Commercial Demonstration and Performance Evaluation of HyperScan™ Technology for Rapid Estimation of Oil Sands Tailings Properties

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Abstract

This paper presents recent advancements in HyperScan™, a technology developed by ConeTec for rapid estimation of oil sands tailings properties. HyperScan combines ex-situ hyperspectral measurements with machine learning to predict bitumen, solids, water, total fines, fines-over-fines-plus-water (FFW), and methylene blue index (MBI). An updated HyperScan model was evaluated through a 2024 commercial demonstration involving over 1,000 samples from multiple tailings storage facilities at a major oil sands mine. The study assessed (1) model performance, (2) block modelling outcomes using HyperScan versus laboratory data, and (3) repeatability of HyperScan and standard laboratory procedures. HyperScan results showed strong agreement with laboratory measurements, with prediction errors of ±0.59% (bitumen), ±2.61% (solids), ±2.69% (water), ±4.21% (total fines), ±4.45% (FFW), and ±0.82 meq/100g (MBI). A block-modelling exercise demonstrated the practical application of HyperScan for oil sands analysis and regulatory reporting. These findings show the capability of HyperScan for fast and reliable tailings characterization, offering efficiency gains for oil sands operations.

Introduction

While laboratory analysis is the standard for accurately measuring oil sands tailings constituents, it is time-consuming, costly, and measurement errors related to oil sands tailings characterization are unquantified. The HyperScan technology is a field-deployable hyperspectral scanning platform developed to enable rapid characterization of oil sands tailings. HyperScan leverages hyperspectral sensing technology to predict key tailings properties directly from bulk tailings samples using machine learning models trained on a paired hyperspectral-laboratory dataset.

Research on the application of hyperspectral sensing for tailings characterization began in 2018 (Entezari et al., 2018, 2019, 2021, 2022, 2024). While early models demonstrated strong potential for estimating tailings characteristics, challenges were encountered related to the impact of incident light intensity on the spectral response. This affected the accuracy of tailings constituent and index property measurements by HyperScan. In addition, the models performed poorly on tailings with solids content in the 40–60% range. To address these gaps, recent developments focused on incorporating unit weight as an additional model input, refining field quality protocols, and validating the technology under operational conditions.

Tailings characterization supports critical operational and planning tasks, including block modelling to describe property variations within a deposit. Block modelling uses deterministic or geostatistical methods to describe how material properties vary within depositional zones. These properties can include bitumen, solids, water, fines content, and MBI, along with derived properties like total and dry density, sand-to-fines ratio, and dry tonnage. These models help inform tailings planning, risk assessment, long-term performance monitoring, and regulatory reporting. While a direct error analysis comparing the HyperScan predictions with the laboratory measurements provides an informative basis for comparison, expanding the analysis to include a comparison of the results of block models can highlight its practical application for Directive 085 reporting or other large-scale geotechnical investigations.

This paper presents the results of a 2024 commercial demonstration of the HyperScan, aimed at evaluating its performance and operational viability. Over 1,000 tailings samples collected during a pond investigation program were analyzed using both HyperScan and commercial laboratory methods. The study assesses the predictive accuracy of HyperScan by comparing model results to corresponding laboratory measurements and evaluates the implications for block modelling by comparing models built from each dataset. Additionally, the results of a repeatability study for both HyperScan and laboratory measurements are presented. Since differences between HyperScan and laboratory data can reflect not only the predictive performance of the HyperScan model but also the inherent variability of laboratory methods, understanding repeatability is essential for interpreting model outputs and the assumptions underlying their use in block modelling.

Methodology

Updated HyperScan Model

The updated HyperScan model was trained on approximately 7,500 tailings samples collected between 2018 and 2021 from four major oil sands operators, including 1,986 samples from the studied site. The dataset includes hyperspectral measurements from a wide range of tailings materials, such as high-water content samples, fluid fine tailings (FFTs), thickened FFTs, sand-dominated beach above water (BAW) and below water (BBW) samples, high-bitumen samples (>10%), and froth treatment tailings. A detailed description of the dataset is provided in Entezari et al. (2022).

