

Integration of Photonics Technology with Cone Penetration Testing: An Update

Joseph Bindner, ConeTec Group, Burnaby, British Columbia, Canada

Iman Entezari, ConeTec Group, Burnaby, British Columbia, Canada

Dallas McGowan, ConeTec Group, Burnaby, British Columbia, Canada

Cecilia Brockett, Colorado State University, Fort Collins, Colorado, USA

Joseph Scalia, Colorado State University, Fort Collins, Colorado, USA

Abstract

Hyperspectral sensing is used to measure the intensity of light reflected from a material surface and has been used to predict tailings moisture content and solids content using commercial spectrometers designed for field or benchtop testing. However, there has not yet been a study on the use of hyperspectral sensing using piezocone penetration test (CPTu) compatible modules for the prediction of tailings moisture and solids content. The objective of this study is to evaluate how hyperspectral data can be used to predict tailings moisture content and solids content using data from a CPTu-compatible module and an existing characterization dataset. The existing benchtop hyperspectral dataset, containing approximately 300 samples, was used to train a neural network. The hyperspectral module was then used to measure the spectral reflectance of 60 archived tailings samples from the existing hyperspectral dataset. The hyperspectral module dataset was used to evaluate how the existing model can be applied to data from new sensors without additional training. The existing model was then fine-tuned using the transfer learning machine learning methodology and again evaluated on the data from the hyperspectral module. The results demonstrate that transfer learning can support the high-accuracy estimation of tailings properties using limited datasets, yielding root mean square errors below 3% and coefficients of determination (R^2) values above 0.94 for the prediction of solids and moisture content.

Introduction

Tailings' moisture properties are critical for both geotechnical and geochemical evaluations, including characteristics such as solids content and moisture content. Solids content is important for understanding tailings yield stress and dry density, as well as for understanding tailings facility water balance (Morrison,

2022). Moisture content plays a key role in determining permeability, bearing capacity, compaction response, and potential for acid rock drainage (Morrison, 2022).

While sampling and standard geotechnical laboratory tests can be used to characterize tailings, these techniques only provide data that represent a limited volume of material and are not practical for the high-resolution characterization of material properties across the vast extent of tailings storage facilities. Hyperspectral sensing has emerged as a promising method for rapid tailings characterization and has been shown to be useful in predicting tailings properties from hyperspectral data collected ex-situ (Entezari et al., 2018, 2019, 2022, 2024, and 2025). Hyperspectral signals quantify how light interacts with tailings across a range of wavelengths in the visible and near infrared portions of the electromagnetic spectrum, with hyperspectral reflectance influenced by material properties, including moisture content, particle shape, particle size, mineralogy, and density, among other material properties.

