A MULTI SENSOR APPROACH FOR GENERATING IN -FIELD PEDOLOGICAL VARIABILITY MAPS

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ABSTRACT

Predicting spatial variations of soil components of fer great promises in term of precision farming and decreased pressure to the environment. This paper outlines some results of a recent collaboration aimed at the development of non - destructive methods to do this. The feasibility of coupling electromagneti c inductance (Geonics EM38©), GPS RTK and radiometric sensors to predict soil parameters (chemical, physical) variability was investigated. Simultaneous measurements of radiometric, GPS RTK, and EM38 sensors have been taken over different fields characterized by different soil properties and climatologic conditions, and for which soil samplings were available. Linear predictive models have been fitted on calibration data and applied on validation data in order to test accuracy of predictions. Also, a comparative study between electromagnetic inductance and electrical resistance has been made in order to validate EM38 sensor data. This study allowed different conclusions:

- MUCEP and EM38 give similar results on the variability mapping for one of the two test fields. On the second field, very dry soil conditions probably explained the poor MUCEP results (difficulty to measure very low resistance with that sensor). On the contrary, EM38 keeps a good sensitivity and remains well adapted for mapping variability ev en in dry conditions
- The innovative coupling process between GPS, EMI and radiometric data revealed to be very efficient and improved the overall prediction. Better results for prediction have been found for clay than for other components (such as pH and MgO). Correlation coefficients between predicted and real test data vary between 0.7 and 0.9.

Keywords: in field variability, linear prediction model, multi sensor approach, precision farming, induction

INTRODUCTION

In Precision farming mnagement mode, it has been ascertain that spatial variability of soil parameters is key to sound management decisions.. Producing accurate maps from soil sampling usually require intense field measurements and scouting, thus rarely cost–effective . Several papers deal with the variability mapping with non destructive methods: yield sensors [Layrol et al., 2000], remote sensing [Dicker et al., 1999] [Varvel et al., 1999], radar images [Moran et al., 1999] or geophysical sensors [Dabas et al., 2000] [Nemdhal et al., 2 001] [Sudduth et al., 1999]. In this paper we propose a multi sensor approach to quantatively predict soils parameters. In this study, the feasibility of coupling an electromagnetic inductance EMI sensor (Geonics EM38©), high precision GPS RTK and surface radiometric data to map field variability is investigated. Also, in order to validate the quality of the EM38 EMI sensor, a comparison study has been made with other geophysical sensors like MUCEP© and portable electrical resistance sensors.

The paper is divided into two main parts. The first part presents briefly the experiment sites and materials. The second part focuses on results and their interpretation (first, the validation of EM38 EMI data by comparison with MUCEP and portable electrode data; then, experimental results of predictive models). Finally, a conclusion is given.

MATERIALS AND METHOD

The field trials were conducted at several locations in France and Spain and for different kind of soil: clayey, silt -laden, sandy. The different experime nt fields are illustrated and briefly described on figure 1 (general characteristics and nature of the collected data on the site). For each field, EMI, GPS RTK, spectral image and soil sampling have been collected. Additionally, MUCEP and portable electro de measurements have be done for some fields as mentioned on figure 1.

1 Gaillac : limestone, various texture.
2 Ondes : sandy and/or clayey alluvium + *MUCEP*
3 Auzeville : clay and limestone, deep soil
4 Baziège : clay and limestone, deep soil
5 Calmont : stony soil, alluvium. + *portable electrodes*
6 Bellvis : clay and limestone, not stony
7 Vallmanya : clay and limestone, stony + *MUCEP*

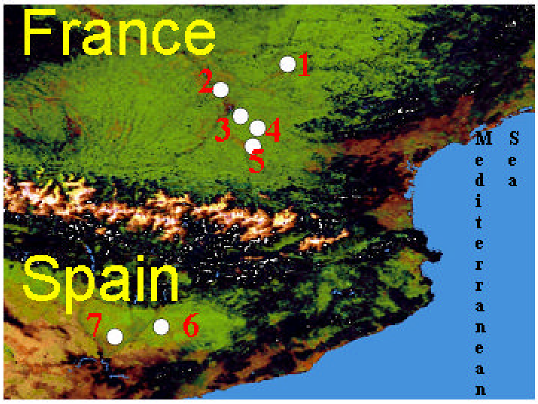


Fig. 1 : Overview of sites location.

