Hyperspectral imaging (HSI) technology for oil sands tailings characterization: practical aspects

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ABSTRACT: This paper presents an update on the use of hyperspectral imaging (HSI) technology for oil sands tailings characterization and demonstrates its practical aspects in estimation of tailings properties. In 2021, hyperspectral data were collected from approximately 5,700 new tailings samples across the oil sands region, expanding the development dataset from 2,773 to 8,495 paired HSI-laboratory data. The HSI models were re-calibrated and validated using this updated dataset. The updated models are robust and capable of estimation of tailings constituents with accuracies comparable to commercial laboratories from across the oil sands region. A blind test on 1,076 samples showed HSI models can predict the contents of bitumen, solids, water, total fines, and fines/(fine+water) with 0.47, 3.74, 3.36, 3.81, 3 wt% error, respectively. Methylene blue index (MBI) of oil sands tailings can also be predicted with 0.81 meq/100g error. Hyperspectral technology enables mine operators to analyze the tailings on-site and quickly provide information on the tailings properties, saving time and expense.

1 INTRODUCTION

Laboratory analysis of the oil sands tailings samples is widely used for accurate measurement of tailings constituents with substantial cost and time investment. Therefore, developing cost-effective, rapid, and repeatable methods for estimation of tailings characteristics with sufficient accuracy is beneficial for tailings management.

Over the past decade, new technologies have been developed for estimation of tailings constituents with acceptable accuracies. Tailings Behaviour Type (TBT) models were developed to estimate tailings constituents from gamma piezocone penetration test (GCPTu) data (Styler et al. 2018 & Entezari et al. 2020). TBT models report continuous profiles of tailings constituents (fines content, solids content, and MBI) with no physical samples required.

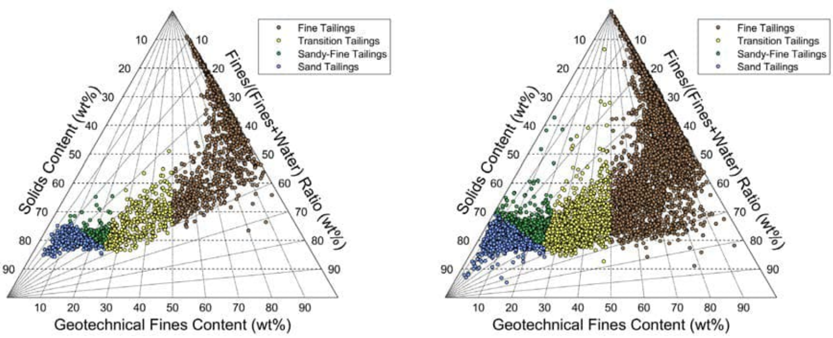
Research and development on the use of hyperspectral imaging (HSI) technology for the estimation of tailings constituents was started in 2018 (Entezari et al. 2018, 2019, 2021). Hyperspectral imaging is a technology based on measuring the reflected light from a target material as a function of wavelength. Since the spectral response is controlled by chemical composition and physical structure of the target, hyperspectral data can be used for qualitative and quantitative characterization of the target under study. In 2021, hyperspectral data were measured from approximately 5,700 new tailings samples across the oil sands region, expanding the development dataset from 2,773 to 8,495 paired HSI-laboratory results. The HSI models have been re-calibrated and validated using this updated dataset. The updated models are robust and capable of estimation of tailings constituents with accuracies comparable to commercial laboratories from across the oil sands region.

The aim of this publication is twofold: 1) to provide an update on the development and performance of the most recent HSI models and 2) to demonstrate how HSI technology could be implemented and used in practice to provide rapid information on tailings constituents.