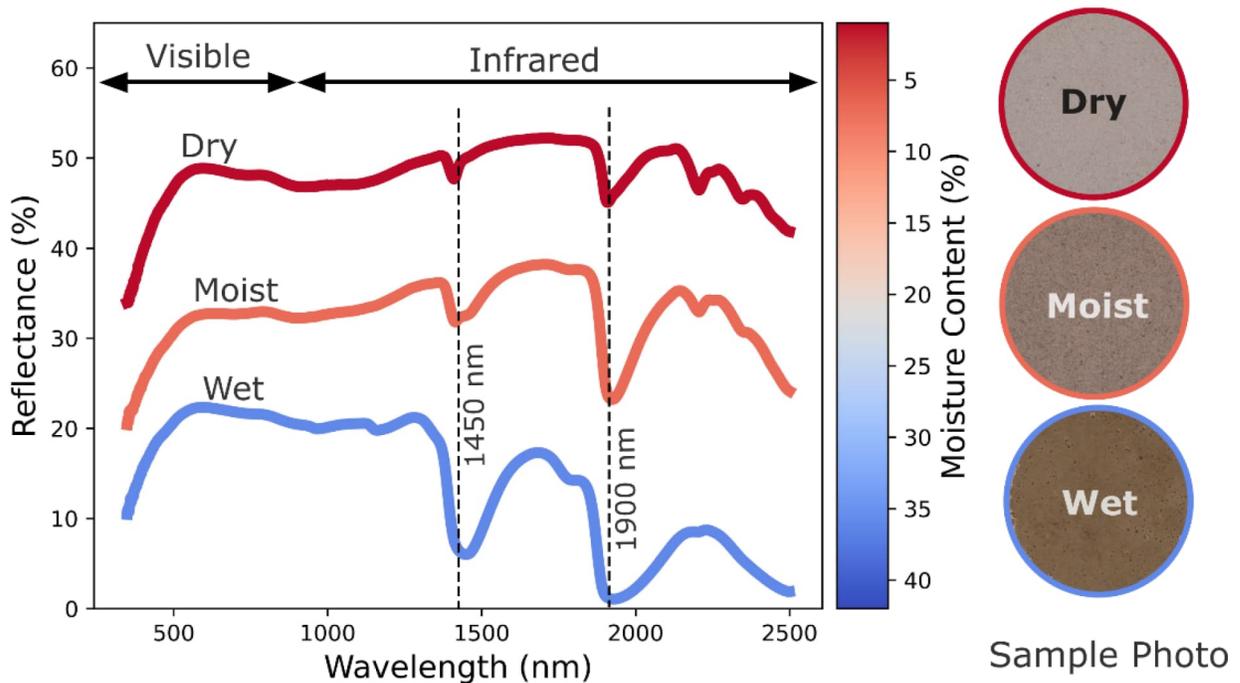


Figure 1: Tailings sample prepared for three moisture conditions, including dry, moist, and wet conditions. Hyperspectral data and RGB images were then collected for each moisture condition and documented to illustrate how the presence of water reduces spectral reflectance, resulting in samples appearing darker when moisture is added. Water adsorption features in hyperspectral data are shown at wavelengths of 1,450 and 1,900 nm

Figure 1 illustrates how the hyperspectral signal for an ex-situ tailings sample varies with changing moisture content. Hyperspectral data collected on samples ex-situ have been shown to be useful in the prediction of oil sands and hard rock tailings properties, including fines content, solids content, and

moisture content (Entezari et al., 2018, 2019, 2022, 2024, 2025; Bindner et al., 2024). However, the collection of hyperspectral data ex-situ requires drilling, sampling, and the manual measurement of hyperspectral reflectance. Direct push tools for capturing hyperspectral data add additional efficiency to the collection of hyperspectral data and show promise for the high-resolution characterization of tailings facilities.

Entezari et al. (2024) presented a novel CPTu-compatible module for the in-situ collection of hyperspectral data. Calibration transfer is a common problem in spectroscopy-based modelling, where models trained on data from one measurement setup often perform poorly when applied to data from a different setup due to variations in sensor characteristics, illumination, or sample presentation. To address this, we explore the use of transfer learning, which allows the model to leverage knowledge from existing datasets while adapting to the specific characteristics of the Hyperspectral CPTu module. This approach is intended to enhance the model's generalizability and predictive accuracy across different data sources.

The objective of this study is to better understand how existing datasets and machine learning can be used to predict tailings properties using the Hyperspectral CPTu module. Hyperspectral data were collected on tailings samples using the hyperspectral module. An existing dataset was used to train a neural network for the prediction of tailings solids content and moisture content. The model performance was then evaluated using data from the hyperspectral module. Finally, the model was fine-tuned using transfer learning and a subset of the hyperspectral module data was used to evaluate the model's predictive performance.

Methods

Figure 2 displays the general procedure for test specimen preparation, laboratory data collection, and machine learning procedures. The following sections cover details of the testing procedures. This study focuses on a material referred to as P-tailings, which have been extensively characterized in past research (Aghazamani et al., 2022; Bindner et al., 2024). The bulk tailings sample was processed to obtain 300 test specimens with unique particle size distributions, densities, and water contents.

The spectral reflectance of the samples at wavelengths in the visible and near-infrared portions of the electromagnetic spectrum was measured using spectrometers, and the test specimen properties were measured using standard geotechnical laboratory procedures. The dataset was compiled, and models were trained and tested to predict tailings solids content and water content.

