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# Spectral analysis as an extra method to soil type discrimination

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***Abstract.*** *The purpose of the study was to test near infrared soil spectra as an extra method for three soil types (Fluvisols, Vertisols and Solonchaks) discrimination from different regions of South Bulgaria. The diffuse reflectance spectra of 177 soil samples (from the 0-20cm layers): 50 samples of Fluvisols soil type, 78 samples of Vertisols soil type and 48 samples of Solonchaks soil type were obtained using a Spectrum NIRQuest (OceanOptics, Inc.) working within the range from 900 to 1700 nm. Soft independent modelling of class analogy (SIMCA) was performed to classify samples according to their taxonomic classes. The results obtained showed that the soil samples are separated accurately according to their soil type based on their spectral information. All this could be used in the future studies related to the application of the NIRS method as a qualitative or quantitative method for soil analysis and also for the purposes of precision farming.*

**Keywords:** SIMCA method, NIRS, soil type, spectral information, soil classification

## Introduction

The information about soil type and soil fertility is of a great importance to farmers in order to build land management strategies. One arable area could contain only one soil type or more than one, characterized with different soil properties such as water regime, organic matter or clay content, soil texture, etc. All of these put challenges in using arable lands. Therefore, knowledge about soil type, its typical soil properties is an important factor for the development of successful land management and a key factor in precision agriculture. Remote sensing applications in precision agriculture began with sensors for organic matter, and have quickly diversified to include satellite, aerial, and hand held or tractor mounted sensors. Wavelengths of electromagnetic radiation initially focused on a few key visible or near infrared bands (Mula, 2013).

During the last 20 years the importance of soil spectra information in the visible and near-infrared region has been proven in the soil science field (Confalonieri et al., 2001; Moron and Cozzolino, 2002; Todorova et al., 2011). That fact explains a growing interest in investigation and application of different rapid and non-destructive spectral methods as an alternative method for soil fertility assessment (Islam et al., 2003; Yong He et al., 2005; Wetterlind et al., 2005). A lot of studies have proved that near infrared spectroscopy (NIRS) is a promising technique for determination of many soil parameters such as organic matter content, total phosphorus (Cohen et al., 2006), organic and inorganic carbon contents (Yang et al., 2012), clay content (Mouazen et al., 2005), soil color (Mouazen et al., 2007), which are also important morphological properties (Viscarra Rossel et al., 2009; Yang et al., 2011). The successful application of that spectral method is possible because soil spectral data contain information on key soil components such as clay minerals - kaolinite, montmorillonite and humic acids (Viscarra Rossel et al., 2006) Therefore, it is not surprising to come across studies in scientific literature connected with the possibility of application of the near infrared spectral method and chemometric procedures for soil classification. For instance, classification of soil according to: soil texture (Mouazen et al., 2005), soil color and its ability to be used as an extra method in soil type diagnostics (Liu et al., 2008; Viscarra Rossel and Webster, 2011; Vasques, 2014). According to Dematte et al. (2012), combining spectral information to detect soil spatial extent (soil limits) to map an area requires special strategies of interpretation and use of different information sources. And that technology will only advance with further research and clearer methodologies for its application.

The aim of the study is an application of near infrared soil spectra as an extra method for discrimination of three soil types Fluvisols, Vertisols and Solonchaks from the territory of Bulgaria.

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**Material and methods**

*Study area*

A total of 177 soil samples from the 0-20cm layers were collected from fields with different cropping systems from South Bulgaria (Figure 1). The soil types were: a) Solonchaks, 50 soil samples from Pomorie region; b) Vertisols, 78 soil samples from Chirpan region; c) Fluvisols, 49 soil samples from Tarnichene region.


**Figure 1**. Soil sampling points from South Bulgaria: a) Pomorie region- Solonchaks; b) Chirpan region- Vertisols; c) Tarnichene region– Fluvisols

*Soil samples preparation and analysis*

Soil samples from surface horizon were collected from every studied area during to period from July to October, 2016. The samples were air-dried, and plant residues and stones were removed, then the samples were crushed and sieved with particle size less than 2 mm. After that every sample was divided into two parts. The first one was used for chemical analysis, the other one for near infrared spectroscopy (NIRS) analysis. The samples were analyzed for soil organic matter content (%) by loss of ignition; pH ($H_2O$) by potentiometric method; electrical conductivity ($mS.cm^{-1}$) as an indicator of salinity. Visual soil assessment of soil texture, soil structure was performed in the field, $CaCO_3$ content (%) using 1n HCl solution, as well (Houškova, 2005).

