Mapping soil salinity in 3-dimensions using an EM38 and EM4Soil inversion modelling at the reconnaissance scale in central Morocco

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Abstract

Large areas of Morocco require irrigation and although good quality water is available in dams, farmers augment river water with poorer quality ground water, resulting in salt build-up without a sufficient leaching fraction. Implementation of management plans requires baseline reconnaissance maps of salinity. We developed a method to map the distribution of salinity profiles by establishing a linear regression (LR) between calculated true electrical conductivity (σ, mS/m) and electrical conductivity of the saturated soil-paste extract (ECₑ, dS/m). Estimates of σ were obtained by inverting the apparent electrical conductivity (ECₐ, mS/m) collected from a 500-m grid survey using an EM38. Spherical variograms were developed to interpolate ECₐ data onto a 100 m grid using residual maximum likelihood. Inversion was carried out on kriged ECₐ data using a quasi-3d model (EM4Soil software), selecting the cumulative function (CF) forward modelling and S2 inversion algorithm with a damping factor of 3.0. Using a ‘leave-one-out cross-validation’ (LOOCV), of one in 12 of the calibration sites, the use of the q-3d model yielded a high accuracy (RMSE = 0.42 dS/m), small bias (ME = −0.02 dS/m) and Lin’s concordance (0.91). Slightly worse results were obtained using individual LR established at each depth increment overall (i.e. RMSE = 0.45 dS/m; ME = 0.00 dS/m; Lin’s = 0.89) with the raw EM38 ECₐ. Inversion required a single LR (ECₑ = 0.679 + 0.041 × σ), enabling efficiencies in estimating ECₑ at any depth across the irrigation district. Final maps of ECₑ, along with information on water used for irrigation (ECₐ) and the characterization of properties of the two main soil types, enabled better understanding of causes of secondary soil salinity. The approach can be applied to problematic saline areas with saline water tables.

Keywords: Soil mapping, electrical conductivity, soil salinity, baseline data, EM inversion modelling

Introduction

Morocco is located in one of the driest regions of the world with most of the land classified as arid (~85%). Of the 9 million hectares of arable land, irrigation is used to supplement the meagre rainfall across 10% of this area. There are nine irrigation districts, of which Tadla is the largest and covers over 120 000 ha. As for many irrigated areas, the quality and availability of water are becoming increasingly problematic. Although water in storage dams has little salinity, its quality diminishes downstream (Badraoui et al., 2002). In addition, farmers augment river water with poorer quality groundwater (Badraoui et al., 2002). Both factors are beginning to limit sustainable soil management as salts build-up in the absence of a sufficient leaching fraction. In addition, the Intergovernmental Panel on Climate Change (IPCC) climate models suggest annual rainfall will decrease over the next few decades (MATUHE, 2001).

Given water authorities are struggling to distribute and provide potable water for domestic and industrial use, knowledge about the current status of soil salinity is necessary to monitor the impacts of applying degraded water to arable land. Collecting the necessary soil baseline information across large irrigated areas and throughout the root-zone is costly and time-consuming (Odeh et al., 1998). However, proximal sensing electromagnetic (EM) induction instruments have been used to augment limited laboratory measurements of extracts of a saturated soil paste (i.e. ECₑ – dS/m). There is a growing body of literature showing increasing research in
developing countries aimed at using such an approach to measure and map soil salinity. This includes Indonesia (McLeod et al., 2010), Turkey (Cetin et al., 2012), Uzbekistan (Akrakhanov et al., 2014) and China (Yao & Yang, 2010; Guo et al., 2013) where in coastal tidallands susceptibility to shallow water tables and saline soil conditions after reclamation requires knowledge for monitoring and management. In Africa, similar work has also been undertaken including South Africa (Johnston et al., 1997), Senegal (Ceuppens & Wopereis, 1999; Barbiero et al., 2001) and Tunisia (Araguës et al., 2011).

Most of the studies have been conducted at the field level. In addition, as described by Amezeta & del Valle de Lersundi (2008), the first step is the development of a linear regression between the measured apparent electrical conductivity (ECa) and average ECe (i.e. for 0–1.0 m depth). A similar approach was used by Triantafilis & Buchanan (2010) to map subsurface saline material (6–12 m) across an irrigated district. The problem with these approaches is that managing the salinity requires knowledge of whether the salt distribution is normal (i.e. increasing salinity with depth), uniform (e.g. nonsaline [≤2 dS/m] or moderately saline [4–8 dS/m]) or inverted (i.e. moderately saline topsoil and slightly saline subsoil). To resolve this, various authors have developed linear regression (LR) models at different depths (e.g. Yao & Yang, 2010). However, this approach requires different models for mapping soil ECe at different depths, and it is not able to predict soil ECe at depths where soil samples are not collected. It can also introduce uncertainty at different depths due to the use of different input data (Huang et al., 2015a).

