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Automated registration of logging residues from fuel-adapted harvesting

A pilot study in central Sweden

Raul Fernandez Lacruz, Siri Westerblom and Björn Hannrup



Final felling site after fuel-adapted harvesting. Tops and branches are piled alongside timber and pulpwood logs for later extraction as forest fuel.

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Foreword

This study was conducted within the project *Improved Forecasts of Logging Residues for Precision Planning*, conducted between 2023 and 2026. The project was led by Skogforsk and funded by the Swedish Energy Agency through the Bio+ research programme (project number 2023-01054), and the project partners Jämtkraft, Holmen Skog, Mellanskog, Stora Enso, Sveaskog, Södra, and Vattenfall.

The authors would like to express their sincere gratitude to the machine manufacturer John Deere, the harvesting contractor (Runebergs Skogsentreprenad, particularly harvester operator Rasmus Bergstedt), the landowner (Sveaskog), and the funding bodies for their valuable contributions, which made this work possible. We also thank Leslie Walke at Communicaid for language editing.

Sävar and Uppsala, October 2026

Raul Fernandez Lacruz, Siri Westerblom and Björn Hannrup.

Summary

Logging residues (tops and branches) from final fellings are an underutilised renewable biomass resource in Sweden used for energy purposes. Several forest enterprises use a forecasting system developed by Skogforsk to plan forest fuel supply. Based on tree species and stem diameter information from harvester production data (hpr-files), the system computes the quantity and spatial distribution of logging residues across the harvesting site. For correct forecasts, harvester operators need to manually register at tree level whether the residues are piled for later extraction (fuel-adapted) or placed on strip roads to reduce the risk of soil damage (non-adapted). Automating this procedure could improve forecast accuracy and fuel stock reliability, reduce operators' workload, and strengthen security of supply.

This pilot study investigated whether fuel-adapted harvesting could be detected automatically using harvester data collected at a harvesting site in central Sweden. The harvester was equipped with boom-tip control and an angle sensor in the harvester head, enabling the positioning and bearing (orientation) of individual logs in the machine's mapping software. Standardised harvester data according to StanForD 2010 were combined with non-standardised data provided by the machine manufacturer John Deere and field measurements of residue piles, strip roads, and areas with conventional (non-adapted) harvesting.

Two variables were derived to describe the position and bearing of the first log from each tree relative to the harvester's position and bearing (direction of travel). These variables were used in a classification and regression tree (CART) model to distinguish between trees whose residues are piled for extraction (here called 'fuel-adapted trees') and trees whose residues are used on strip roads (here called 'non-adapted trees'). The model achieved an accuracy of 90 percent, a sensitivity of 96 percent, and a precision of 92 percent. Log bearing relative to harvester bearing was the most important predictor. The model overestimated residues from fuel-adapted trees by 6 dry tonnes, equivalent to 4 percent of the reference quantity.

The results demonstrate the technical feasibility of automating the registration of residues from fuel-adapted harvesting using data collected by modern harvesters. Although the proposed approach requires an angle sensor in the harvester head, this technology is available on newer machines, and StanForD 2010 supports the recording of log position and bearing in hpr-files. However, the model was based on data from only one site, one machine, and one operator, limiting its ability to handle operational exceptions. In future studies, collecting data on boom angle or boom-tip position when treetops are released could potentially improve the identification of such exceptions, as fuel-adapted harvesting involves piling tops and branches in piles outside the strip roads.

Although the conditions for implementation are in place, the model should be regarded as a prototype requiring further development and independent validation before operational implementation.

Sammanfattning

Grenar och toppar (grot) från föryngringsavverkningar är en underutnyttjad förnybar biomassaresurs i Sverige som används för energiändamål. Flera skogsföretag använder ett system för grotprognoser utvecklat av Skogforsk för planering av försörjning av grot. Baserat på information om trädslag och stamdiameter från skördarens produktionsdata (hpr-filer) beräknar systemet mängden grot och dess placering i hygget. För korrekta prognoser behöver skördarföraren manuellt registrera om groten samlas i högar för senare uttag (grotanpassat) eller om den används för att förstärka basvägar och minska risken för körskador (inte grotanpassat). Att automatisera denna registrering skulle kunna förbättra prognosernas precision och tillförlitlighet, minska förarnas arbetsbelastning och öka leveranssäkerheten.

I denna pilotstudie undersöktes om grotanpassning kan registreras automatiskt med hjälp av skördardata som samlats in vid en slutavverkning i mellersta Sverige. Skördaren var utrustad med kranspetsstyrning och en vinkelgivare i skördaraggregatet som möjliggjorde positioneringen och riktningsbestämning av enskilda stockar i maskinens kartprogram. Standardiserade skördardata enligt StanForD 2010 kombinerades med icke-standardiserade data från maskintillverkaren John Deere samt fältmätningar av grothögar, basvägar och områden utan grotanpassning.

För varje avverkat träd togs två variabler fram för att beskriva den första stockens position och riktning i förhållande till skördarens position och färdriktning. Variablerna användes i en modell baserad på klassificerings- och regressionsträd (CART) för att skilja mellan grotanpassade och icke grotanpassade träd. Modellen uppvisade en träffsäkerhet på 90 procent, en sensitivitet på 96 procent och en precision på 92 procent. Stockens riktning i förhållande till skördarens färdriktning var den viktigaste förklarande variabeln. Modellen överskattade biomassan från grotanpassade träd med 6 ton torrsubstans, vilket motsvarade 4 procent av referensmängden.

Resultaten visar att det är tekniskt möjligt att automatiskt registrera grotanpassning med hjälp av data som samlas in av moderna skördare. Den föreslagna metoden kräver en vinkelgivare i skördaraggregatet, men denna teknik finns i nyare maskiner. Dessutom stöder StanForD 2010 registrering av stockarnas position och riktning i hpr-filer. Modellen baserades dock på data från endast en trakt, en maskin och en förare, vilket begränsar dess förmåga att hantera avvikelser som kan uppstå i det praktiska arbetet. I framtida studier skulle insamling av data om kranvinkel eller kranspetsens position när trädtoppen släpps kunna förbättra identifieringen av sådana avvikelser, eftersom grotanpassning innebär att grenar och toppar samlas i högar utanför stickvägarna.

Även om förutsättningarna för implementering finns på plats bör vår modell betraktas som en prototyp som kräver fortsatt utveckling och oberoende validering innan praktisk implementering.

Background

Logging residues (tops and branches) from final fellings are an underutilised residual stream from forestry with the potential to double current extraction levels in Sweden (Bergqvist et al. 2022). Reliable estimates of forest fuel stocks are essential for efficient planning, management, and logistics throughout the supply chain. Skogforsk developed a system for forecasting the quantity and spatial distribution of logging residues at harvesting sites based on tree species and stem diameter data from harvester production (hpr) files and biomass functions (Möller et al. 2009, Hannrup et al. 2009). The system is already used operationally by several forest companies. However, a recent large-scale evaluation (Fernandez-Lacruz et al. 2026) comparing predicted and measured biomass at energy plants found low accuracy and precision, with substantial variation among harvesting contractors. The same study also identified several improvement areas, including more consistent use of the system, standardised feedback routines across the supply chain, and automated registration of residues from fuel-adapted harvesting.

