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PREDICTION OF SOIL UREA CONTENT USING RF SPECTROSCOPY AND PARTIAL LEAST SQUARE REGRESSION

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ABSTRACT

Soil analysis plays a crucial role in increasing the crop yield and in the conservation of soil resources. Conventional methods of soil analysis are expensive, time consuming and do not take into account the spatial and temporal variability of a field which can lead to over or under application of fertilizers. Thus, in the long run the soil loses its fertility and also causes ground water contamination. Hence, there is a need for in-situ measurement of soil parameters that takes into account the spatial and temporal variability of the field. The objective of this study is to predict soil urea content using RF spectroscopy and partial least square regression. Around 20 samples having different concentrations of urea, sodium chloride, calcium carbonate, potash and phosphate were taken for the study. Out of which 16 samples were used for calibration and 4 samples were used for prediction purpose. The coefficient of determination R^2 obtained was 0.987 and RMSE was found to be 3.183 for urea which corresponds to an error rate of 1.84%.

Keywords: RF spectroscopy, Partial least squares regression

1.   INTRODUCTION

Soil is a heterogeneous system whose processes and mechanisms are complex and difficult to fully understand. Various conventional soil analytical techniques are used to establish the relationship between physical and chemical properties and individual soil components. These techniques often do not take into consideration the complex and multi-component interactions in the soil [1] (Rossel et.al 2006). Our understanding of the soil system and assessment of its quality and function has been gained through this type of laboratory analysis. There is a need to further develop our analytical techniques for better understanding of the soil as a complete system and as a resource so that we can make more efficient use of it and simultaneously preserve it for future generations.

This is more important now than ever before since the acquisition of large amount of accurate soil data is essential for managing our base resources sensibly to meet the food and fiber demands of our future populations [2] (Viscarra Rossel and McBratney, 1998a).

It is very important to have proper knowledge about the spatial variability of soil nutrients so that we can refine the agricultural management practices and improve on sustainable land use [3] (McGrath and Zhang, 2003). According to [4] Bouma and Finke (1993), soil variability can occur on any scale including area, field and regions within the field and even between a few millimeter spacing. This makes the task of matching the supply of nutrients from the soil to the needs of the crop very complex. Thus, to achieve high nutrient use efficiency, an integrated approach which is based on spatial and temporal data is necessary. This implies that we need to have fast and real time measuring systems that will provide the necessary inputs.

Spectroscopic techniques (e.g. mass spectroscopy (MS), nuclear magnetic resonance (NMR), visible (VIS), near infrared (NIR) and mid infrared (MIR) spectroscopy) are being considered as possible alternatives (or surrogates) to enhance or replace conventional laboratory methods of soil analysis [5] (Janik et al., 1998).

This paper is based on the application of RF spectroscopy and partial least square regression (PLSR) for the prediction of soil urea content in the frequency range of 10MHz-500MHz.

2. EXPERIMENTAL SETUP

The experimental setup consists of a cell designed to obtain the RF spectra of the soil components. The samples of various concentrations of the different soil nutrients are prepared as per the data collected from the department of agriculture. The nutrients considered are urea, potash, calcium carbonate, phosphate and sodium chloride. The concentrations of the various samples were varied from 0.5 to 1.5 namely 0.5, 0.75, 1, 1.25 and 1.5. The value 0.5 represents half the normal value of a particular soil nutrient, while 1 is the normal concentration and so on. The experimental setup is as shown in Fig.1 below. The cell is enclosed in an iron box to minimize the external RFI interferences.

Figure1: Experimental Setup.