Sites were selected over different soil types as indicated in Fig.1 and data were gathered early in the growing season, on bare soil prior to planting in early April 2001. EM38 and GPS are mounted on 2x4 quad (see Fig. 2a) and a digital camera was set on a Unmanned Aerial Vehicle UAV (radio controlled) (see Fig. 2b).

Fig. 2 : EMI EM38 sensor mounted on a 2x4 quad (fig. 2a) and UAV (radio controlled) used for taking spectral images of the fields (fig 2b).

- EMI measurements were continuously taken at two depths (75 cm, 150 cm) with a 5 meters grid sampling, with the EM38 sensor developed by Geonics.
- MUCEP data were collected and delivered by Geocarta. MUCEP measures continuously resistance at 3 depths: 50, 100 and 150 cm.
- Portable electrodes have been used for measuring electrical resistance at 7 depths (10, 20, 30, 45, 65, 80 et 105cm).
- A digital camera was mou nted on an UAV. The UAV was piloted with the help of a navigation software, based on video parameters and GPS location transmissions on a digital map (see Fig 3). This software has been developed by GEOSYS.

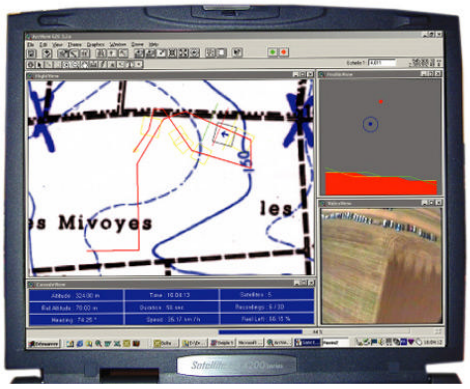


Fig. 3 : View of the help UAV navigation softw are developed by Geosys .

- Topography of each site has been done in collaboration with Toposat. A Real Time Kinematic RTK GPS receiver with a less than 1 cm accuracy for X(latitude) , Y (longitude) and Z (elevation)

- A grid soil sampling over the field was also performed with a density of 13 points per hectare at two depths (10-30cm, 60-80cm).

Based on these data sets, we investigated the possibilities to predict soil properties (physical, chemical, and physico-chemical). A fist step has been to georeference all data set into a common geographical system. Then, the aim of the study was to define which kind of inputs give the best prediction for the output parameters: texture components, organic matter, chemical components.… as summarized in figure 3.

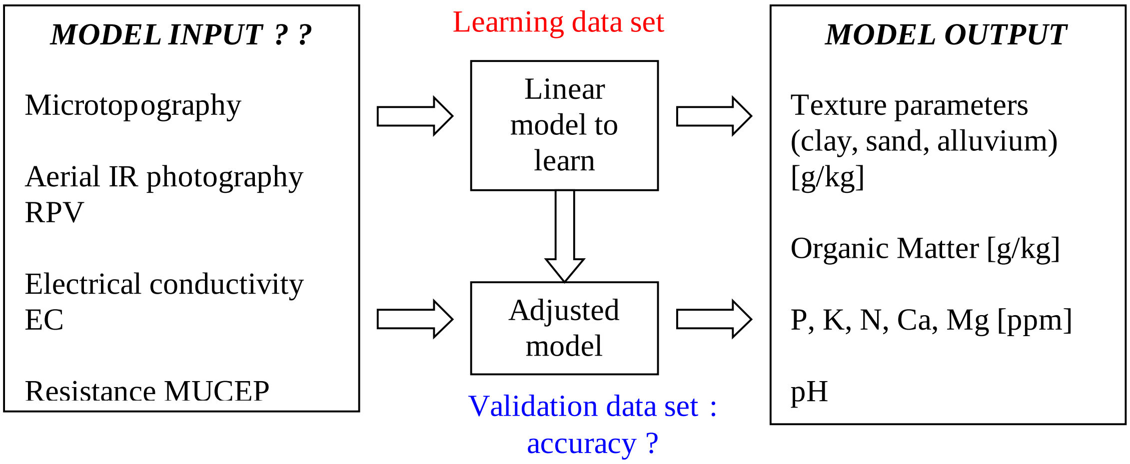


Fig. 3 : Scheme of the study.

RESULTS

Comparative study of sensors

EMI was measured with EM38 sensor. On particular fields, we added resistance measurements (MUCEP or handy electrodes) for:
- cross validation of EM38,
- cost/quality comparison between sensors for further studies.