2 UPDATED HSI MODELS

2.1 *Updated development dataset (2021)*

In 2021, hyperspectral data were collected from approximately 5,700 new tailings samples across the oil sands region, expanding the development dataset from 2,773 to 8,495 paired HSI-lab results. Figure 1 shows a comparison between ternary diagrams of the 2020 and 2021 development datasets. The 2021 development dataset is much denser than the 2020 dataset and includes wider range of tailings material. It includes hyperspectral data collected from a variety of tailings samples including high water samples, fluid fine tailings (FFTs), thick FFTs and samples from sand dominated materials from beach above water (BAW) and beach below water (BBW), samples with high bitumen concentration (more than 10 wt% bitumen), froth treatment tailings, and tailings solvent recovery unit (TSRU) tailings, collected from multiple tailings storage facilities (TSFs) in pond investigations spanning 2018 through 2021. The samples are from four oil sands operators anonymized as Mine Operators A, B, C, and D in this paper. Tailings characteristics including the contents of bitumen, solids, water, fines, and clays through MBI testing were measured through laboratory programs. The laboratory measurements were from multiple commercial laboratories, using industry standard practices. It should be mentioned that not all the tailings constituents or index properties were analyzed for each sample.



n = 2,773 n = 8,495

Figure 1. Ternary diagram of the 2020 (left) and 2021 (right) development datasets. The ternary diagram is according to the COSIA's Unified Oil Sands Tailings Classification System (COSIA 2014).

To recalibrate and update the HSI models (i.e. develop 2021 HSI models) and assess the performance of the updated models, the development dataset was split into training and test sets. From the data collected during 2021 field season, approximately 13% was selected and added to the 2020 test set to generate the updated 2021 test set. This was done by random selection of entire sample holes. The remaining data was added to the 2020 training set to generate the updated 2021 training set used to train the 2021 models. Table 1 compares the number of HSI-laboratory data pairs used in training and test sets from each oil sands operator in 2020 and 2021. The histogram of various tailings constituents in the updated 2021 training set is shown in Figure 2.

Table 1. Number of HSI-laboratory data pairs in the training and test sets.

Mine Operator	2020		2021	
	Training	Test	Training	Test
A	1959	240	2560	380
B	463	111	2761	429
C	0	0	853	88
D	0	0	1245	179
Total	2422	351	7419	1076

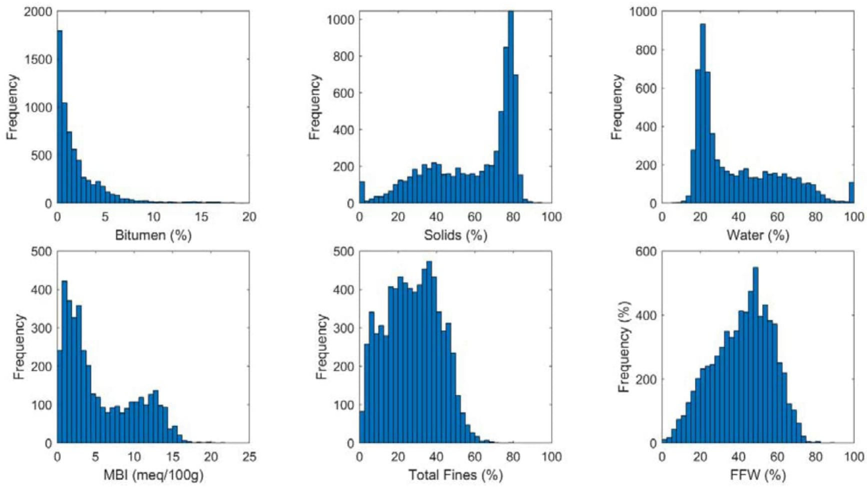


Figure 2. Histogram of tailings characteristics in the 2021 training set.

2.2 *Performance of the updated models (2021)*

Similar to 2020 models (Entezari et al. 2021), the 2021 models were trained using ensembles of neural networks using bootstrap aggregation (Bagging) technique (Sollich & Krogh 1996, Breiman 1996). In the Bagging method, several training sets are randomly selected from the original training set and neural networks are trained using each of these training sets. The outputs of these trained neural networks are averaged to generate the final prediction results. The models were trained to predict the contents of bitumen, solids, water, total fines, fines/(fines+water) (FFW) as well as MBI. The performance of the HSI models was evaluated by quantifying properties of the cumulative distribution function (CDF) of errors on the test set (Error = Lab -HSI).

