AN INNOVATIVE APPROACH BASED ON NEURAL NETWORKS FOR PREDICTING SOIL COMPONENTS VARIABILITY

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ABSTRACT

In this paper, we report some results of a recent collaboration aimed to develop low cost and non-destructive methods for characterizing spatial variations of soil components. Producing accurate maps from soil sampling involves high field measurements density, thus finally becomes expensive without a satisfactory geospatial resolution. In this study, the feasibility of coupling an electromagnetic inductance EMI sensor (Geonics EM38©), a high precision GPS RTK, and surface radiometric data to map field variability was investigated. EM38 and GPS are mounted on 2x4 quad and a digital camera is put on a Unhumaned Aerial Vehicle UAV (radio controlled). EMI measurements are continuously taken at two depths with a 5 meters grid sampling. Based on these data sets, we investigated the possibilities to predict soil properties (physical, chemical, and physico-chemical). For this purpose, we tested two kinds of predictive models: linear regression and artificial neural network. Each type of predictive model has been fitted on calibration data and applied on validation data in order to test the resolution and accuracy of prediction. Several kinds of soil types have been considered (clayey, silt-laden, sandy). Neural network predictive models are suitable for this problem and good results are obtained for predicting texture parameters, some chemical components (CaO, K_2O), organic matter and pH. Correlation coefficients between predicted and real test data vary between 0.7 and 0.9, which is better than usual approaches (linear model with only one kind of source data): the innovative coupling process between GPS, EMI and radiometric data revealed to be very efficient. To make the method operational, the number of soil sampling needed for the learning process is then minimized. We propose a methodology for optimizing soil data collection based on an unsupervised classification of EMI, GPS and radiometric data. It has been assessed that 4 soil samplings per field appear to be sufficient to fit a good predictive neural network model. Finally, high spatial resolution soil properties maps are generated.

Keywords: precision agriculture, soil parameters variability, artificial neural networks, induction

INTRODUCTION

The knowledge of spatial variability of soil components is critical to implement an efficient precision farming program. To generate accurate maps from soil sampling usually require intense field measurements, which is rarely cost effecive and deliver a non-continuous set of data. Then this set of data usually require heroic assumptions to use a krigging method that will then deliver a geospatially distributed variable 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., 2001] [Sudduth et al., 1999]. In this paper we propose an innovative method to quantify variability of soil components. This method is based on artificial neural network (ANN) models. ANN models are well adapted for modeling non-linear behaviors. In this study, the feasibility of coupling an electromagnetic conductivity EMI sensor (Geonics EM38©), a high precision GPS RTK and surface radiometric data to map field variability is also investigated.
The paper is divided into 4 main parts. After a brief presentation of materials and recall of the objective, the second part introduces the theory behind artificial neural network models. The third part presents applications of neural networks on our data set and results. In addition, a comparison is made with linear regression. Then, in the fourth part, commercial or operational use of this method is introduced.

MATERIALS AND OBJECTIVE

Field trials were conducted at several locations in France and Spain and for different types of soil: clayey, silt-laden, sandy. The different experiment fields are illustrated and briefly described on figure 1.

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

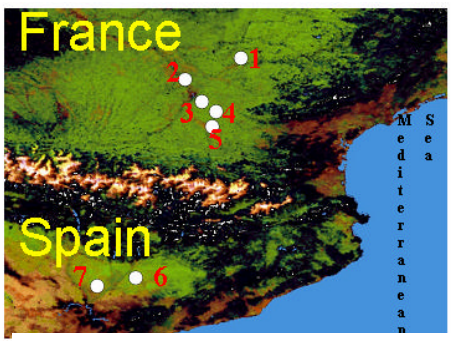


Fig. 1 : Overview of sites location.

Sites have been chosen in order to consider various kind of soil. Data (non destructive data and soil sampling) have been collected just before planting on each field (i.e. corresponding to bare soil conditions).

EM38 and GPS were mounted on a 2x4 quad, and a digital camera installed on a Unmanned Aerial Vehicle UAV (radio controlled equipment) as illustrated on figure 2.

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

- EMI measurements were continuously taken at two depths with a 5 meters grid sampling, with the EM38 sensor developed by the Geonics society.
- A digital camera was mounted 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 software developed by Geosys .