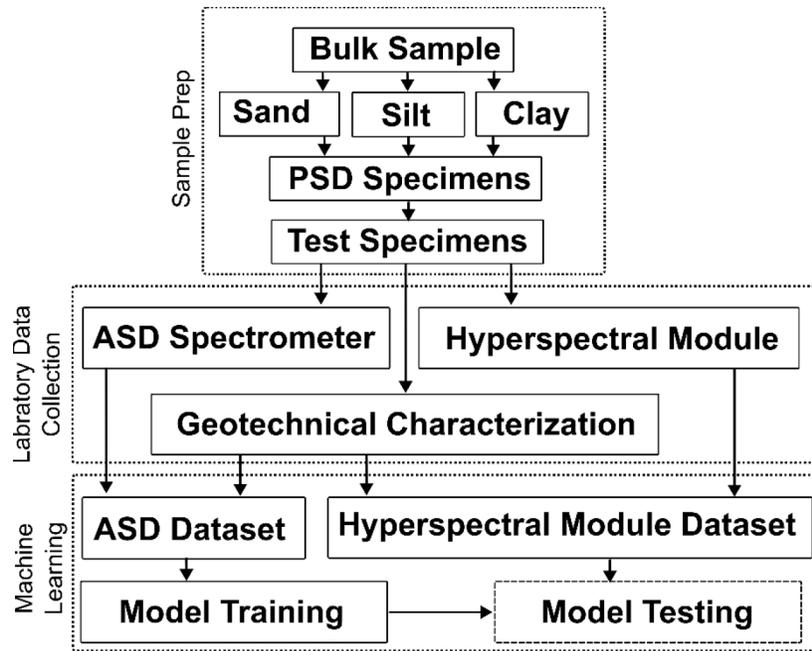


Figure 2: Flowchart of generalized steps involved in the sample preparation, data collection, and machine learning

Tailings Materials

A bulk tailings sample from a gold mine, designated as Mine P, was subjected to sieving and sedimentation processes to isolate three primary particle size fractions: sand, silt, and clay. Then, varying proportions of the sand, silt, and clay fractions were combined to create a total of 100 particle size distribution (PSD) specimens with varying PSDs. Figure 3 illustrates the PSD of the whole tailings sample alongside the typical PSD range reported in existing literature for tailings materials.

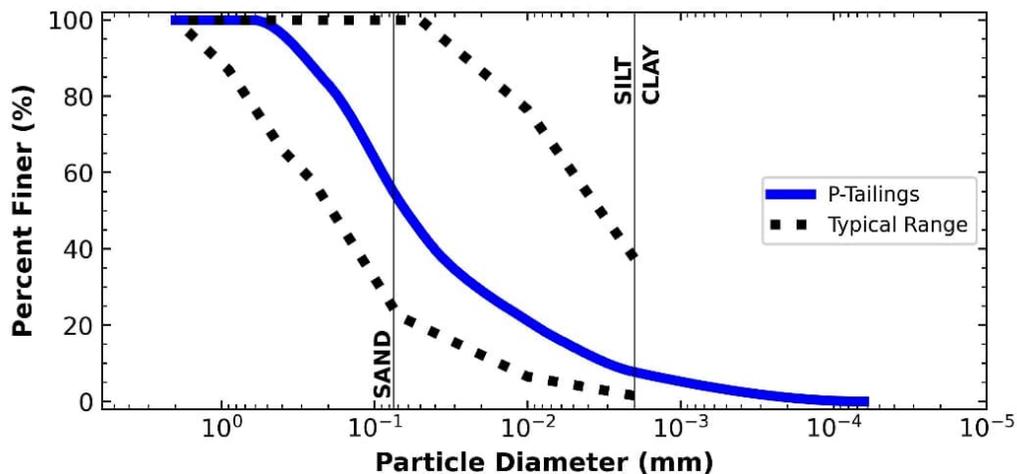


Figure 3: Particle size distributions of the whole P-tailings sample. Black dashed lines are the average upper and lower tailing bounds of mine tailings PSD from literature (after Gorakhki et al., 2019, adapted from Hamade, 2017)

Each sample was then prepared to a target moisture content and density in a small petri dish. The geotechnical properties of each test specimen were measured using ASTM International laboratory procedures standard for geotechnical characterization.

