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LETTER

Using L-band radar data for soil salinity mapping—a case study in Central Iraq

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Abstract

Soil salinization is a critical environmental problem for dryland agriculture. Mapping its distribution and severity in space and time is essential for agricultural management and development. Recently, remote sensing technology has been widely applied in such mapping but mostly using optical remote sensing data. In conjunction with the field surveys, this case study was aimed at developing an operational approach for this purpose by employing ALOS (Advanced Land Observing Satellite) L-band radar data with support of Landsat 5 TM (Thematic Mapper) imagery acquired at almost the same time. The test was conducted in the Mussaib site in Central Iraq. The innovative procedure involved was the removal or minimization of the impact of vegetation cover and moisture on the backscattering coefficients by Water Cloud Model. The results revealed a strong correlation between the corrected backscattering coefficients of soil and the measured soil salinity ($R^2 = 0.565–0.677$). The radar-based salinity models developed through multivariate linear regression (MLR) analysis were able to predict salinity with reliability of 70.05%. In conclusion, it is possible to use radar data for soil salinity prediction and mapping in dry environment.

1. Introduction

As one of the environmental disasters, soil salinization has become a key problem in agricultural management and development, especially, in irrigated areas in dryland systems. Quantification and mapping of soil salinity in space and time to provide relevant advice for decision-makers and land managers have become a pressing issue. For this purpose, optical remote sensing has been successfully utilized for soil salinity mapping in the past decades (Dwivedi and Rao 1992, Mougenot et al 1993, Rao et al 1995, Metternicht and Zinck 2003, Farifteh et al 2006, Farifteh et al 2007, Eldeiry and Garcia 2010, Wu et al 2014a and 2014b, Gorji et al 2015, Scudiero et al 2015, Ivushkin et al 2017, Bannari et al 2018, Wu et al 2018, Paliwal et al 2019). Mature approaches have been proposed, for example, best band combination, multiyear maxima-based multivariate modeling and quantification, shortwave infrared (SWIR) band-based discrimination, and machine learning regression, etc.

In comparison with optical remote sensing, radar has its specific advantages such as cloud-free signal, and penetration into subsoil to a depth of >50–150 cm depending on the wavelength/frequency of the emitted waves and soil moisture. However, the majority of radar applications is focused on soil moisture retrieval and few attempts have been made to detect salinity using radar backscattering signatures. Among the limited studies, Sreenivas et al (1995), Shao et al (2003), Aly et al (2004), Lasne et al (2008) and Gong et al (2013) have conducted laboratory-based simulation and discovered that the real part ($\varepsilon'$) of the soil dielectric constant is responsive to soil moisture while its imaginary part ($\varepsilon''$) is associated with both soil moisture and salinity. Shao et al (2003) had further calculated the correlation coefficient ($R$) between the backscattering coefficient ($\sigma^0$) of the RADARSAT
C-band data and $\varepsilon''$ of the soil samples ($R = 0.7$ or $R^2 = 0.49$). Based on this, it seems still not possible to retrieve and map soil salinity as the relation was obtained for both moisture and salinity. Taylor et al (1996) used AIRSAR C-, L- and P-band data to analyze the real and imaginary parts of wet soil and map relatively the salinized and non-salinized areas. These studies revealed the possibility to use the microwave C-band, and especially L-band for detecting salinity in different settings. Yet, dielectric constant-based simulations did not provide a promising partition leading to development of intuitive radar-based salinity model and mapping. Taghadosi et al (2019) have applied a texture-based support vector regression (SVR) analysis on Sentinel 1 C-band data for mapping salinity, avoiding the complex real and imaginary parts of the radar backscattering coefficient. This is a different effort to employ radar data for the salinity mapping purpose but intuitive model was still not reported.

From this brief review, we got to know that the difficulty of using radar data for salinity detection, modeling and mapping lies in the decomposition of soil salinity from soil moisture, or rather, to exclude the impacts of soil moisture and vegetation cover on the salinity part of the radar backscattering coefficients.

Viewing this difficulty, we saw the need to develop approaches avoiding the complex dielectric constant issue as Taghadosi et al (2019) have done but allowing development of intuitive $\sigma_0$-based salinity model(s) for pixel-level salinity mapping. Hence, the main objective of this study was to find operational approaches to minimize the impacts of vegetation cover and moisture on the backscattering coefficients instead of using dielectric constant so as to model and map salinity. A specific objective is to test and build the intuitive radar-based remote sensing salinity model(s) for croplands in dryland environment taking the Mussaib site in Central Iraq as an example.