The RF spectra of 20 different samples were recorded in the frequency range of 10MHz to 500MHz using a Signal Hound Spectrum Analyzer. The spectra obtained are as shown in Fig.2.
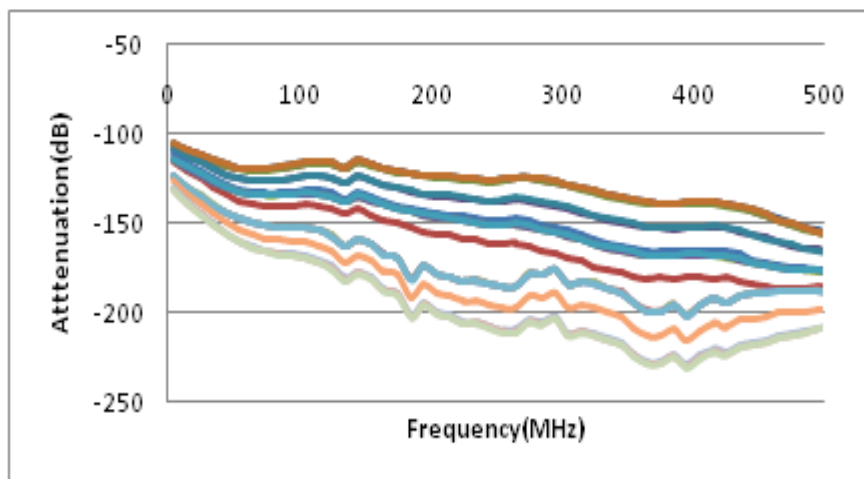
Figure2: RF spectra of different samples.

These spectra are used for the prediction of urea content using Partial Least Square Regression Analysis.

3.   PARTIAL LEAST SQUARES REGRESSION ANALYSIS

Partial least squares regression (PLSR) deals with prediction of a set of dependent (y) variables from set of independent (x) variables. PLSR is particularly important while dealing with large number of variables that express common information [6] (Brereton, 2000; [7] Wold et al., 2001; [8] Yeniay and Goktas, 2002). Another multivariate approach, principal component regression (PCR) analysis decomposes set of predictors into eigen vectors and scores to overcome collinearity. After achieving optimal projection of x variables in few principal components, it regress them against the responses in a separate step. Unlike PCR, PLSR decomposes both predictors and responses simultaneously to capture their common variation, which will be projected into a small number of mutually independent factors. Decomposition and regression is a single step, through a few principal components than that required by PCR. Hence, PLSR reduces the impact of irrelevant x variations in the calibration modeling by balancing the information in the x and y spaces (Martens and Naes, 1989; Wold et al., 2001). More information on the differences of the three multivariate calibration methods and their algorithms can be found in Brereten (2000), [9] Martens and Naes (1989), Wold et al., (2001), Yeniay and Goktas (2002), [10] http://www.camo.com.

The present study used ParLe's software for the prediction of soil urea content. Spectra of 20 samples were recorded. Out of the 20 samples, 16 were used for the calibration and the remaining 4 spectra were used as unknown for the prediction of urea content.

4.   RESULTS AND DISCUSSION

Table 1 shows the actual and predicted values of urea

Urea Actual(mg)	Urea Predicted(mg)	%Rate of Error
112.5	109.96	2.25
168.75	164.05	2.78
281.25	279.87	0.49

From Table 1 it can be observed that the % rate of error for the prediction of urea content from unknown spectra using PLSR ranges from 0.49% to 2.78%. The coefficient of determination R^2 is found to be 0.987. In regression, the R^2 coefficient of determination is a statistical measure of how well the regression line approximates the real data points. An R^2 between 0 and 1 indicates the extent to which the regression line fits the data. The value of R^2 0.987 indicates that 98% of the variation in the response variable y i.e urea is explained by the independent variables X i.e the frequency.

Thus, we can say that RF spectroscopy along with PLSR can be used for the prediction of soil nutrients quite accurately. We can extend this study to predict other soil nutrients present in a particular soil sample.

5. CONCLUSION

This study demonstrates the possibility of using RF spectroscopy for the prediction of soil nutrients. The study is limited to 20 samples which were prepared in the laboratory and not to the actual soil samples. The spectra treated as unknown can also be used for the prediction of other soil nutrients such as potash, phosphate, calcium and sodium chloride.

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