Measuring Surface Soil Moisture and Salinity using a Miniaturized Spectrometer

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Introduction / Background

Surface soil moisture and soil salinity play crucial roles in agricultural applications such as irrigation and precision agriculture. The developments to sense surface soil moisture and salinity are important to improve sustainability and efficiency of food production. Traditional methods of measuring soil properties such as soil organic carbon are labor-intensive and costly, as it involves soil sampling, laboratory testing, and data processing to obtain ground truth data [1]. This brings the need to develop effective and low-cost methodologies for monitoring soil properties.

Study Goals

This study investigates the use of a point sensing system using a miniaturized spectrometer to sense surface soil moisture and salinity. Our main research questions are:

1. Can we predict surface soil moisture and salinity using explainable machine learning and VIS-NIR spectroscopy?
2. What is the relationship between soil properties and spectrum response?

Study System

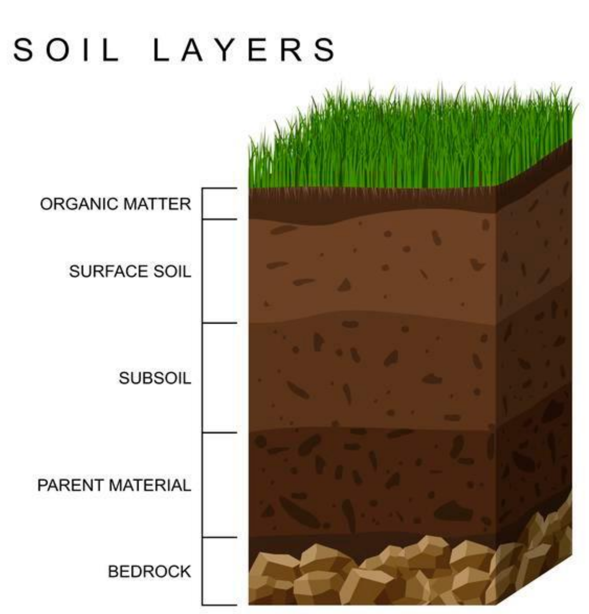


Figure 1: Soil hierarchy [2]

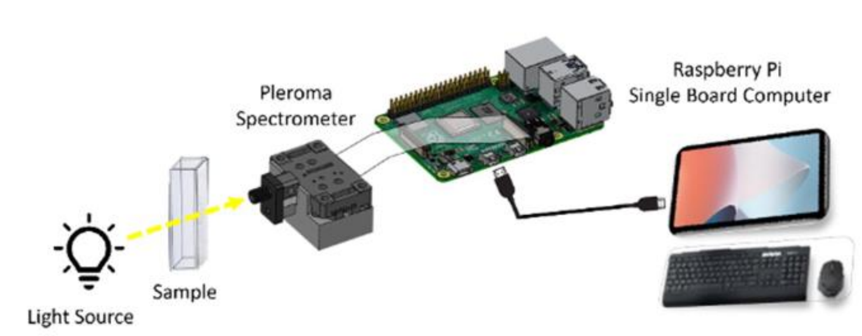


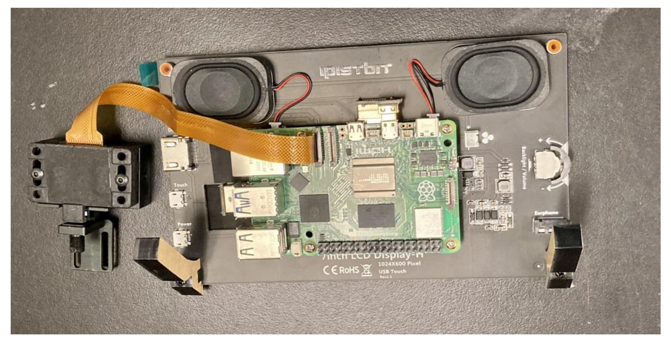
Figure 2: Spectrochip [2]

Acknowledgements

Thanks to Joy Baccei for providing equipment to help collect soil samples.

