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Estimating Soil Carbon Stocks with in-field Visible and Near-Infrared Spectroscopy

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Abstract.

Agricultural lands can be a sink for carbon and play an important role in offsetting carbon emissions. Current methods of measuring carbon sequestration—through repeated temporal soil samples—are costly and laborious. A promising alternative is using visible and near-infrared (VNIR) diffuse reflectance spectroscopy. However, VNIR data are complex, which requires several data processing steps and often yields inconsistent results, especially when measurements are taken in situ. Using a convolutional neural network (CNN) could bypass these steps and incorporate measurements from multiple sensors to predict three-dimensional carbon stocks. Using data previously collected (n = 1,069; from 2014 to 2020), a CNN modeling framework was developed to predict soil carbon by incorporating information from profile VNIR, soil apparent electrical conductivity (ECa), penetration resistance, and soil moisture. The developed CNN framework demonstrated moderate accuracy for predicting soil carbon (R^2 =0.68) but was not as accurate as the partial least squares regression model (PLSR) used as a benchmark (R^2 =0.70). Additional improvements to the CNN results could occur with further attempts to optimize the parameters.

Keywords.
Visible and near infrared (VNIR); soil carbon; deep learning; machine learning; spectroscopy

Introduction

Visible and near-infrared (VNIR) diffuse reflectance spectroscopy is a promising method to measure soil organic carbon in situ and on-the-go. However, there are several challenges with VNIR data that hinder its utility. The spectra, by nature, exhibit high multi-collinearity in reflectance among the many (typically 100s to 2000+) wavelengths present. Especially when collecting data in-field, variation in external factors (e.g., soil moisture, structure, and sensor movement) can mask the response from the soil property of interest (i.e., carbon; Sudduth & Hummel, 1993), requiring sophisticated preprocessing (Veum et al., 2018).

One promising alternative is to use deep learning algorithms, such as the convolutional neural network (CNN), which are less affected by nonlinearity, collinearity, and high dimensionality in the data. Some success was reported using CNN to predict soil properties from raw soil spectra, which avoided the preprocessing and wavelength filtering process (Padarian et al., 2019). Furthermore, CNN modeling could incorporate data from multiple sensors (Ng et al., 2019), estimate soil properties at multiple depths, and incorporate spatial covariates (Wadoux et al., 2019). The aim of this research is to develop a CNN modeling framework that will use data from mobile in-field VNIR spectroscopy and auxiliary sensors to quantify soil carbon concentrations.

Materials and Methods

A total of 271 sites were characterized using a Veris P4000 unit (Veris, Technologies, Inc., Salina, KS, USA) following methods detailed in Veum et al. (2018). In summary, the P4000 unit uses a soil probe that collects VNIR absorbance readings, bulk soil electrical conductivity (ECa), and penetration resistance measurements. At each site, 3 to 5 probes were collected to a target depth of 0.90 m. In addition, a soil core was taken to a similar depth, separated by diagnostic horizon, air-dried, and passed through a 2-mm sieve for a total of 1,069 samples. Soil samples were analyzed for total organic carbon (Leco TruMac C/N combustion analyzer; LECO Corp., St. Jospeh, MI, USA), texture (pipette method), and gravimetric moisture.

Data was averaged for each horizon to provide mean values for absorbance at each wavelength, ECa, and penetrometer force (i.e., penetration resistance). A standard normal variate transform (SNV) preprocessing method was performed on the absorbance data. The data was then separated randomly using an 80/20% split into a training and a testing dataset. A partial least squares regression (PLSR) model was built with a 10-fold cross-validation to determine the optimum number of components. Meanwhile, a CNN model (a simplified diagram shown in Figure 1) was built using the same structure as an optimal 1D-CNN developed by Shen et al. (2022) using data obtained in the USA. The dropout layer was used to prevent overfitting and the flatten layer was included to convert the learned features into a long vector. The number of epochs and batch size used were 1000 and 1500, respectively. Four different models (each for PLSR and CNN) were developed using different dependent variables (see Table 1) and were tested using the testing dataset. Accuracy based on R^2 was computed to evaluate the models. Model training and testing were performed using Python (version 3.9).