Problem definition

When trees are felled and processed by the harvester, logging residues can serve two purposes. Residues can either be placed on strip roads to reduce the risk of soil damage (conventional, non-adapted harvesting) or accumulated in piles outside the strip roads alongside roundwood for later extraction (fuel-adapted harvesting) (Figure 1). As both practices may be applied within the same site, harvester operators must record at tree level when trees are fuel-adapted and when they are not. This is currently done manually through a dedicated harvester function, known as the ‘residue button’. The operator activates the function using a button combination on the keyboard, after which a symbol is displayed (Figure 2). Registration can also be recorded and edited afterwards via the onboard computer touchscreen. Fuel-adaptation is saved in the hpr-files through the attribute *BioEnergyAdaption*, enabling the system to exclude trees whose residues are used conventionally on strip roads (here called ‘non-adapted trees’). Automating this registration could improve stock estimates by reducing the risk of operators forgetting to activate or deactivate the function, while also reducing operators’ workload. Since forwarder operators may also reinforce strip roads with residues, they must also record this to ensure correct estimates.



Figure 1. Final-felling site with both conventional (non-adapted) and fuel-adapted harvesting areas. The main extraction road is reinforced with residues to avoid soil damage (non-adapted), while residues along the strip road on the left are piled next to roundwood for extraction (fuel-adapted).

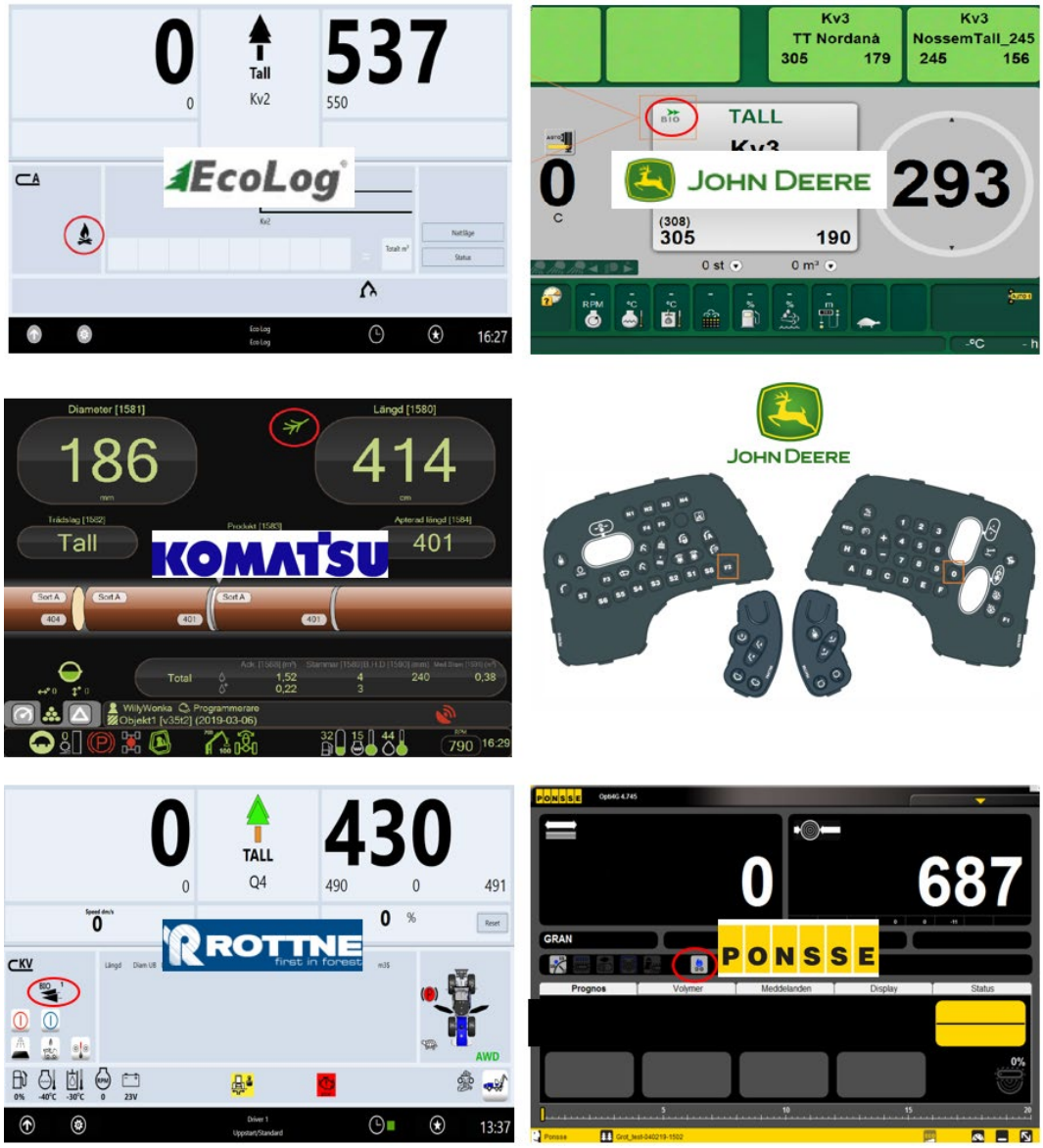

Figure 2. Harvester operator's display with the fuel-adaptation function activated (symbol circled in red). The symbol's appearance and location of the controls used to activate and deactivate the function vary between manufacturers, machine model and year, and versions of the control system.

Aim of the study

This study aimed to:

1. Identify variables in standardised and non-standardised harvester data that could distinguish between non-adapted and fuel-adapted trees within a harvesting site.
2. Develop a prototype model for the automatic detection of logging residues within a harvesting site.

Our hypothesis was that log position and bearing (orientation) relative to harvester position and bearing (direction of travel) would differ between non-adapted and fuel-adapted trees.

Material and Methods

Study site

A field study was conducted on a final-felling site (7 ha) located in Surahammar, central Sweden. Whenever possible, the operator fuel-adapted the harvesting operation to enable future extraction of logging residues. However, all main extraction roads, as well as strip roads in wet areas, were reinforced with residues (non-adapted), to reduce the risk of soil damage. The harvested roundwood volume comprised Norway spruce (42%), European aspen (34%), birch (23%), and Scots pine (1%). Roundwood harvesting and forwarding were carried out in January 2025. The logging residues were left on site to dry during summer and forwarded to a roadside landing in August 2025. The material was chipped and delivered to a combined heat and power plant during January and February 2026.

Base machine

The base machine was a John Deere 1470G harvester (model year 2024) equipped with an H425 harvester head (Figure 3). The machine featured Intelligent Boom Control (IBC) 3.0, which automatically adjusts boom trajectory and extension according to the harvester's work phase using several sensor-based inputs (John Deere 2026a). IBC also includes safety functions for both the operator and the machine, such as protection against over-rotation and prevention of feeding towards the cab, enabled by an angle sensor in the harvester head. The harvester used a standard global navigation satellite system (GNSS) receiver mounted on the operator cab. The hardware enabled log positioning, which was visualised in the mapping and production management system TimberMatic™ Maps (John Deere 2026b), version 2.10.15 (Figure 4).



Figure 3. John Deere 1470G driving over logging residues on a strip road in a conventional (non-adapted) harvesting area.