Another approach is first to invert ECa into estimates of true electrical conductivity (σ, mS/m) at depths of interest; whereby σ can be directly related to ECe at the same depths. Hendrickx et al. (2002) used Tikhonov regularization to invert EM38 ECa at different depths to model salinity at individual sites. Li et al. (2013) used a similar 1-d inversion at each site prior to mapping ECe. To calibrate σ and ECe using a single equation, Goff et al. (2014) and Huang et al. (2015b) established calibrations by inverting ECa from a single-frequency and multiple-coil DUALEM-421 to predict salinity across estuarine-alluvial and semi-arid gilgai clay plains, respectively. More recently, using a quasi-3d inversion model, Davies et al. (2015) showed how saline wedges in a swash-zone (i.e. upper part of the beach between backbeach and surf zone) can be discerned with Zare et al. (2015) and Huang et al. (2017a) mapping ECe in 3-d across, respectively, irrigated and dryland fields affected by salinity. The aim of our study was to map the variability of ECe across an irrigated alluvial plain in the Tadla irrigation district of central Morocco. We approached this by producing a reconnaissance set of EM38 ECa acquired across an area of 2000 ha. Using a quasi-3d algorithm we established a single LR equation between σ and ECe and mapped ECe for any depth within the electromagnetic conductivity image (EMCI) generated. We compared accuracy, bias and Lin’s concordance with that of LR relationships established between EM38 ECa and ECe at three depth increments (i.e. 0–0.3, 0.3–0.6 and 0.6–0.9 m). We evaluated the model uncertainty for the inversion-based approach, and identified where improvements in mapping might be achieved. We have discussed the results in terms of the causes of the minor soil salinization relative to various soil properties and briefly the implications in terms of appropriate soil management to mitigate the problem.

Materials and methods

Study area

The study area, located ~260 km south-east of Rabat in the Tadla irrigation district (Figure 1), consisted of two subdistricts straddling the Oum Rabia River, including the Beni Amir to the north and Beni Moussa to the south. The study area was located in the northern part of the Ben Amir in a semi-arid zone, with an annual rainfall ~250 mm, varying between a minimum of 140 and maximum of 400 mm. The potential evaporation was large (1800 mm). Daily temperature (18 °C annual average) varied between a maximum of 40 °C in August (summer) and a minimum of 3 °C in January (winter). The study area covered 2066 hectares with the predominant crops being wheat (40%), alfalfa (34%), olive groves (15%), vegetables (7%) and sugar beet (4%).

The soil was predominantly of two different types (Figure 2a). The largest area was an Isohumic (Chernozem, FAO 2006) soil, containing medium brown subtropical soils, saline and saline-sodic brown subtropical soils and medium chestnut soils. This soil class, characterized by clayey and clayey-silt textures, is deep to moderately deep with limestone present throughout. The other class was the Fersialitic (Chromic Luvisol, FAO 2006). A small part of the area was characterized by calcimagnesic soil, which includes brown limestones and ‘rendzimonform’ soils. These highly calcareous soils are generally shallow (i.e. 0.2–0.4 m).

There are two sources of water for irrigation: the primary source of water originates from the El-Hansali dam (storage capacity 800 million m³) and reaches the study area by canals from the river Oum Rabia. Water quality is fair (Dakak, 2015) with an average electrical conductivity (ECa) of 1.9 dS/m having slight to moderate (0.7–3.0 dS/m) degree of restriction (Ayers & Westcot, 1985). Irrigation is gravity fed. Groundwater also augments river water. In the northern area, ECw varies from 0.73 to 3.8 dS/m and between 0.64 and 4.87 dS/m in the southern half. Values of ECw >3.0 dS/m may be problematic.

EM38 data collection and interpolation

The ECa data were acquired using an EM38 instrument (Geonics Limited, Mississauga, ON, Canada). The instrument operates at a low frequency (14.8 kHz). The transmitter (Tx) is located at one end with the receiver located at the other end and
1 m away. Depth of exploration (DOE) of ECa by EM38 is a function of coil spacing ($s$) and array orientation. When placed on the ground, DOE for an EM38 is $0.5s$ and $1.6s$ for measurements made in the vertical (EM38v) and horizontal (EM38h) positions, respectively. DOE, determined as the depth of an array, accumulates 70% of its total sensitivity when operating at low induction numbers (LIN) (McNeill, 1980).

The EM38 survey involved traversing the area in a pseudo-regular grid, where sites were spaced $500 \times 500$ m apart. The EM38 was placed on the ground. A total of 92 ECa measurement locations were visited (Figure 2b) with the horizontal and vertical modes and with the data geo-referenced in latitude and longitude using a Garmin Dakota 20 Global Positioning System (GPS) (Garmin Ltd., Kansas, USA), with an accuracy of $<10$ m.

To understand the spatial variability of ECa across the whole area, we fitted two variograms for EM38h and EM38v using the residual maximum-likelihood (REML) method. This was because when the sample size is small, REML has been reported as a more robust approach than the traditional ‘method-of-moments’ approach (Lark & Cullis, 2004; Lark et al., 2006; Kerry & Oliver, 2007). The fitting was carried out using the ‘likfit’ function of the geoR package (Ribeiro & Diggle, 2001) in R software (R Core Team, 2016).

Once the variograms were calculated, EM38h and EM38v ECa values were kriged onto a 100 m grid across the study area using ordinary kriging with a maximum neighbour of 5 points. This was carried out using the gstat package (Pebesma, 2004) available in R software. We used 5 points as the maximum neighbour for kriging because we only had 92 ECa measurements and we did not want to over smooth the ECa data.