Hyperspectral Sensing

Hyperspectral data were first collected from all test specimens using a commercial spectrometer (referred to as the COM spectrometer), following the procedure outlined in Bindner et al. (2024). The COM spectrometer measures the light reflected from the soil at wavelengths ranging from 350 nm – 2,500 nm. Then a subset of the test specimens was dried and prepared to new moisture and density conditions before measuring the spectral reflectance using the Hyperspectral CPTu module, which captures reflectance data between approximately 450 – 850 nm and 950 – 1,700 nm. While the Hyperspectral CPTu module is intended to be compatible with standard CPTu data collections, no CPTu data were collected as part of this study.

Figure 4 presents an overview of the ConeTec patent-pending Hyperspectral CPTu module, which involves directing light at a material and measuring the reflected radiation intensity from the material’s surface. Figure 5 shows labelled photos of the prototype Hyperspectral CPTu module used in this study.

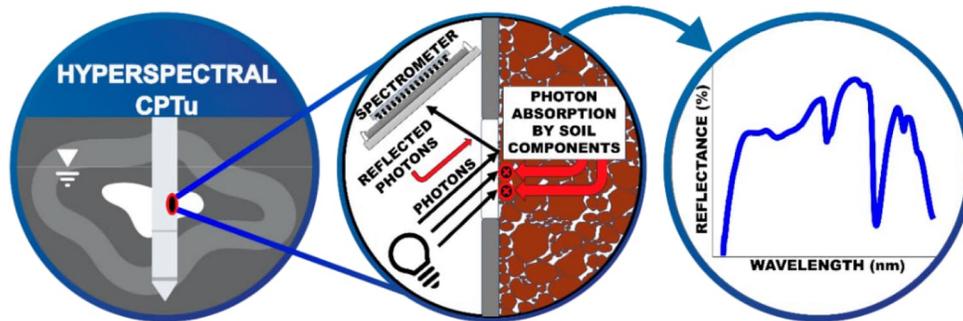


Figure 4: Conceptual overview of in-situ operation of the Hyperspectral CPTu module, including the generalized internal components of the hyperspectral module and the data produced

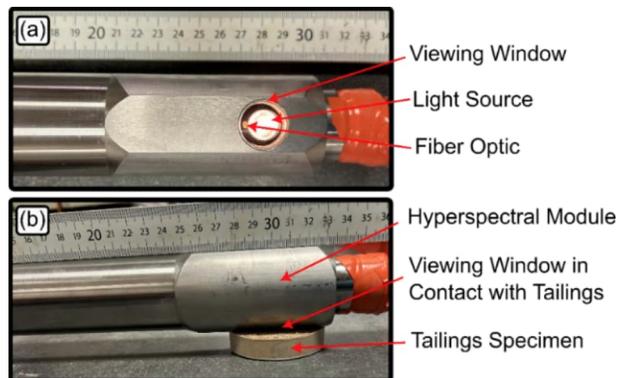


Figure 5: Images of (a) the front view of the hyperspectral module and (b) profile view of the hyperspectral module in contact with a tailings specimen

Machine Learning

First, hyperspectral data from the COM spectrometer datasets were interpolated to produce reflectance at wavelengths measured by the hyperspectral module. The reduced wavelength hyperspectral data were then used to train the machine learning model presented in Bindner et al. (2024) to produce a trained model for the prediction of solids content and moisture content for the P-tailings. After model training, the hyperspectral module datasets were used to evaluate the performance of the models trained on COM data and tested on hyperspectral module data.

A key objective of this study is to address the common challenge of calibration transfer, where spectral data from different instruments, even of the same make and model, often vary due to hardware or environmental differences. These inconsistencies limit the direct applicability of models trained on one spectrometer's data to another. To overcome this, transfer learning is explored as a method to adapt models trained on commercial spectrometer data to the Hyperspectral CPTu module data. Transfer learning is a method that uses machine learning algorithms that have been trained for one task to be applied to a similar task. Neural networks have multiple layers, which typically identify general patterns in the input data in early layers and fine-resolution patterns in later layers.

