Innovative Measurements to Drive Sustainable Agriculture: The Agroecology Case

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***Abstract*—The situation of our food and agricultural system, facing the effects of the climate change and linked to the rise of both global population and needs is more than worrying. The need of production can no longer be solved by the excessive exploitation of our soils which has only led to the degradation of lands. This paper presents multidisciplinary researches that combine research on new indicators (such as redox potential which could be considered as key measure for agroecology and state-of-art in photonics which can miniaturize Near InfraRed spectrometer associated to advanced AI research in chemo metrics. They can altogether provide, at low-cost, measurements useful to drive the farms towards agroecological practices. Results will be presented on analysing 1000 samples of rapeseed measurements which lead, for the first time, to determine potential redox by spectrometry combined with the use of deep learning approaches.**

***Index Terms*—agroecology, AI, NIR, redox potential (Eh spectrometry**

I. Conservation Agriculture: An Agronomic Base for Agroecology

The situation of our food and agricultural system, facing the effects of the climate change and linked to the rise of both global population and needs is more than worrying. The need of production can no longer be solved by the excessive exploitation of our soils which has only led to the degradation of lands, one-third of the planet's soils are now concerned according to the FAO, and worse to the irreversible loss of arable lands.

Conservation Agriculture proposes a resilient, production system. It is based on the consideration of the soil health and is led by three principles (Fig. 1): the reduction of tillage, the diversification of crops and the longest possible soil cover.

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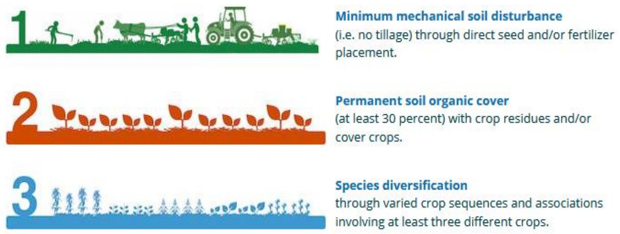

Figure 1. Three principles of agroecology.

Conservation Agriculture intends to regenerate degraded lands, meaning bringing back life in soils. By focusing on the organic matter's presence in soil which is connected to the biological activity, these agricultural techniques aim to intensify the fertility circle. Mushrooms and soil fauna, especially earthworms, play indeed a key role in the organic matter accumulation and carbon sequestration which enable a plant to grow by finding the necessary nutrients. The more you feed with vegetal residues the life of soil, the more you gain fertility, and therefore performance of your farm.

A living soil enables healthy plants to grow, with a reduced use of fertilizers and pesticides, and produces quality vegetables. With those practices farmers can maintain or increase their crop yield and simultaneously stop the use of fungicides, insecticides and reduce herbicides up to 80%.

Agroecology will enlarge the concept of Conservation Agriculture, find real alternatives to develop organic conservation agriculture, pay attention to recreate a link between consumer and producers.

Such changes in agricultural plots give rise to completely modified agro-ecosystems both in their thermodynamic dynamics and in their responses (biotic and abiotic) to the actions of farmers (pesticides, tillage, compaction).

<u>The need to measure to drive the transition:</u>

It is essential to provide to agriculture stakeholders measurement solutions that are simple to use, but complete in the results obtained. Agroecology must therefore move from an empirical appreciation of plots as is traditionally done in agriculture, to an easy measurement of the biotic and abiotic parameters of plots for the purpose of understanding and progress. Also, today traditional indicators, even often measured in laboratories, are not enough to understand new agroecological environment related to living soils and its impact on the full chain. New indicators have to be identified such the potential redox described here after.

II. Redox Potential: The Innovative Measures to Drive Agroecology

Soil health or quality has been defined in many ways that usually include various aspects of physical and chemical soil properties and some biological indicators. Thus, various indicators proposed to assess soil health [1]-[4] all reflect the importance of soil organic matter, nutrient cycle, biological activity and soil structure in soil health. Interestingly, these parameters both impact and are impacted by soil redox potential (Eh, assessing the availability of electrons) and pH (assessing the availability of protons), and it was proposed to assess soil health through Eh and pH [5]. Eh and pH signaling and homeostasis are also regarded as key processes on almost all aspects of plant biology [6], [7], and as for soil health, the various methods developed to assess plant stress/health, as chlorophyll fluorescence, photo-oxidative stress markers (including photosynthetic pigments, PSII efficiency, ROS, reactive carbonyl species, antioxidant systems) are all related to Eh and pH. Thus, it was proposed to use Eh-pH also as indicators of plant health [8].