The relationships between the laboratory measured and HSI predicted tailings properties for the test set are shown in Figure 3. The CDF of errors on the test set is also shown for each model output. Table 2 summarizes the error values of the model outputs on the test set. As can be seen, there is a strong correlation between the HSI predicted and laboratory results for all tailings characterizations. The bias of the estimated results is also very low and close to zero. It is noted that the FFW model is a model directly calibrated to FFW calculated from lab results and is not an indirect estimation from HSI estimated total fines and water.

Since the test set includes tailings samples from multiple TSFs operated by multiple oil sands operators, the developed HSI models are regional models that are capable of predicting tailings constituents from across the oil sands region. Therefore, the error assessment performed on the test set is considered the overall performance of the models, taking into account factors including instrument repeatability, laboratory repeatability, laboratory variance, and field sub-sampling to collect samples for HSI testing. Field sub-sampling was periodically conducted so samples could be analyzed with HSI at a later time or to be treated with polymer to prevent segregation during HSI testing.

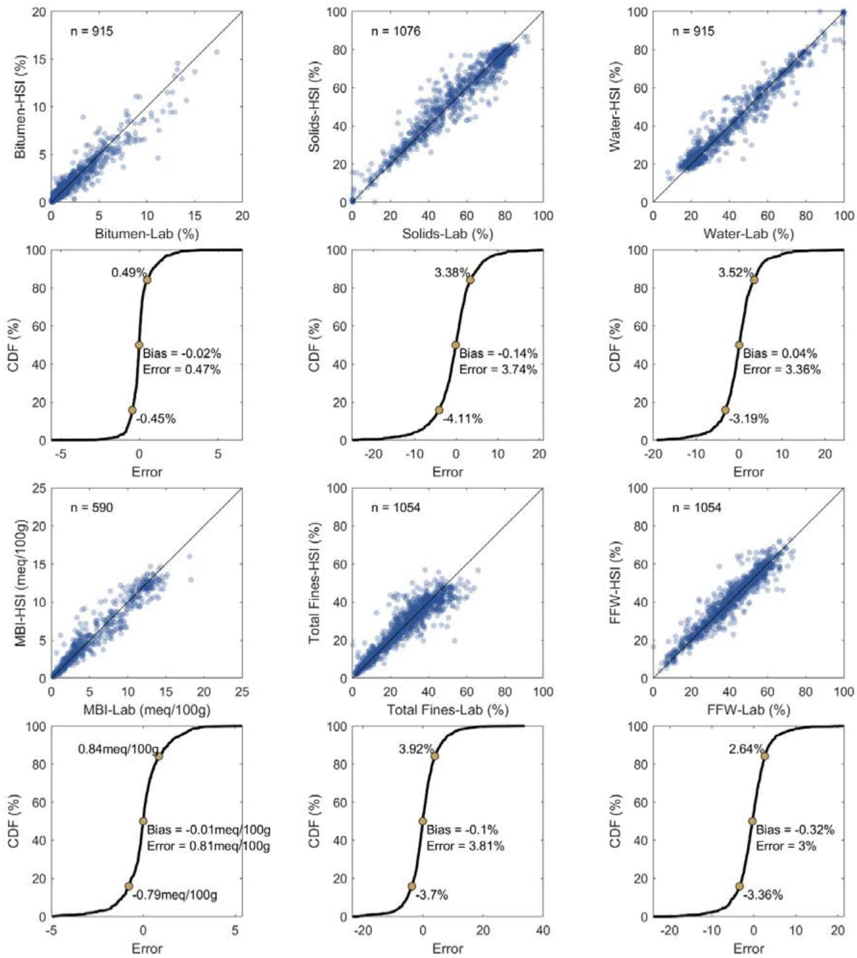


Figure 3. Relationship between HSI estimated vs laboratory measured tailings properties along with CDF of errors for the test set.