2. Methods and material

2.1. Study area

The study area, Mussaib site, was one of the pilot sites in our previous studies where we had already conducted field survey and soil salinity mapping using multiyear spring and summer Landsat data (Wu et al 2012, Wu et al 2014a). Situated in-between the Tigris and the Euphrates Rivers in Central Iraq (figure 1), a national agriculture development project has been conducted in this site for grain production since 1950s. Crops include wheat and barley in spring and corn, vegetables and fruits (e.g., tomato and watermelon), and locally cotton in summer.
Perennial alfalfa (*Medicago sativa*) and date palm as permanent tree crop may be also locally cultivated. The total area of the project site is around 250,000 ha.

The dominant soil is silt clay loam to silt loam with more than 20% of lime. Most of the soils are slightly saline to highly saline, e.g., from 4 to 30 dS/m (Wu et al. 2014a).

Climatically, the Mussaib site belongs to the subtropical zone, characterized by short warm winter and long hot summer. Rainfall is concentrated in winter and spring from December to March with an annual average of about 82.5 mm in the past 60 years (recorded in the adjacent station, Hillah). The mean minimum temperature is 6.25 °C from December to February in winter while the mean maximum is 43.2 °C in July and August in summer.

2.2. Data

2.2.1. Field data

Field investigation including soil sampling and measurement of EM38-MK2, an instrument to measure the apparent electrical conductivity (ECa in mS/m) by Geonics Ltd, was undertaken from July 2011 to July 2012.

EM38 readings were conducted in two campaigns: one was in spring (March-April, $3 \times 15 = 45$ pairs of vertical and horizontal readings, respectively denoted as $EM_V$ and $EM_H$) and the other was in early summer (June-July, when the dry season started after harvesting of barley and wheat, $3 \times 7 = 21$ pairs of readings) in 2012. As designed, both $EM_V$ and $EM_H$ readings were taken in the plots ($1 \times 1$ m) distributed at three corners of triangles. The averaged values of the three corners were regarded as the representatives of the triangle centers. The designed distance between each two corners of a triangle was about 15–20 m so that the triangular area can represent more or less a Landsat TM pixel. The objective of such averaging was to have more comparability between the field sampling and satellite images, for example, Landsat TM data with a pixel size of 30 m. Also, two triangles of measurements situated nearby the Mussaib site conducted in the regional validation campaign in June 2013 (see Wu et al. 2014a for detail) were also integrated into this study. In total, 24 averaged pairs of EM38 readings were made available for modeling as training set (TS, figure 1).

One of the three corners of a triangle was randomly selected to constitute a validation set (VS) which also have 24 pairs of $EM_V$ and $EM_H$ readings (see figure 1).

Soil samples were taken in croplands or under halophytes from 13 pedons (the surface horizon part, 0–30 cm in depth) and 17 auger holes of 0–30 cm in the study area in Jul-Nov 2011, when EM38 instrument was not available. These samples were laboratory analyzed to measure soil electrical conductivity (ECe) using 1:1 dilution method.

EM38 readings were not measured at the same plots as soil sampling due to accessibility problem. These soil samples were used neither for calibrating the EM38 readings (ECa) nor for salinity modeling because of the difference in sampling locations.

2.2.2. Satellite data

The Level 1.5 L-band radar product of the Japanese ALOS satellite was obtained from the European Space Agency (ESA: https://alos-palsar-ds.eo.esa.int) in the frame of the project ‘Soil salinity mapping by ALOS radar data (https://earth.esa.int/web/guest/pi-community/myearthnet)’. The L-band images were produced by a microwave radar sensor with a wavelength of 23 cm (frequency of 1.27 GHz) in Fine Beam Double (FBD) Polarization Mode (HH/HV). The images were acquired with an off-nadir angle 34.3° and incidence angle of 7.5–60° on November 26, 2010. The Level 1.5 Product has a spatial resolution of 12.5 m.

As auxiliary remotely sensed dataset, Landsat 5 TM images (30 m in resolution) dated November 23, 2010, close to the acquisition date of ALOS images, were also obtained from ESA (https://landsat-ds.eo.esa.int).

When both satellite images were being acquired, summer crops (mainly maize) started to become mature, and perennial forage crop, alfalfa, was still green. Winter crops such as barley and wheat were just sown or to be sown, and the rainy season had not yet started in Mesopotamia.