These same parameters are related to, and can explain fundamental processes not only in soils and plants, but more generally in biology, including also animals/human as reflected in the increasing recognition of the importance of Eh and pH homeostasis in health [9]-[11]. Thus, an Eh-pH perspective could become a very powerful tool to develop a "one health approach" [12], addressing and encompassing the many interactions between environment (soil, climate, etc.), plants, microorganisms and animals.

However, measurement of these parameters based on electrochemistry, face several difficulties especially redox potential. Variations in the methodology and instrumentation for measuring the associated voltages often lead to imprecise and inaccurate estimates of redox potential [9] and electromagnetic fields can dramatically perturb Eh measurement [10]. Furthermore, even when these constraints are overcome, electrochemical measurements are time consuming and fastidious, which strongly limits the possibility to use such measurements to drive the design and the implementation of agroecological practices. Hence, there is an urgent need to develop innovative measurement tools for in situ rapid and reliable measurement of Eh and pH in plants and soils.

III. Measuring Redox Potential: Operational Difficulty

Measures on the field (Fig. 2) were made in partnership with the enterprise Ver de Terre Production which is recognized in France to lead the open source diffusion of agroecology knowledge and pilot farmer portraits. This French agroecological farms ecosystem allowed to quickly find a high variability of farm practices from conventional agriculture to no-till farming with carbon-rich soils. A campaign of measurement has therefore been done on wheat and rapeseed, spanning several months, from December 2019 to June 2020. Around 1200 leaves of wheat and 650 leaves of rapeseed have been measured from several farming management systems. First NIR spectra were done (see more info in Section VI), then, redox potential was measured directly by inserting a platinum electrode into the foil as described in [8]. Once these measurements were made, a mortar and pestle then a syringe were used to extract the juice, on which the pH was measured with a Laquatwin pH 22 meter.

The collected data were directly sent to the NIR sensor with the dedicated application (see part VI).

Although accurate, the method applied for the redox measurement has the following drawbacks:

- The equipment used for the measurement of the ORP being extremely sensitive to electromagnetic disturbances, care must be taken to analyse the samples collected in areas free from such disturbances.

- The electrodes used for the redox potential measurement being sensitive to temperature variations, it is necessary to accompany each measurement point with a temperature reading, which will subsequently make it possible to correct the measurement affected in the field.

- The redox potential measurement may vary slightly with the pressure exerted by the platinum electrode on the sheet.

- The redox potential measured on a sheet varies greatly during the day. We observed a plateau from 11 a.m. to 4 p.m. which makes it possible to compare the different modalities among themselves [8].

Figure 2. Measuring redox potential in the field.

IV. The "Redox" Scanner: Tool of the Future

As introduced in previous section, Redox potential (Eh) is not easy to measure on day-to-day practices also due to electromagnetic sensitivity where measurements can differ even taken at few cm in distance. While some measurement kit exists [13], few farmers actually use it and that prevents to acquire the information needed to drive the farms towards greener practices. Usual measurements are done in laboratories sometime using laboratory spectrometer. With the recent miniaturization of spectrometers on MEMS chip [14], we decided to conduct some research to explore the feasibility to develop a portable and low-cost spectrometer with the challenge to measure new indicators such as Eh. We set a multi-disciplinary research team with agronomist, electronics and photonics specialists to work on the hardware integrating a Near Infra-Red (NIR) spectrometer and Data Scientist to interpret the light spectrum with AI-based chemometrics.