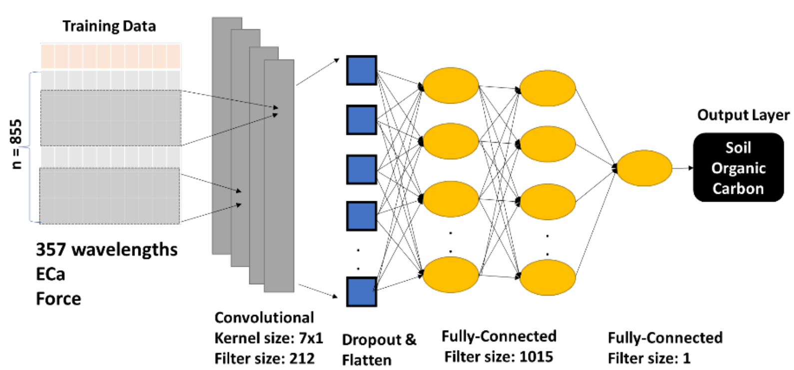

Figure 1: Diagram of the 1D-CNN model framework used to predict soil organic carbon.

Results and Discussion

Figure 1 and Table 1 compare results with the CNN framework to those using PLSR for predicting soil organic carbon with VNIR. The initial CNN performance was not any better than the PLSR. While adding additional auxiliary measurements improved both methods, albeit slightly, CNN still underperformed compared to the PLSR.

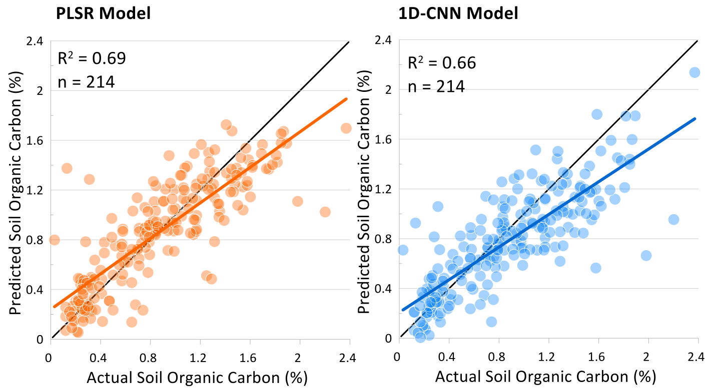

Figure 1: Testing model results of predicting soil organic carbon using VNIR with a PLSR and 1D-CNN.

Table 1: Four different models using PLSR or CNN for predicting soil organic carbon with VNIR, soil moisture, bulk electrical conductivity, and penetrometer force as the independent variables. Model accuracy is reported as R^2 values.

	PLSR		CNN	
Independent Variables	Training	Testing	Training	Testing
f(VNIR)	0.71	0.69	0.68	0.66
f(VNIR + moisture)	0.74	0.70	0.71	0.68
f(VNIR + moisture + ECa)	0.74	0.70	0.78	0.59
f(VNIR+ moisture + ECa + Force)	0.74	0.70	0.62	0.54

Conclusion

Expectations for the CNN model to better predict soil carbon concentrations compared with the traditional PLSR method were not realized. However, CNN models could still be improved by optimizing the hyper-parameters or changing the structure. Achieving a high-performance CNN model will help minimize many of the computational steps required in PLSR and provide a more robust method for predicting soil carbon. As part of this effort, concurrent research is underway to determine the spatial scale at which VNIR measurements are needed to accurately estimate soil carbon at the field scale. Overall, this framework will contribute to multiple stakeholder goals, including monitoring changes in soil carbon over time and quantifying the effects of varying management practices on soil carbon for enhanced agronomic sustainability.

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