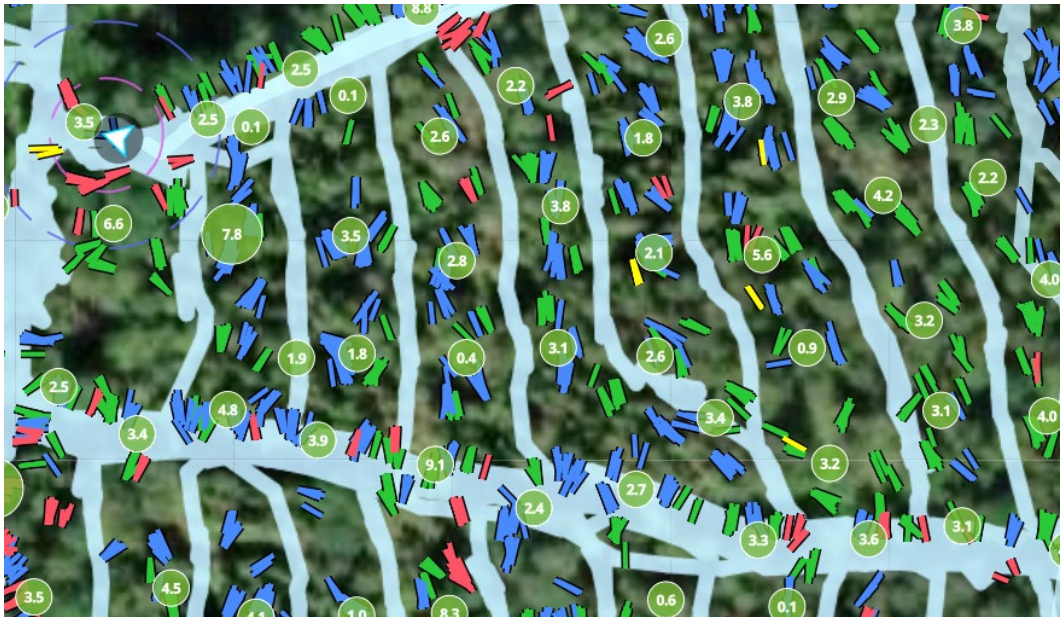

Figure 4. Screenshot of TimberMatic™ Maps on the harvester computer. The machine location, strip road network, and log positions are represented together with colour-coded roundwood assortments and quantity (in solid cubic metres) of the harvested roundwood volume across the study site.

Harvester data

Standardised hpr-files compliant with StanForD 2010 (Skogforsk 2026a) were obtained from the harvester and processed in *hprThinning* (Skogforsk 2026b) to determine harvester bearing using the algorithm developed by Bhuiyan et al. (2016) and the recorded coordinates at each tree-felling event. The hpr-files were also processed using the calculation module *hprCM* (Siljebo et al. 2017) to compute biomass for tops and living and dead branches (including needles) for each harvested tree.

Non-standardised machine data were extracted from the TimberMatic™ Maps database, provided by John Deere. The data included geographic coordinates of the butt and top ends of each produced log, together with the corresponding harvester standing position on the strip road during processing. The hpr-files and non-standardised machine data were linked using the unique log identifier (attribute *StemKey*), common to both datasets.

Ground truthing

An exploratory study visit was conducted during harvesting in January 2025 to observe the position of logging residue piles and roundwood (Figure 5). A subsequent field survey was conducted on the site in June 2025 to map fuel-adapted and non-adapted harvesting areas. A GNSS receiver (ArduSimple, ZED-F9P) operating with real-time kinematic (RTK) corrections from the Swedish national reference network SWEPOS was used to record the midpoint of each residue pile. A total of 491 piles were mapped (Figures 6-7), with a median horizontal accuracy of 0.01 m. The centreline of each strip road was also mapped using the same receiver configured to record a position every second, resulting in approximately 10 km of strip roads. Non-adapted harvesting areas with visible residues on strip roads were also recorded. Due to technical problems with the RTK receiver caused by rainfall, part of the mapping had to be completed using a differential GNSS receiver (EOS Arrow 100). The receiver achieved a median horizontal accuracy of 1.8 m.

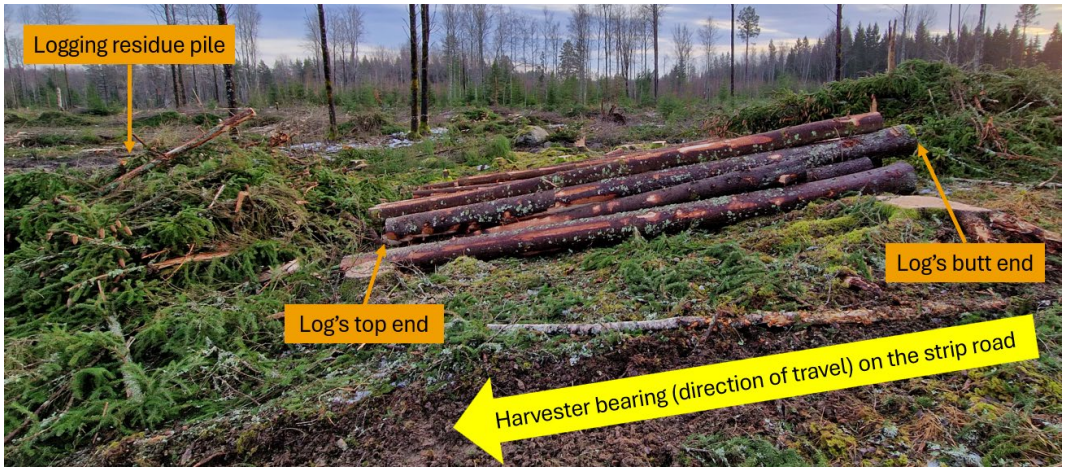

Figure 5. Pile of roundwood logs and associated pile of logging residues at the study site.



Figure 6. Ground-truth data acquisition: midpoints of residue piles (left) and strip roads (right).

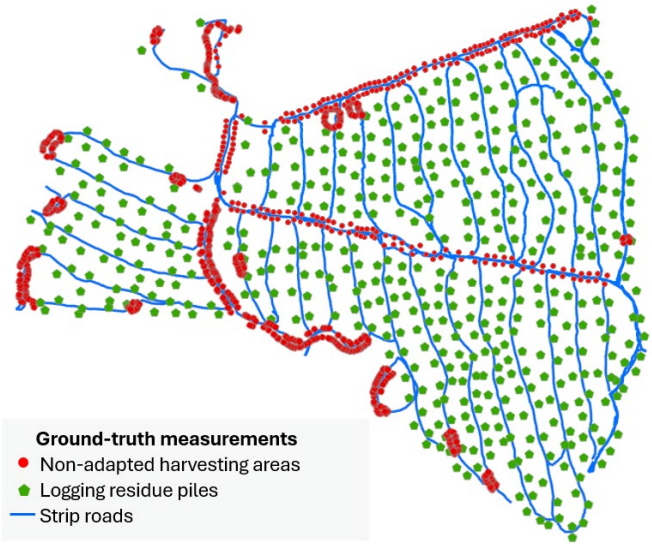

Figure 7. Ground-truth measurements for non-adapted harvesting areas, residue piles and strip roads.