A key enhancement in this model version is the inclusion of unit weight as an input feature. As direct measurements were unavailable in the training set, unit weight was estimated from laboratory solids content, assuming a specific gravity (G_s) of 2.6 for solids and 1 for water and bitumen (Equation 1). A limited field trial conducted in 2023 indicated that field-measured unit weight values based on sample mass and volume had an error margin of ±0.25 kN/m³ relative to laboratory-derived estimates. To simulate this uncertainty, normally distributed noise (mean = 0, σ = 0.5 kN/m³) was added during training, representing twice the observed field error.

$$UW = \frac{9.8}{1 - Soilds\left(\frac{G_{S-1}}{G_S}\right)} \tag{1}$$

Similar to previous models (Entezari et al., 2021, 2022), the updated model was trained using ensembles of neural networks using the 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.

Previous studies and experience with the prediction of MBI at this oil sands site have demonstrated a systematic offset of HyperScan MBI predictions by a factor of approximately 1.75. This offset is hypothesized to be associated with procedural differences in the measurement of MBI at this site and the procedures used in the development of the HyperScan model training dataset (which did not include MBI data from this site). MBI predictions from HyperScan presented in this study were divided by 1.75 to account for this observed systematic offset.

To evaluate the performance of HyperScan, error analysis was conducted using the cumulative distribution function (CDF) of the differences between laboratory and HyperScan results, defined as: Error = Laboratory result – HyperScan result. The 50th percentile of the error distribution represents the bias; a positive bias indicates underestimation by HyperScan, while a negative bias indicates overestimation. Assuming normally distributed errors, the values at the 15.9 and 84.1 percentiles correspond to ±1 standard deviation, capturing 68.2% of the error distribution. The average absolute value of these bounds is taken as the overall prediction error at a 68.2% confidence level.

HyperScan Commercial Demonstration

A commercial demonstration of HyperScan was carried out in 2024 at several tailings storage facilities (TSFs) operated by a major oil sands operator. To test the samples, the HyperScan field laboratory was mobilized to the site following sample collection. Prior to scanning, each sample was homogenized using a drill mixer; in cases of visible segregation, a subsample was stabilized with a sand-suspending polymer to ensure uniformity (Entezari et al., 2022). Three hyperspectral scans were acquired per sample and averaged to enhance measurement robustness. Unit weight was measured in the field using mass and volume data from each sample. Figure 1 displays the process of capturing hyperspectral data on homogenized samples and the field measurement of tailings unit weight. With a streamlined workflow and a two-person crew, it was possible to test approximately 100 samples per day, immediately after sample collection, demonstrating the suitability of the system for high-throughput field operations. All data were uploaded to a centralized network drive, processed using the HyperScan model, and the resulting predictions were shared with the oil sands operator. Once laboratory analyses became available, a detailed error analysis was conducted to assess model performance. In total, 1,109 samples from the 2024 annual tailings investigation were analyzed using HyperScan. A ternary diagram of the tested samples is shown in Figure 2.

Figure 1: Collecting hyperspectral data from a tailings sample (left) and (right) measuring unit weight from sample mass and volume

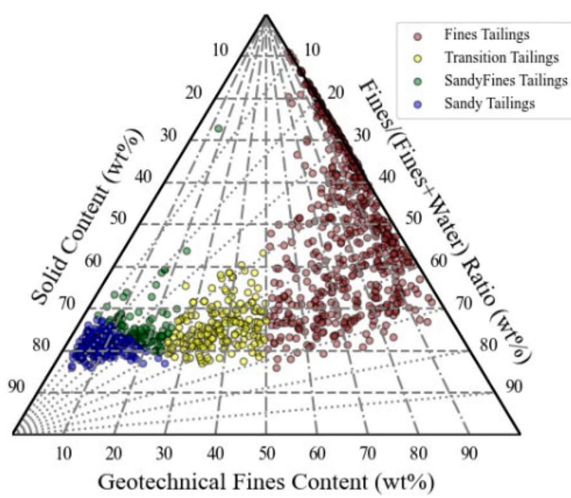

Figure 2: Ternary diagram of the tested samples in 2024 based on laboratory results, classified using COSIA's Unified Oil Sands Tailings Classification System (COSIA, 2014)

Block Modelling

Tailings composition data is typically categorized and averaged to determine representative properties of specific units or regions. In some cases, straight averages of the individual test results provide a useful representation of the bulk performance of the material of interest. However, when investigating these materials, local variability may result in data bias. Consequently, a common approach is to geospatially reconcile the data using a block model. In this study, three block models were prepared using HyperScan and laboratory results, each describing zones containing different material types. Relevant details for the three models are provided below:

- Model A characterizes the fluid contained in a TSF receiving coarse sand tailings, thickened tailings and centrifuged tailings. Deposition has continued for over 10 years, resulting in a dense, high-fines fluid with minimal debris, low residual bitumen content, and solids contents ranging from 20% to 70%. Model A incorporates results from 191 samples.
- Model B characterizes the fluid contained in a TSF receiving coarse sand tailings, thickened tailings and froth treatment tailings. Deposition has been ongoing for over 20 years and has resulted in a dense fluid with some sandy regions, occasional debris, bitumen contents up to 11%, and solids contents ranging from 30% to 70%. Model B incorporates results from 45 samples.
- Model C characterizes the settled deposit formed from coarse sand tailings being deposited into mature fluid tailings over one year. This has resulted in a sandy soil-like material with high potential variability in fines and bitumen contents. Solids contents typically exceed 69%. Model C relies on results from 74 samples within the region of interest but is impacted by historic sampling (150 samples) from adjacent soil-like material deposited under similar conditions.

Each model was prepared using the same estimation parameters typically applied for Directive 085 reporting. Although variations in these parameters can substantially influence block model outcomes, the scope of this study was limited to comparing results obtained from HyperScan and laboratory measurements, with all other aspects of the block model held constant. Accordingly, the estimation parameters are not discussed herein. To facilitate interpretation of the results, the following assumptions are noted:

- All models assume substantially greater variability in the vertical direction than in the horizontal. This results in broad flat blocks (25 m length and width × 1 m height), and a horizontally extended search radius (2 to 10m vertical search radius vs. greater than 400 m horizontal search radius).
- Block models characterizing fluids assume tailings stratify based on density, resulting in little to no horizontal variability. In line with this assumption, the horizontal search radius for fluid materials is typically set to a value larger than the width of the model (4 km in the case of Models A and B).

By producing these block models that simultaneously estimate the composition from laboratory and HyperScan results, several informative outputs can be produced that provide additional insight into the performance of HyperScan. This study focused on three key areas of block modelling, including bulk performance, localized performance, and mass of fines calculations.

Bulk Performance

Bulk performance analysis was conducted to estimate the average tailings properties within each model. This approach involves aggregating spatial data to generate representative average values that characterize the overall tailings composition within each model.

Localized Performance

While determining bulk performance is a critical function of the tailings data, understanding and tracking local performance is also necessary. Specific zones of material, typically with outlying properties, need to be identified and evaluated. This evaluation can be more qualitative in nature, with the main goal of accurately delineating the extent and continuity of a zone of interest and relating it to its geotechnical behaviour. Alternatively, in some more quantitatively focused applications, such as consolidation analysis and computational fluid dynamics modelling, the critical function of the data is its precision.

To assess differences between block models generated from HyperScan and laboratory data, two comparisons were performed. The first was qualitative, using cross-sections through the block models that display solids and fines content, providing insight into the comparability of the two block models. The second was quantitative, directly comparing solids and fines content as a function of elevation within the fluid bodies of the models. In this analysis, geotechnical solids content and geotechnical fines content were used. Geotechnical solids content was calculated as the sum of bitumen and mineral solids content, and geotechnical fines content was calculated as the mass of < 44um fines divided by the total mass of solids. Since HyperScan reports total fines (mass of <44 μm fines divided by total sample mass), geotechnical fines from HyperScan were derived from the predicted total fines and predicted solids.

Mass of Fines Calculations

An important aspect of regulatory reporting for Alberta oil sands operators is the annual quantification and tracking of the mass of < 44 μm particles (mass of fines) contained in the fluid zones of their TSFs. Block models provide a convenient way to determine the geospatially reconciled mass of fines. This calculation incorporates the measured volume of fluid tailings, the measured geotechnical solids content and the measured geotechnical fines content. As HyperScan and its associated error affect two of these inputs, their impact on the mass of fines determination was included in this study.

Repeatability of Laboratory and HyperScan

To assess the repeatability of laboratory measurements and HyperScan predictions, four tailings samples were selected. All laboratory and HyperScan tests were conducted by the Centre for Energy and Environmental Sustainability at the Northern Alberta Institute of Technology (NAIT). Each sample underwent a series of standard laboratory tests, including Dean & Stark (D&S) extraction to measure bitumen, water, and solids content, methylene blue titration to determine MBI, and wet sieving to quantify fines and FFW content. Each test was performed with five replicates per sample to assess repeatability. Similarly, HyperScan measurements were conducted on the same four samples, also with five replicates each, under consistent operating conditions. Repeatability was evaluated by calculating the standard deviation across replicates for each sample and analytical method. It should be noted that although the laboratory tests on the samples during the commercial demonstration were performed at a different commercial laboratory, the analyses conducted at NAIT offer general insights into laboratory repeatability.