- Topography of each site has been done in collaboration with Toposat. We used for this a Real Time Kinematic RTK GPS receiver with a less than 1 cm accuracy for both X (longitude), Y (latitude) and Z (elevation).
- A grid sampling over the field was also done with a density of 13 points per hectare at two depths (10-30cm, 60-80 cm).

As a prerequisite, the entire dataset was geo-referenced and “cleaned” by removing outliers. Based on these data sets, we investigated the possibilities to predict soil properties (physical, chemical, and physico-chemical) from these non-destructive data as summarized in figure 4.

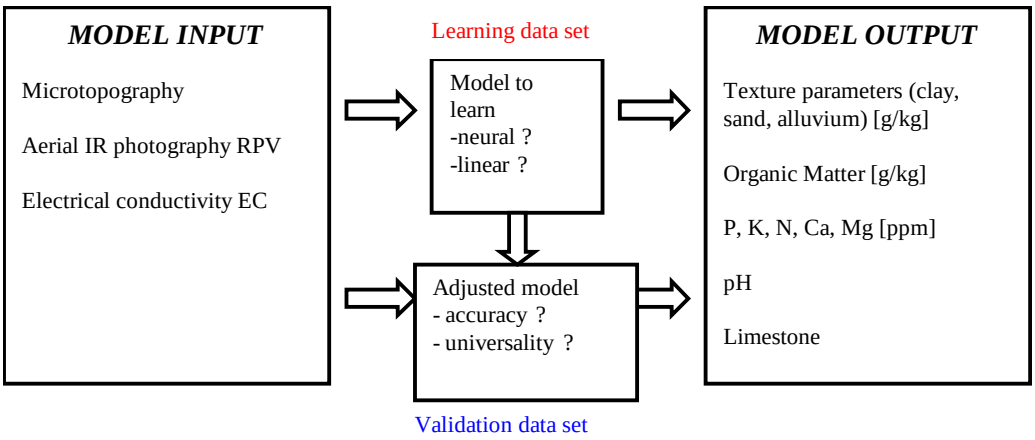


Fig. 4 : Scheme of the study.

ARTIFICIAL NEURAL NETWORKS: THEORY

This part aims to give to the reader notions about Artificial Neural Networks. For more explanation, a lot of books and paper are available on this subject [Kröse et al., 1993][Hornik et al, 1989].

Glossary

The basic computational element (model neuron) is often called a node or unit. It receives input from some other units, or perhaps from an external source. Each input has an associated weight *w*, which can be modified so as to model synaptic learning. The unit computes some funct ion *f* of the weighted sum of its inputs:

$$y_i = f\left(\sum_j w_{ij}\, y_j\right) \qquad (1)$$

Its output, in turn, can serve as input to other units.

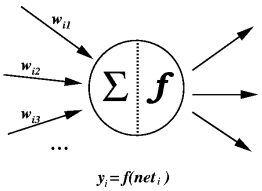


Fig. 5 : Schematic representation of a neuron.

- The weighted sum $\sum_j \omega_{ij}\, y_i$ is called the net input to unit i, often written net_i.
- Note that w_{ij} refers to the weight from unit j to unit i (not the other way around).
- The function f is the unit's activation function. In the sim plest case, f is the identity function, and the unit's output is just its net input. This is called a linear unit.

The loss function

In order to make precise what we mean by being a "good predictor", we define a loss (also called objective or error) funct ion E over the model parameters. A popular choice for E is the sum-squared error:

$$E = \frac{1}{2}\sum_{p}(t_p - y_p)^2 \qquad (2)$$

In words, it is the sum over all points i in our data set of the squared difference between the target value t_i and the model's prediction y_i, calculated from the inp ut value x_i. For a linear model: $y = w_1 x + w_0$ with slope w_1 and intercept w_0, the sum-squared error is a quadratic function of the model parameters.

Minimizing the loss:

The loss function E provides us with an objective measure of predictive error for a specific choice of model parameters. We can thus reformulate our goal of finding the best model as finding the values for the model parameters that minimize E. For linear models, linear regression provides a direct way to compute these optimal model param eters. However, this analytical approach does not generalize to nonlinear models. Even though the solution cannot be calculated explicitly in that case, the problem can still be solved by an iterative numerical technique called gradient descent. It works a s follows:

1. Choose some (random) initial values for the model parameters.
2. Calculate the gradient G of the error function with respect to each model parameter.
3. Change the model parameters so that we move a short distance in the direction of the greatest r ate of decrease of the error, i.e., in the direction of -G.
4. Repeat steps 2 and 3 until G gets close to zero.