**Soil sampling and laboratory analysis**

To calibrate the calculated estimates of ECa, a total of 36 samples were collected from 12 locations. To cover the spatial extent, the sampling points were taken on an $\sim 1$ km grid in the east-west orientation and on transects spaced $\sim 2$ km apart from north to south (Figure 2c). In addition, to account for the maximum and minimum ECa and the range, sampling
Figure 2 (a) Map of soil types in the Ben Amir section of the Tadla Irrigation District and spatial distributions of the (b) EM38 survey locations, (c) soil sampling points and (d) contour plot of elevation (m).
Quasi-3d inversion of EM38 data

The EM4Soil V2.02 software package (EMTOMO, 2014) was used to invert the EM38 ECa data. EM4Soil is able to invert 1-dimensional (1d), 2d and 3d ECa data. The quasi-3d (q-3d) inversion was used. It assumes that below each measured location, 1-dimensional variation of calculated soil conductivity (σ, mS/m) is constrained by variation under neighbouring locations.

The inversion algorithm is based on Occam’s regularization (Sasaki, 1989), with the best q-3d model of σ, compared to measured soil ECa. This was achieved by varying parameters used by EM4Soil, including; choice of forward modelling (cumulative function [CF] and full solution [FS]), choice of inversion algorithm (S1 or S2) and the damping factor (λ) (Triantafilis & Monteiro Santos, 2013; Triantafilis et al., 2013a,b).

With respect to the inversion algorithm to be used, there is a choice of S1 and S2; whereby S2 (see Sasaki, 2001) has more constraints than S1 (see Sasaki, 1989) and therefore would produce smoother results than S1. Under low induction number conditions, the CF model is based on the ECa cumulative response and is used to convert depth-profile σ to ECa (McNeill, 1980). FS considers the Maxwell equations of the propagation of EM fields (Kaufman & Keller, 1983) and is not limited to the low induction number condition (i.e. conductivity <100 mS/m).

As a result the FS can improve models calculated from ECa data acquired over highly conductive soil.

Here, the quasi-3d inversion was carried out on the 92 ECa measurements and on the kriged ECa locations across the whole study area. A three-layer model with depths of layers of 0.3, 0.6 and 0.9 m and initial σ of 100 mS/m was used to estimate σ, with the λ set from 0.07, 0.3, 0.6 and at 0.6 increments thereafter to a maximum value of 3.0. In this study, 20 iterations were used to determine the best inversion parameters, based on our previous experience. Generally, too few iterations produce inversion results with abrupt changes in σ with depth while too many iterations are time-consuming.

A comparison was made between estimated σ and ECa at all depths considering the coefficient of determination (R2). The set of parameters (CF or FS, S1 or S2 and λ), which gave the largest R2, was used to establish a linear regression (LR) between σ and ECa. Note that the process of varying inversion parameters is equivalent to the parameters optimization or tuning in machine learning algorithms such as the artificial neural network (Taghizadeh-Mehrjardi et al., 2015), support vector machine (Ji et al., 2014) and ensemble Kalman filter (Huang et al., 2017b).

Validation and comparison with LR established using ECa

Once the optimal inversion parameters were determined, we used the corresponding set of σ generated by inverting 92 ECa points to produce a linear regression (LR) model to predict ECa at different depths. The LR model was also applied to the set of σ generated by inverting the kriged ECa points to obtain the predicted ECa across the whole study area and on a 100 m grid. To determine the robustness of the LR, a cross-validation procedure was conducted. Here, a single sample point was removed, and a calibration was developed from the remaining points (i.e. 11). This leave-one-out cross-validation (LOOCV) procedure was carried out 12 times with each one of the sampling points excluded in turn.

This approach was compared with a traditional LR established directly between ECa and the raw ECa data following Yao & Yang (2010). Here, we fitted three LR models for predicting ECa at each depth, including the topsoil (0–0.3 m), subsurface (0.3–0.6 m) and subsoil (0.6–0.9 m), but using only the most highly correlated EM38 ECa. The same LOOCV procedure was used to evaluate the LR model predictions.

The accuracy of the predictions was assessed using the root mean square error (RMSE) of prediction; whereby the closer the value to zero the more accurate the prediction. Prediction bias was calculated using the mean error (ME). Again the closer to zero then the less biased is the prediction. The Lin’s concordance correlation coefficient (ρc) was calculated to determine how close the model was to the 1:1 relationship for the various depth increments (i.e. 0–0.3, 0.3–0.6 m and 0.6–0.9 m). We chose this because the Lin’s coefficient (Lin, 1989) measures agreement between two variables (here the measured and predicted ECa) and was calculated:

\[
ρ_c = \frac{2S_{XY}}{S_X^2 + S_Y^2 + (\bar{X} - \bar{Y})^2}
\]

where \(\bar{X}\) and \(\bar{Y}\) are the means for the two variables, \(S_X^2\) and \(S_Y^2\) are the corresponding variances, and \(S_{XY}\) is the covariance between the two variables:

\[
S_{XY} = \frac{1}{n} \sum_{i=1}^{n} (X_i - \bar{X}) (Y_i - \bar{Y})
\]

Evaluation of the model uncertainty

To evaluate the model uncertainty for the inversion-based approach, we used a LOOCV approach. That was, for each of the 12 iterations of LOOCV process introduced in the...
previous section, we predicted soil EC_e onto the 100 m grid using the LR model established with the 11 soil samples. This process was carried out 12 times. The standard deviation of the predicted soil EC_e was calculated as the model uncertainty.

