where each observation was sequentially removed from the regression model and then predicted using the remaining sample data (Lesch *et al.*, 2000).

Statistical significance was reported at the 0.05 (*), 0.01 (**), and 0.001 (***) probability levels.

Spatial variability of soil salinity estimates

The calibration equations for the three sampling depths and for the bulk profile (average profile) were used to predict the ECe values at all of the remaining nonsampled sites from the EM readings. Then, a soil salinity raster map was generated from the 180 electromagnetically estimated ECe data for the average profile (0-90 cm) using the ESAP-SaltMapper program, which employs inverse-distance-squared (IDS) interpolation. Finally, field average salinity estimates were obtained with the ESAP-Calibrate program, computing the average level of the predictions (0-90 cm) within the entire survey area. The proportion of the survey area within different salinity intervals was established.

Results and Discussion

Exploratory data analysis and salinity profiles

Frequency histograms of EMh and EMv pointed out that these variables were not normally distributed (data not shown), so, they were logarithmically transformed for the regression analysis. An outlier (unusual value; i.e. #6) was detected and excluded for the study. The relevant statistics of the EM38 readings (EMh and EMv), and of the values of SP, WC and ECe are shown in Table 1.

The coefficients of variation of EMh, EMv and ECe were very high (in particular for ECe), confirming the large variability in soil salinity within the field.

The EMh and the EMv readings were linearly correlated ($P < 0.001$; Fig. 3), confirming colinearity between both readings. Most of the points are in or above the 1:1 line, indicating the predominance of uniform (EMv ≈ EMh) or regular (EMv > EMh) salinity profiles. Points under the line 1:1 show the presence of inverted profiles (EMv < EMh).

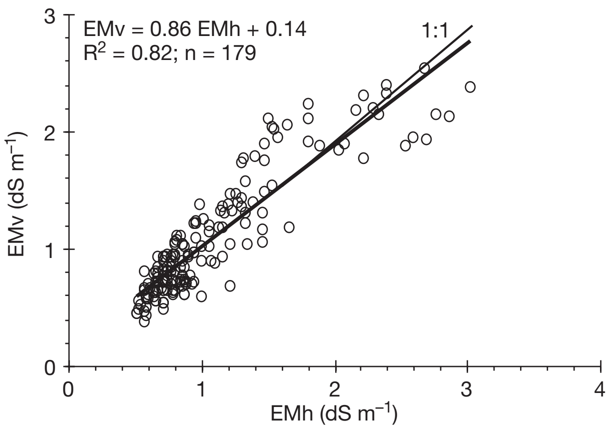

Figure 3. Linear regression equation between EMh and EMv readings obtained at the 179 monitoring points.

Inverse-distance-squared interpolated maps of EMh and EMv readings taken at the monitoring sites are shown in Fig. 4. These EM data provide a rapid and easy means of establishing the spatial distribution and variability of the electrical conductivity (ECa). Mean and maximum values of ECe reflect that the soil is from moderate to very strongly saline (Table 1).

The ECe salinity profiles plot (Fig. 5) reveals that most of the profiles appear to be either inverted (ECe of the surface layer greater than the ECe of the deeper layers) or uniform (ECe fairly constant in depth), and the salinity levels throughout most of the profiles are above 4 dS m^{-1}. This suggests rather poor management; i.e., either insufficient water application or perhaps a drainage problem.