Multiple regression

We may want to predict more than one variable from the data that we're given. This can easily be accommodated by adding more output units (Fig. 6). The loss function for a network with multiple outputs is obtained simply by adding the loss for each output unit together. The network now has a typical layered structure: a layer of input units (and the bias), connected by a layer o f weights to a layer of output units.

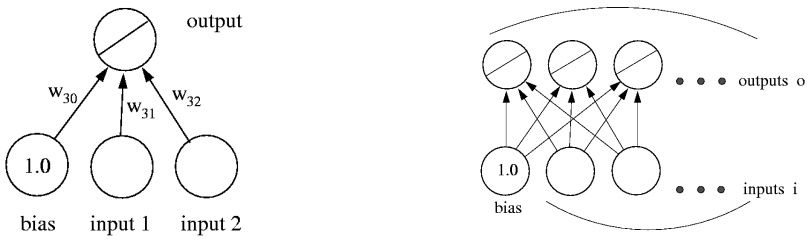


Fig. 6 : Schematic representation of a multiple regression in an ANN model.

Multi-layers networks for nonlinear problems

Consider again the case of non -linear model fitting the experimental data: we can enable our neural network to do such curve fitting by giving it an additional node

with a suitably curved (nonlinear) activation function. A useful function for this purpose is the S-shaped hyperbolic tangent (tanh) function (Fig. 7).

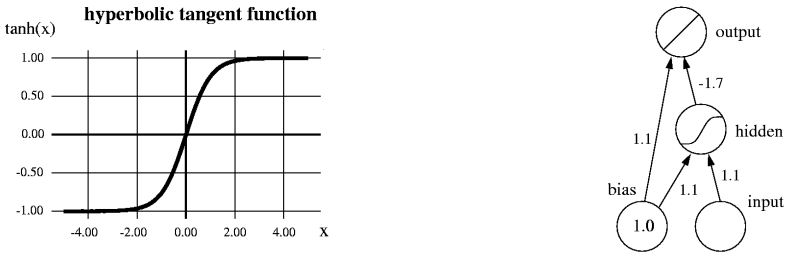


Fig. 7 : Schematic rep resentation of a hyperbolic tanget function and a hidden layer in a ANN model..

Fig. 7 shows a new network: an extra node (right) with the tanh activation function (left) inserted between input and output.
Since such a node is "hidden" inside the network , it is commonly called a hidden unit. Note that the hidden unit also has a weight from the bias unit. More complex models can be then built in order to simulate complex behaviors between input and output (figure 8).

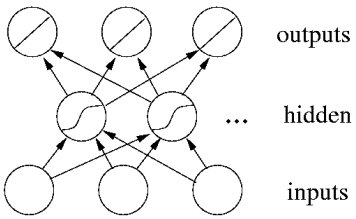


Fig. 8 : Schematic representation of a complex ANN model with hiddden layers.

Backpropagation
We have already seen how to train linear networks by gradient descent. In trying to do the same for multi-layer networks we encounter a difficulty: we don't hav e any target values for the hidden units. This seems to be an insurmountable problem - how could we tell the hidden units just what to do? This unsolved question was in fact the reason why neural networks fell out of favor after an initial period of high p opularity in the 1950s. It took 30 years before the error backpropagation (or in short: backprop) algorithm popularized a way to train hidden units, leading to a new wave of neural network research and applications. This algorithm is explained in details i n [Kröse et al, 1993].

APPLICATION AND RESULTS

We divided our data set into two parts: a learning data set (2/3) and a validation data set (1/3) as commonly done [Lin and Wang, 2000].
We made the scientific choice to use a backpropagation algorithm wh ich has been applied with success in several scientific domains [Yang et al. 1997] [Fourty 1996] [Rummelhart et al. 1986] and a single hidden level [Kröse and Van der Smagt, 1993]. The activation function has been chosen as a hyperbolic tangent