Transfer learning leverages the generalizations made in early layers while later layers are re-trained to learn the fine-resolution patterns that manifest in the new dataset. Transfer learning is a powerful methodology since large datasets can be leveraged to aid in the training of new models to solve problems for limited datasets. Transfer learning was used in this study to evaluate how neural networks and existing datasets can be used for the prediction of tailings solids content and moisture content using hyperspectral data collected using the hyperspectral module. The transfer learning modelling procedure included optimization of the number of layers and the number of samples in the hyperspectral module dataset to be used for retraining of the model.

Results

Hyperspectral Module Validation

Figure 6 displays the hyperspectral signals for a tailings sample scanned by the COM spectrometer and the hyperspectral module. Results show the hyperspectral signals produced for the two sensors are similar at the wavelengths measured by both spectrometers. While the data is comparable in this range, the spectral reflectance varies slightly between the two instruments. Variability between instruments is expected when using two different spectrometers.

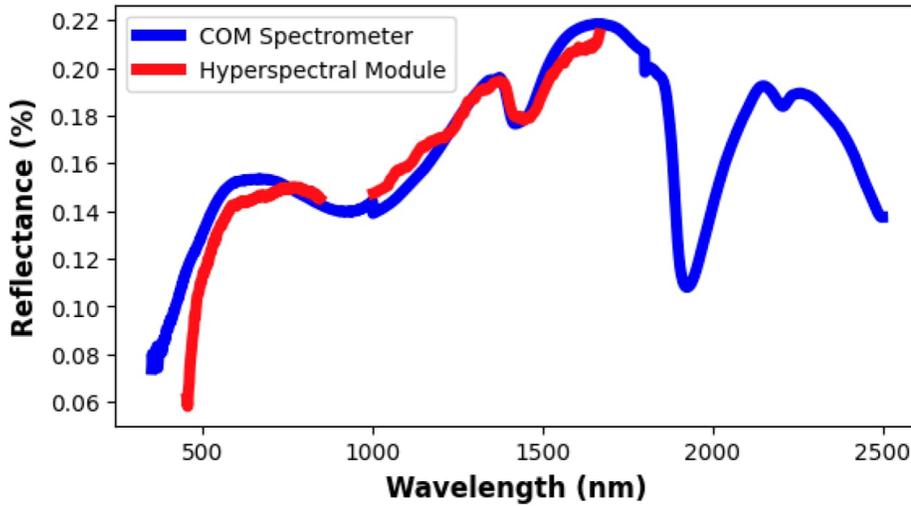


Figure 6: Results of the initial study on P-tailings, which compares the hyperspectral signal for a tailings sample that was prepared and scanned with a commercial spectrometer (COM spectrometer) and the hyperspectral module

COM Model Predictions

Figure 7 displays the results of the model trained on COM data and tested on hyperspectral module data for predicting solids content and water content. Predictions of solids content resulted in a root mean squared error (RMSE) of 5.9%, a mean bias error (MBE) of 3.9%, and a coefficient of determination (R^2) of 0.48. The predictions of water content yielded an RMSE of 8.4%, an MBE of -5.4%, and an R^2 of 0.38.