Table 1. Relevant statistics of the EM38 (EMh and EMv, dS m^{-1}), electrical conductivity of the soil saturation extract (ECe, dS m^{-1}), saturation percentage (SP, %) and water content (WC, %) values measured for the 180 monitoring points and the 20 soil sampling points

Parameters	n	Mean	Standard deviation	Coefficient of variation (%)	Minimum	Maximum
EMv	180	1.064	0.514	48.3	0.370	2.540
EMh	180	1.058	0.538	50.9	0.510	3.030
EMv	179[a]	1.060	0.513	48.4	0.370	2.540
EMh	179[a]	1.060	0.539	50.8	0.510	3.030
ECe (0-30 cm)	20	8.83	5.87	66.5	3.06	28.40
ECe (30-60 cm)	20	7.77	4.98	64.1	1.21	17.63
ECe (60-90 cm)	20	7.45	5.55	74.6	1.44	20.50
SP (0-30 cm)	20	38.03	2.82	7.4	31.58	42.11
SP (30-60 cm)	20	35.86	5.22	14.6	26.32	44.47
SP (60-90 cm)	20	36.43	4.98	13.7	26.32	43.89
WC (0-30 cm)	20	19.34	1.57	8.1	16.52	22.04
WC (30-60 cm)	20	17.59	2.22	12.6	13.13	22.29
WC (60-90 cm)	20	18.32	2.71	14.8	14.35	22.88

[a] Outlier #6 excluded.

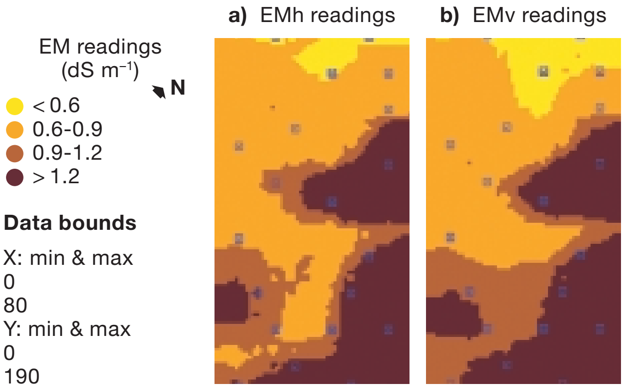

Figure 4. Raster maps of (a) EMh and (b) EMv readings (dS m^{-1}) taken at the survey sites (blue points).

The slight disagreement on the predominant profile-type, based on EMv/EMh readings or ECe values, comes from the fact that the EM38 instrument measures soil salinity to a 1.5 m-depth while the ECe values correspond to a depth of up to 0.9 m. This implies that soil layers below the maximum depth of sampling contributed significantly to the EM38 readings.

In the past, a salinity map would have been prepared by the interpolation of the ECe values measured at only 20 points. However, nowadays, the low resolution of that map reduces its potential use for any specific decision-making strategy-purpose. Moreover, in the classical soil survey methodology the sampling density would have been much lower, reducing further the map resolution.

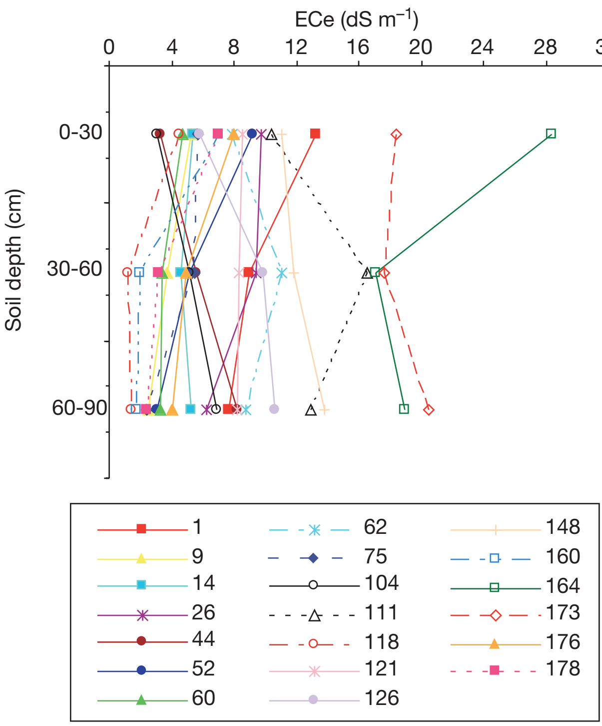

Figure 5. Salinity (ECe, dS m^{-1}) profiles (0-90 cm) of the 20 soil sampling sites.