Data preparation

The ground-truth measurements were combined with the hpr-files and John Deere machine data. Using log positions and bearings, mapped residue piles, strip roads, and non-adapted harvesting areas, each log was classified by visual interpretation in ArcGIS Pro 3.7. Each log was assigned a binary value indicating whether it originated from a non-adapted tree (0) or a fuel-adapted tree (1). The dataset was filtered to retain only the first log from each tree for further analysis (Figure 8).

This approach was adopted because the adaptation decision is made by the harvester operator at tree level and therefore applies to all logs originating from the same tree. In addition, the first log (often a sawlog) is typically located closest to the strip road, whereas subsequent logs tend to follow a fan-shaped pattern behind it.

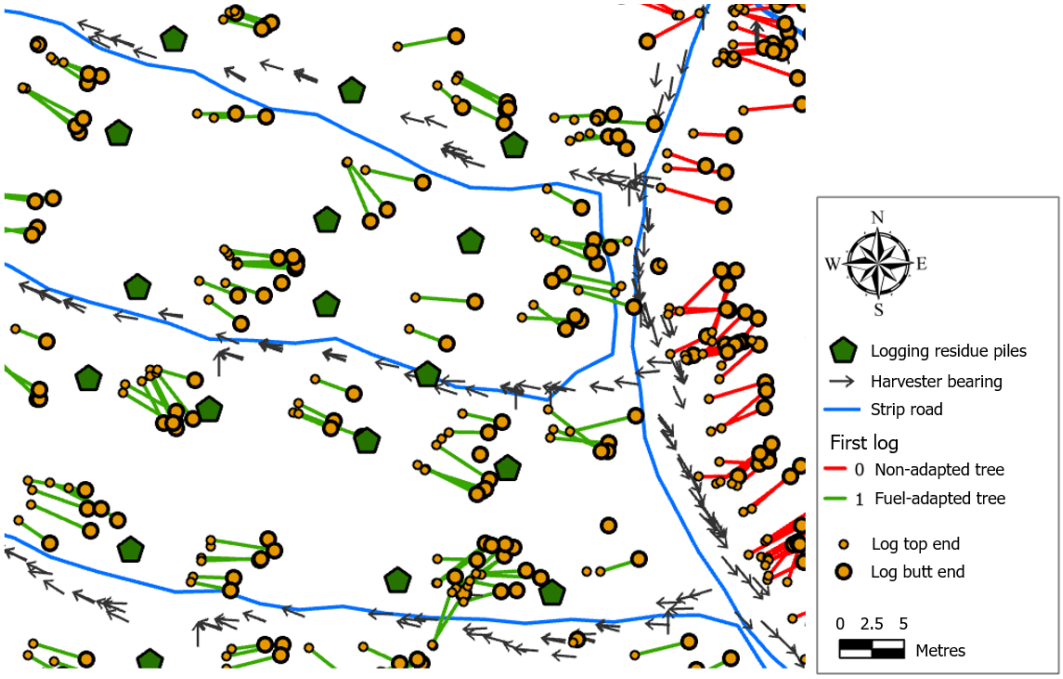

Figure 8. Detail of the binary classification of non-adapted (0) and fuel-adapted (1) trees. Only the first log from each tree is shown. Every residue pile is associated with the preceding log pile (adjacent to the top ends), as verified during harvesting (Figure 5). Apparent offsets are likely due to differences in positioning accuracy between the harvester's standard GNSS receiver and RTK-corrected field data, as well as coordinate reference systems (harvester data in WGS 84 and field data in SWEREF 99 TM).

Two new variables (Variable 1 and Variable 2) were derived to describe the position and bearing of the first log relative to the harvester position and bearing, and consequently relative to the strip roads.

Variable 1

Variable 1 (V_1) was defined as the difference in metres between the distance from the harvester position to the log's butt end (d_{butt}) and the distance from the harvester position to the log's top end (d_{top}) (Equation 1, Figure 9). The geographic coordinates provided in WGS 84 were projected to the Swedish coordinate reference system SWEREF 99 TM. Planar distances were calculated as Euclidean distances.

$$V_1 = d_{butt} - d_{top} \qquad (1)$$

where

$$d_{butt} = \sqrt{(x_{butt} - x_{machine})^2 + (y_{butt} - y_{machine})^2}$$

$$d_{top} = \sqrt{\left(x_{top} - x_{machine}\right)^2 + \left(y_{top} - y_{machine}\right)^2}$$

and x and y denote projected easting and northing coordinates in metres, respectively.

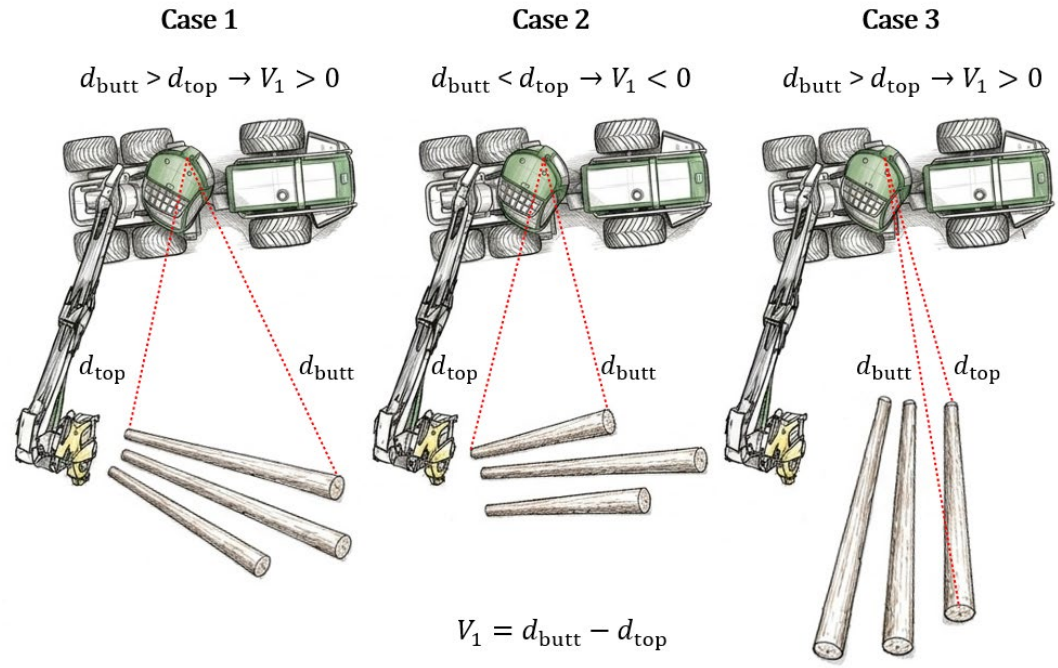

Figure 9. Examples of Variable 1 (V_1). Positive values occur when the butt end is farther from the harvester than the top end (Cases 1 and 3) and negative values when the butt end is closer (Case 2).

Variable 2

Variable 2 (V_2) (Equation 2, Figure 10) was defined as the angular difference, in degrees, between the log bearing (β_{log}) and the harvester bearing (β_{harv}). The log bearing was calculated as the planar bearing from the log's butt end to the top end using the two-argument arctangent function *atan2*. Both the log bearing and harvester bearing were expressed within the interval 0-360°. To facilitate subsequent analyses, V_2 was normalised to the interval [-180°, 180°], where a value of 0° indicates that the log bearing is aligned with the harvester bearing.

$$V_2 = \beta_{log} - \beta_{harv} \qquad (2)$$

where

$$\beta_{log} = atan2(x_{top} - x_{butt}, y_{top} - y_{but}) \frac{180}{\pi}$$

and x and y denote projected easting and northing coordinates in metres, respectively.