It is noted that in the surrounding weather stations of the study area, namely Baghdad, Karbala, Najaf, Diwaniyah, and Hillah (figure 1), there was no rainfall recorded in May-November 2010. Thus, the rainfall-related moisture problem that may arise in spring images (Wu et al. 2014a and 2014b) could be avoided.

2.3. Approaches and procedures

In this study, our effort was focused on the processing of the ALOS L-band radar data to minimize the impact of vegetation and moisture on the backscattering coefficients with support from the TM data.
2.3.1. TM image processing
The Landsat 5 TM images were radiometrically calibrated to convert Digital Number (DN) of pixel into radiance, and then the FLAASH (Fast Line-of-sight Atmospheric Analysis of Spectral Hypercubes) model was applied to remove the atmospheric effects (Wu et al. 2014a, 2014b, Wu et al. 2018).

As revealed in our recent study (Wu et al. 2018), the relevant vegetation indices required for vegetation removal on the radar backscattering coefficients from TM images are the Normalized Difference Vegetation Index (NDVI), the Generalized Difference Vegetation Index (GDVI, Wu 2014) with power number of 2 and 3 (denoted respectively GDVI2 and GDVI3). Vegetation fraction or fractional vegetation cover ($f_v$), the rescaled NDVI (Gutman and Ignatov 1998, Wu 2014) was also derived from the TM images.

\[
f_v = \frac{(NDVI - NDVI_{s})}{(NDVI + NDVI_{f})}
\]

where $NDVI_{f}$ and $NDVI_{s}$ are respectively the NDVI value of bare soil and fully vegetated pixels.

2.3.2. L-band radar processing
The Level 1.5 radar product has been geometrically rectified, and its spatial deformation induced from landform and variation of incidence angle also corrected, and pixels were resampled to 12.5 m in size by the provider. The DNs of the two polarization bands, HH and HV, were respectively calibrated and converted into backscattering coefficients ($\sigma_{HH}^0$ and $\sigma_{HV}^0$) in terms of Shimada et al. (2009):

\[
\sigma_0^d[\text{dB}] = 10 \log_{10}(DN)^2 + CF
\]

where $CF = -83.0$ for Level 1.5 product.

An Enhanced Lee filter (Lee, 1980), $3 \times 3$ in size, was then applied to the sigma naught ($\sigma_0^d$) to remove speckles and noise. $\sigma_{HH}^0$ and $\sigma_{HV}^0$ were hence derived and resampled to 30 m in pixel size to match the TM data.

2.3.3. Minimizing the impacts of vegetation cover

2.3.3.1. Water cloud model
As mentioned in section 1, the difficulty to use radar backscattering signatures to characterize soil salinity is related to soil moisture, especially, where there is vegetation cover. Attema and Ulaby (1978), and Ulaby et al. (1978) have proposed a Water Cloud Model for characterizing the effect of vegetation water content (VWC) on radar backscattering coefficient, which can be expressed as follows (Kumar et al. 2012):

\[
\sigma_0^d = \sigma_0^{\text{veg}} + L^2 \sigma_0^{\text{Soil}}
\]

with

\[
\sigma_0^{\text{veg}} = AV_i \cos(\theta_i)(1 - L^2)
\]

\[
L^2 = \exp(-2BV_6 \text{sec}(\theta_i))
\]

\[
\sigma_0^{\text{Soil}} = (\sigma_0^d - \sigma_0^{\text{veg}}) / L^2
\]

where $\sigma_0^d$ is the total backscattering coefficient (i.e., $\sigma_{HH}^0$ and $\sigma_{HV}^0$ in our case), $\sigma_0^{\text{veg}}$ is the backscattering contribution of the vegetation cover, $\sigma_0^{\text{Soil}}$ is the backscattering contribution of the soil, and $L^2$ is the two-way vegetation attenuation; $\theta_i$ is the incidence angle; $A$ and $B$ are the vegetation parameters. $V_1$ represents a canopy descriptor, e.g., LAI (Leaf area index, m²/m²), and $V_2$ is the vegetation water content (VWC) (Moran et al. 1997, Kumar et al. 2012).