Results

HyperScan Performance Evaluation

Figure 3 shows the relationship between the laboratory-measured and HyperScan-predicted tailings properties, along with their CDF of errors for all the tested samples. Overall, HyperScan demonstrated strong agreement with laboratory results across all tailings properties. Notably, it slightly overpredicted solids content (and underpredicted water content) when solids were below 30%, and underpredicted solids content in the 40–70% range. This pattern requires further investigation and model adjustments to correct the observed bias. Table 1 summarizes the bias and error of the model for all samples as well as for fluid and FIS, sonic, and polymer-treated samples (sandy segregated samples were treated with sand-suspending polymer to achieve homogenization prior to HyperScan testing (Entezari et al., 2022).

Table 1: Summary of HyperScan Performance on Tested Tailings in 2024

	All Samples		Fluid & FIS		Sonic		Polymer Treated	
	n	Bias ± Error	n	Bias ± Error	n	Bias ± Error	n	Bias ± Error
Bitumen (%)	1109	-0.07 ± 0.59	413	-0.53 ± 0.55	696	-0.12 ± 0.48	211	-0.09 ± 0.12
Solids (%)	1109	0.38 ± 2.61	413	-0.99 ± 2.99	696	1.12 ± 2.28	211	0.0 ± 2.1
Water (%)	1109	-0.2 ± 2.69	413	1.32 ± 3.1	696	-1.02 ± 2.21	211	-0.12 ± 2.09
MBI (meq/100 g)	349	-0.06 ± 0.82	130	0.11 ± 0.81	219	-0.12 ± 0.81	36	0.00 ± 0.11
Total Fines (%)	1109	0.41 ± 4.21	413	-0.46 ± 3.89	696	0.78 ± 3.99	211	-0.72 ± 2.1
FFW (%)	1109	0.84 ± 4.45	413	-0.81 ± 3.71	696	2.14 ± 4.31	211	-1.87 ± 4.96