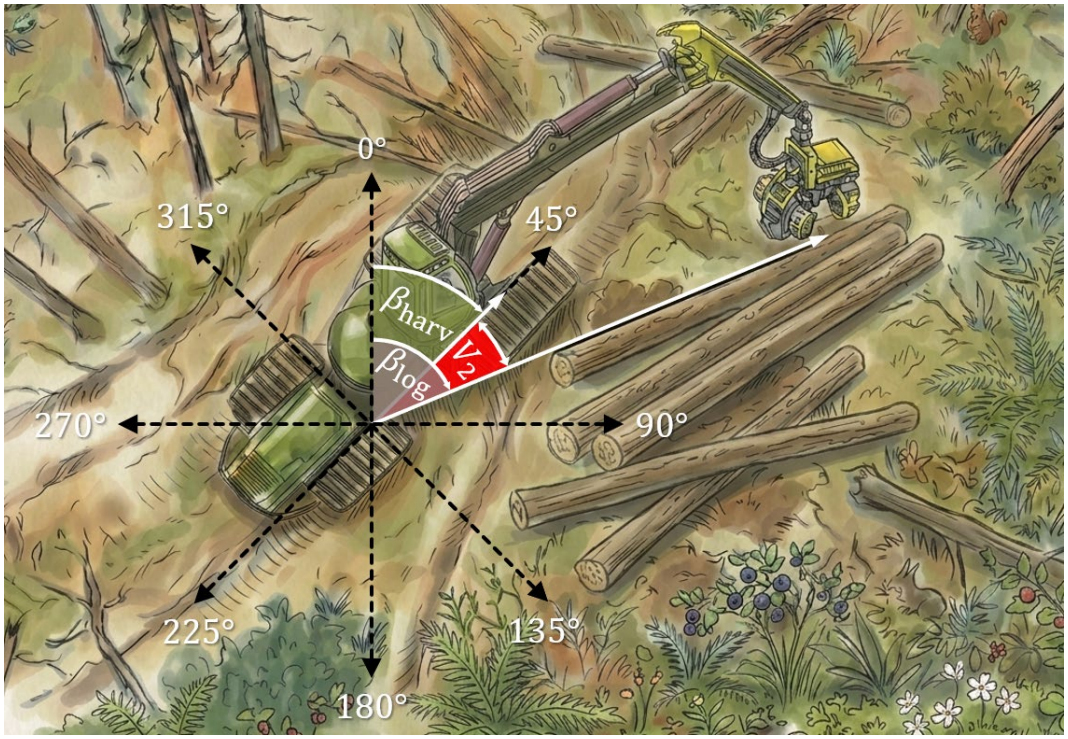

Figure 10. Variable 2 (V_2), representing the angular difference between the log bearing from butt to top end (β_{log}) and harvester bearing (β_{harv}). In the example, β_{log} = 70°, β_{harv} = 45°, and V_2 = 25°.

Statistical analysis

All data processing, visualisation, analysis and modelling were performed using R (R Core Team 2026) within the RStudio environment (version 2026.10) and primarily using the packages *readxl*, *dplyr*, *ggplot2*, and *rpart*.

Exploratory data analysis

An initial visual screening of numerical machine variables was conducted using standardised z-scores, allowing variables measured on different scales to be displayed together. The derived variables V_1 and V_2 were selected for further graphical examination using histograms, boxplots, and scatter plots.

Decision tree modelling

A decision tree is a supervised machine-learning method that generates predictions through a series of hierarchical decision rules organised in a tree-like structure. To predict fuel-adaptation, the Classification and Regression Tree (CART) algorithm was applied, using V_1 and V_2 as predictor variables and fuel-adaptation as the binary response variable (0 = non-adapted tree, 1 = fuel-adapted tree). CART was preferred because it provides transparent decision rules compared with more complex machine learning methods, such as random forests.

Model performance was evaluated using stratified five-fold cross-validation. Within each fold, the model was trained on four-fifths of the data and used to predict probabilities for the remaining fifth. Inverse-frequency class weights were applied during model fitting to account for class imbalance by increasing the influence of the less frequent non-adapted

trees. The resulting out-of-fold probabilities were pooled, and sensitivity was constrained to at least 95%. Among the thresholds satisfying this constraint, the threshold with the highest specificity was selected, with precision, the number of false positives, and accuracy used sequentially as tie-breaking criteria. This procedure prioritised the identification of true positives while limiting false positives.

To improve model interpretability, facilitate practical implementation, and reduce the risk of overfitting, maximum tree depth was restricted to four, allowing no more than four successive splits until reaching a terminal node. The pooled out-of-fold classifications were used to construct a cross-validated confusion matrix comparing predicted and observed class memberships (Table 1), from which the performance metrics (Table 2) were calculated. After cross-validation, a final decision tree was fitted to the full dataset using the same model settings. Variable-importance scores were extracted from the final model to quantify the relative contributions of V_1 and V_2 to its predictions.

The developed CART model was also tested at a second study site (a final felling of 2.6 ha nearby), harvested using the same machine and operator as the primary study site. As no ground-truth inventory was available for this second site, operator registrations using the 'residue button' were used as a reference for comparisons.

Table 1. Interpretation of the model outcomes for prediction of fuel-adaptation at tree level.

Outcome	**Meaning**
True Positive (TP)	Model predicts 1, actual is 1: correctly finds a fuel-adapted tree
True Negative (TN)	Model predicts 0, actual is 0: correctly finds a non-adapted tree
False Positive (FP)	Model predicts 1, actual is 0: false alarm
False Negative (FN)	Model predicts 0, actual is 1: missed a fuel-adapted tree

Table 2. Performance metrics used to evaluate the decision tree model.

Metric	**Formula**	**Interpretation**
Accuracy	$\frac{TP + TN}{TP + TN + FP + FN}$	Overall proportion of correct predictions
Sensitivity (Recall)	$\frac{TP}{TP + FN}$	Ability to correctly identify actual fuel-adapted trees
Specificity	$\frac{TN}{TN + FP}$	Ability to correctly identify actual non-adapted trees
Precision	$\frac{TP}{TP + FP}$	Reliability of positive predictions (fuel-adapted trees that were truly adapted)
Negative Predictive Value (NPV)	$\frac{TN}{TN + FN}$	Reliability of negative predictions (non-adapted trees that were truly non-adapted)
Balanced accuracy	$\frac{\text{Sensitivity} + \text{Specificity}}{2}$	Average of sensitivity and specificity (accounting for both classes equally)
F1-score	$\frac{2TP}{2TP + FP + FN}$	Balance between precision and sensitivity
ROC-AUC	Area under the receiver operating characteristic curve	Overall discrimination ability between fuel-adapted and non-adapted trees across thresholds

Results

Exploratory analysis

In the standardised graphical comparison (Figure 11), V_1 and V_2 showed the most pronounced differences between the two groups, particularly in their median values and interquartile ranges. In the scatter plot (Figure 12), observations from non-adapted trees were concentrated at higher values of both V_1 and V_2, whereas those from fuel-adapted trees were more widely distributed and generally associated with lower values. Although the groups partially overlapped, V_1 and V_2 jointly provided clear separation between non-adapted and fuel-adapted trees (Figures 12-14).