V. The NIR Spectrometry

The spectroscopy is not new and first industrial applications began in the 1950s. Many laboratory spectrometers are available on the market but they are often quite bulky and expensive. What is new is the miniaturization of the technology which allow small handheld device together with cost reduction to be affordable to end-users (e.g. farmers). We present here the potential of spectrometry in the light band of Near Infra-red. Near-Infrared Spectroscopy (NIRS) [15] is a spectroscopic method that uses the near-infrared region of the electromagnetic spectrum (from 780 nm to 2500 nm). Near-infrared spectroscopy is widely applied in agriculture for determining the quality of forages, grains, and grain products, oilseeds, coffee, tea, spices, fruits, vegetables, sugarcane, beverages, fats, and oils, dairy products, eggs, meat, and other agricultural products. It is widely used to quantify the composition of agricultural products because it meets the criteria of being accurate, reliable, rapid, non-destructive, and inexpensive [16]. Near-infrared spectroscopy is based on molecular overtone and combination vibrations. There is absorption of light energy when the frequency of the radiation hitting the molecular bound is equal to the frequency of vibration of this bond. We can therefore link a wavelength to a given bond ex 1900 nm and H-OH of the water molecule. The molecular overtone and combination bands seen in the near-IR are typically very broad, leading to complex spectra; it can be difficult to assign specific features to specific chemical components. For each product we get a spectra with level of light absorbance per wavelength (see example Fig. 3) The interpretation of the spectra is the chemometrics science, where innovative approach using AI techniques have recently emerged and which have be used in this project.

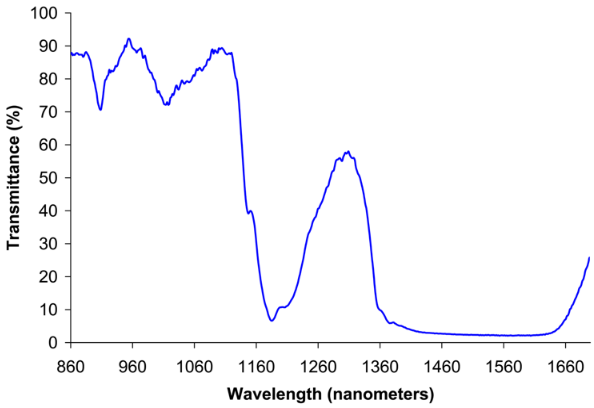

Figure 3. Near-infrared spectrum of liquid ethanol.

VI. The AI Based Chemometrics

Because of the complexity of measuring the redox potential, we have looked at other ways of getting an accurate value for this quantity. Given the current trend and success of the NIR spectroscopy in agriculture, it made sense to attempt inferring the redox potential value from a NIR scan.

A campaign of measures has therefore been done on rapeseed, spanning several months, from December 2019 to June 2020.

Two quantities were measured on wheat and rapeseed leaves:

- Redox potential, using a standard redox potential measurements kit,
- And leaves absorbance, measured using a NIR sensor. The sensor used was based on the Texas instrument NIR scan module [17], of which the spectral wavelength goes from 900nm to 1700nm. Several scans (from 2 to a dozen) were done for each sample, and therefore several scans were associated with the same redox potential measurement.

  A scan is basically made of 256 data points (absorbance value at a specific wavelength).

The distribution of the redox potential for the rapeseed is shown below (Fig. 4).

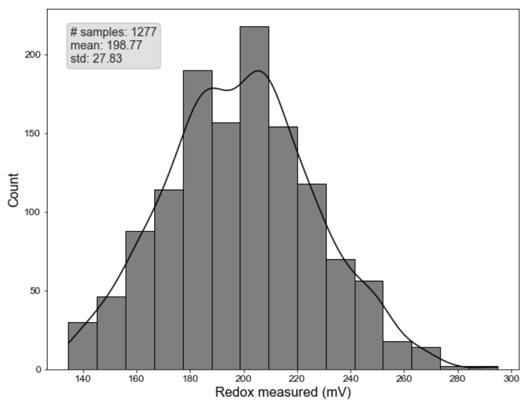

Figure 4. Redox potential distribution.