Resistance and electromagnetic inductance are two inverses phenomenon. Consequently, we aim to find inverse relation $f(x)=1/x$ between these two data sets. MUCEP continuously measures resistance at 3 depths: 50, 100 and 150 cm. EM38 continuously measures conductivity at 2 depths: 75 and 150 cm. Finally, point resistance has been measured with portable electrodes at 7 depths (10, 20, 30, 45, 65, 80 et 105cm). We studied 3 cases:
- EM38 (75cm depth) *vs*. MUCEP (R1 50cm depth)
- EM38 (75cm depth) *vs*. MUCEP (R1 100cm depth)
- EM38 (75cm depth) *vs*. Point resistance (80cm depth)

EMI vs. handed ponctual resistance

Figure 4 displays obtained results on the Calmont site. We represent there the relationship between EM38 data and resistance portable data.

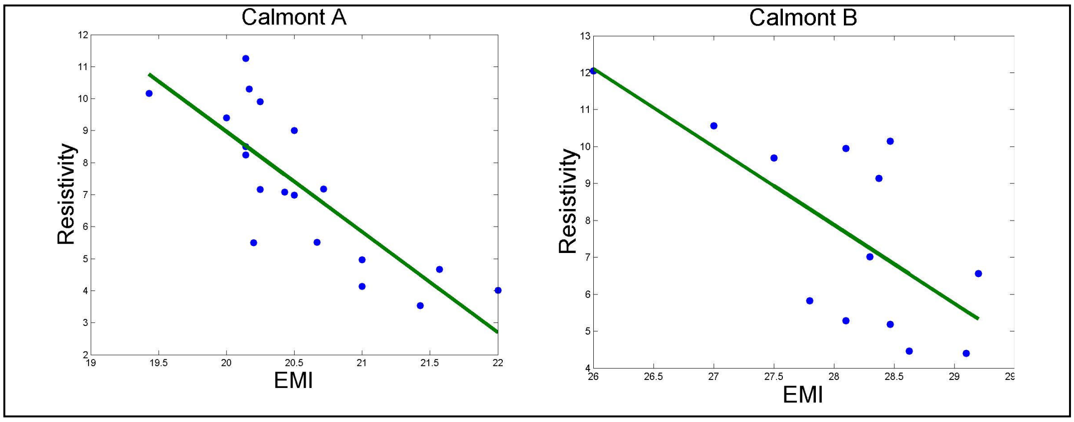
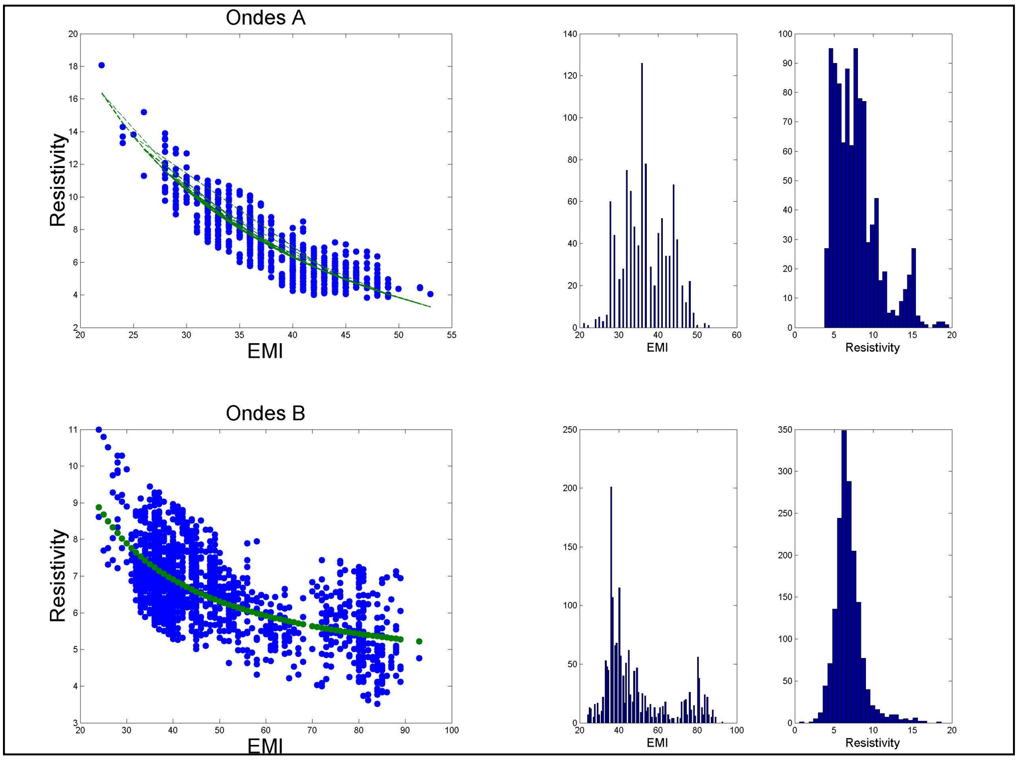