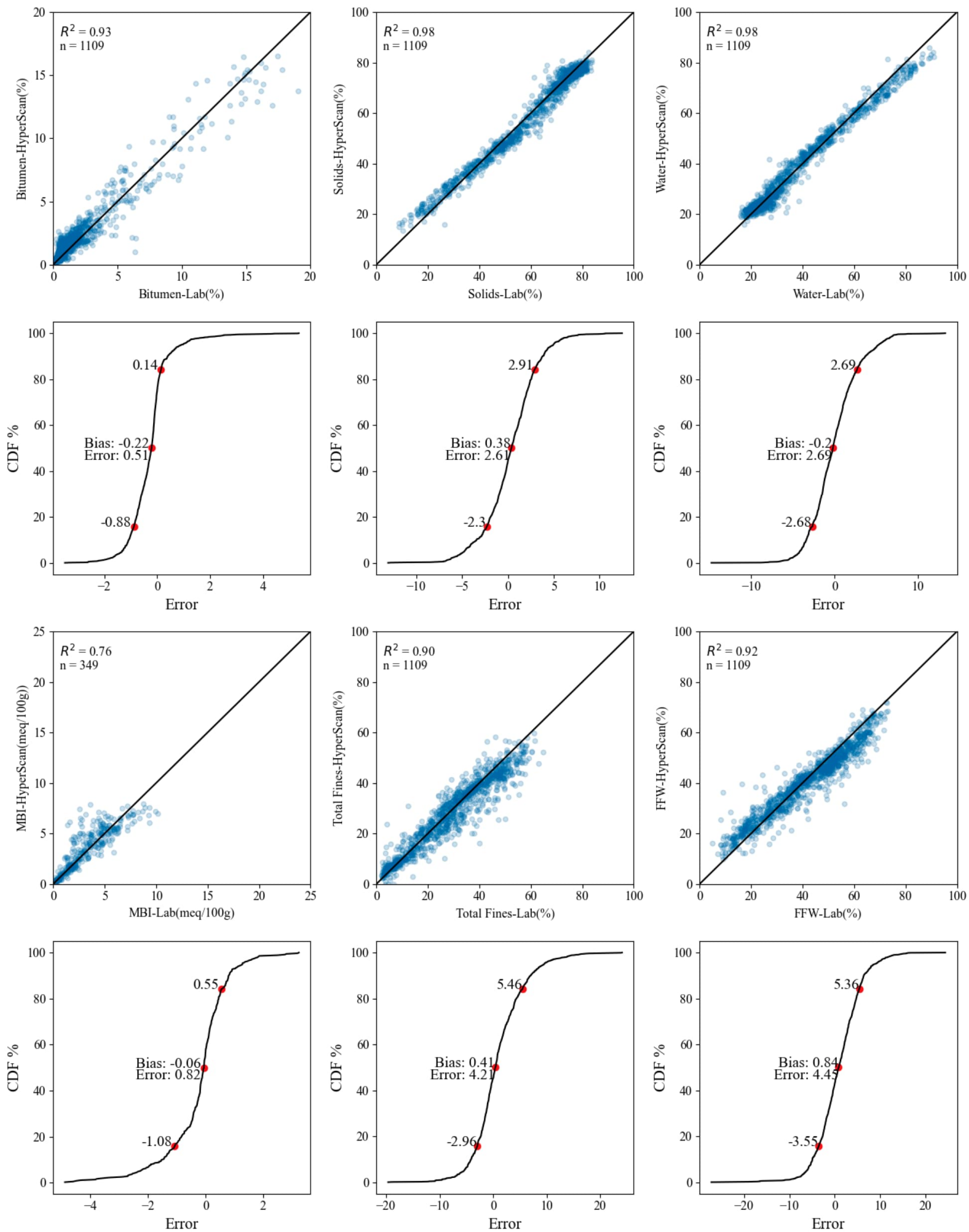

Figure 3: Relationship between measured and estimated tailings properties from laboratory vs. HyperScan model, along with CDF of errors for all samples

Block Model Results

Bulk model performance

The average tailings properties estimated by the models are presented in Table 2. As shown, block models generated using HyperScan data produced average bulk properties comparable to those obtained from laboratory measurements. However, even for Model A, which was informed by 191 samples, the difference between the two averages did not fully converge to the average bias calculated from the earlier error analysis (see Table 1). This highlights the importance of evaluating and understanding the specific errors associated with the subset of materials of interest. Further analysis is needed to identify the precise drivers of these deviations.

Table 2: Summary of Block Model Results

	Model A			Model B			Model C		
	Lab	HyperScan	Difference	Lab	HyperScan	Difference	Lab	HyperScan	Difference
Bitumen (%)	1.4	1.8	-0.4	4.5	4.6	-0.1	3.5	3.4	0.1
Solids (%)	46.3	46.2	0.1	54.3	53	1.3	69.5	68.9	0.6
Water (%)	52.3	52	0.3	41.2	42.4	-1.2	27	27.7	-0.7
Total Fines (%)	37.7	37.4	0.3	44.3	42.2	2.1	27.8	26.8	1.0

Local Model Performance

Figure 4 presents cross-sections of the three models, depicting the geotechnical solids content and geotechnical fines content spatially across the plane of interest. These sections show functionally similar features with some subtle differences. Given the scale of the plane of interest and the typical variability of the tailings properties, a qualitative assessment of the block models from HyperScan is expected to produce results comparable to those from laboratory measurements.

Figure 5 shows a direct comparison of geotechnical solids content and geotechnical fines content as a function of elevation within the fluid bodies of Model A and Model B. While the shape of these curves is of engineering interest and is used for qualitative interpretation, the exact values reported for geotechnical solids content feed directly into consolidation analysis and have a relatively high requirement for precision. Reasonable alignment was observed between the block model results based on laboratory measurements and HyperScan, as shown in Figure 5.

Geotechnical fines content in Model B between elevations 320 and 327 m was observed to deviate more significantly than elsewhere in the profiles. The discrepancy was determined to be based on three individual sample measurements. While the consistent discrepancy over three samples may indicate an underperformance of the HyperScan in this specific material type, it should be noted that material from 320 to 327 m accounts for only 1.6% of the total volume of the pond, and this deviation is less impactful on the other block model outputs than is visually suggested by Figure 5.