This distribution is changing across the season/months as shown below (Fig. 5):

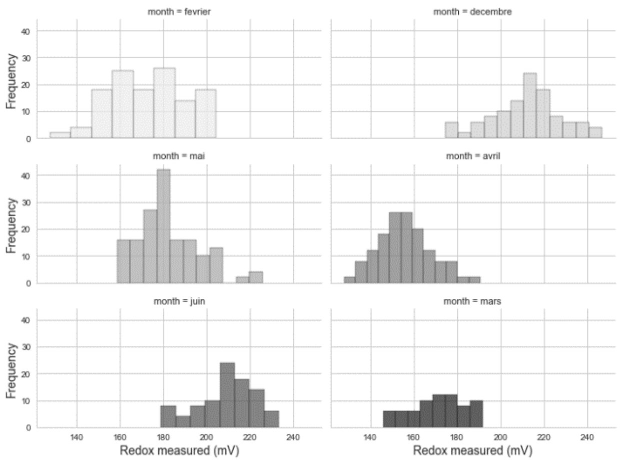

Figure 5. Monthly variation of the redox potential distribution.

The collected data has been cleaned, particularly we have retained only two scans (chosen randomly) per sample, to avoid any bias due to the different number of measurements per redox potential value.

After cleaning, we had a set of around 650 samples for rapeseed.

The challenge was then to understand if there exists a relationship between a 900nm-1700nm absorbance scan and the redox potential value. And if we could find this relationship with a good enough precision so that it can be used.

A. Traditional Approaches, PCR & PLSR

The first obvious solutions were to use traditional approaches, i.e. algorithms that have already been used in the context of NIR spectroscopy and gave correct results. PCR (Principal Components Regression) and PLSR (Partial Least Squares Regression) were two good candidates as suggested by numerous scientific papers describing the use of these two algorithms for NIR predictions, as for instance [18].

PCR and PLSR are dimensionality reduction algorithms and therefore appropriate to our high dimensional data (256 wavelength points for each sample).

Both algorithms work by transforming the explanatory variables into a number of components and performing a linear regression using these components. The main (and significant) difference between these two algorithms is that PCR is using only the explanatory variables for the transformation whereas PLSR using both the explanatory variables and the response variable (e.g. the redox potential value).

We've performed regressions with different configurations, particularly with regards to how the data were pre-processed. We applied:

1) *None*: no pre-processing, i.e. using using raw data,
2) *StdScl*: standard scaling (removing the mean and scaling to unit variance),
3) *SavGol*: Smoothing using the Savitzky-Golay [19] method (order 3, derivative 1),
4) *SavGol-StdScl:* Savitzky-Golay smoothing followed by standard scaling,
5) *Outliers-SavGol-StdScl:* Removing outliers, Savitzky-Golay smoothing followed by standard scaling.

Datasets have been split into a training set and a test set with a 0.2 ratio (20% of the dataset is reserved for test set, i.e. for estimating the performance of the algorithms. The test set is never used for training).

To compare the performance of each model, we used the following metrics: RMSE (Root Mean Standard Error), ***MAE*** (Mean Absolute Error) and $\boldsymbol{R^2}$ (R-Squared).

The number of components for both PCR and PLSR have been determined by cross validation on the train dataset:

- A regression is performed with growing number of components [1, 130],
- Performance of the regression is evaluated by computing the RMSECV,
- The number of components to perform the final regression is the one that gave the best (lowest) RMSECV.

The results of our tests for PCR and PLSR are summarise in the flowing Table I:

TABLE I. METRICS RESULTS PCR & PLSR ON TEST DATASET

	PCR	PLSR
Raw data	R^2: -0.10 RMSE: 26.26 MAE: 21.16	R^2: 0.66 RMSE: 14.46 MAE: 11.77
Standard scaling	R^2: -0.26 RMSE: 28.03 MAE: 22.32	R^2: 0.68 RMSE: 14.04 MAE: 11.60
Savitzky-Golay	R^2: 0.27 RMSE: 21.29 MAE: 16.52	R^2: 0.71 RMSE: 13.62 MAE: 10.81
Standard scaling + Savitzky-Golay	R^2: 0.02 RMSE: 24.76 MAE: 19.79	R^2: 0.71 RMSE: 13.53 MAE: 10.34
Outliers + Standard scaling + Savitzky-Golay	R^2: 0.172 RMSE: 21.33 MAE: 16.53	R^2: 0.67 RMSE: 13.47 MAE:11.01

The following observed vs predicted plots show the best results obtained for PCR and PLSR (Fig. 6 & Fig. 7).

