

Human-Guided Decision Support for Selective Harvesting in Tropical Forests: Scenario Simulation, Growth Prediction, and Expert Evaluation at Pasoh Forest Reserve

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Abstract—Sustainable forest management requires analytical tools that enable forest managers to evaluate how harvesting decisions affect future forest structure and ecosystem services. An increase in the reliability of predicting how trees will develop has occurred because of the use of models and machine learning techniques over the past several years, however, there are limitations for support management decisions at an operational level. The purpose of this study is to propose a decision-support system that uses artificial intelligence and scenario simulation to develop an intelligent prescription for managing tree selection, applied to long-term inventory data from permanent plots, with the implications visualised in an interactive dashboard. Linear regression modelling yielded the best prediction models, with the root mean square error being 0.988 cm on absolute diameter. Benchmarked against a persistence rule that predicts no change between censuses, which attains a root mean square error of 1.124 cm, the fitted model improves on doing nothing by approximately 15%. On the increment scale, which is the quantity the simulation propagates, the coefficient of determination is 0.174, so accuracy measured on absolute diameter substantially overstates the modelling of growth itself. An interactive dashboard has been developed that provides forest practitioners with tools to aid in both automatic and manual tree selection. The results of the test of the system were evaluated by twelve forest management professionals who compared two separate dashboard designs (DSS A and DSS B). The DSS B interface received a higher mean usability score, although the difference was not statistically significant and the analytical value ratings of the two interfaces were indistinguishable. The evaluation is therefore formative rather than confirmatory, and a counterbalanced task-based study is reported as ongoing work. In conclusion, the results indicate the efficacy of using predictive modelling coupled with scenario simulation to provide forest management professionals with intelligent tools to help make their management decisions.

Keywords—Decision support system; scenario simulation; selective harvesting; forest growth prediction; selective management system; human-centred artificial intelligence

I. INTRODUCTION

Forests play a critical role in sustaining biodiversity, regulating ecological processes, and providing ecosystem services such as carbon storage, climate regulation, and the

supply of natural resources [1]. Tropical rainforests are among the most varied and complex ecosystems on Earth and are frequently described as the planet's lungs because of their role in global carbon cycles and climate stabilisation [2]. The health and resilience of tropical forests therefore need to be prioritised both for the conservation of ecological systems and for resource management. Sustainable Forest Management (SFM) is one widely adopted mechanism for balancing conservation with resource extraction. Under SFM, harvesting methods aim to sustain forest productivity while preserving ecological integrity, typically through selective cutting that removes individual trees but keeps the canopy intact to allow natural regrowth [3]. To implement SFM effectively, forest managers must understand how harvesting decisions will affect stand structure, species composition, and ecosystem processes over time [4], [5]. Managers consequently need the ability to anticipate how current practices will shape forest characteristics in the long term.

Empirical data from long-term monitoring programmes describe how forests change over time by recording the structure of the stand together with the number and condition of the trees it contains. Permanent sample plots and repeated forest censuses generate multi-temporal inventory datasets that capture key attributes such as tree diameter, species composition, and stand density [6]. Information from these collections can then be used to build models that project future forest conditions and growth.

Traditionally, forestry Decision Support Systems (DSS) have produced management prescriptions from rule-based best practice, static growth tables, or standard harvesting regimes established prior to use. Although these systems provide a structure for management decision making, they do not support the exploration of alternative harvesting strategies; a forest manager is instead left to conduct manual analysis or to rely on expert knowledge. This creates a gap between prediction and actual decision making, particularly in complex situations where managers must balance multiple objectives, including timber production, biodiversity conservation, and carbon storage.

Recent advances in decision intelligence and Artificial Intelligence (AI) offer an opportunity to close this gap. Human-

guided AI decision support uses AI to enhance the decision process while allowing human experts to guide, validate, and refine the resulting decision [7], [8]. Within such an approach, integrating predictive modelling with simulation gives the forest manager an opportunity to explore alternative management options interactively. One promising avenue is scenario simulation, in which predictive models project what would follow had the manager selected a different management strategy. This is distinct from causal counterfactual inference [9]. The method used here is a deterministic what-if simulation that rests on prediction alone and contains no causal model, so its outputs are projections under an assumed intervention rather than estimated causal effects, and the term counterfactual is therefore reserved throughout for the causal inference literature rather than applied to the method.

The capacity to integrate predictive modelling with scenario-based simulation for real-time evaluation is currently limited in forestry DSS. Few available systems allow forest managers to analyse systematically how different stand prescriptions and tree selection strategies affect future forest conditions. Existing tools tend to offer either predictive modelling or visualisation, and rarely provide an integrated, human-centred decision-support structure.

To address this gap, this research proposes a human-guided AI DSS that integrates forest growth prediction, scenario-based harvesting simulation, and scenario exploration through an interactive dashboard. Using forest inventory data from a 50-hectare and a 2-hectare permanent plot collected over multiple census years, the tool allows users to experiment with harvesting strategies by generating alternative tree selections for a given stand prescription and comparing the projected consequences across several criteria. Positioning predictive modelling alongside interactive exploration reflects a decision intelligence approach in which users experiment with options and iteratively refine strategy while remaining firmly in charge of the actual decision.