Results and discussion

Preliminary data analysis: soil properties

Table 1 shows the average soil properties of the soil samples obtained from the calibration sites. It is evident that the Fersialitic profiles in the north had slightly alkaline pH (~7.5) with increasing bulk density and what appeared to be a texture change at a depth of 0.3 m; whereby clay increased from the topsoil (28.1%) to subsurface (57.6%). By comparison, the Isohumic profiles in the south had a more alkaline pH (~8.45), which was a function of the large amounts of calcium carbonate present, particularly in the subsoil (i.e. 25.35%). The clay was uniform throughout subsoil (33.41%) clay almost half of that present in the north.

Table 2 shows that the mean EM38h EC_a (87.6 mS/m) was only slightly smaller than the average EM38v (88.4 mS/m). This was also the case with the maximum values (i.e. 130.1 and 132.2 mS/m, respectively) with the minimum values reversed (39.2 and 33.1 mS/m, respectively). Given that the median for the EM38h (89.3 mS/m) and EM38v (91.5 mS/m) was equivalent to the mean, we conclude the EM38h and EM38v data were normally distributed. This was reinforced by the small skewness in the EM38h (0.4) and EM38v (0.8).

Table 2 also shows the summary statistics for the EC_a measured at the 12 calibration points shown in Figure 2c. The mean EM38h (82.9 mS/m) was slightly larger than EM38v (81.2 mS/m). This was also the case with the maximum (i.e. 130.1 and 113.1 mS/m, respectively), with the minimum values showing the EM38h (41.1 mS/m) was slightly larger compared with the EM38v (33.1 mS/m). The median values were similar with the mean with the EM38h (84.3 mS/m) was slightly larger than the mean. Again the data were approximately normally distributed. We surmise there was a good agreement between the sample sites selected for calibration and the survey data.

Table 3a shows the mean EC_e of the topsoil (0–0.3 m) samples was largest (4.2 dS/m), with the largest individual EC_e (6.5 dS/m) measured in the topsoil. The salinity in the topsoil was on average nominally of moderate (4–8 dS/m) salinity but the largest value suggested that it did not approach concentrations where germination might be problematic in legumes (i.e. 2 dS/m) and some wheat cultivars (i.e. 6 dS/m). The average EC_e decreased ever so slightly with depth with the smallest being the subsoil (4.0 dS/m) where the minimum EC_e (1.6 dS/m) was also recorded. At these levels, which would be considered nonsaline (<2 dS/m), most arable crops including legumes would not be susceptible to any perceptible problems with salinity. The decreasing EC_e with depth was consistent with the slightly larger EM38h compared with EM38v measured at the calibration points, because DOEs were 0.75 and 1.5 m for EM38h and EM38v, respectively.

Table 1 Soil properties for the two soil types at three depths

<table>
<thead>
<tr>
<th>Soil property</th>
<th>Soil type</th>
<th>Fersialitic</th>
<th>Isohumic</th>
</tr>
</thead>
<tbody>
<tr>
<td>Soil depth (m)</td>
<td></td>
<td>0–0.3</td>
<td>0.3–0.6</td>
</tr>
<tr>
<td>Bulk density (g/cm³)</td>
<td>1.3</td>
<td>1.43</td>
<td>1.76</td>
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<tr>
<td>Sand content (%)</td>
<td>36.3</td>
<td>30.7</td>
<td>26.8</td>
</tr>
<tr>
<td>Silt content (%)</td>
<td>35.6</td>
<td>26.9</td>
<td>27.9</td>
</tr>
<tr>
<td>Clay content (%)</td>
<td>28.1</td>
<td>57.6</td>
<td>54.7</td>
</tr>
<tr>
<td>pH</td>
<td>7.6</td>
<td>7.4</td>
<td>7.6</td>
</tr>
<tr>
<td>Organic carbon (%)</td>
<td>2.2</td>
<td>1.4</td>
<td>0.4</td>
</tr>
<tr>
<td>Calcium carbonates (%)</td>
<td>1.6</td>
<td>1.5</td>
<td>1.6</td>
</tr>
<tr>
<td>N-NO₃ content (g/N)</td>
<td>22.6</td>
<td>15.7</td>
<td>11.9</td>
</tr>
<tr>
<td>Field capacity (m³/m²)</td>
<td>14.8</td>
<td>12.2</td>
<td>10.9</td>
</tr>
<tr>
<td>Wilting point (m³/m³)</td>
<td>18.7</td>
<td>19.6</td>
<td>20.7</td>
</tr>
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</table>

Table 2 Summary statistics of apparent electrical conductivity (EC_a – mS/m) measured by an EM38 for the entire survey area and at the 12 calibration sites