Fig. 4 : Relationship between EMI EM38 data and portable resistance electrode data, Calmont site.

Observed relations have for equations: (Y for handed resistance data, X for EMI data)
Calmont, parcel A: Y= -55.62+1288.45 1/X R=0.88
Calmont, parcel B: Y= -55.85+1780.68 1/X R=0.80
The high R correlations are coherent with the expected inverses behaviors of these two sensors. This result is a first validation of the EMI data.

EMI vs MUCEP
Figure 5 displays obtained results on the Ondes and Vallman ya sites. We represent there the relationship between EM38 data and resistance MUCEP data. Histograms of the values are also given for each kind of data.



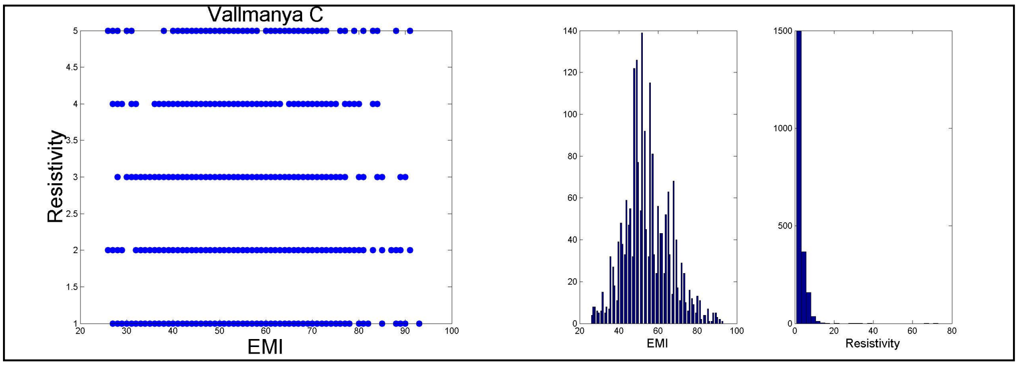


Fig. 5 : Relationships between EM38 EMI data and MUCEP resistance data , on two sites, with histograms of data values.

Observed relations have for equations: (Y for MUCEP resistance data, X for EMI data)
Ondes, parcelle A : Y= -6.02+492,95 1/X R=0.89
Ondes, parcelle B : Y= 3.97+118,23 1/X R=0.64
The high R correlations validate the inverse behaviors of these two sensors. We can also infer of second validation of EMI data from this result. We also note the bimodal character of EMI data on parcel B, which illustrates an important within-field variability not detected with MUCEP data.
It is easy to see that obtained results are very bad for Vallmanya field: no inverse relation, and no dynamic in MUCEP data as depicted on the histogram. An explanation can be the extreme dryness of the field. MUCEP sensor does not appear to be well adapted for measuring low resistance values, as related by Geocarta who made the experiment over Vallmanya. On the contrary, EM38 keeps a good sensitivity (illustrated by the good dynamic of the histogram) and remains well adapted for mapping variability **.** This can be explained by the fact that EM38 doesn't have any contact with the surface, contrary to resistance electrodes.
These two comparative studies between EMI EM38 data and both types of resistance data confirm the quality of the data acquired with the EM38 sensor mounted on a 2x4 quad. Also our experiments showed a good sensitivity of the EM38 sensor in difficult conditions.