2.3 *Performance on samples from individual mine operators*

The performance of the models was also assessed on samples from each mine operator. The error and bias of the models on samples from each mine operator are listed in Table 2.

It should be noted that for Mine Operator B, not all the samples were analyzed for MBI in the laboratory. Also, a subset of the MBI laboratory results from this operator was screened out from the development dataset (i.e. training and test sets) due to a suspected data quality issue highlighted by Mine Operator B.

Mine Operator D does not conduct MBI analysis in laboratory. Also, the lab bitumen and water contents were reported on only a small fraction of the samples. Consequently, HSI results were generated for all samples, but it was not possible to compare HSI to laboratory results and perform an error analysis for MBI prediction. In addition, the error analysis on bitumen and water content results was limited to a small number of samples with existing bitumen and water content results analyzed in the lab. It should also be mentioned that samples from Mine Operator D were sub-sampled in the field in 250ml bottles for the lab analysis. Also, separate sub-samples were taken for HSI testing.

2.4 *Performance on segregated sandy samples*

An area of development in 2021 was to develop a standard procedure for hyperspectral data acquisition from segregated sandy samples. When a sample segregates, the probe only measures the fluid phase of the sample and the HSI scan is not representative of the entire sample. For such samples, a procedure was developed to sub-sample and homogenize the segregated samples by adding a sand suspending polymer. Figure 4 shows photos of a segregated sandy sample before and after polymer treatment.

A total of 83 samples in the test set were polymer treated samples (i.e. samples that were identified as segregated samples and treated with sand drill polymer for homogenization). The error values of the model outputs on these samples are summarized in Table 2. Evidently, the polymer addition process has been effective in measuring representative hyperspectral data from segregating samples as the HSI estimated and lab measured results were observed to be in good agreement.

Figure 4. A segregated sandy sample before (left) and after (right) homogenization with sand suspending polymer.

Table 2. Bias and error values* of HSI models.

Model	Overall	Polymer-treated	Mine Operator A	Mine Operator B	Mine Operator C	Mine Operator D
Bitumen (wt%)	-0.02 ± 0.47	-0.03 ± 0.12	0.01 ± 0.75	-0.03 ± 0.24	-0.07 ± 0.34	0.85 ± 1.28
Solids (wt%)	-0.14 ± 3.74	0.12 ± 2.22	0.09 ± 3.98	0.08 ± 3.05	-0.67 ± 3.23	-1.33 ± 6.17
Water (wt%)	0.04 ± 3.36	-0.17 ± 2.21	-0.16 ± 3.48	-0.01 ± 3.08	0.78 ± 3.23	0.54 ± 2.10
MBI (meq/100g)	-0.01 ± 0.81	-0.21 ±0.13	-0.11 ± 1.12	0.01 ± 0.21	0.08 ± 0.65	NA
Total Fines (wt%)	-0.1 ± 3.81	0.02 ±2.19	-0.22 ± 4.33	-0.1 ± 2.55	-2.32 ± 7.67	0.94 ± 4.61
FFW (wt%)	-0.32 ± 3.00	-0.23 ± 3.34	-0.05 ± 2.40	-0.2 ± 3.07	-2.33 ± 4.32	-0.98 ± 3.38

*The error values are absolute errors not relative.

2.5 *Repeatability and reproducibility of HSI testing*

Table 3 lists the repeatability and reproducibility standard deviations of the HSI testing on fine tailings. Repeatability and reproducibility statistics for HSI testing were derived using 60 measurements collected of a fine tailings sample with ~ 70 wt% water content using two HSI systems (30 measurements with each system).

The repeatability standard deviation represents the root of the mean of the squares of the standard deviations for estimated results from HSI data collected using individual spectrometers for a given material. The reproducibility standard deviation is a combination of the repeatability standard deviation and the standard deviation of mean estimated results from spectrometers about the global mean.