Svoray and Shoshany (2003) and He et al. (2014) proposed a modified backscattering coefficient equation by introducing the vegetation fraction ($f_v$) into the Water Cloud Model. They considered equation (3) was effective only for vegetated area but not for bare soil. The modified equation is written as follows:

\[
\sigma_0^d = f_v \sigma_0^d + (1 - f_v) \sigma_0^{\text{Soil}}
\]

where $\sigma_0^d$ is the total backscattering coefficients of a pixel including bare soil. Replacing the vegetation contribution ($\sigma_0^d$) with equation (3), then, we got,

\[
\sigma_0^d = f_v (\sigma_0^{\text{veg}} + L^2 \sigma_0^{\text{Soil}}) + (1 - f_v) \sigma_0^{\text{Soil}}
\]

So,

\[
\sigma_0^{\text{Soil}} = (\sigma_0^d - f_v \sigma_0^{\text{veg}}) / (1 + f_v L^2 - f_v)
\]

2.3.3.2. Determination of canopy descriptors and vegetation parameters
As the tests of Wu et al. (2018) revealed, the vegetation descriptors $V_1$ and $V_2$ can be relevantly represented respectively by LAI and VWC, which have the following forms:
\[ V_1: \text{LAI} = 0.091 \exp(3.7579GV12)(R^2 = 0.932, \text{Wu} 2014) \]  
\[ V_2: \text{VWC} = 192.64NDVI^3 - 417.46NDVI^2 + 347.96NDVI^1 - 138.93NDVI^0 + 30.7NDVI - 2.82(R^2 = 0.990, \text{Jackson et al} 2004) \]

Regarding the vegetation parameters \( A \) and \( B \), among a number of the proposed pairs, Wu et al. (2018) found that the 2\(^{nd} \) case of Dabrowska-Zielinska et al. (2007) designed for ALOS L-band radar data performed best, i.e., \( A = 0.0045, B = 0.4179 \). This pair of parameters was selected for our further analysis.

Such determination and selection could lead to the best correlation between the vegetation-removed backscattering coefficients \( (\sigma^0_{\text{Soil}}, \text{equation (6)}) \) and the field measured apparent soil salinity (ECa).

### 3.1. Improvement in correlation

It is interesting to see that the measured EM\(_{V}\) and EM\(_{H}\) were negatively correlated with the radar backscattering coefficients \( (\sigma^0_{\text{HH}} \text{ and } \sigma^0_{\text{HV}}) \), in particular, with those whose influences of vegetation and moisture were removed \((\sigma^0_{\text{HH(Soil)}} \text{ and } \sigma^0_{\text{HV(Soil)}}) \) using equation (6) (table 1). The removal procedure has gained an increase of
The sum of these two sigma naught, \( \sigma_{HH}^0 + \sigma_{HV}^0 \), and an increase of 11.5%–21.4% in that of \( \sigma_{HH}^0 \) in comparison with \( \sigma_{HV}^0 \). The sum of these two sigma naught, \( \sigma_{SUM}^0 = \sigma_{HH}^0 + \sigma_{HV}^0 \), has gained relatively less, by 7.5%–16.3%. This demonstrates the importance to conduct this removal procedure in which the improved correlation coefficient reached \( R^2 = 0.565–0.677 \).

However, the second removal procedure taking the vegetation fraction \( f_v \) into account as shown in equation (9) did not derive any enhancement in such correlation (\( \sigma_{HH}^0(\text{Saloli}) \) and \( \sigma_{HV}^0(\text{Saloli}) \)) with the measured soil salinity. PCA did not ameliorate the correlation itself but inherited the improvement from the first removal procedure by 4.2%–22.4%, i.e., \( 1^\text{st} \text{PC1} \) versus \( \sigma_{SUM}^0 \) against the field measured salinity.

### 3.2. MLR models and salinity maps

The results of MLR modeling are presented in Table 2. \( EM_H \) and \( EM_V \) models are either associated with \( \sigma_{HH}^0(\text{Saloli}) \), \( \sigma_{HV}^0(\text{Saloli}) \) or PC1 of different sets of the backscattering coefficients. Model 1 is of high predictivity with a modeling accuracy of 78.3%. This indicates the importance of minimization of vegetation and VWC on the backscattering coefficients using the Water Cloud Model of Attema and Ulaby (1978) (equation (6)).

Then, both Models 1 and 2 were applied back to the dataset consisted of different sets of radar backscattering coefficients to produce the apparent soil salinity maps, which were further converted into lab-measured soil salinity (ECe) in terms of equations (12) and (13). The maps are presented in Figure 2 as continuous ramp.

### 3.3. Discussion

As commonly known, the difficulty to use radar data for soil salinity mapping lies in the removal of the impacts of vegetation cover and its moisture on the backscattering coefficients. Hence, an effort was made in this study to find approximation ways to remove or minimize such influences. Our study showed that the minimization approach based on equation (6) rather than the Water Cloud Model (Attema and Ulaby 1978) led to a good correlation with the measured salinity.