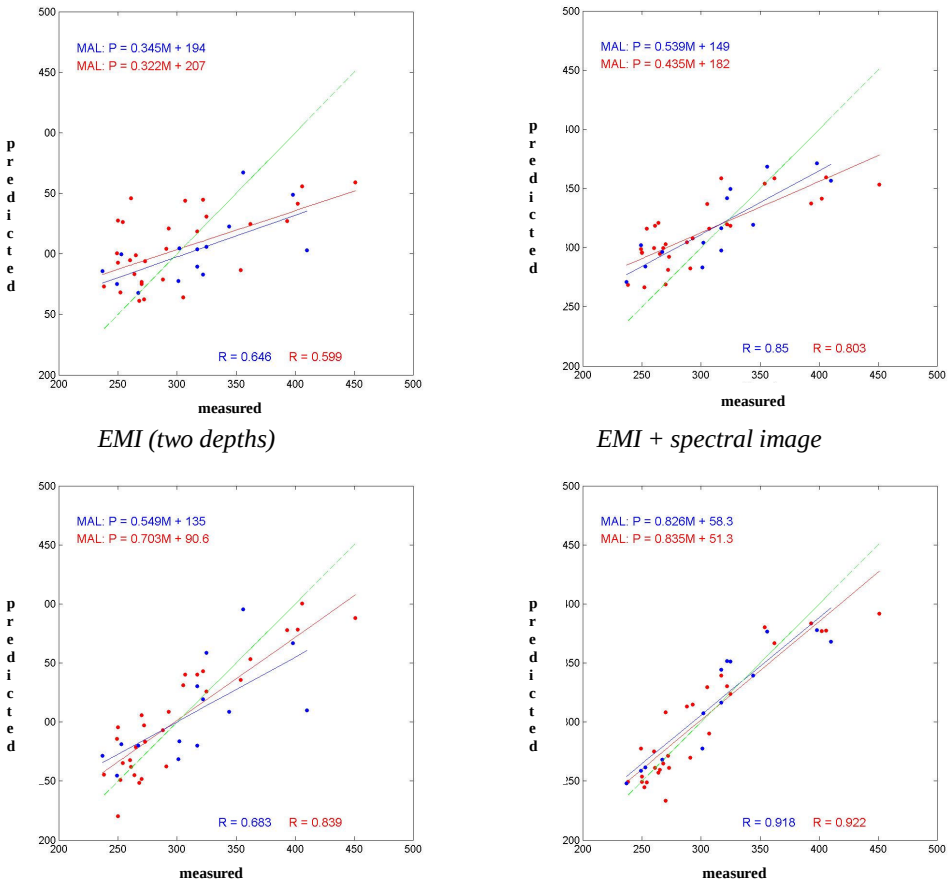
(tanh) function. Also, we have chosen the Nguyen-Widrow method for the initialization of weights and biases.

We used *Matlab software* and its *neural network toolbox* for implementation. The different tested models have been applied on all input configurations (EMI, EMI + microtopography, spectral image+EMI…) and for all desired outputs (chemical, physical, physico-chemical). Different results are presented:

- selection of the best input configuration ,
- comparison with linear models,
- universality of the obtained models.

Input data configuration

For each point (learning and validation) we have several parameters: electromagnetic inductance at two depths, microtopography, and spectral information over the surface. We tried all configurations on the input parameters in order to determine where is the most relevant information. The following charts depicts results for the clay content parameter. Each diagram on figure 9 represents the relation between measured and predicted values (using ANN) for the two data sets: learning (in red) and validation (in blue). Correlation coefficients and best linear fit equation between predicted and real values are also displayed.



EMI (two depths) *EMI + spectral image*

EMI + microtopography *EMI+spectral image + microtopography*

Fig. 9 : Result of clay content prediction with ANN models and for different input configurations. Results over the Auzeville site, France .

The data presented on figure 9 shows the efficiency of a multi -sensor approach to model clay content. Similar results have been obtained for all of the predicted parameters. The Figure 10 presents the correlation for all the variables at two depths (10-30 cm and 60-80 cm) when data in input are EMI, spectral image of the surface and microtopography.