Methods

- Multiple sets of varying levels of soil moisture and salinity were prepared, ranging from plain soil to 32% soil moisture
- The soil samples were measured and prepared for analysis using a miniaturized spectrometer – SpectroChip at range of 300-1000 nm
- A polarized filter was added to the spectrometer to remove surface reflections from the surface soil moisture
- Soil moisture was measured using a capacitive moisture sensor to serve as a ground truth
- Spectra was normalized to reduce noise



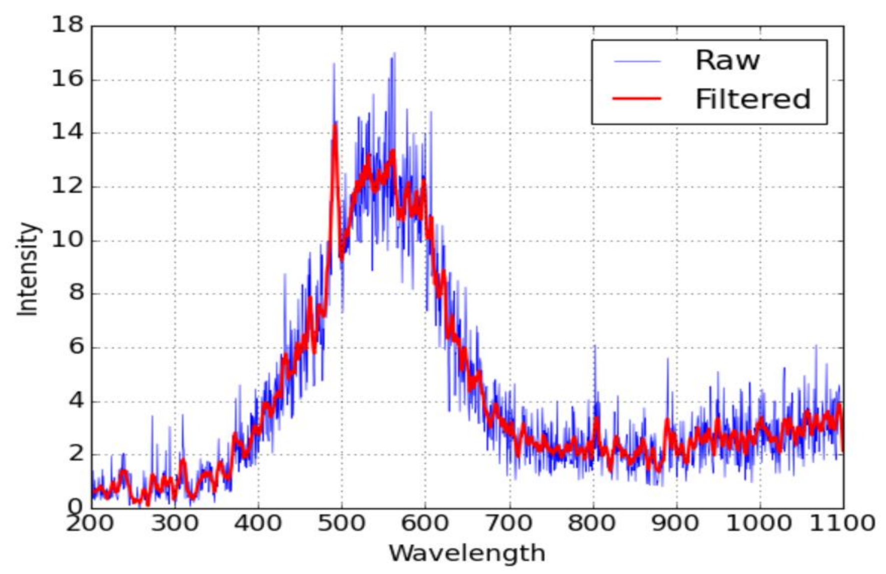


Figure 3: Spectochip Hardware

XAI Analysis

Layer (type)	Output Shape	Param #
conv1d_4 (Conv1D)	(None, 1278, 32)	128
max_pooling1d_4 (MaxPooling1D)	(None, 639, 32)	0
conv1d_5 (Conv1D)	(None, 637, 64)	6,208
max_pooling1d_5 (MaxPooling1D)	(None, 318, 64)	0
flatten_2 (Flatten)	(None, 20352)	0
dense_4 (Dense)	(None, 128)	2,605,184
dropout_2 (Dropout)	(None, 128)	0
dense_5 (Dense)	(None, 7)	903

Total params: 2,612,423 (9.97 MB)
Trainable params: 2,612,423 (9.97 MB)
Non-trainable params: 0 (0.00 B)

Figure 5: CNN model layout

- The loss function used during training is categorical crossentropy and accuracy was used as validation metric.
- 8 layers were used