Results of prediction

According to our methodology summarized on fig. 2, we have built a linear predictive model between input data (EMI , GPS RTK and spectral data) and output data (soil components). Models were defined on 2/3 of data set and validation is applied on the remaining 1/3 data. These data sets (learning and validation) were randomly generated. Fig 6 displays, the accuracy of prediction for clay content over the Auzeville site with 4 different configurations of input data (learning data set is in red, validation data set is in blue). The figure presents:

- correlation R values between predicted and observed data
- best linear fit equations between predicted and observed values.

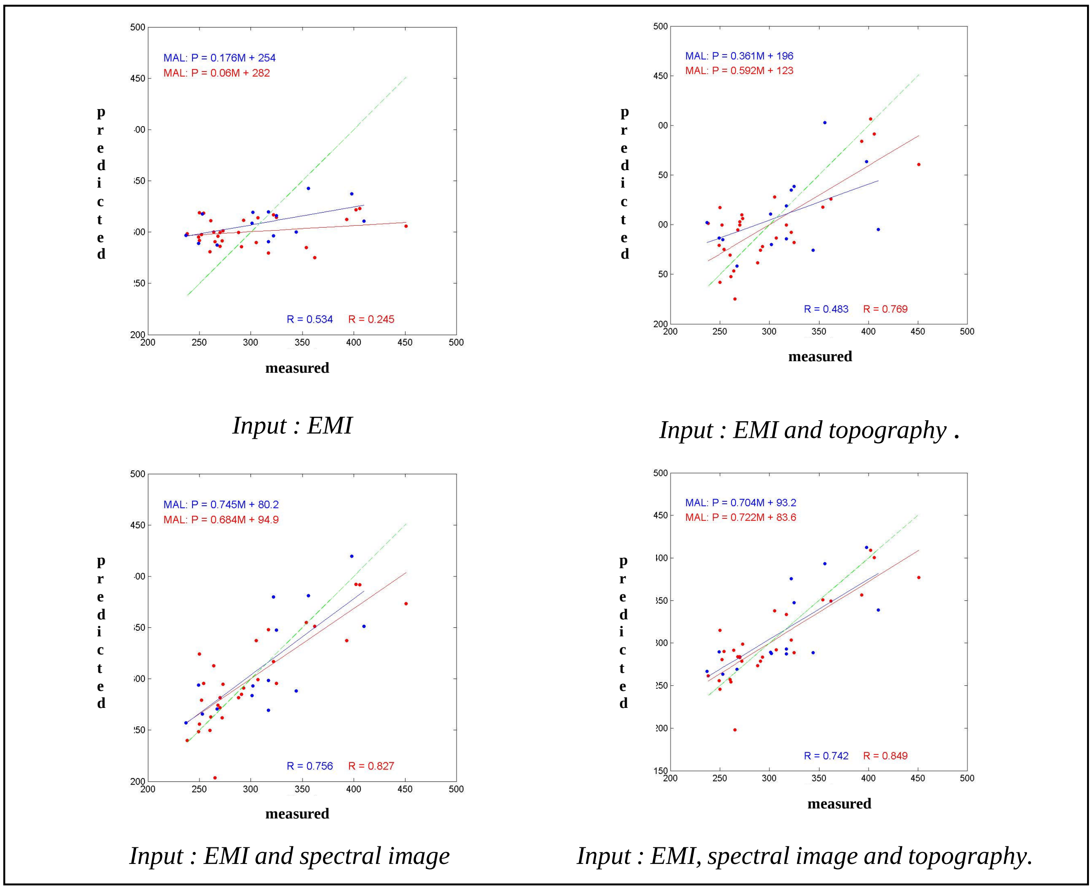


Fig. 6 : Relationships between predicted and real values of clay conte nt over Auzeville site,with four input data configurations.

Every correlation between observed parameters and predicted data were computed and are compiled in the following chart.. Figure 7 displays the evolution of R-values of all variables (mean over al l sites) for four different input data configurations.