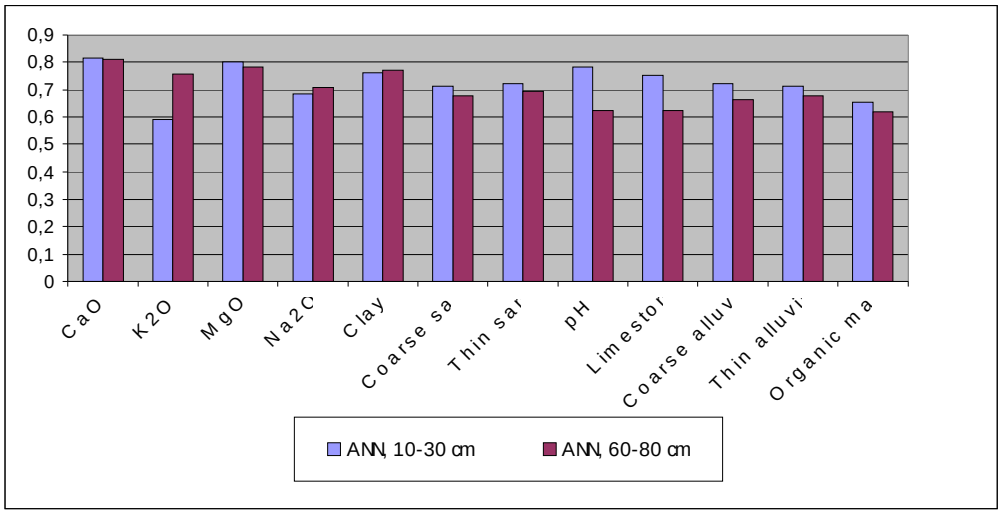


Fig. 10: Accuracy of prediction (R value) with ANN models for all variables at two depths.Input data : EMI, spectral data and topography.Values are means over all sites

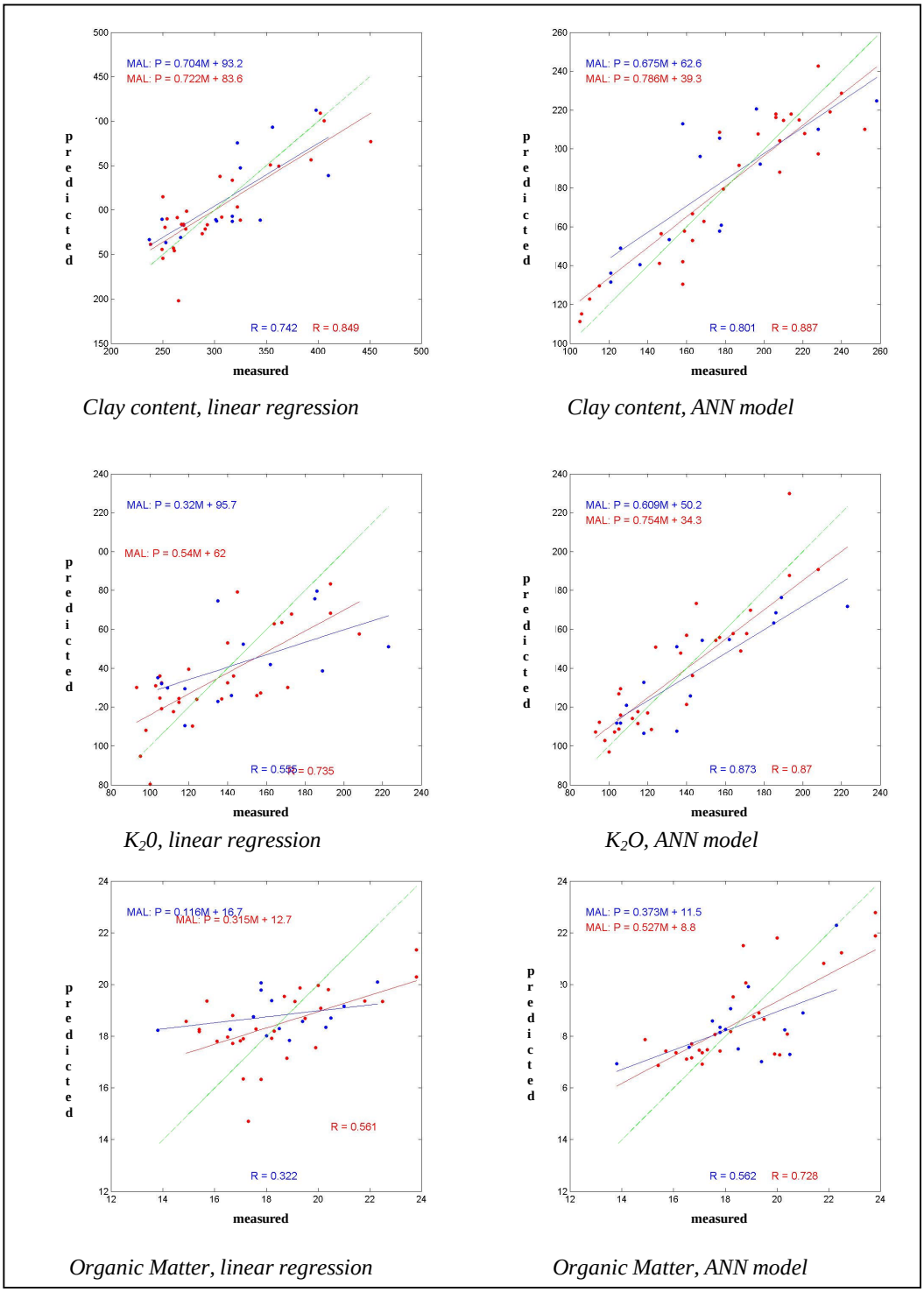
Coments:

- Very good prediction of texture parameters (clay, sand, alluvium)
- Very good results obtained also for pH (correlation about 0.80)
- Good results for chemical components and organic matter (about 0.7)

Comparison linear regression – neural network

For each data set and for each variable, we tested also linear regression. We found a good use of the linear model for clay but in general neural networks perform better for all the variables, as it is shown on figures 11 and 12.

Not only do ANN models and linear regression models give similar results for clay content, but also ANN model becomes efficient for other variables not modeled by linear regression, such as CaO and MgO. The figure 12 presents how ANN models are better predictors than linear regression for all of the variables studied.



Clay content, linear regression *Clay content, ANN model*

K_20, linear regression *K_2O, ANN model*

Organic Matter, linear regression *Organic Matter, ANN model*

Fig. 11: Comparison between linear regression and ANN models for clay, K_20 and organic matter prediction (Auzeville site, France).

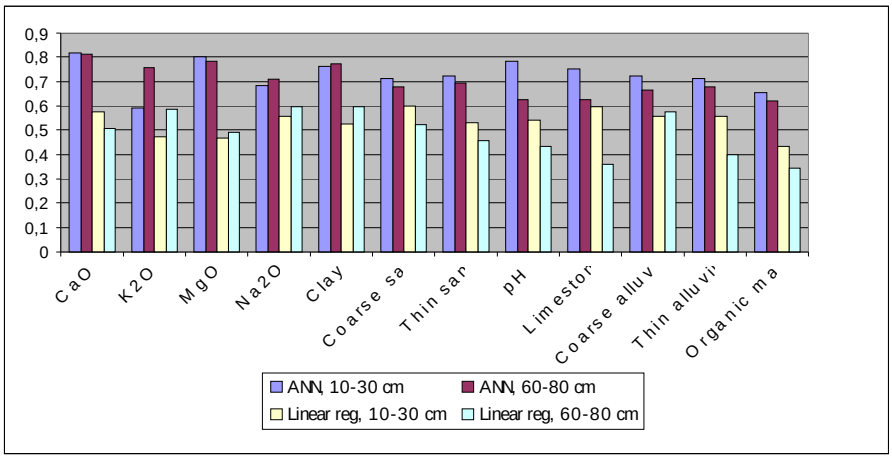
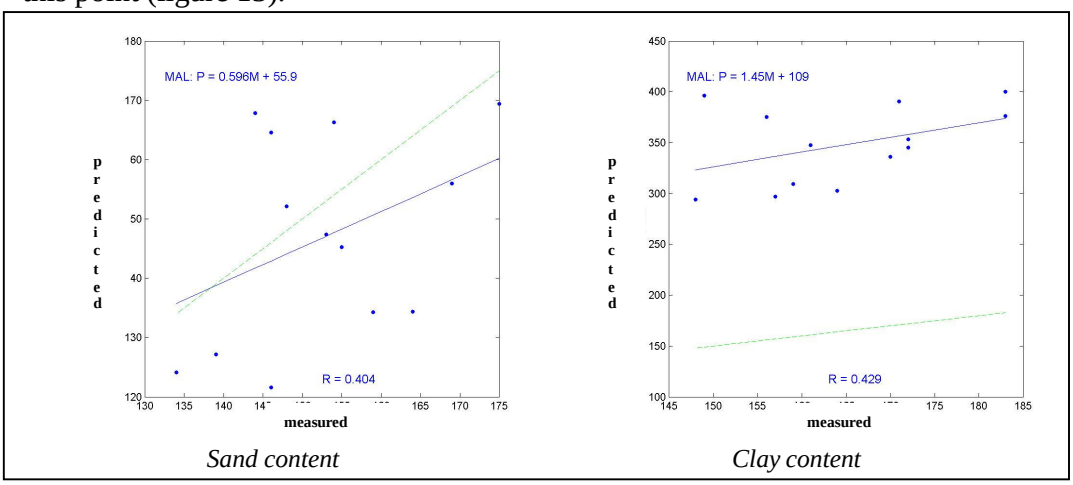