On the contrary, the procedure by introducing the fractional vegetation cover \( f_v \) (equation (9)) did not perform as expected, though it could improve estimation of moisture (He et al. 2014) and biomass (Svoray and Shoshany 2003).

An attempt has been also made on PCA to improve the correlation between the first principal components (PC1) of the three sets of radar backscattering coefficients and the measured soil salinity, but no amelioration has been found. We had also tried to derive VWC from the L-band radar data as Pampanoni et al. (1997) did to achieve the minimization of the vegetation cover by radar data themselves. Tests were neither successful.

Hence, for the time being, we think that the approach using Water Cloud Model of Attema and Ulaby (1978) by introducing the LAI-GDV12 model of Wu (2014) to \( V_V \) and VWC-NDVI model of Jackson et al. (2004) to \( V_2 \) and using vegetation parameters A and B of Dabrowska-Zielinska et al. (2007) could achieve the best retrieval of the soil components by minimizing the impacts of vegetation and moisture on the backscattering coefficients.

The produced salinity map by Model 1 was compared to that obtained using multiyear maxima of the biophysical indicators derived from Landsat images of 2009–2012 by Wu et al. (2014a) with validation accuracy of 83%, and found that they were more or less comparable except for a bit lower prediction accuracy of the former. Nevertheless, radar-derived map predicted better salinity in halophytes. Another comparison was taken with the results derived by machine learning regression, in particular, Random Forest Regression (RFR) using the combined optical and radar dataset by Wu et al. (2018). We noted that the latter has a better mapping accuracy as.

### Table 1. Correlation coefficients between the radar backscattering coefficients and measured apparent soil salinity.

| ECe (mS/m) | \( \sigma_{HH}^0 \) | \( \sigma_{HV}^0 \) | \( \sigma_{SUM}^0 \) | \( \sigma_{HH}(\text{Saloli})^0 \) | \( \sigma_{HV}(\text{Saloli})^0 \) | \( \sigma_{SUM}(\text{Saloli})^0 \) |
|------------|----------------|----------------|----------------|----------------|----------------|----------------|
| EM_H       | -0.699        | -0.693        | -0.738        | -0.765        | -0.718        | -0.741        |
| EM_V       | -0.638        | -0.619        | -0.668        | -0.823        | -0.776        | -0.799        |

### Table 2. Radar-based apparent soil salinity models.

| Model No | Model in ECe (mS/m) | Multiple \( R^2 \) | RMS Error | F-Ratio | p-Value |
|----------|---------------------|-------------------|-----------|---------|---------|
| 1        | \( EM_H = -22.971–12.286*\sigma_{HH}(\text{Saloli})^0 + 7.92*\sigma_{HV}(\text{Saloli})^0 \) | 0.783           | ± 90.746  | 37.922  | 0.000   |
| 2        | \( EM_V = -1386.945 + 9638.2^0*\text{PC1} – 22.2^1*\text{PC1} – 13.502^2*\sigma_{SUM}(\text{Saloli})^0 \) | 0.755           | ± 93.113  | 20.523  | 0.000   |
it has taken both advantages of optical and radar data. This means that radar-based approaches still have space of improvement.

We would like to draw attention to the fact that our results from this study can be applied to elsewhere using ALOS L-band or other L-band radar data with similar incidence angle but cannot be directly applied to other radar data with different wavelength and incidence angles.

As mentioned before, it would be neither practical nor possible to extract salinity from the imaginary part of the total backscattering coefficients. A more operational and efficient way is to consider the backscattering coefficients as a global proxy, a mixture of vegetation, moisture and salinity. After removal of vegetation cover and moisture parts, the remained backscattering coefficients ($\sigma^0_{HH(Soil)}$ or $\sigma^0_{HV(Soil)}$) are related to soil salinity.

4. Conclusions

This case study presents L-band radar-based approaches for soil salinity assessment with support from optical data. Our study revealed that it is possible to employ radar data for soil salinity modeling and mapping as a complement to the existing optical methods (e.g., Wu et al 2014a and 2014b, Scudiero et al 2015, Bannari et al 2018, Paliwal et al 2019) or optical-radar combined ones (Wu et al 2018). Improvement in radar approaches is still expected.

It is worthy of notice that while implementing the radar-based models to other similar environment for salinity assessment, it is recommended to select its appropriate LAI, VWC and vegetation parameters $A$ and $B$ in line with the vegetation types in the study areas. Approaches solely based on radar data still need further effort to find an appropriate way of minimization of the impact of vegetation cover and soil moisture by radar data themselves.

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