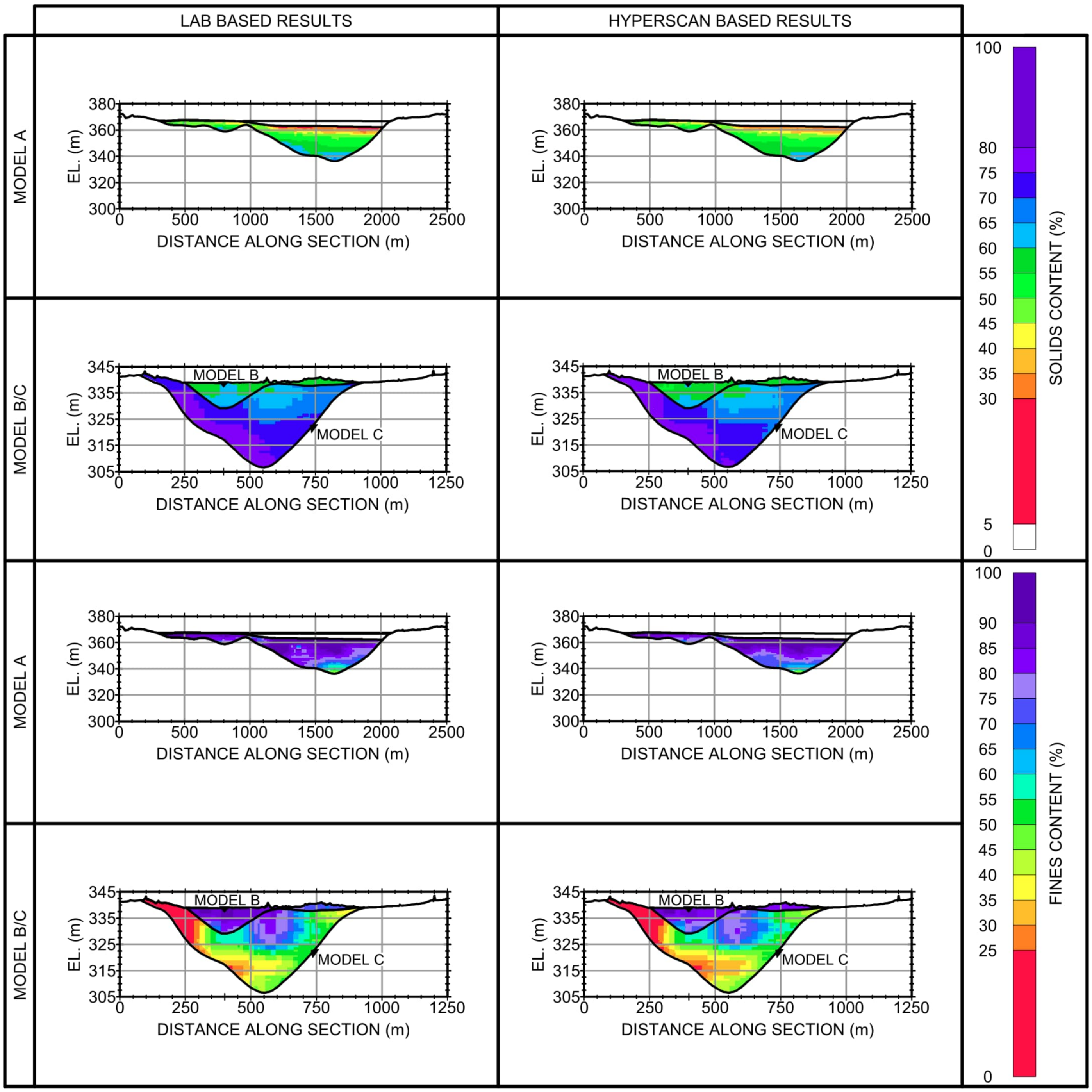

Figure 4: Cross-sectional comparison of block-modelled tailings properties from laboratory measurements and HyperScan