Fig. 12: Comparison between linear regression and ANN models forall variables. Values are means over all sites.

In red and purple are represented R values between predicted and real values for each variable with ANN models. In yellow and cyan blue are represented R values between predicted and real values for each variable with linear regression models. R values obtained wit h ANN models are quite better than those obtained with linear regression.

An universal model ?

The presented results have been obtained by computing a new predicting model on each field. Tests have been done on the potential of ANN models for predicting soil components on other fields than the one used for learning. In other words, can we build a model (learn and validate) on a well documented site and apply the found model over sites where no sampling points are available? Obtained results don't justify t his hypothesis. The relationship between predicted and real values over one field with a model learned over another field illustrates this point (figure 13).



Sand content *Clay content*

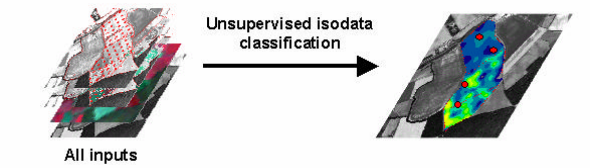
Fig. 13: Accuracy of prediction for clay and sand contents over Calmont site with a model learned with Auzeville data.

Similar results have been found for all variables (text ure, chemical and physico-chemical), and most field combinations. It seems then inadequate to consider a single model for all sites. Consequently, this method still require to collect soil samples over each field to build appropriate ANN models.

Operational method

Previous results show a good prediction of soil parameters using neural network models. However, the number of learning points was too important (13 per hectare) to be feasible with a low cost budget. We present then the first results of a methodology to make our method operational. The difficulty is to define the best way to acquire ground-sampling data for initializing the model (few but well located points). We propose the following scheme:

- Process an unsupervised ISODATA classification on inp uts data with a pre-defined number of classes,



- Choose a sampling point in each of the detected classes. At the time being the point is chosen as more representative of the mean behavior of its class,
- Build and learn the model on these points,
- Predict soil characteristic values for each input point and build the corresponding map.

We present, figure 14, the first obtained result: prediction of clay content at 90 cm depth using EMI data, surface spectral information and micro-topography (red points for learning, blue points for validation) and with only 4 learning points.
The correlation coefficient is about 0.7, which is a very valuable result. Work is currently made on the classification process, on the learning point selection and also on the model itself to improve the prediction accuracy.

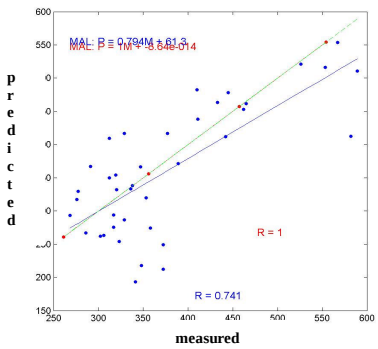


Fig. 45: Result obtained for clay content prediction with four le arning points.

CONCLUSION

This paper presents an innovative method for predicting field soil properties: variability and numerical values of soil components (texture and chemical). We show in fact several improvemen ts for this. Artificial Neural Networks ANN models seem well adapted and more accurate than usual linear model; with good predictive ability for physical texture properties, some chemical components and pH. On the other hand, the study demonstrates the imp ortance of a multi sensor approach for the prediction: the innovative coupling process between GPS, EMI and radiometric data revealed to be very efficient. An important conclusion was the non-universality of the prediction models: it is necessary to comput e a model on each field to analyze. Consequently, we propose a methodology to make our method operational by reducing the number of learning points on each field. At the time being, our first results show that 4 sampling points per field seem to be efficient. Work with the learning points selection and the prediction model are currently carried in order to improve the accuracy. The proposed method is thus less destructive and more informative than the usual method based on grid sampling only as no "heroic" krigging methods are used.

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