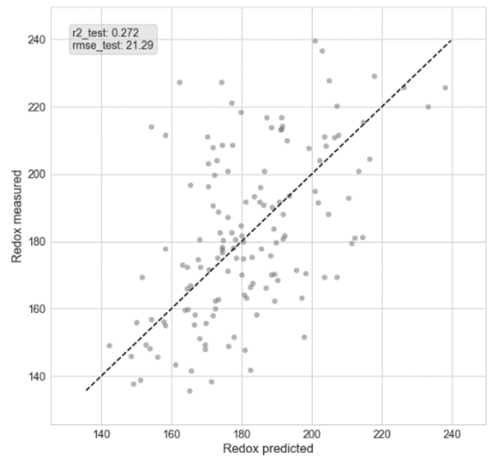

Figure 6. Redox potential predictions using PCR (SavGol).

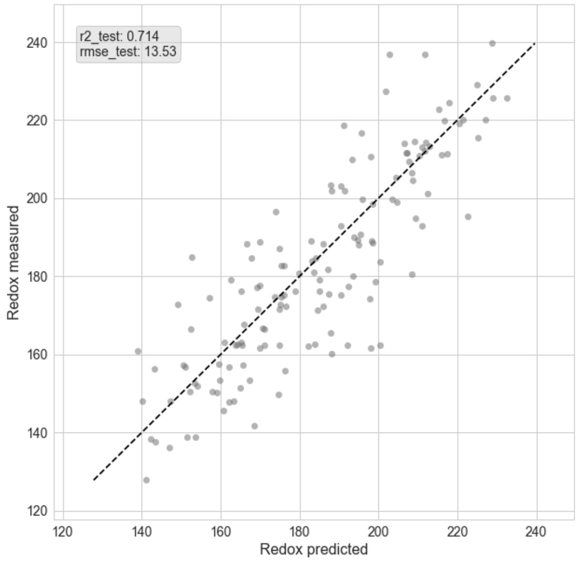

Figure 7. Redox potential predictions using PLSR (SavGol).

B. Successful Results Using Deep Learning

The results obtained with PCR and PLSR are good, but there is definitively room from improvements.

Both PCR and PLSR being linear regression algorithms, they may not be capturing non-linear relationships between the explanatory variables and the response variable. It therefore made sense to attempt improving results by using Deep Learning algorithms which are, by nature, non-linear.

We've chosen to use an MLP (Multi-Layer Perceptron). MLP algorithms are based on the Perceptron invented in the late fifties by Frank Rosenblatt [20]. It is a type of artificial neural network composed of multiple layers of perceptron having a non-linear activation function. The number of layers can vary as can the number of perceptron per layer. An MLP having a minimum of 3 layers, an input layer, and hidden layer and an output layer.

We've tried different architecture for the MLP (different number of layers, number of neurons (perceptrons + non-linear activation function) per layer, regularization techniques to avoid overfitting), the best results obtained are listed below (Table II):

TABLE II. METRICS RESULTS MLP ON TEST DATASET

	MLP
Raw data	R^2: -0.09 RMSE: 25.79 MAE: 20.17
Standard scaling	R^2: 0.89 RMSE: 8.02 MAE: 6.16
Savitzky-Golay	R^2: 0.65 RMSE: 14.66 MAE: 10.86
Standard scaling + Savitzky-Golay	R^2: 0.91 RMSE: 7.31 MAE: 5.09
Outliers + Standard scaling + Savitzky-Golay	R^2: 0.84 RMSE: 9.15 MAE: 5.92

These results show that the MLP definitively give superior results than PCR/PLSR with a best RMSE found being 7.31 mV.

The observed vs predicted plot for the best MLP results is shown below (Fig. 8):

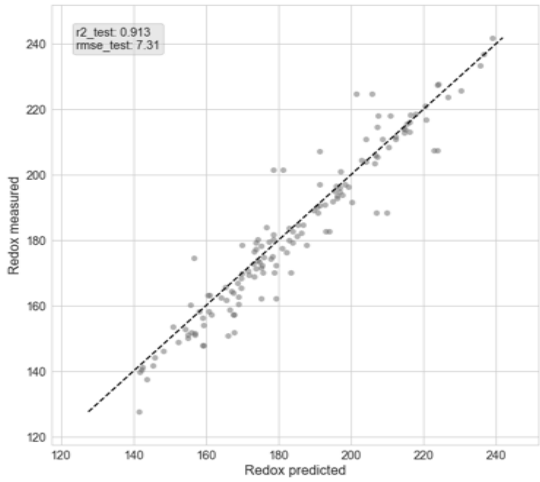

Figure 8. Redox potential predictions using MLP (SavGol-StdScl).