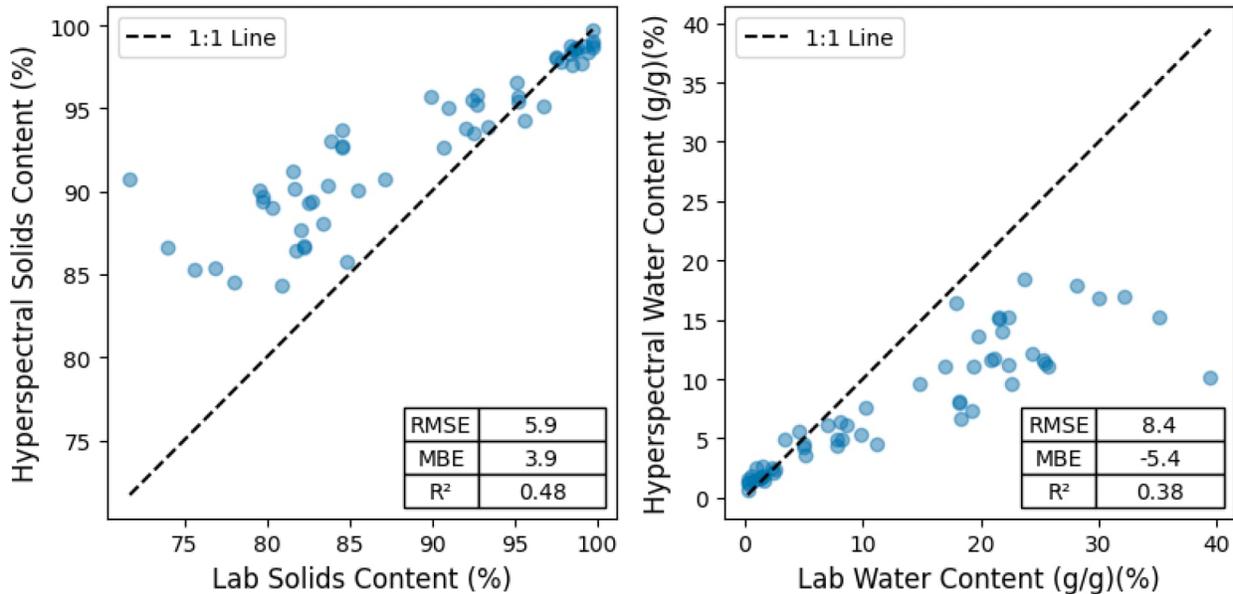


Figure 7: Predictions of solids content and water content using the hyperspectral module compared to laboratory-measured values. Results generated in these plots were produced using a model trained on COM data and testing on data from the hyperspectral module

Transfer Learning

Figure 8 displays the predictions of solids content and water content for 43 tailings samples after the model was fine-tuned on 25% data (n = 15) from the hyperspectral module. Model performance was greatly improved compared to performance before transfer learning. Predictions of solids content produced and RMSE of 3.0%, an MBE of -2.0%, and an R² of 0.86. The predictions of water content produced an RMSE of 3.8%, an MBE of 2.0%, and an R² of 0.86%.

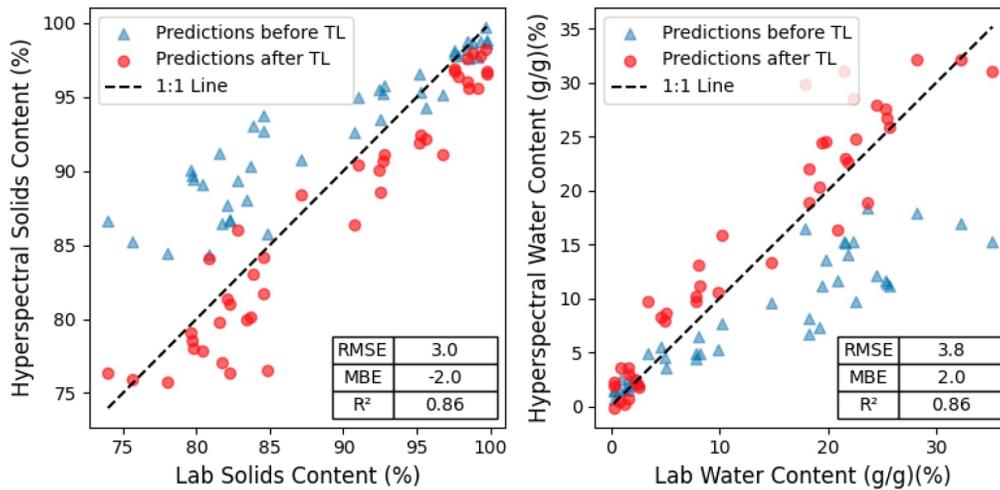


Figure 8: Predictions of solids content and water content after the model trained on COM data was fine-tuned using 25% of the hyperspectral data and transfer learning and tested on 75% of the collected hyperspectral data

Figure 9 displays the predictions of solids content and water content for 15 tailings samples after the model was fine-tuned to 75% of the data from the hyperspectral module (n = 43).