The contribution of this work is fourfold. First, it proposes a scenario simulation framework that couples stand prescription with projected forest outcomes across five structural indicators and reports the outcomes of alternative harvesting intensities on a 50-hectare permanent plot. Second, it identifies a binding constraint on the application of the Selective Management System (SMS) in a reserve-condition stand, namely that the density of stems meeting the cutting limits falls below the lightest prescribed regime, so that the regime caps do not discriminate between strategies and harvest intensity must instead be expressed relative to the available pool. Third, it develops and benchmarks a Diameter at Breast Height (DBH) growth prediction module through a feature ablation study across five machine learning algorithms and reports its accuracy against a persistence baseline so that the contribution of the model is separated from the serial dependence between successive census measurements. Fourth, it reports an expert evaluation in which two dashboard designs were compared by twelve forest management professionals using the System Usability Scale (SUS), analytical value ratings, and user acceptance items.

II. RELATED WORK

A. Forest Growth Modelling and DBH Prediction

Forest growth modelling is fundamental to forestry science, allowing researchers and practitioners to predict how forest stands evolve over time. Growth and yield models produce predictions of tree diameter change, mortality, recruitment, and stand structure [10], [11]. DBH is a particularly important variable because it characterises stand development and, through allometric relationships, underpins many ecological indicators of forest structure. Estimates of basal area, stand volume, biomass, and stored carbon are all derived from DBH measurements. Predicting future DBH is therefore central both to ecological assessment and to management planning [12], since accurate DBH prediction supports forecasts of future forest conditions and evaluation of the effect of management interventions.

Traditional forest growth modelling uses either statistical regression models or mechanistic growth models driven by variables such as location, competition, and environmental conditions. More recently, machine learning algorithms have been introduced for predicting tree growth and forest productivity because they accommodate nonlinear relationships among complex ecological variables. Random Forests (RF), gradient boosting, and Neural Networks (NN) have been used to improve the accuracy and reliability of predictive models of tree growth [13], [14].

Limitations remain despite these improvements. Most growth prediction models have been developed as forecasting methods rather than as operational decision support. Many predictive models are also not connected to operational forestry tools, which limits their practical utility when the results are used to inform management decisions. Because of this disconnect, forest managers often find it difficult to convert predictive model output into actionable management decisions.

Comparing the available modelling pathways makes the increase in complexity evident. Early statistical growth models offered a simple framework for estimating growth from a relatively small number of observations and parameters, but they represent poorly the ecological interactions between trees and their environment, such as competition and mortality. Mechanistic models provide greater ecological realism because they represent these dynamics explicitly, yet they are difficult to develop and calibrate and demand considerable time and effort.

Machine learning methods are gaining popularity because of their predictive accuracy and their capacity to model nonlinear relationships between predictors and response variables. However, machine learning based forest growth models offer little support for the decision process itself. As summarised in Table I, most existing DBH growth prediction models remain disconnected from interactive decision support systems for forest management, preventing managers from using model output to evaluate a range of possible long-term outcomes under alternative harvesting options [15], [16].

TABLE I. COMPARISON OF FOREST GROWTH MODELLING APPROACHES USED FOR DBH PREDICTION

Approach	Description	Strengths	Limitations
Statistical growth models	DBH growth estimated through traditional regression models involving tree size, site productivity, and stand density [10], [11].	Straightforward, widely used in forestry research, and workable with a small amount of data.	Often assume linear relationships and cannot represent the interactions between complex ecological processes.
Mechanistic / process-based models	Tree growth dynamics simulated through resource capture, mortality, and competition, giving greater insight into stand processes [10], [11].	Suited to long-term forest modelling and to projecting how the forest will develop under a prescription.	Have many parameters and assumptions, are computationally intensive, and are difficult to calibrate.
Machine learning models	Data-driven methods, including random forests, gradient boosting, and neural networks, that learn complex nonlinear patterns within forest data [13], [14].	High predictive accuracy and able to capture complex nonlinear relationships.	Often require large datasets, offer limited interpretability, and usually focus on prediction rather than decision support.
Current limitation in forest DSS	Existing DBH prediction models are rarely integrated into interactive forest management decision-support systems [15], [16].	Can provide accurate predictions of tree growth.	Predictions are often disconnected from operational tools, making it difficult for managers to evaluate alternative harvesting strategies.

This gap suggests that the next phase in the evolution of forest growth modelling is not simply to develop more accurate predictive models, but to combine those models with frameworks designed to support better management decisions. There is a need for systems that connect the output of growth models to the user's ability to generate and explore alternative management strategies. The present study builds on this observation and investigates how integrating growth prediction with a human-guided AI DSS can support scenario-based exploration of forest management options.