<table>
<thead>
<tr>
<th></th>
<th>N</th>
<th>Min</th>
<th>Mean</th>
<th>Median</th>
<th>Max</th>
<th>Skewness</th>
<th>CV</th>
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<tr>
<td>EM38h (mS/m)</td>
<td>92</td>
<td>39.2</td>
<td>87.6</td>
<td>89.3</td>
<td>130.1</td>
<td>−0.4</td>
<td>23.2%</td>
</tr>
<tr>
<td>EM38v (mS/m)</td>
<td>92</td>
<td>33.1</td>
<td>88.4</td>
<td>91.5</td>
<td>132.2</td>
<td>−0.8</td>
<td>23.8%</td>
</tr>
<tr>
<td>Calibration data</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>EM38h (mS/m)</td>
<td>12</td>
<td>41.1</td>
<td>82.9</td>
<td>81.9</td>
<td>130.1</td>
<td>0.22</td>
<td>27.0%</td>
</tr>
<tr>
<td>EM38v (mS/m)</td>
<td>12</td>
<td>33.1</td>
<td>81.2</td>
<td>84.3</td>
<td>113.1</td>
<td>−0.9</td>
<td>25.6%</td>
</tr>
</tbody>
</table>
The constant trend in ECe with depth indicated on average the salinity profiles was uniform at the time of sampling. Whereas the levels of salinity varied from nonsaline, to slightly saline and moderately saline, the uniformity suggested accumulation of salts was occurring as a function of irrigation with poorer quality water and that the leaching fraction was insufficient to facilitate the removal of the salts added.

Table 3b also shows the correlation coefficient (r) between soil ECe and the EM38 ECa. In general, all ECa measurements were statistically correlated with soil ECe (P < 0.001). The most statistically significant (P < 0.001) and largest correlation was between the EM38h ECa and topsoil (r = 0.92) and subsurface (r = 0.93) ECe. The EM38v ECa was statistically significant (P < 0.0001) with subsoil (0.91) ECe.

Preliminary data analysis: ancillary data

A contour plot of elevation shows the land surface was higher (i.e. >435 m) at the northern end with elevation generally decreasing gradually towards the south (<420 m) (Figure 2d). The spatial distribution of kriged EM38h shows that small (<60 mS/m) and intermediate-small values (60–75 mS/m) of ECa characterized the southern end (Figure 3a). At a few sites, ECa was similarly intermediate–small in the central areas, where ECa was generally intermediate (70–90 mS/m). Intermediate–large (90–105 mS/m) and large (>105 mS/m) values of ECa were generally found along the western flank and north-eastern corner of the study area. Spatial distribution of kriged EM38v shows that patterns of ECa values were similar to those for EM38h (Figure 3b).

The spherical model parameters of the variograms, fitted for EM38h and EM38v (Table 4), were selected according to the log-likelihood values (~399.7 and ~404.8, respectively). The EM38h had a smaller nugget:sill ratio (74.3%) compared with EM38v (84.7%). Within the range 1627 and 2000 m for EM38h and EM38v, respectively, the spatial dependence values for horizontal and vertical configurations were not strong and more ECa data need to be collected to characterize the short-scale variation.

Figure 3c,d show the kriging variance for EM38h and EM38v, respectively. The patterns were similar. Here, large error occurred in the central and north-eastern margins of the study area, where no samples were collected. However, EM38h had smaller kriging variance (460–490 mS²/m³) compared with EM38v (380–440 mS²/m³). This was consistent with the larger nugget:sill ratio of EM38h.

Table 3 (a) Summary statistics of measured electrical conductivity of the saturated soil-paste extract (ECe – dS/m) at the calibration sites, (b) correlation coefficient (r) between soil ECe and the measured apparent electrical conductivity (ECa) of each of the EM38 arrays and (c) the calibration linear regression models with their coefficient of determination ($R^2$) used to predict ECe from the EM38 which was most highly correlated with ECa and for each depth increment. Note: *, P < 0.05; **, P < 0.001; ***, P < 0.0001

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<td>N</td>
<td>Min</td>
<td>Mean</td>
<td>Median</td>
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<tr>
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<td>4.2</td>
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<td>6.5</td>
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<tr>
<td>ECe (0.3–0.6 m)</td>
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<td>2.1</td>
<td>4.1</td>
<td>4.1</td>
<td>6.2</td>
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<tr>
<td>ECe (0.6–0.9 m)</td>
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<td>1.6</td>
<td>4.0</td>
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<td></td>
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<tr>
<td>EM38h</td>
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<tr>
<td>ECe (0–0.3 m)</td>
<td>0.92***</td>
<td>0.78*</td>
</tr>
<tr>
<td>ECe (0.3–0.6 m)</td>
<td>0.93***</td>
<td>0.84**</td>
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<tr>
<td>ECe (0.6–0.9 m)</td>
<td>0.90**</td>
<td>0.91**</td>
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<td></td>
<td>Equation</td>
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<tr>
<td>EM38h</td>
<td></td>
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<tr>
<td>ECe (0–0.3 m)</td>
<td>0.4680 + 0.0447 × EM38h</td>
</tr>
<tr>
<td>ECe (0.3–0.6 m)</td>
<td>0.7153 + 0.0404 × EM38h</td>
</tr>
<tr>
<td>ECe (0.6–0.9 m)</td>
<td>0.3360 + 0.0449 × EM38h</td>
</tr>
</tbody>
</table>

Determination of optimal quasi-3d inversion parameters

The coefficient of determination ($R^2$) between the calculated true electrical conductivity ($σ$) from the q-3d inversion and ECe at all depths is shown in Figure 4a and when different sets of inversion parameters were considered. This includes forward modelling (i.e. CF and FS) and inversion (i.e. S1 and S2) algorithms versus λ.