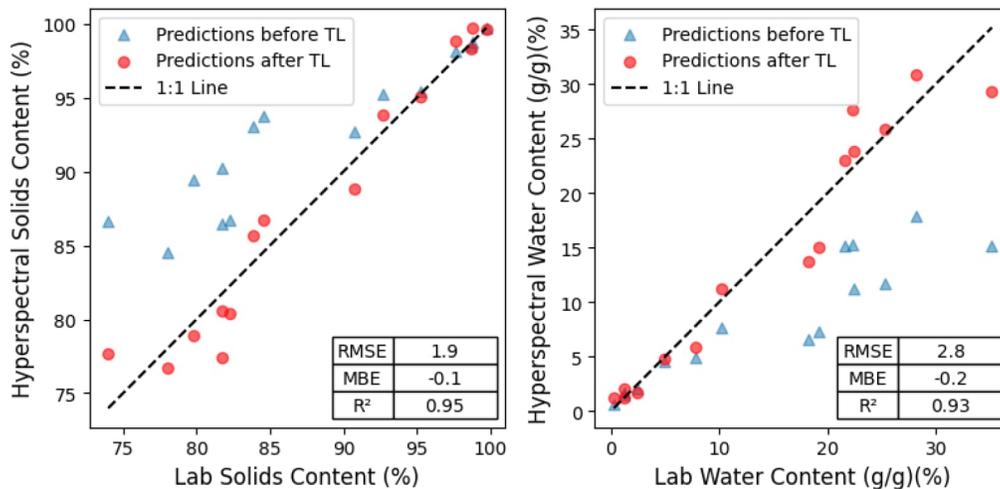


Figure 9: Predictions of solids content and water content after the model trained on COM data was fine-tuned using 75% of the hyperspectral data and transfer learning and tested on 25% of the collected hyperspectral data

Results demonstrate that error metrics are substantially improved compared to the model solely trained on COM data. The prediction of solids content resulted in an RMSE of 1.9%, an MBE of -0.1%, and an R^2 of 0.95. The prediction of water content yielded an RMSE of 2.8%, an MBE of -0.2%, and an R^2 of 0.93.

Discussion

Bindner et al. (2024) demonstrated that when training a neural network on COM data from the P-tailings and applying the model to COM data, the resulting model produced an RMSE, MBE, and R^2 of 1.4%, -0.1%, and 0.97, respectively, for solids content and 2.2%, 0.2%, and 0.96, respectively, for water content. The model trained on hyperspectral data from the COM spectrometer and tested on data from the hyperspectral module shows poorer performance than when trained and tested on COM data. This is generally expected, as the data produced by the COM and hyperspectral module spectrometers vary slightly due to the optical properties of the two instruments. However, the results from applying the model to hyperspectral module data demonstrate that the neural network establishes a general pattern recognition during model training.

After the application of transfer learning, the model applied to hyperspectral module data shows performance similar to Bindner et al. (2024). The results from transfer learning indicate that small quantities of hyperspectral data can be used to refine the predictions of tailings properties using hyperspectral data and existing neural networks. During transfer learning optimization (i.e., testing the optimum number of layers to retrain and quantities of data used in retraining), the authors observed that greater quantities of data used in model retraining resulted in better model performance. Future studies might consider the optimum number of samples required for tailings-specific model fine-tuning.

Results from this study demonstrate that transfer learning methodologies may be used to leverage existing datasets for the prediction of tailings properties using laboratory hyperspectral data. Provided that developing tailings-hyperspectral datasets is generally less costly in laboratory environments than field sampling followed by laboratory testing, using transfer learning may reduce the time and resources needed to develop well-trained models for predicting tailings solids content and moisture content from in-situ hyperspectral module data.

While this study demonstrates that transfer learning can be used for predicting tailings properties from hyperspectral module data, several key studies are still required to understand how this methodology can be applied to hyperspectral module data collected in situ. First, the test specimens used in this study did not experience sample disturbance. In-situ collection of hyperspectral data using the Hyperspectral CPTu may result in material disturbance in the immediate vicinity of the hyperspectral module; studies are needed to understand how sample disturbance impacts model performance. Additionally, all test specimens used in

this study were prepared from one whole tailings sample, resulting in limited mineralogical diversity. Future studies should assess how varying specimen mineralogy and pore water chemistry influence the predictive performance of similar modelling procedures. Finally, future studies should also investigate the use of the tools and methods presented herein for the evaluation of soils.