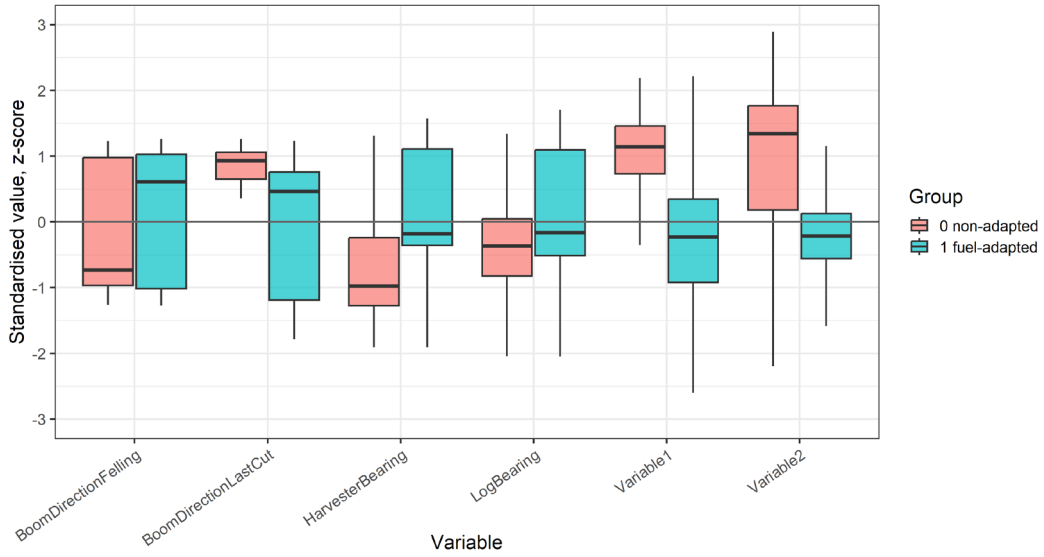

Figure 11. Standardised distributions of numerical machine data variables by group.

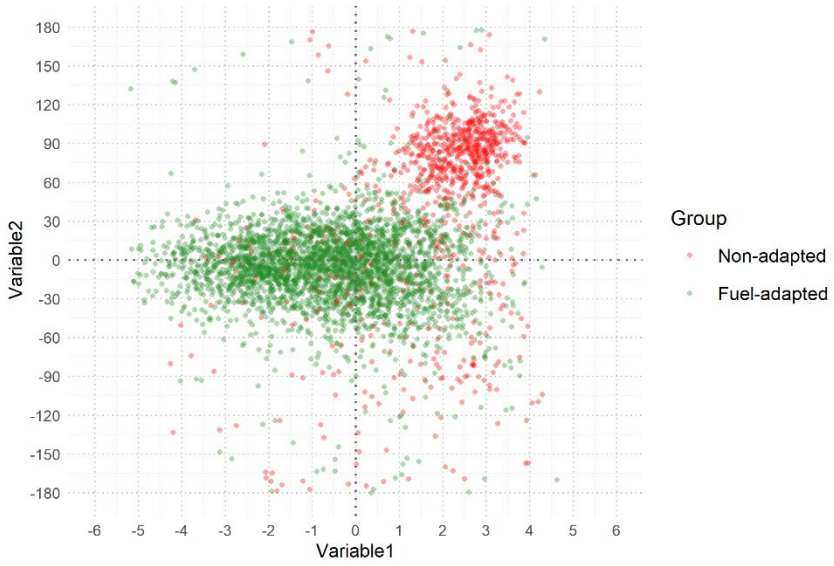

Figure 12. Scatter plot of Variable 1 versus Variable 2 for non-adapted and fuel-adapted trees.

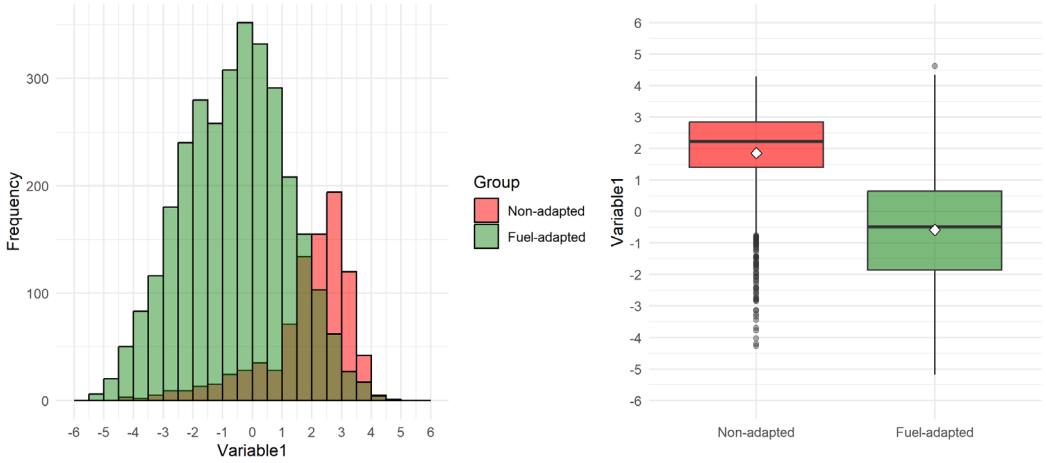

Figure 13. Histogram and boxplot of Variable 1 for non-adapted and fuel-adapted trees.

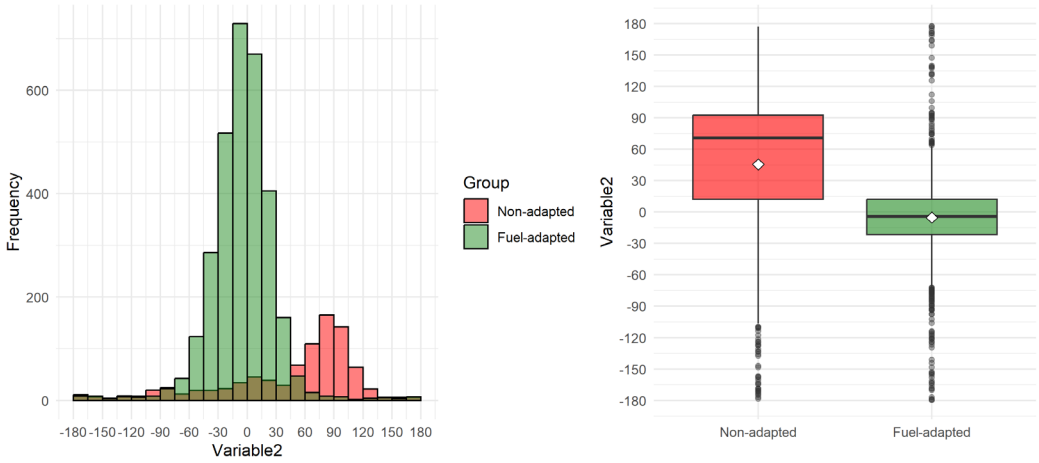

Figure 14. Histogram and boxplot of Variable 2 for non-adapted and fuel-adapted trees.