C. Other Quantities Related to the Redox Potential

Given these good results with the redox potential quantity, we then followed up by looking at predicting other quantities of the redox potential framework, namely pH and Conductivity.

We used the same rapeseed dataset and similar MLP architecture. The distribution of both pH and Conductivity are shown below (Fig. 9 & Fig. 10):

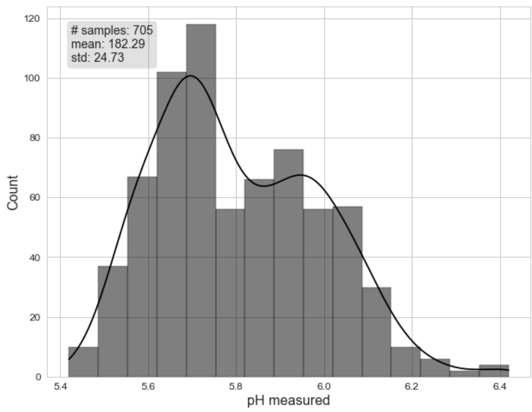

Figure 9. pH distribution.

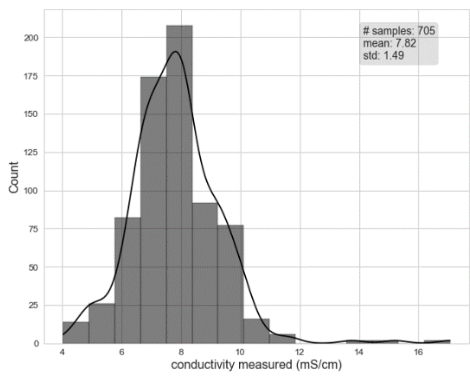

Figure 10. Conductivity distribution.

We again achieved good results predicting pH and Conductivity. Best results are shown in the table below (Table III):

TABLE III. METRICS RESULTS MLP

	pH	Conductivity
Standard scaling	R^2: 0.79 RMSE: 0.084 MAE: 0.057	R^2: 0.77 RMSE: 0.63 MAE: 0.42
Savitzky-Golay	R^2: 0.8 RMSE: 0.084 MAE: 0.056	R^2: 0.76 RMSE: 0.65 MAE: 0.44
Standard scaling + Savitzky-Golay	R^2: 0.91 RMSE: 0.055 MAE: 0.035	R^2: 0.91 RMSE: 0.40 MAE: 0.26
Outliers + Standard scaling + Savitzky-Golay	R^2: 0.92 RMSE: 0.05 MAE: 0.031	R^2: 0.89 RMSE: 0.4 MAE: 0.24

The observed vs predicted plots for the best MLP results for pH and conductivity are shown below (Fig. 11 & Fig. 12):

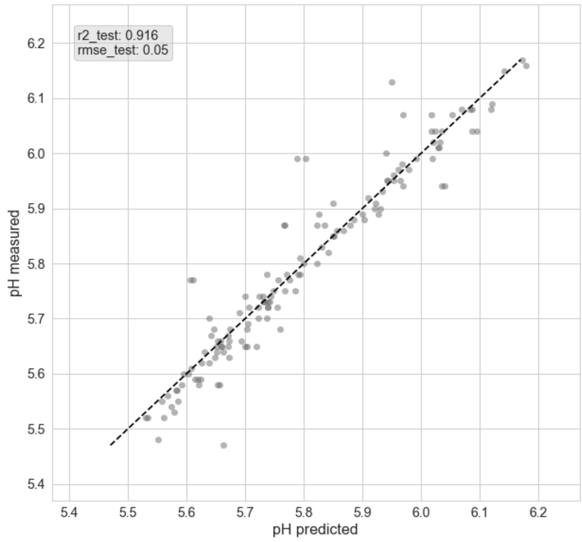

Figure 11. pH predictions using MLP (Outliers-SavGol-StdScl).