Conclusion

The objective of this study was to evaluate the use of existing benchtop tailings hyperspectral datasets for the prediction of tailings solids content and moisture content from hyperspectral data using a novel downhole CPT-compatible hyperspectral module. Hyperspectral data were measured for tailings from a gold mine using the hyperspectral module. Existing tailings hyperspectral datasets were used to train a tailings-hyperspectral model, and its performance was evaluated using data from the hyperspectral module. The model was then fine-tuned to data from the hyperspectral module using transfer learning, and the model was re-evaluated using a subset of the hyperspectral module dataset. The key findings from this study are:

1. Hyperspectral signals from the hyperspectral module and the COM spectrometer measure reflected light intensity from tailings materials in similar ways. Direct comparisons of the hyperspectral data from the instruments yield similar spectral responses at the wavelengths measured by both instruments. When neural networks are trained on data from the COM spectrometer and applied to data from the hyperspectral module, the trend of the variability in solids content and water content is generally captured. However, the model performs more poorly using the Hyperspectral CPTu module compared to when applied to COM data, which is generally expected.
2. Transfer learning shows promise for the prediction of tailings solids content and moisture content using Hyperspectral CPTu module data. The predictions of tailings properties using the transfer learning model demonstrate performance similar to past studies, which have used COM data for both model training and testing. The results from transfer learning produced low errors with RMSEs below 3%, model bias less than 1%, and R^2 values greater than 0.94.

The results of this study imply that hyperspectral datasets developed in laboratory environments, which are typically lower cost than dataset development from field samples, may be used to build site-specific hyperspectral models. Future studies should consider how transfer learning can be used to fine-tune models developed at one site to another. Additionally, future studies should assess how this methodology might be applied to Hyperspectral CPTu data collected in the field.

References

- Aghazamani, N. A., Scalia, J. I. A., Bareither, C. A., Shackelford, C. D., & Ham, J. M. (2022). *Unsaturated fluid flow and volume change behavior of filtered tailings*. Colorado State University.
<https://mountainscholar.org/items/9843498d-a22e-4880-835e-587505fd6c55>
- Bindner, J., Scalia, J., Bareither, C., & Entezari, I., McGowan, D. (2024). Predicting tailings properties using hyperspectral sensing and machine learning. In *Proceedings of Tailings and Mine Waste 2024*.
- Entezari, I., McGowan, D., & Glavina, J. (2022). Hyperspectral imaging technology for oil sands tailings characterization: Practical aspects. In *Proceedings of Tailings and Mine Waste 2022* (pp. 1243–1252).
- Entezari, I., McGowan, D., & Rudolf, K. (2025). Commercial demonstration and performance evaluation of HyperScan™ technology for rapid estimation of oil sands tailings properties. In *Proceedings of Tailings and Mine Waste 2025*.
- Entezari, I., McGowan, D., Bindner, J., Glavina, J., & DeJong, J. (2024). Enhancing soil and tailings characterization: Integration of photonics technology with cone penetration testing. In *Proceedings of Tailings and Mine Waste 2024* (pp. 2027–2038).
- Entezari, I., Rivard, B., Sharp, J., Wells, P. S., Styler, M. A., & McGowan, D. (2018). Real-time prediction of oil sands tailings properties using hyperspectral observations. In *Proceedings of the 6th International Oil Sands Tailings Conference* (pp. 102–106).
- Entezari, I., Sharp, J., & McGowan, D. (2019). Characterization of oil sands tailings using hyperspectral technology. In *Proceedings of Tailings and Mine Waste 2019* (pp. 519–528).
- Gorakhki, M. R. H., Bareither, C. A., Scalia, J., & Jacobs, M. (2019). Hydraulic conductivity and soil water retention of waste rock and tailings mixtures. In *Proceedings of the Eighth International Conference on Case Histories in Geotechnical Engineering*.
- Hamade, M. M. (2017). *Undrained shear behavior of mixed mine waste rock and tailings* [Master's thesis]. Department of Civil and Environmental Engineering, Colorado State University, Fort Collins, CO.
- Morrison, K. F. (2022). *Tailings management handbook: A lifecycle approach*. Society for Mining, Metallurgy & Exploration, Incorporated.