From Table 3, it is evident that the repeatability and reproducibility standard deviations of HSI testing are less than the model's errors. For the HSI estimated geotechnical 44 µm fines (estimated from total 44 µm fines and solids content), the repeatability and reproducibility standard deviations are 2.29 and 2.78 wt%, respectively. The published study by COSIA and InnoTech Alberta (ITA) on the precision of fines measurement (Hiltz & McFarlane 2017) reports that the repeatability and reproducibility standard deviations for measuring the geotechnical 44 µm fines of fine tailings in laboratory are 1.45 and 3.23, respectively, in the interlaboratory study (ILS) Round 2.

Table 3. Repeatability and reproducibility standard deviations of HSI testing.

Model	HSI		Lab	
	Repeatability	Reproducibility	Repeatability	Reproducibility
Bitumen (wt%)	0.10	0.16	NA	NA
Solids (wt%)	0.85	1.42	NA	NA
Water (wt%)	0.89	1.58	NA	NA
MBI (meq/100g)	0.48	1.03	NA	NA
Total 44 µm Fines (wt%)	0.57	0.95	NA	NA
FFW (wt%)	0.63	1.06	NA	NA
Geotechnical 44 µm Fines (wt%)	2.29	2.78	1.45	3.23

3 HSI TESTING IN PRACTICE

This section demonstrates the results of HSI testing performed on some test sample locations in 2021. HSI estimated results were generated using the updated 2021 models and were compared to laboratory results. The comparative examples are blind as the presented data examples are from the test set and were not used in model development.

3.1 *HSI testing in FFTs*

Example HSI tailings characterization results from a sample hole with FFT samples is presented in Figure 5. The laboratory measured results are overplotted for visual comparison with HSI results. Also, some of the sample photos at some depth intervals are displayed. All samples were collected with a fluid sampler. The location includes low bitumen FFT samples with a gradual increase in solids content as depth increases. As can be seen, HSI estimated and laboratory measured results are in very good agreement for all tailings characterization. MBI testing was not performed in the laboratory for these samples so HSI results could not be compared to laboratory results. However, HSI was able to produce MBI predictions with no additional time or expense.

3.2 *HSI testing in high solids tailings*

Figure 6 shows an example profile of HSI results from a test sample location where majority of the samples were high solids tailings (solids content of ~75 wt%). Samples at 2, 4, and 6 m were collected using a fluid sampler, whereas the rest of the samples were collected using a sonic sampler. The samples between 10-15 m were identified as segregated sandy samples and were treated with sand suspending polymer to homogenize for HSI testing. Overall, the HSI and laboratory results agree well for all the samples including the polymer treated samples. The close agreement between the HSI estimated and laboratory measured results for the polymer treated samples demonstrates that the polymer addition process has been effective in measuring representative HSI data from segregating samples.