The S2 performs better than the S1 given the consistently larger $R^2$ produced. In addition, the CF for the S2 algorithm produces slightly larger $R^2$ than S1. The best $R^2$ (0.87) was achieved when the S2 was used in concert with the CF and when the λ value of 3.0. As an increase in λ after 3.0 did not significantly increase $R^2$ (data not shown), we therefore selected these parameters to estimate σ from a linear regression relationship between $σ$ and ECe and to map the latter across the field at various 0.3 m depth increments.

Model fitting was conducted using the bivariate fit tool (JMP software, SAS Institute Inc., 2014). Figure 4b shows the fitted lines and confidence curves (confidence limits for the mean value) and individual confidence curves (confidence limits for individual predicted values) between ECe and $σ$.

The significant level ($α$) was set to 0.05. As shown in Table 5, the regression equation was $EC_e = 0.679 + 0.041 \times σ$. Given the large coefficient of determination...
Figure 3 Contour plot of kriged apparent electrical conductivity (ECa, mS/m) collected using an EM38 in the (a) horizontal (EM38h) and (b) vertical (EM38v) modes and the kriging variance (mS$^2$/m$^2$) of (c) EM38h and (d) EM38v across the Ben Amir section of the Tadla Irrigation District. Note: EM38 survey points were marked in black dots.
(i.e. $R^2 = 0.87$), the use of $\sigma$ should yield good estimates of EC$_e$ at all depths from this single equation.

Table 3c shows the summary statistics of the LR models established between the raw EM38 EC$_a$. It was evident that the best coefficient of determination ($R^2 = 0.85$) was achieved for the topsoil (0–0.3 m) and using the EM38h. This was also the case for the subsurface (0.3–0.6 m) EC$_e$ where the correlation was a little stronger ($R^2 = 0.87$). Subsoil (0.6–0.9 m) EC$_e$ was best predicted using only the EM38v EC$_a$ ($R^2 = 0.82$), however.

Evaluation of soil salinity prediction

A leave-one-out cross-validation (LOOCV) approach was applied on each calibration location. In the first instance, we describe the results achieved using the q-3d calibration approach and to predict EC$_e$ from $\sigma$. Figure 4c shows that predicted EC$_e$ at each location was in general accurate and unbiased given the RMSE (0.42 dS/m) and small ME (-0.02 dS/m), respectively. This was also reflected in the Lin’s concordance (0.91), which was very large and which for the most part showed excellent agreement between measured and predicted EC$_e$.

Figure 4d shows similar results from the LOOCV obtained by establishing a LR relationship at each depth. The Lin’s concordance was the same (0.89), RMSE higher (0.45 dS/m) with predictions unbiased (0.00 dS/m) overall. One of the differences between the methods was the q-3d modelling approach better accounted for and predicted the largest measured EC$_e$ and produced predictions with short ranges where EC$_e$ was near the average (i.e. 4 dS/m).

In addition, the LR approach requires three models to be established and cannot predict soil EC$_e$ at the depths below 0.75 m. This was not the case for the inversion approach as it was designed to predict soil EC$_e$ at any depths within the DOE of the EM38 (~1.5 m) without using any depth functions for interpolation (Malone et al., 2009).

Nevertheless, the results achieved with the q-3d modelling were comparable to recent investigations conducted at the field level using more densely collected EC$_a$ data. For example, at the field scale and in a highly saline area of Bourke in northwest New South Wales, Australia, Zare et al. (2015) achieved a larger Lin’s concordance (0.93) between measured and predicted EC$_e$, however, their q-3d model was based on DUALEM-421 data collected along transects spaced 50 m apart. Moghadas et al. (2016) carried out an equivalent modelling approach but across a much larger area with EM38 data across the Ardakan area of central Iran. They achieved progressively smaller Lin’s concordance with increasing depth from the topsoil (0.75) to the subsurface (0.35). However, the reduced ability to predict EC$_e$ was a function of the EM38 survey spacing with the requirement to collect EM38 data on a closely spaced and denser survey grid of <500 m.

Comparison between measured and predicted EC$_e$ profiles

To better understand the predicted EC$_e$ achieved using the q-3d modelling approach and against the measured EC$_e$. Figure 5a shows the measured EC$_e$ for each of the calibration sites with predicted EC$_e$ shown in Figure 5b. With respect to sampling site 10, the measured EC$_e$ (2.3 dS/m) in the topsoil was only slightly saline (2–4 dS/m) and decreased to nonsaline levels in the subsurface (2.1 dS/m) and subsoil (1.6 dS/m). In general, the predicted EC$_e$ at this site was satisfactory for subsurface equivalent to measured EC$_e$ (2.2 dS/m), with topsoil (2.7 dS/m) and subsoil (1.9 dS/m) EC$_e$ slightly overestimated.