*Near infrared soil spectra method used*

The diffuse reflectance spectral data of air-dried soil samples were obtained using NIRQuest (OceanOptics, Inc.) working from 900 to 1700 nm. The absorbance was recorded as log 1/R, where R is diffuse reflectance. Soft independent modelling of class analogy (SIMCA) was performed to classify samples, according to their soil taxonomic classes. Samples were divided into three classes in calibration set: Vertisols class, Fluvisols class and Solonchaks class on the basis of prior knowledge of their taxonomic classes. Spectra pre-treatment and chemometrics were carried out using Pirouette 4.5 (Infometrix. Inc., WA, USA). SIMCA models were developed using the following data pretreatment options - smoothing and second derivatives. Two results from SIMCA models are possible – classification in one of the formed classes or not classified in any class.

For estimation of SIMCA models the parameter used was class distance (CD). Class distance describes distance between centre of the classes. The class distance is used to measure the distance (dissimilarity) between two classes: CD<1 indicates that the two classes overlap, 1<CD<3 indicates partial separation of the classes, and CD>3 indicates good separation of the classes.

**Results and discussion**

The soils included in our study are characterized by significant differences in soil formation factors, mineral composition, color, clay content, salt content, etc. (Shishkov and Kolev, 2014). For example, saline soils Solonchaks are characterized with sandy color, sandy texture, with low organic matter content of less than 1%, an alkaline reaction with values of pH ($H_2O$) between 7.6 and 9.1 and a degree of salinity from unsalted to high salinity (Table 1). Fluvisols formed at the foot of Stara Planina Mountain are characterized with high content of skeletal materials, non-saline with low organic matter content and acid reaction, with values of pH ($H_2O$) less than 5.3. In contrast to that soil type, Vertisols are characterized with dark black color, high clay content, neutral to slightly alkaline reaction. It was not found $CaCO_3$ content in the surface horizon of the studied soils.

**Table 1**. The range of values of analyzed parameters in studied soil samples

| Class/ Soil type | pH ($H_2O$) | EC, $mS.cm^{-1}$ | Organic matter, % |
|---|---|---|---|
| Solonchaks | 7.6-9.1 | 1.0-12.0 | 0.5-1.5 |
| Fluvisols | 7.0-7.8 | 0.4 | 2.5-3.4 |
| Vertisols | 3.8-5.3 | 0.3 | 0.1-1.8 |

Figure 2 presents transformed spectral data by smoothing and second derivative of the sample spectra of the soil units studied, showing clear similarities and differences in absorption maxima. Maxima are observed at the following wavelengths: 1345 nm, 1375 nm, 1400 nm, 1418 nm, 1422 nm and 1530 nm.