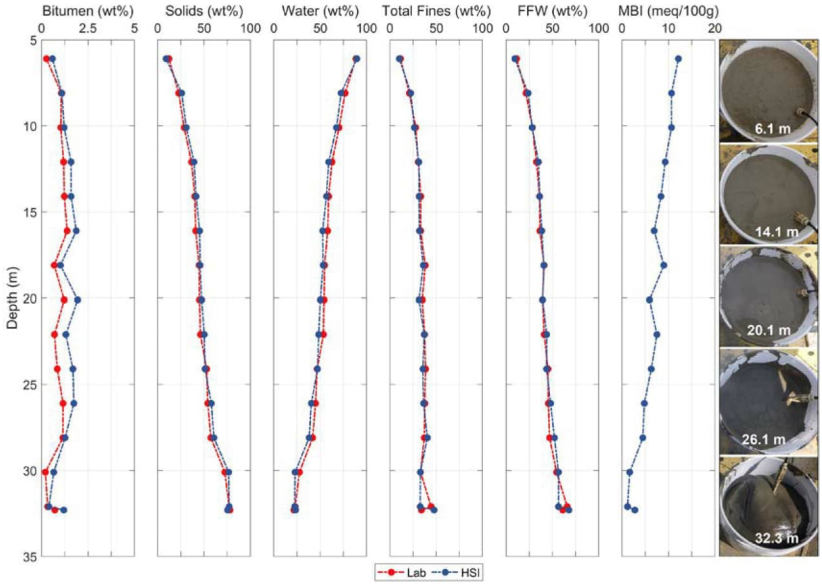


Figure 5. Comparison between tailings characterization profiles generated using HSI and lab in FFTs.

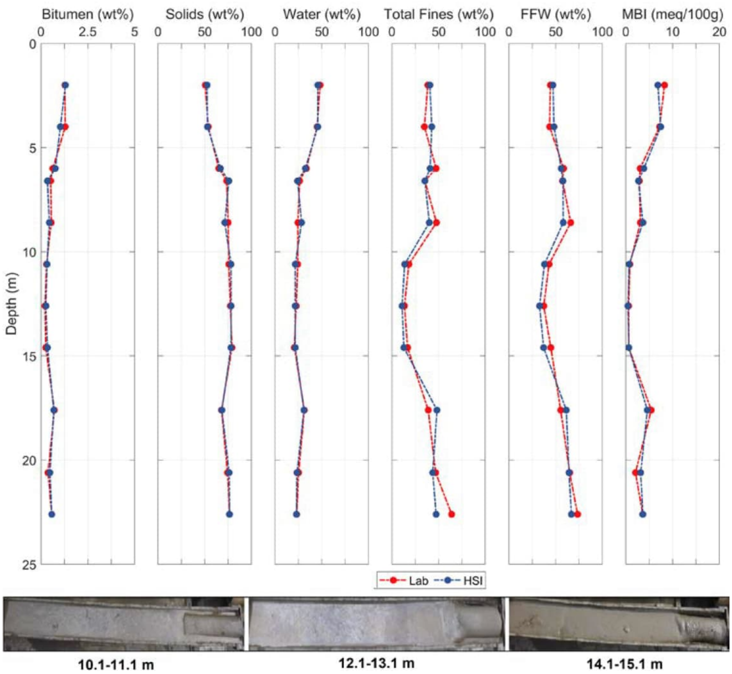


Figure 6. Comparison between tailings characterization profiles generated using HSI and lab in high solids tailings. Samples from 10-15 m were identified as segregated samples after mixing and were sub-sampled and polymer treated for HSI testing.

3.3 *HSI testing in TSRUs*

The HSI results from a sample location in TSRU tailings is shown in Figure 7. All samples were collected using a sonic sampler. Most of the samples were visually very dark and had high bitumen content in general. As can be seen, the bitumen content has been predicted with high accuracy overall. The agreement between laboratory and HSI results for this location suggests that HSI models have been well trained for TSRU and froth treatment tailings. Also, it can be concluded that the variation in the bitumen content of the samples does not impact the HSI estimation results (and thus errors) for other tailings characteristics.