Mean values of the SP reflect the loam texture of the soil, and mean and minimum values of WC confirm that soil water content was at or near field capacity (field capacity = SP/2; Rhoades *et al.*, 1999) during the survey process (Table 1), a prerequisite for the optimum sensor operating procedure. Both soil variables (SP, WC) present low spatial variability within the field according to the low CV values of their means (lower than 15%; Table 1). The low variability of WC is consistent with the entire field being managed by surface irrigation and the heavy rain that fell prior to the EM38 survey. Minimizing texture and water content variation within the field maximizes the correlation between salinity and ECa, mainly in saline soils, improving the salinity data estimation and interpretation. The interpretation of ECa measurements as spatial variation in soil salinity is straightforward when other potential contributing factors (WC and SP) show only minor spatial variability.

Preliminary correlation analysis results: DPPC correlation analysis

The high correlation (r = 0.954***) between predicted ECa (calc ECa) and observed/acquired ECa (*z*1 or transformed EM readings) data shows that the DPPC model is fairly robust, and validates the survey data under these circumstances.

The observed correlation between EM38 readings and soil properties (Table 2) indicates that only soil salinity (ECe) strongly correlates with the EM data, confirming that salinity is the dominant factor influencing the ECa measurement. The predicted correlation between those variables strengthens that conclusion (Table 2). The minimal sample variation of SP and WC within the field (Table 1) and the lack of correlation between them and salinity (Table 2) is probably responsible for their poor correlation with the EM data. According to Corwin and Lesch (2003), the final correlation estimates in any specific survey situation are strongly influenced by both the variability of each (primary) soil property and the degree of correlation between the soil property and the EM data.

The field studied represents the best scenario for the prediction of salinity from ECa signal data, because

Table 2. Dual pathway parallel conductance (DPPC) correlation analysis for the bulk average profile: Observed and predicted correlation coefficients between ECa/EM values and soil properties, and observed correlation coefficients among the soil properties themselves

	ECa/EM correlation with soil properties		Correlation among soil properties		
	Observed correlation	Predicted correlation			
Soil properties	**Acquired ECa (variable $z1$)**	**Predicted ECa**	**ECe**	**SP**	**WC**
ECe	0.937***	0.942***	—		
SP	0.398ns	0.345ns	0.214ns	—	
WC	0.495*	0.370ns	0.387ns	0.091ns	—

ECa: apparent electrical conductivity. ECe: electrical conductivity of the soil saturation extract. EM values: electromagnetic values. SP: saturation percentage. WC: water content. Levels of significance: $*p < 0.05$, $***p < 0.001$, $^{ns}p > 0.05$

of the high correlation between ECe and ECa data and the minimal variation of SP and WC within the field.

The good agreement between the *observed* correlation (correlation between the measured ECa and the specific soil property) and the *predicted* correlation (correlation between the predicted ECa using the DPPC model and the specific soil property) confirms the robustness of the model used under these circumstances.

Analysis of the EM38-ECe calibration equations

The best calibration equation to convert EM38 measurements into ECe data for our data set was:

$$Ln(ECe) = b0 + b1(z1) \quad [5]$$

The regression model summary statistics and parameter estimates are shown in Table 3. The R^2 values of the regression models for the different sample depths ranged between 0.38 and 0.90, being significant at $P < 0.01$ for the 0-30 cm depth and at $P < 0.001$ for the remaining depths. Thus, the calibration model accounted for 38% to 90% of the observed salinity variability at different depths. All coefficients were significantly different from zero ($P < 0.001$ except for $b1$ of the surface horizon, for which $P < 0.01$; Table 3). The residuals of all regression models appeared normally distributed with homogeneous variance, and the Moran spatial autocorrelation test statistics were nonsignificant (data not shown). As the residuals displayed no assumption violations, the calibration equations were accepted for prediction purposes (predictions of ECe from EM38 readings).