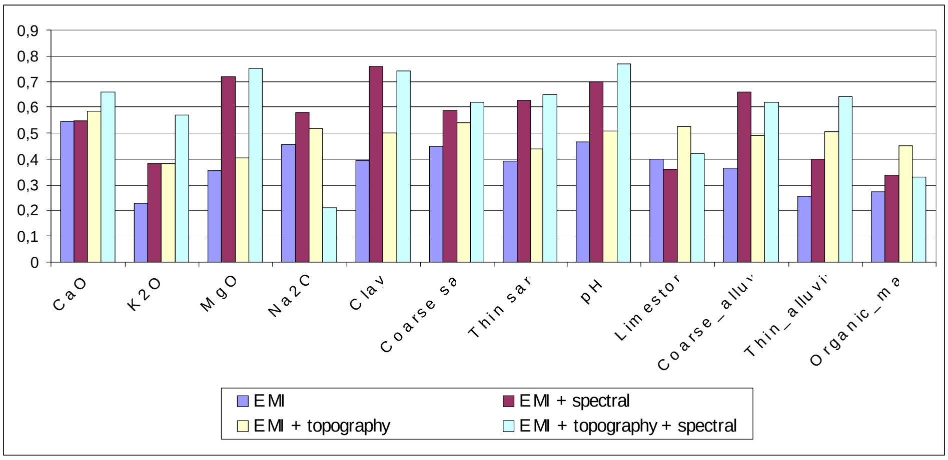


Figure 7 : R-values between predicted and observed values for the validation data set of all variables and four input data configuration (30cm depth, mean over all sites)

Figure 7 indicates that the innovative coupling process between GPS, EMI and radiometric data revealed to be very efficient and improves the prediction for several variables. In particular, prediction of pH improves from 0.4 to around 0.75. Prediction remains inefficient for orga nic matter or limestone. For these variables, linear predictive models are not useful, and more complex models should be investigated, such as neural networks.

These prediction models will be used for generating pedological variability maps with the same high spatial resolution as EMI, GPS RTK and spectral data. Figure 8 displays a first obtained result over a parcel (predicted clay content at 30cm depth from EMI, GPS RTK and spectral data).

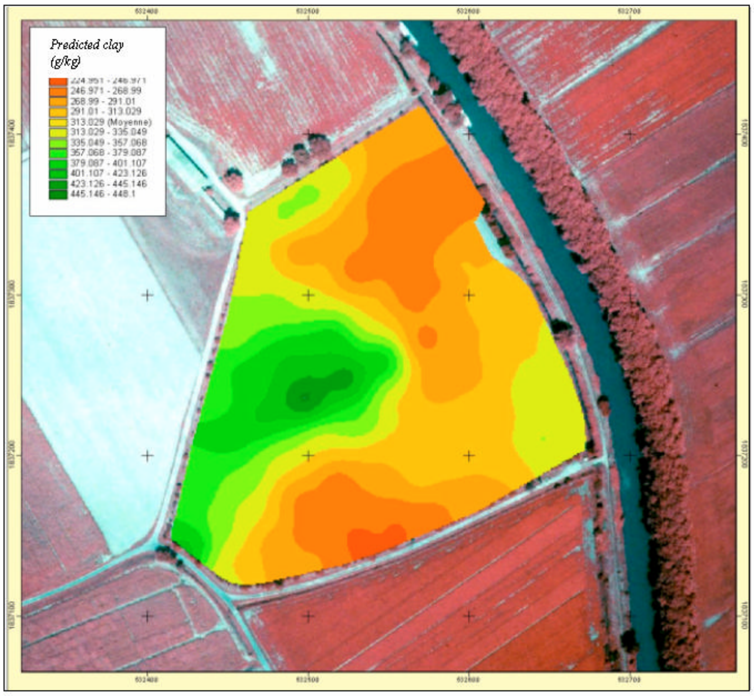


Figure 8 : Example of predicted clay content over a field (Auz eville site, France). Inputs of the model are EMI, GPS RTK and spectral data.

CONCLUSION

This paper presents a multi sensor approach for characterizing in -field variability. Linear predictive models of soil properties (texture, chemical, physicochemical) were fit on calibration data and applied on validation data in order to test accuracy of predictions. In addition, a comparative study has been made by varying the number of inputs for each model. This study revealed that the innovative coupling process between GPS, EMI and radiometric data is very efficient and improves the prediction compared to predictions solely based on one type of data. Better results for prediction were achieved for clay than for other components (such as pH and MgO). However, it is worth noting that correlation coefficients between predicted and real test data vary from 0.7 to 0.9.

Also, a comparative study has been made for cross validating the EMI data with resistance sensors. MUCEP and EM38 give similar results for one of the two test fields. On the second field, very dry soil conditions probably explained the poor MUCEP results (difficult to measure very low resistance with that sensor). On the contrary, EM38 keeps a good sensitivity and remains well adapted for mapping varia bility even in dry conditions.

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