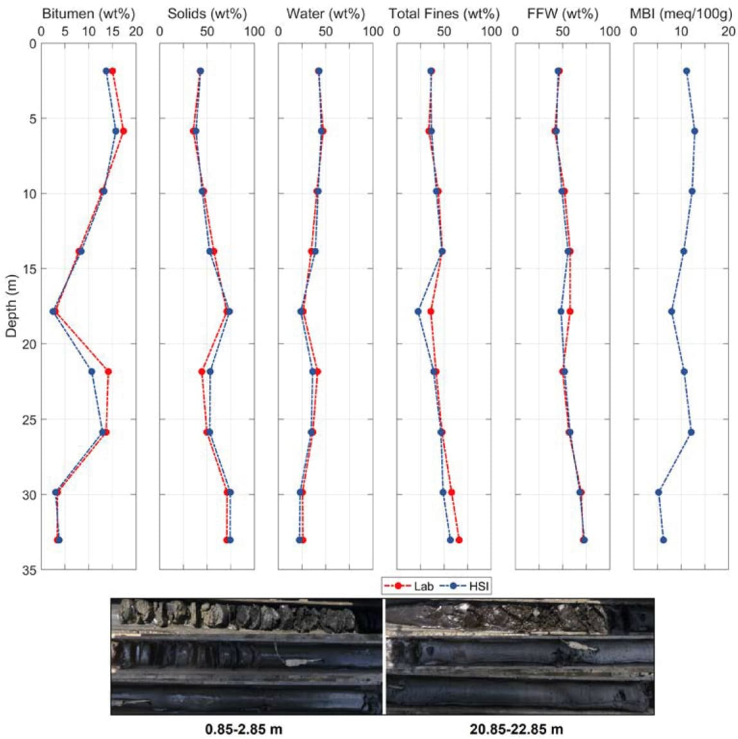


Figure 7. Comparison between tailings characterization profiles generated using HSI and lab in TSRUs.

3.4 *HSI and TBT*

For locations with paired sample holes and GCPTu data, HSI results can be reported along with TBT results. HSI and TBT models have been developed using different and independent technologies. Therefore, good agreement between the two could be a good indicator of accurate tailings characterization, while poor agreement could indicate the need for laboratory analysis. HSI and TBT can also be employed to validate laboratory results and identify samples that may have not been analyzed properly in the laboratory.

Figure 8 illustrates an example profile showing the corrected cone tip resistance (q_t), porewater pressure (u_2), gamma measurements, and generated TBT results from GCPTu data along with HSI results from samples collected from a paired sample hole with all samples collected using a sonic sampler. The laboratory results are also overplotted to visually compare with the TBT and HSI results. The offset between GCPTu sounding and sample hole was 4 m. Of note, the TBT results are predicted every 2.5 centimeters of depth, whereas the samples and resulting lab and HSI measurements represent an average of the constituents over the cored interval of 2 meters.