The prediction accuracy of the calibration models is shown in Figure 6. This plot shows a good 1:1 correspondence between observed and predicted soil salinity, indicating that reasonable estimates of soil ECe were achieved. Thus, the fitted calibration equations adequately predicted the soil salinity levels from the acquired EM data.

Table 3. Multiple linear regression model summary statistics and parameter estimates for the three sampling depths and for the average profile

Anova	Soil depth (cm)			
	0-30	**30-60**	**60-90**	**0-90**
R^2	0.375	0.901	0.882	0.882
MSE[a]	0.196	0.053	0.077	0.042
Model F Test	10.82	163.33	134.58	134.09
$P > F$	0.0041	0.0001	0.0001	0.0001
Parameter estimates				
$b0$ (intercept)	1.980*** (0.099)[b]	1.748*** (0.052)	1.638*** (0.063)	1.845*** (0.046)
$b1$	0.297** (0.090)	0.601*** (0.047)	0.658*** (0.057)	0.485*** (0.042)

[a] MSE: Mean square error. [b] Standard errors in parenthesis. Levels of significance: $**p < 0.01$, $***p < 0.001$.

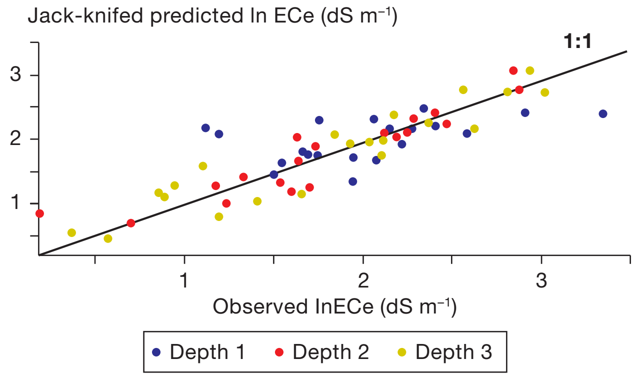

Figure 6. Plot of the observed *vs.* Jack-knifed predicted soil 1n(ECe) values from the calibration model. Depths 1, 2 and 3 correspond respectively to 0-30 cm, 30-60 cm, and 60-90 cm.

Soil salinity map

The MLR calibration model was used to predict the depth specific-ECe values at the remaining non-sampled locations. Spatial distribution of soil salinity for the bulk profile (0-90 cm) is shown in Fig. 7. As expected, there is a general spatial pattern similarity between EM maps (Fig. 4 a and b) and the estimated ECe map (Fig. 7). This confirms that maps of EM38 readings are appropriate for reconnaissance surveys to provide a priori spatial information about soil salinity, allowing allocation of the most- and least-saline areas.

The salinity distribution within the average profile is relevant for assessing crop response and predicting productivity loss. Figure 7 shows that most of the plot is saline (i.e., ECe > 4 dS m^{-1}). Only a small patch in the upper area of the salinity map had ECe values lower than 4 dS m^{-1} (near the drainage collector). The strongly to very strongly saline areas (i.e., ECe > 8 dS m^{-1}) were located in the center-right-side and lower right corner of the plot (Fig. 7), which corresponds to the depositional-fan of the gullies ending in the flood plain (Fig. 1 A and B). This suggests differences in drainage between the top and bottom ends of the field (Fig. 7). The leakage of the Tauste irrigation canal, which is not lined, may contribute to worse drainage and salts leaching at the center-east and southeast areas of the plot.