Decision tree modelling

Performance metrics derived from the cross-validated confusion matrix (Figure 15, Table 3) showed a strong classification performance, with high accuracy (0.901) and precision (0.921). Sensitivity (0.955) exceeded specificity (0.714), indicating that fuel-adapted trees were classified more accurately than non-adapted trees. The high F1-score (0.937) and ROC-AUC (0.897) indicated good discrimination within the internal cross-validation.

The decision tree classified fuel-adaptation using threshold values of V_2 and V_1 (Figure 16). V_2 provided the primary split, whereas V_1 further refined classification within the resulting groups. High V_2 values (≥ 45°) were strongly associated with non-adapted trees, whereas fuel-adapted trees were primarily characterised by lower and negative V_1 values and intermediate V_2 values. These thresholds were translated into eight classification rules, providing an easily implementable framework (Table 4). Feature importance analysis identified V_2 as the strongest predictor, with an importance score approximately 1.6 times greater than that of V_1, indicating that the angular difference between the log bearing and harvester bearing contributed more to distinguishing fuel-adapted trees from non-adapted trees.

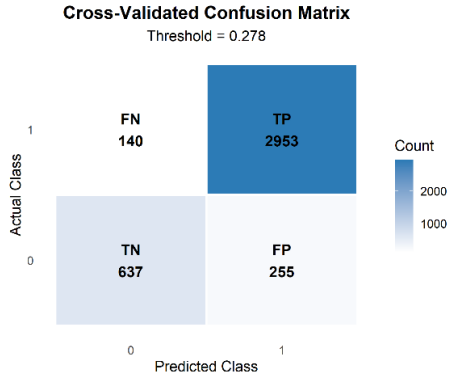

Figure 15. Cross-validated confusion matrix for the decision tree model, where TP = true positives, TN = true negatives, FP = false positives, and FN = false negatives.

Table 3. Values (scale 0 to 1) of the performance metrics used to evaluate the decision tree model.

Metric	Value
Accuracy	0.901
Sensitivity (Recall)	0.955
Specificity	0.714
Precision	0.921
Negative Predictive Value (NPV)	0.820
Balanced accuracy	0.834
F1-score	0.937
ROC-AUC	0.897

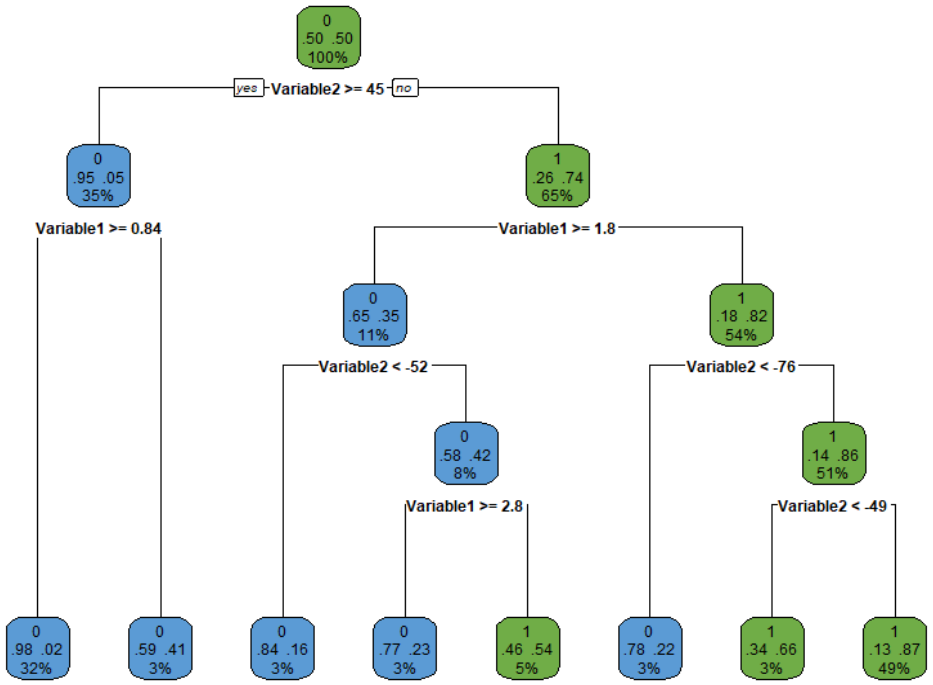

Figure 16. Final classification tree model for the prediction of fuel-adaptation. Terminal nodes display the predicted class (0 = non-adapted, 1 = fuel-adapted), the probabilities of each class, and the percentage of observations within each node.

Table 4. Classification rules from the decision tree model. Terminal-node predictions are shown as the predicted class (0 = non-adapted, 1 = fuel-adapted) and the corresponding class probability.

Rule	Decision rule	Class	Probability
1	$V_2 \geq 45$ & $V_1 \geq 0.84$	0	0.98
2	$V_2 \geq 45$ & $V_1 < 0.84$	0	0.59
3	$V_2 < 45$ & $V_1 \geq 1.8$ & $V_2 \geq -52$	0	0.84
4	$V_2 < 45$ & $V_1 \geq 1.8$ & $V_2 < -52$ & $V_1 \geq 2.8$	0	0.77
5	$V_2 < 45$ & $V_1 \geq 1.8$ & $V_2 < -52$ & $V_1 < 2.8$	1	0.54
6	$V_2 < 45$ & $V_1 < 1.8$ & $V_2 < -76$	0	0.78
7	$V_2 < 45$ & $V_1 < 1.8$ & $-76 \leq V_2 < -49$	1	0.66
8	$V_2 < 45$ & $V_1 < 1.8$ & $V_2 \geq -49$	1	0.87

Application of the classification rules (Table 4) showed strong agreement between the reference classification (ground-truth measurements) and model predictions. At the primary site (Figure 17), the model predicted 44 and 163 dry tonnes of biomass from non-adapted and fuel-adapted trees, respectively, compared with reference values of 50 and 157 dry tonnes (calculated in *hprCM*). The predicted quantity of fuel-adapted biomass therefore overestimated the reference value by 6 dry tonnes (4%), representing an overall misclassification of 3%. At the second site (Figure 18), the predicted fuel-adapted biomass was 2.5 dry tonnes below the reference value, representing a misclassification of 4%.

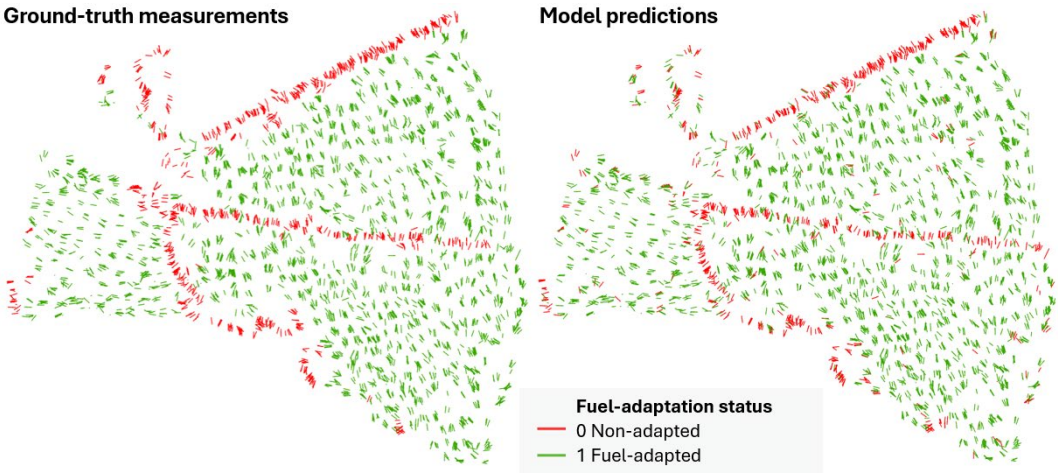

Figure 17. Observed (left) and predicted (right) fuel-adaptation at the primary study site.