With respect to the slightly saline measured EC$_e$ profiles (i.e. sites 15, 21, 49, 53 and 72) the predicted EC$_e$ was also satisfactory. Issues arise in prediction where sites were located near areas where EC$_a$ changes rapidly. This was the case around site 53, where predicted subsoil EC$_e$ (4.3 dS/m) was slightly saline, which was much greater than measured (3.4 dS/m) EC$_e$ that was nonsaline. Figure 3b shows this clearly and specifically where EM38v EC$_a$ increased from intermediate (75–90 mS/m) to large (>105 mS/m) values over a distance of <500 m either side of site 53. This was the scale of the EC$_a$ surveying interval.

With regard to the moderately saline profiles (i.e. sites 28, 46, 60, 84 and 90), similarly good predictions were also achieved. There was, however, an issue with underestimation of topsoil EC$_e$ (3.9 dS/m) at site 90 which was predicted to be slightly saline when it was moderately saline (4.6 dS/m). Here, as with the predictions at site 53, the prediction error was a function of site 90 being close to an area of rapid change in EC$_a$. This was evidenced in Figure 3b in the northeast corner of the study area.

In terms of the most saline and inverted salinity profile of site 31, the predicted EC$_e$ was generally satisfactorily resolved in the topsoil and subsoil depths. However, the measured subsurface EC$_e$ (6.2 dS/m) was slightly under-predicted (5.7 dS/m) in terms of the salinity class. Again, as with the other sites cited and for that matter most

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Table 4 Summary statistics of the variograms fitted for apparent electrical conductivity (EC$_a$) data measured by the EM38 in the horizontal (EM38h) and vertical (EM38v) modes using residual maximum-likelihood method

<table>
<thead>
<tr>
<th>Mode</th>
<th>EM38h</th>
<th>EM38v</th>
</tr>
</thead>
<tbody>
<tr>
<td>Variogram model</td>
<td>Spherical</td>
<td>Spherical</td>
</tr>
<tr>
<td>Log-likelihood</td>
<td>-399.7</td>
<td>-404.8</td>
</tr>
<tr>
<td>Nugget</td>
<td>302</td>
<td>375.4</td>
</tr>
<tr>
<td>Partial sill</td>
<td>104.6</td>
<td>68.0</td>
</tr>
<tr>
<td>Nugget/sill</td>
<td>74.3%</td>
<td>84.7%</td>
</tr>
<tr>
<td>Range (m)</td>
<td>1627</td>
<td>2000</td>
</tr>
</tbody>
</table>
sites where errors in salinity classification occurred, the short-range spatial variation at less than the survey interval of 500 m was problematic.

Another reason for the slight errors in prediction was a function of the 100 m grid, which the ECₐ data needed to be gridded onto to enable the q-3d inversion of the ECₐ data.
In this regard, the collection of ECa data on a 100 m grid would lead to less smoothing. This was not a problem with the LR method, because the EM38 ECa data collected above each calibration site was directly correlated with ECe at each depth. To improve the results in q-3d modelling, we recommend in future research that EM38 ECa data should be collected at either 250 or 100 m apart or smaller, because the gridded data would be less smoothed.

**Interpreting ECe maps at the three depths**

Figure 6 shows predicted ECe spatially distributed using the relationship established between σ and ECe with the q-3d inversion. With respect to topsoil ECe, Figure 6a shows that there were only a few isolated areas where soil ECe was nonsaline (<2 dS/m). These occurred in the southern part of the study area, associated with the sands of Isohumic soil profiles in the lower landscape positions. Interestingly, ECe gradually increased from slightly saline (2–4 dS/m) to moderately saline (4–8 dS/m) in areas immediately to the north and similarly characterized by Isohumic profiles. In the areas to the north, soil became mostly slightly saline (2–4 dS/m) as characterised by Fersialitic profiles.

Figure 6b,c show the spatial distribution of predicted ECe at depths of 0.3–0.6 and 0.6–0.9 m, respectively. For the most part, the patterns in ECe distribution were equivalent. We note, however, that the areas where predicted salinity in subsurface and subsoil ECe was smaller in terms of being moderately saline. This was particularly the case in the contiguous area in the central southern part of the study area characterized by the Isohumic profiles. Conversely, the area to the north as characterized by the Fersialitic profiles was predicted to have larger and moderately saline ECe (i.e. >4 dS/m) in the subsoil in particular.

The reasons for the differences in ECe appear to be a function of the ECw and the soil properties. In the south-eastern half, the generally smaller ECe was most likely a function of the uniformly siltier nature of the soil (~46%).