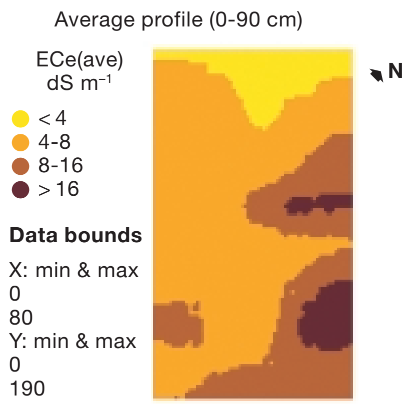

Figure 7. Raster map of the predicted ECe values for the average profile (0-90 cm) using the selected calibration equation. The top end of the contour plot corresponds to the west of the field.

The field range interval estimates for the entire profile indicated that 0.3% of the field had salinity levels (ECe) below 2 dS m^{-1}, 18.9% had salinity levels between 2 and 4 dS m^{-1}, 51.2% had levels between 4 and 8 dS m^{-1}, 22.8% had levels between 8 and 16 dS m^{-1}, and 6.8% of the field exceeded 16 dS m^{-1}. Considering that for alfalfa, the threshold soil saturation extract electrical conductivity (ECe above which there is yield reduction) is 2 dS m^{-1}, and the percentage-reduction in yield given 1 dS m^{-1} increase in ECe is 7.3% (Mass, 1986), it can be concluded that ECe values of CAB1 are excessive for successful alfalfa production. By reference to salt-tolerant tables, the ESAP-Calibrate program estimated that the relative alfalfa yield loss occurring in this field would be about 40%. The very deficient development of the alfalfa in the field led the farmer to replace it with rice in the following growing season.

The methodology of intensive EM38 readings and their calibration to ECe data resulted in a map of soil salinity with improved resolution compared to that of a map obtained by the interpolation of only 20 measured ECe data. Thus, the inclusion of the 160 ECe estimates may improve map detail. This detailed salinity map (Fig. 7) certainly provides a potential tool for decision-making strategies. This information is valuable for selecting alternate crops or alternate irrigation management practices to maintain crop productivity while minimizing the environmental impacts of salinity.

Finally, the spatial pattern of root-zone salinity (Fig. 7) presents certain similarity with the heterogeneity of the map of soil aptitude for agriculture (Fig. 1B). In Figure 1B, the green, brown, grey, blue and pink colors represent aptitude classes 3, 4, 5, 6 and 7 (SEA, 2002), respectively, directly reflecting the degree of restriction of the soil for agricultural purposes. A greater number means greater restriction for the agricultural use of the soil. The most saline areas in the field (Fig. 7) coincide with the most restricted areas for agricultural use of the soil (classes 6 and 7; Fig. 1B).

Conclusions

The strong correlation obtained between EM38 readings and the measured ECe values, and the minimal spatial variation of SP and WC in the soil studied demonstrated that salinity accounted for most of the response of the EM38 sensor. The well-calibrated model from the intensive set of EM38 readings and the limited number of soil samples allowed accurate predictions of soil ECe values at multiple-depths. The calibration model also allowed field range average estimates of soil salinity. Nineteen percent of the field was considered as non-saline (ECe values of the average profile below 4 dS m^{-1}), 51% was considered as slightly saline (ECe values between 4 and 8 dS m^{-1}), 23% as moderately saline (ECe values between 8 and 16 dS m^{-1}), and 7% was considered as strongly saline (ECe > 16 dS m^{-1}). These ECe values are considered excessive for the sustainable production of alfalfa.

The electromagnetically estimated ECe values may improve the mapping of details, as compared to those maps obtained from the few measured ECe values. The detailed salinity map proves very helpful in displaying the spatial patterns of soil salinity and identifying sources/causes of salt-loading. While controlling the soil salinity levels, salt-tolerant crops should be grown in this field.

The electromagnetic induction sensor (EM38) and the ESAP software package have been proved to be very useful for assessing, predicting and mapping the soil salinity in the field studied. The rapidity and ease of use of the EM38 and the customized ESAP software package quickly enabled the prediction of the spatial distribution of the soil salinity, overcoming the limitations of the traditional methodology.

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