

# SOIL ORGANIC CARBON MULTIVARIATE PREDICTIONS BASED ON DIFFUSE SPECTRAL REFLECTANCE: IMPACT OF SOIL MOISTURE

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## INTRODUCTION

Remote and on-the-go proximal sensors can measure diffuse soil reflectance spectra to assess soil carbon spatially across landscapes for precision agriculture and natural resources management. Unfortunately, predictions of carbon are biased by differences in soil moisture, which vary tremendously across landscapes and with depth because of spatial changes in topography, surface and subsurface water flow, and soil parameters (e.g., clay, organic matter). This bias result from water absorption peaks masking -OH peaks associated with organic matter (Reeves, 2010). Our objective was to determine how soil moisture impacts spectral properties and Walkley-Black OC predictions in order to develop a nation-wide prediction model for soil carbon based on spectral reflectance.

## MATERIAL AND METHODS

Samples were obtained from the North American Proficiency Testing (NAPT) program dataset ( $n = 220$ ) from all soil orders and with a range of organic carbon (OC) ( $2 - 40 \text{ g kg}^{-1}$ ). Diffuse reflectance was measured with a laboratory grade spectrometer (340-2220 nm) at several gravimetric moisture levels (0, 15, 20, 25, 30, and 45%). The data were randomly partitioned into training ( $n=110$ ), validation ( $n=66$ ), and test ( $n=44$ ) subsets. Principal component analyses (PCA) were performed for data characterization and partial least squares regression (PLS) and neural network (NN) analyses were used for predictions. Partial least squares regression was conducted using the RLGW algorithm to calculate score and loadings was implemented because this algorithm is efficient when there are many predictors and few variables (Rannar et al 1994). Factors were selected using a leave-one-out cross validation approach. Neural network with funnel layers architecture was implemented. The predictions were validated with the independent test data set.

## RESULTS AND CONCLUSIONS

The first principal component was correlated with soil moisture ( $r=-0.71$ ) and wavelengths between 548 and 2220 nm ( $r>0.9$ ). The second component was correlated with OC ( $r=0.50$ ), wavelengths between 592 and 634 nm ( $r = 0.4$ ), and

wavelengths between 1428 and 1492 nm ( $r = -0.24$ ). Neural networks (RMSE=0.68%) and partial least regression (RMSE=0.72%) procedures seem to perform similarly when observations included moisture levels of 20, 25, and 30% without the known moisture included as a predictor variable. This work suggests that a nation-wide model can be developed to estimate OC from reflectance spectral even when moisture content varies between 20 and 30%, a range that is common in typical agricultural fields.

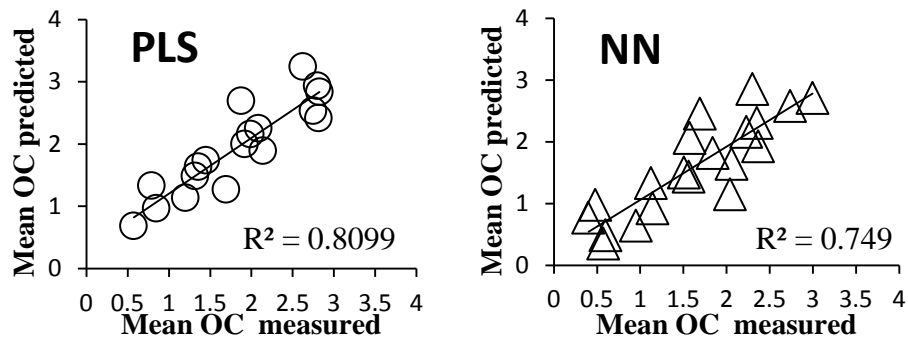


Figure 1. Plots of mean predicted versus measured for organic carbon (%) for partial least squares (PLS) and neural network (NN) analyses.

## REFERENCES

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Reeves, J. B., 2010, Near- versus mid-infrared diffuse reflectance spectroscopy soil analysis emphasizing carbon and laboratory versus on-site analysis: Where are we and what needs to be done?: *Geoderma*, v. 158, no. 1-2, p. 3-14.