**Table 5** Summary statistics of the linear regression model established between calculated true electrical conductivity (σ) and measured electrical conductivity of the saturated soil-paste extract (ECe)

| Parameter estimates | Estimate | Standard error | t Ratio | Probability>|t| | Coefficient of determination (R^2) |
|---------------------|----------|----------------|---------|----------------|------------------|
| Intercept           | 0.679    | 0.232          | 2.93    | 0.0060         | 0.87              |
| σ                   | 0.041    | 0.003          | 15.23   | <0.0001        |                   |

**Figure 5** Plot of (a) measured and (b) predicted electrical conductivity of the saturated soil-paste extract (ECe – dS/m) with depth (m) at the soil sampling locations generated using quasi-3d (q-3d) inversion model of the EM38 ECa (mS/m), cumulative function (CF) forward modelling and S2 inversion algorithm with a damping factor (λ) of 3.0.
and smaller bulk density (e.g. average subsoil = 1.46 g/cm³) of the Isohumic profiles. This was despite the generally larger ECₜw of ground water (i.e. 0.64 and 4.87 dS/m), which in some cases seemed to produce moderately saline conditions in the central and western parts of the area. Conversely, in the areas associated with the Fersialitic profiles to the north, whilst the ECₜw was slightly smaller (0.73–3.8 dS/m) the larger subsurface (57.60%) and subsoil (54.70%) clay and bulk density appeared to favour the accumulation of more salts, particularly in the subsoil.

Overall, the maps of predicted ECₑ were generally in accord with the measured ECₑ profiles (Figure 6a). The unity of the results was therefore informative in terms of soil use and management and as a function of the salinity tolerance of the main agricultural crops used within the Tadla irrigation district. In terms of olives (Olea sylvestris) which are grown in 15% of the area, the ECₑ at current levels is generally satisfactory given olives are moderately tolerant; albeit they prefer conditions where ECₑ was <4.5 dS/m.

With respect to wheat (T. turgidum L. var. durum Desf.), which is commonly grown across 40% of the area, the levels of ECₑ currently prevailing should not be overly problematic given the threshold ECₑ is 5.9 dS/m (Francois et al., 1986). This was because this was larger than most predicted topsoil ECₑ, albeit that at site 31 and surrounds this may not be the case given measured ECₑ (6.5 dS/m) exceeded this value (Table 3a). However, this was not the case for alfalfa (Medicago sativa L.), which is grown in 34% of the area and usually in rotation with wheat. In this regard, the ECₑ tolerance is 1/3 that of wheat and at 2 dS/m (Bower et al., 1969; Bernstein & Francois, 1973) this value was exceeded across most of the area and at all soil depths investigated. This was therefore problematic given the role of alfalfa was to provide carbon and nitrogen to the soil and for the benefit of wheat cropping.

Evaluation of the model uncertainty

Figure 7 shows the standard deviation of predicted ECₑ at different depths using the LOOCV approach. We note that the model uncertainty illustrated by the standard deviation was small (<1.2 × 10⁻⁸ dS/m). This was most likely due to the limited soil samples (i.e. 12) used in the LOOCV.

Figure 6 Spatial distributions of predicted electrical conductivity of the saturated soil-paste extract (ECₑ–dS/m) at depths of (a) 0–0.3 (topsoil), (b) 0.3–0.6 (subsurface) and (c) 0.6–0.9 m (subsoil) across the Ben Amir section of the Tadla Irrigation District using the quasi-3d (q-3d) inversion algorithm with cumulative function (CF) forward modelling and S2 inversion algorithm with a damping factor (k) of 3.0.
approach, whereby all the iterations with the remaining 11 samples produced similar linear models. To better account for the model uncertainty, a conditional simulation (Nelson et al., 2011) could be carried out with more soil samples collected.

Conclusions

A quasi-3d (q-3d) inversion algorithm was used to invert kriged EM38 ECa data across a small part of the Beni Amir irrigated district, in the Tadla area, central Morocco. The true electrical conductivity (σ) was strongly correlated with ECe when we used the q-3d and CF, S2 algorithm and λ = 3.0. We also achieved equivalent results by developing individual LR equations at each depth increment with the raw EM38 ECa. We conclude that the inversion approach was more efficient as a single LR equation was needed to apply it to a quasi-3d electromagnetic conductivity image (EMCI). This approach also allowed prediction of ECe at not only the depths of sampling but at any depth within a quasi-3d EMCI.

The final maps of the estimated ECe at various depths allowed the causes and potential management of secondary soil salinity to be understood and appropriate management strategies to be initiated and with respect to the application of poorer quality groundwater for irrigation. This was particularly the case with respect to the larger amounts of ECe accumulating in the northern part of the study area associated with the Fersialitic profile, which was characterized by larger subsoil clay and bulk density, and with Isohumic profiles in the central and western parts of the study.

In either case, the methodology provides for baseline data, which can be used to monitor the effect of continued use of poorer quality groundwater for irrigation. The methods developed also have application for extending the area mapped to other areas where salinity is more problematic and in areas where saline ground waters are known to exist to the south and in other parts of the Tadla irrigation district as well as in other parts of Morocco such as the Skhirat region (Zouahri et al., 2015). The results also point to where more detailed studies are needed and to better understand the cause of the uniform and moderately saline profiles. In this regard, the approach of Zare et al. (2015) might be useful to measure, map, manage and monitor salinity at the field scale and using q-3d inversion modelling of DUALEM-421 ECa data.

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References