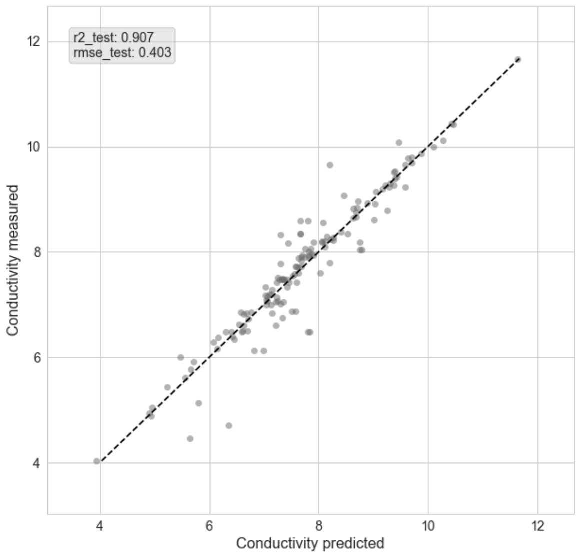

Figure 12. Conductivity predictions using MLP (SavGol-StdScl).

VII. RESULTS AND LOOK AHEAD

With this multi-disciplinary approach, we succeeded to cope with the challenge of measuring redox potential with a remarkable accuracy, in an easy way with a first prototype of an affordable handheld scanner (Fig. 13). We will now start several validation campaigns to confirm the accuracy of the data models and to acquire data for a broad range of new products such as tomatoes, potatoes, grapes, etc.

Figure 13. Measures in fields with the handheld scanner already working.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

Philippe Cousin conducted the research. Didier Dumet analyzed the data. Martin Rollet and Vincent Levavasseur conducted the measurement in the field. Olivier Husson conducted the agronomy research.

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Philippe Cousin, after successful involvement in +40 EU R&D projects leading to the set-up of a very large network of worldwide contacts and partnerships, he is today capitalizing his large experience gained in R&D projects for developing a vision to support Sustainable Development Goals and EU Green Deal in particular in using miniaturized spectrometry combined with AI. His objective is to bring and improve low cost scanners for a broad range of use. In May 2020 he created a spin-off Senseen to implement his vision. Authors of +50 scientific papers, he has 38 years of rich and diverse professional experience in ICT including many years in R&D, at top management level of private companies and few years with a broad insight into Information Communication Technology (ICT) at the European policy-making level (e.g. European Commission, EOTC).

Didier Dumet has been involved in delivering telecoms projects, ranging from telecom infrastructure (Intelligent Networks) to 4G consumers services for more than 30 years. Since 2018, he took the turn of Artificial Intelligence. He has been then working in the agroecology, using AI to facilitate measurements of agriculture quantities (redox potential, conductivity, etc.) from Near InfraRed sensors.

Olivier Husson, Engineer in agronomy (ENSA Montpellier, FR) and Doctor in Agronomy (Wageningen University, NL), Olivier Husson works at CIRAD (Centre for International Cooperation in Agronomic Research for Development), in the AIDA Research Unit (Agroecology and Sustainable Intensification of Annual crops). For 30 years, he has been working on co-designing with farmers Conservation Agriculture systems based on Direct Seeding on permanent soil cover in tropical areas (West Africa, Viet Nam, Madagascar), alternating fundamental research, applied research, training and extension works. Since 2010, he has been developing an approach to soil and plant health based on fundamental biological processes, regulated by pH, Eh (redox potential) and EC (electrical conductivity), developing measurement methods to use these indicators as management tools for agroecological crop protection.

Vincent Levavasseur has worked as market gardener for 5 years in his own farm. Develop the first vegetable farm installation without till and chemistry. Contribute on farmer based movement like Maraichage Sol Vivant, La Vache heureuse, Pour une agriculture du vivant. He is leading many current projects to develop agroecology like massive open online courses on living soils, knowledge management in agroecology, quality measurement of soil and food.

Martin Rollet is agronomist for 3 years, he is working as agronomist at Ver de Terre Production. Specialized in crop production and measurement technologies he is in charge of the operational application of measurement campaigns and on field experiments. In this context, he offers training courses for the agricultural world on reducing tillage and applying measurement techniques to diagnose the health of agricultural plots.