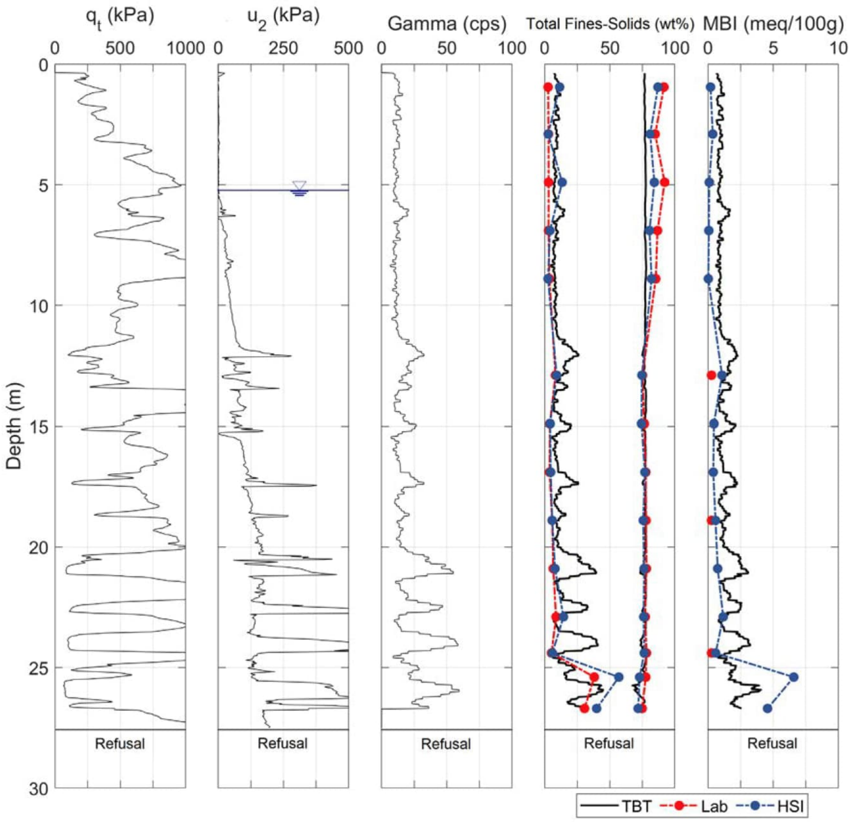


Figure 8. Example profile showing the TBT, HSI, and laboratory test results.

4 CONCLUSIONS

The updated HSI models were calibrated using the training set consisting of more than 7,400 paired HSI-laboratory data from tailings samples collected from multiple oil sands operators. A test set consisting of 1,076 samples, which was not seen by the neural networks during training phase, was used to evaluate the performance of the HSI models. This can be considered a class-A error assessment or a blind test to evaluate the generalization and robustness of the models when applied on data other than the data used for the calibration of the models. Results showed HSI models can predict the contents of bitumen, solids, water, total fines, and FFW with 0.47, 3.74, 3.36, 3.81, 3 wt% error, respectively. MBI of oil sands tailings can also be predicted with 0.81 meq/100g error.

The primary advantages of HSI for tailings characterization are: 1) rapid and objective predictions that are less prone to human errors in shipping, storage, and sub-sampling, 2) analyze the tailings on-site to quickly provide operators with the assessment of the tailings properties, saving time and expense, and 3) eliminate the chain of custody, sample handling, and disposal issues as samples are immediately returned to the tailings pond after spectral measurement, eliminating offsite waste and emissions.

Mine operators can significantly reduce cost and improve the adaptive management of tailings operations and tailings treatment by having access to accurate and rapid tailings constituents. HSI can also be used as a rapid and independent method to validate and readily identify problematic laboratory data for re-analysis. HSI testing is environmentally conscious as it eliminates emissions from shipping samples to the laboratories and eliminates landfill disposal of plastic and tailings.

REFERENCES

Breiman, L. 1996. Bagging predictors. *Machine Learning* 24 (2): 123-140.

COSIA (Canada's Oil Sands Innovation Alliance). 2014. Oil sands tailings measurement protocol. Report to COSIA by Thurber Engineering Ltd. and Barr Engineering.

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. *Proceedings of 6th International Oil Sands Tailings Conference*, Edmonton, Alberta: 102-106.

Entezari, I., Sharp, J., and McGowan, D. 2019. Characterization of oil sands tailings using hyperspectral technology. *Proceedings of Tailings and Mine Waste 2019*, Vancouver, British Columbia: 519-528.

Entezari, I., McGowan, D., and Sharp, J. 2020. Tailings characterization using cone penetration testing and machine learning. *Proceedings of Tailings and Mine Waste 2020*, Ft. Collins, Colorado: 695-704.

Entezari, I., McGowan, D., Glavina, J., and Parkinson, D. 2021. Hyperspectral imaging technology for oil sands tailings characterization: An update. *Proceedings of Tailings and Mine Waste 2021*; Banff, Alberta: 953-963.

Hiltz, M. and McFarlane, R. 2017. Precision of particle size measurements for minus 44 micron solids from oil sands; an interlaboratory study. Prepared by InnoTech Alberta on behalf of COSIA.

Styler, M.A., McGowan, D., and Sharp J. 2018. Characterizing soft oil sand tailings by gamma cone penetration testing. *Proceedings of the 6th International Oil Sands Tailings Conference*; Edmonton, Alberta: 112-120.

Sollich, P. and Krogh. A. 1996. Learning with ensembles: how over-fitting can be useful. In D.S. Touretzky, MozerM.C. Touretzky and M.E. Hasselmo (eds), *Advances in Neural Information Processing Systems*, MIT Press, Cambridge, MA: 8: 190–196.