Model Results

- Model shows high accuracy in validation (98.2%) and training (89.97%) data

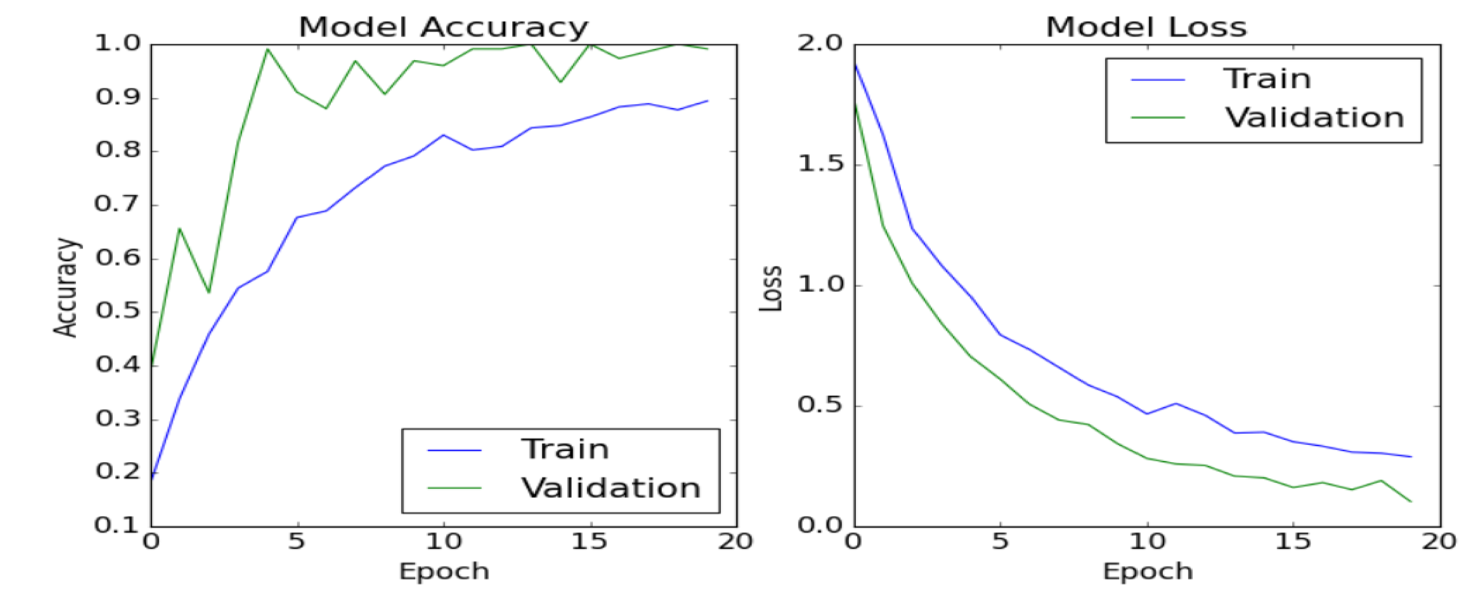


Figure 6: Model accuracy and model loss for training and validation loss

Wavelength has correlation with feature

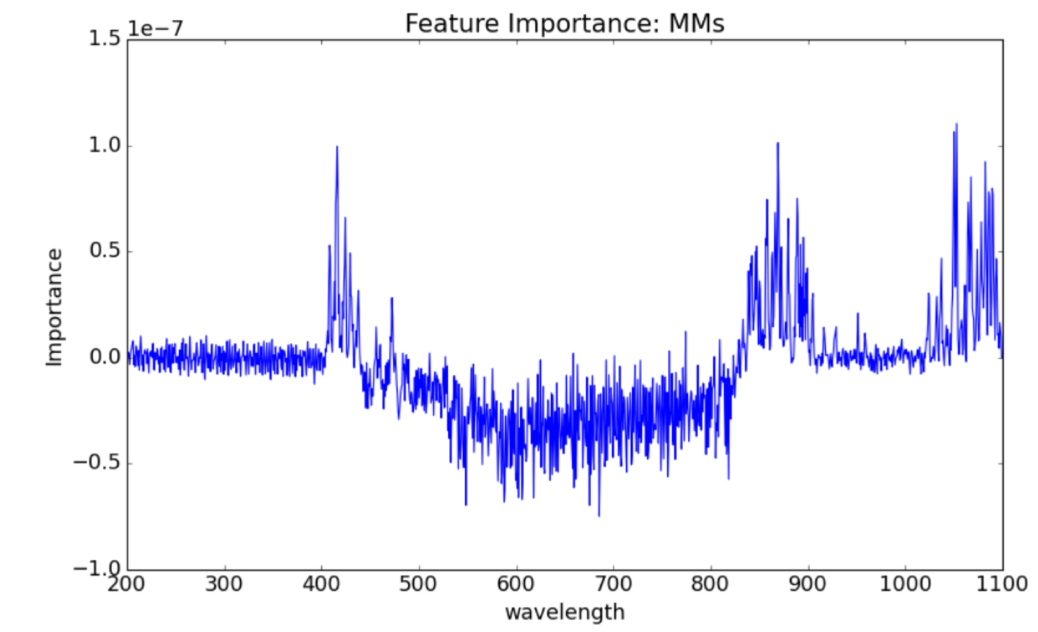


Figure 9: Graph shows feature importance by wavelength

Discussion/Conclusion

- The data shows that there is positive correlation between the surface soil moisture and spectrum absorption
- The model has high accuracy in predicting the soil moisture by analyzing spectrum data where soil moisture is normally found

Building on the Future

- Field soil samples should be collected to validate the model as soil samples were obtained in laboratory and not in field
- More data is needed to train the model, as factors such as different soil types should be accounted into estimating soil moisture [4]
- Other soil properties such as soil organic carbon or soil pH should be investigated if they can be predicted
- Model should be compared with ground truth