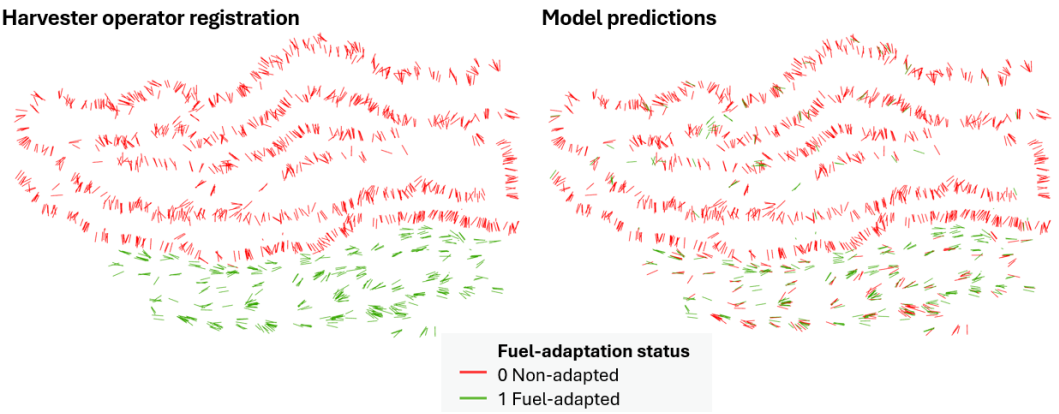

Figure 18. Operator-registered (left) and predicted (right) fuel-adaptation at the second study site.

Discussion

The results of this pilot study are promising for the investigated site and demonstrate the potential for automated registration of fuel-adaptation. The decision tree model showed a good ability to distinguish between fuel-adapted and non-adapted trees, and its predicted fuel-adapted biomass exceeded the reference value by only 6 dry tonnes (Figure 17). The relatively few misclassifications (false positives and false negatives) could potentially be reduced through GIS-based post-processing techniques, such as spatial smoothing or neighbourhood majority voting. Performance metrics (Table 3) should be interpreted as internal cross-validation results, rather than as an independent estimate of model performance on new sites. Even though the test of the model at a second study site (Figure 18) does not represent an independent model validation (nor was this the goal of the study), it provides additional evidence of the model's ability to predict fuel-adaptation under new site conditions.

Model predictions at the primary study site were also compared with measured wood chip deliveries to the energy plant during January and February 2026, revealing a model overestimation of 16%. Although this comparison was outside the scope of the study, the bias was within the expected range when fuel-adaptation is correctly registered by harvester operators (Hannrup et al. 2009) and considerably lower than the values usually reported from the use of the forecast system in practice (Fernandez-Lacruz et al. 2026).

One study limitation is that the ground-truth measurements were collected after roundwood forwarding. The forwarder operator may have used residues to reinforce strip roads, thereby altering their original locations and potentially causing misclassification of some observations in the reference dataset. Ideally, the field survey should have been conducted immediately after harvesting, while logs and logging residues remained in their original positions. Another limitation is that our model was developed using data from a single machine, a single operator, and a single study site. The operator applied a consistent and established method for conventional (non-adapted) and fuel-adapted harvesting (Figure 19). Consequently, the model's ability to handle exceptions remains unknown. Such exceptions may occur at strip-road intersections, sharp bends, and stand boundaries, where operators may need to deviate from the standard working method.

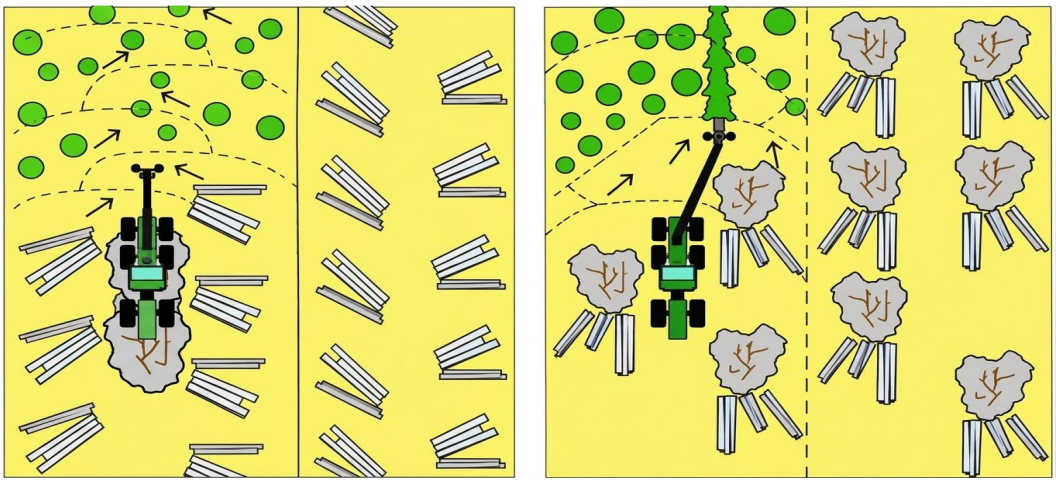

Figure 19. Double-sided final felling without residue recovery (conventional, non-adapted harvesting; left) and with residue recovery (fuel-adapted harvesting; right). Modified from Mörk (2013a, 2013b).

Pathways towards implementation

The harvester in this study was equipped with a conventional GNSS receiver, IBC 3.0, and an angle sensor, enabling the calculation of log's butt and top end coordinates. Unlike stem positioning, log positioning requires both the centre coordinate and bearing for each log. Combined with log length, these variables were used to calculate butt and top end coordinates, which form the basis of the proposed model. This also means that an angle sensor in the harvester head is a prerequisite for implementation of the presented solution. Bearing of single stems is available or can be derived on modern harvesters manufactured by John Deere (as in this study) and Komatsu Forest (Hannrup et al., 2026). StanForD 2010 already supports the storage of log coordinates and bearings in hpr-files, meaning that the necessary data infrastructure is already in place.

In addition to the machine and log coordinates and bearings used in the model, other machine data could potentially improve classification accuracy in future studies. For example, collecting information on boom angle or crane-tip position when treetops are released could provide valuable information for detecting fuel-adaptation and handling exceptions. Since fuel-adapted harvesting involves placing tops and branches in piles outside the strip roads, these variables could help distinguish fuel-adaptation more reliably.

Overall, this study demonstrated the technical feasibility of automating the registration of logging residues from fuel-adapted harvesting using data already collected by modern harvesters. However, the proposed model should be regarded as a prototype and must be further refined, trained on larger datasets, and independently validated across a broader range of machines, operators, and forest conditions before practical deployment.

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