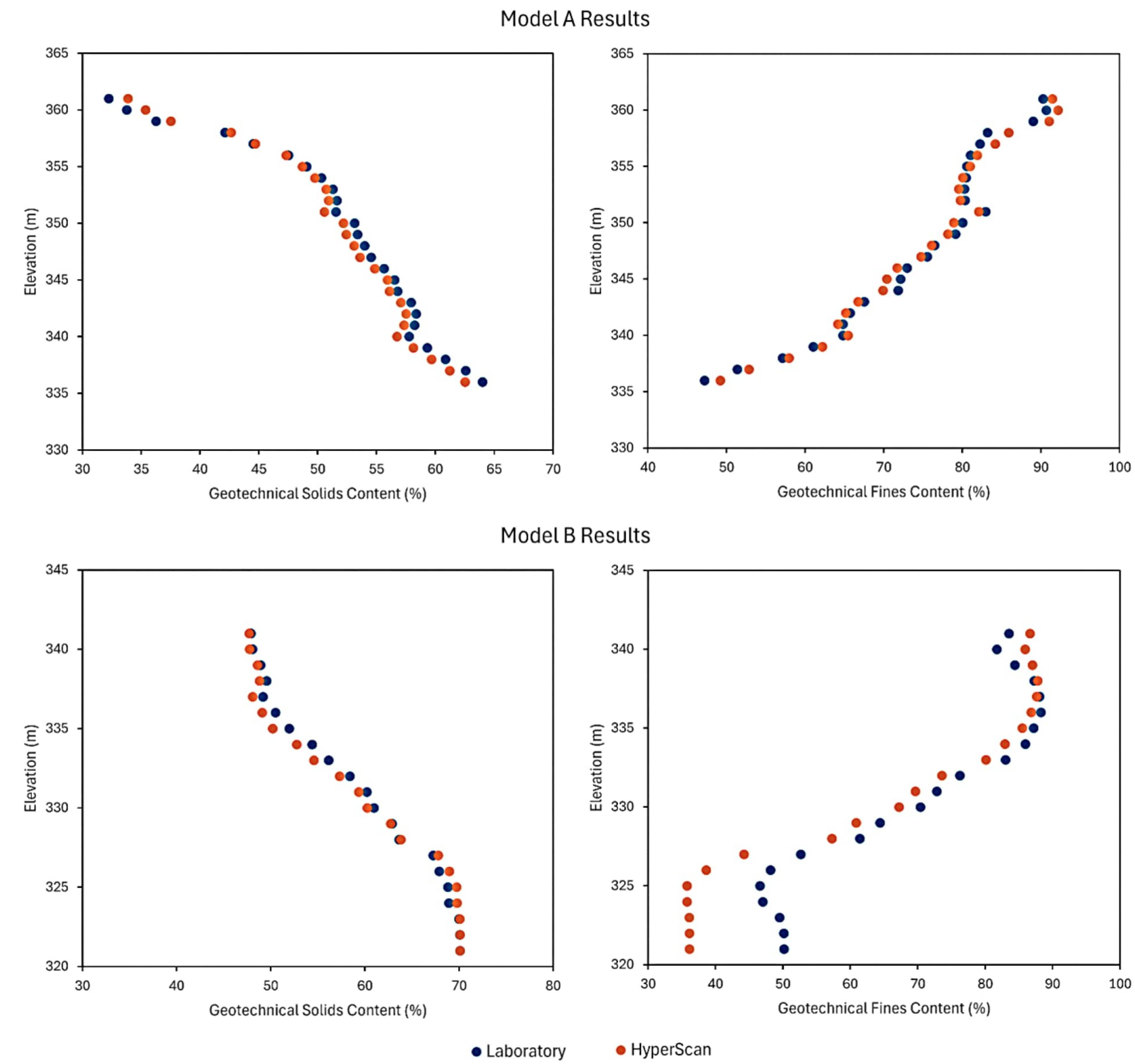

Figure 5: Estimated fluid composition profiles from block models generated using laboratory and HyperScan data, shown as a function of elevation

Mass of Fines Calculation

The mass of fines for each model calculated using the laboratory measurement and HyperScan is listed in Table 3. This calculation was performed within the block modelling software, where the mass of fines is calculated for each block (multiplying the block volume by the estimated density, measured geotechnical solids content, and measured geotechnical fines) and then summed to produce a "mass of fines" contained within the region of the model. As seen, Model A produced good agreement between laboratory measurements and HyperScan predictions, while Models B and C produced higher errors. This is a result of the compounding error inherent in the calculation (i.e., the multiplication of the density calculated from the measured solids content and the fines content).