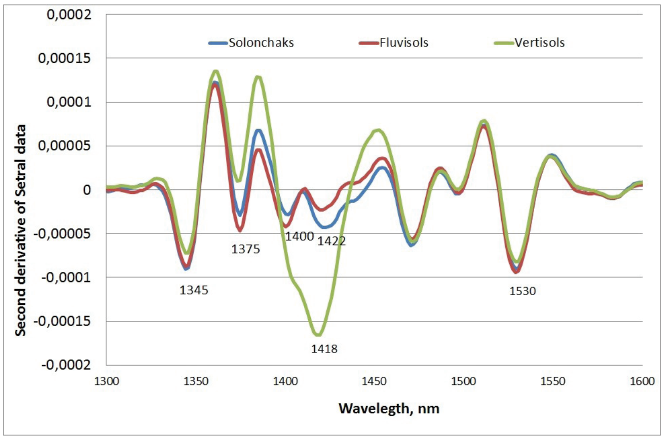


**Figure 2.** Average 2nd Derivative of soil spectra of studied soil taxonomic classes in the range from 1300 to 1600 nm

According to the figure, the transformed spectra of Vertisols soil showed an intense peak at 1418 nm, whereas this is not observed in the other two soil types. Viscarra Rossel et al. (2006) reported that absorption close to 1400 nm was associated with the first overtone of OH-vibrations. Therefore, the high intensity peak observed at 1400 nm is mainly due to high montmorillonite content in that soil. A difference in the intensity of the absorption is observed at 1375 nm wavelength. The reason of that could be the difference of sand content in the studied soil. According to Gaydon (2009), absorption at 1375 nm is due to the O-H groups in quartz, which is the predominant primary mineral in saline soils – Solonchaks in comparison to Vertisols and Fluvisols.

The values of class distance (CD) for all three soil classes vary between 3.9 and 10.3 (Table 2) These values indicate that there are good SIMCA models available to perform good class separation. The highest value CD=10.3 is between the Vertisols Class and Fluvisols Class, which could be due to crucial difference in that soil type, as soil parent material, soil forming process, soil color, sand and clay content, etc.

**Table 2.** The class distance (CD) between soil classes, according to SIMCA models obtained

| Class/ Soil type | Class Solonchaks | Class Fluvisols | Class Vertisols | No much |
|---|---|---|---|---|
| Solonchaks | 50 | 0 | 0 | 0 |
| Fluvisols | 1 | 48 | 0 | 0 |
| Vertisols | 0 | 0 | 78 | 0 |

Xie et al. (2015) also reported accurate recognition of soil type using NIR spectral data of 230 samples collected from top soils, representing five soil taxonomic classes – Albic Luvisols, Haplic Luvisols, Chernozems, Eutric Cambisools and Phaeozems in northeast China. Graphical illustration of class distance (CD) according to SIMCA analysis expresses clearly differentiation of samples according to their soil type (Figure 3). All samples formed three clear groups far from each other. The SIMCA models obtained in our study for the discrimination of soil samples according to their soil type have been successful. The results, pointed in Table 3 showed that all 50 soil samples belonging to Solonchaks type have been successfully recognized by Solonchaks class. All 78 soil samples belonging to Vertisols type have been successfully recognized by Vertisols class. About Fluvisols - 48 soil samples from a total of 49 Fluvisols samples have been recognized by Fluvisols class, only one of them has been wrongly recognized by Solonchak class. The results obtained showed that there is more than 98% success rate of the SIMCA models.

**Table 3.** The results of SIMCA models for discrimination of soil type according to spectral data

| Class/ Soil type | Class Solonchaks | Class Fluvisols | Class Vertisols |
|---|---|---|---|
| Solonchaks | 0.0 | 9.3 | 3.9 |
| Fluvisols | 9.3 | 0.0 | 10.3 |
| Vertisols | 3.9 | 10.3 | 0.0 |

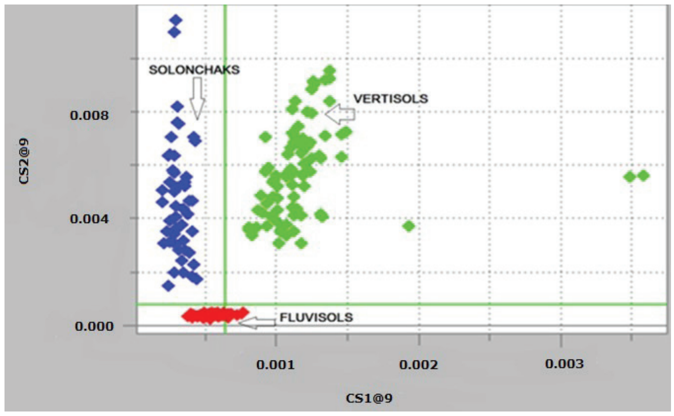


**Figure 3.** Graphical illustration of class distance (CD) according to SIMCA analysis

## Conclusion

The results showed that the soil samples taken from surface horizon were distinguished according to their taxonomic classes as the SIMCA models correctly classified of the samples to their soil unit. These spectral data could be used to develop models for soil discrimination on the basis of soil taxonomic classes. The SIMCA method allowed establishment of models with very good classification accuracy.

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