Table 3: Mass of Fines Calculated from Block Models

	Model A	Model B	Model C
Laboratory Based (Mtonne)	8.88	3.63	6.70
HyperScan Based (Mtonne)	8.87	3.46	6.43
Percent Difference Error (%)	0.1	4.7	4.0

Repeatability Results

Table 4 lists the repeatability standard deviations for HyperScan and laboratory measurements on tailings samples. Repeatability tests were conducted on four tailings samples, each with five replicates, and the table reports the range and average standard deviations for each property across all samples. As shown, laboratory methods exhibit higher repeatability standard deviations compared to HyperScan. This indicates that HyperScan measurements are more consistent across replicates, reflecting lower variability and higher precision in repeated measurements of the same sample. The laboratory repeatability assessment in this study was conducted within a limited scope using the same equipment and procedures, and therefore represents a lower bound on laboratory variability. When measurements are performed across different laboratories, with varied equipment, procedures, and operators, variability is expected to increase.

It is important to recognize that the observed error of HyperScan relative to laboratory measurements arises from two sources: the inherent deviation of HyperScan predictions from laboratory values and the repeatability of the laboratory methods. As a machine learning based model, HyperScan predictions are empirical and subject to model uncertainty, meaning some differences from the laboratory reference are intrinsic to the predictive model. At the same time, a portion of the observed difference reflects laboratory variability. Because HyperScan has been trained on laboratory measurements, any variability in the laboratory data has been incorporated into the model. Consequently, some of the predictive error can be attributed to the inherent noise in the laboratory reference. Accounting for both contributions is essential when interpreting errors and evaluating the reliability of HyperScan data relative to laboratory results.

Moreover, the repeatability of laboratory measurements has direct implications for block model outputs. Variability in laboratory data—whether from repeated tests in the same laboratory or from measurements in different laboratories—can produce different block models for the same material. Quantifying this effect is critical to evaluate the uncertainty inherent in laboratory-based block models and to enable a methodologically consistent comparison with HyperScan-based block models.

Table 4: Repeatability Standard Deviations (SD) for Laboratory and HyperScan

	Laboratory		HyperScan	
	SD Range	**SD Average**	**SD Range**	**SD Average**
Bitumen (%)	0.08–0.29	0.22	0.06–0.10	0.07
Solids (%)	0.31–1.20	0.63	0.13–0.52	0.33
Water (%)	0.15–1.44	0.92	0.11–0.48	0.29
MBI (meq/100g)	0.06–0.47	0.29	0.06–0.18	0.12
Total Fines (%)	0.29–1.21	0.65	0.21–0.67	0.46
FFW (%)	0.37–0.94	0.76	0.28–0.59	0.51

Conclusion

This study demonstrated the continued advancement and commercial viability of HyperScan, ConeTec's hyperspectral sensing-based technology for rapid oil sands tailings characterization. The 2024 commercial deployment at a major oil sands site involved 1,109 samples and provided a robust dataset for evaluating model performance and comparing block modelling outcomes.

The updated HyperScan model showed strong alignment with laboratory results, with low average prediction errors across key tailings parameters. Comparison of block models generated from laboratory and HyperScan data indicated that HyperScan performed well in determining the bulk performance of tailings materials. HyperScan also adequately represented features of interest within the block model, enabling qualitative assessment. However, some local features deviated sufficiently from laboratory measurements to affect certain quantitative assessments. The observed errors both in the bulk properties of materials and in local regions within the block models did not uniformly align with the calculated biases, suggesting that the current HyperScan model may perform better on some material types than others. Further evaluation is required to understand the drivers of these deviations, as well as potential errors in derived outputs, such as the mass of fines.

Repeatability analysis showed that HyperScan measurements were more consistent across replicates compared to conventional laboratory tests. While laboratory methods remain the reference standard, their inherent variability contributes to the observed differences between HyperScan and laboratory measurements, as well as block modelling results. The repeatability study was conducted within a single laboratory, using a controlled set of procedures and equipment, to provide a baseline estimate of laboratory variability. Considering this baseline and the greater variability expected across multiple laboratories, the differences between block models generated from laboratory measurements and those generated from HyperScan are of comparable magnitude to the variability inherent in laboratory testing.

Overall, HyperScan enables faster and more cost-efficient tailings characterization, allowing a greater volume of data to be collected within the same operational and budgetary constraints. Future work will focus on the in-situ application of HyperScan using the patent-pending hyperspectral CPTu module (Entezari et al., 2024; Bindner et al., 2025). This approach could support high-resolution in-situ tailings characterization, providing dense vertical measurements and potentially broader horizontal coverage, as hyperspectral CPTu testing is less resource-intensive than conventional sampling and laboratory analysis. These measurements can help generate block models that are more accurate and spatially representative.

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