B. Decision Support Systems in Forest Management

DSS are valuable tools for helping forest managers evaluate management strategies and plan interventions. A forestry DSS typically combines inventory data, growth models, and analytical tools to support sustainable management practice. Early forestry systems used static growth tables and yield models to project future forest conditions. Although useful for establishing a baseline, they were inflexible when evaluating a range of management alternatives and often required manual interpretation by the manager.

To overcome the limitations of static growth tables, simulation-based DSS have been developed to model stand development under different management strategies. Simulation allows managers to examine how a forest may evolve under various harvesting regimes and environmental conditions. Previous studies, for example, have used simulation to evaluate selective logging by analysing cutting limits and estimating felling damage within forest stands [17]. However, many of these systems concentrate on operational parameters and offer limited insight into the long-term ecological implications of harvesting decisions. A further challenge is that current platforms mainly provide retrospective analysis of inventory data rather than prospective reasoning about forest trajectory, so the evaluation of management options still rests largely on expert opinion and manual analysis.

Table II compares four established forestry decision support systems with the system proposed here, along the dimensions that matter for selective harvesting: how growth is modelled, how a harvest is specified, what outcomes are reported, and how the practitioner interacts with the system.

TABLE II. COMPARISON OF ESTABLISHED FORESTRY DECISION SUPPORT SYSTEMS WITH THE PROPOSED SYSTEM

System	Growth model	Harvest specification	Outcome reporting	User interaction and evaluation
Heureka [18]	Empirical tree- and stand-level models for boreal species	Predefined treatment programmes, optimised across a landscape	Timber, carbon, dead wood, habitat, recreation and damage risk	Desktop planning software; no published usability evaluation
SIMO [19]	Open, XML-configurable model base of tree-level growth models	User-defined treatment schedules combined with optimisation	Configurable indicator set defined by the user	Framework for analysts; assumes modelling expertise
FVS [20]	Distance-independent individual-tree growth and yield, regional variants	Silvicultural treatment keywords applied at stand level	Stand structure, yield, mortality, with fire and pest extensions	Keyword and batch driven; no interactive tree selection
FORMIND [17], [21], [22]	Process-based individual tree model with light competition and carbon balance	Logging scenarios varying cycle, method, cutting limit and intensity	Yield, canopy opening, species composition, biomass and diversity	Research simulator; scenarios evaluated offline by MCDA
This study	Machine learning model of diameter increments from repeated census data	Automatic prescription under SMS limits, or manual selection of individual stems	Stand density, basal area, volume, biomass and carbon of the residual stand	Interactive dashboard evaluated with twelve forest professionals

Two observations follow. The first is that the established systems are considerably stronger on ecological process representation. FORMIND simulates light competition, mortality, and regeneration explicitly, and has been applied to selective logging in Malaysian dipterocarp forest with multicriteria evaluation of scenarios that vary cutting limit and intensity [17], [21]. Relative to that work, the growth component proposed here is deliberately simpler, and the system makes no claim to ecological realism of the same order.

The second observation identifies where the gap lies. In each of the established systems a harvest is specified as a treatment programme, a schedule, or a scenario, and is evaluated offline by an analyst. None of them allows a forest manager to select individual stems interactively and see the projected consequences of that specific selection, and none reports a usability evaluation with practitioners. The contribution of the present work is therefore not a better growth model but a decision layer: it places prescription, simulation, and outcome reporting inside an interface that a forest manager operates directly, and it evaluates whether practitioners can in fact use it. This positions the system as complementary to the simulators above rather than as a replacement for them.

C. Human-Centred AI and Decision Intelligence

Despite advances in modelling, several limitations persist. The first is the trade-off between model accuracy and interpretability [23]: a complex model may be highly accurate yet difficult for a non-expert to interpret. The second is that most DSS depend on human judgement, which introduces subjectivity and inconsistency into the outcomes they produce. The third is that the effectiveness of a DSS depends heavily on the quality of its user interface, since poorly designed dashboards lead to confusion and misinterpretation of system output [24]. A further limitation is that many systems struggle to represent uncertainty and complex ecological dynamics such as competition and environmental variability.

Recent AI research emphasises human-centred design, in which AI systems improve human judgement and reasoning instead of replacing them. AI enhances human decision making by providing interpretable outputs, enabling interactive exploration of complex data, and supporting human reasoning [8]. Decision intelligence builds on this foundation by combining prediction models, simulation, and decision processes into an integrated framework for generating actionable insight [7]. Within this framework, the effectiveness of an AI system can be evaluated in terms of how far it supports understanding of complex systems, exploration of scenarios, trade-off analysis, and confidence in the resulting decision. Interactive dashboards and business intelligence tools provide the visual interfaces through which users explore data, compare scenarios, and interpret model output [24].

D. Scenario-Based Reasoning for Environmental Decision Making

Forest managers traditionally rely on established guidelines, developed through expert judgement or silvicultural practice, to determine harvesting decisions. These guidelines combine stand inventory data with expert judgement to set harvest limits, assess stand condition, and guide decisions under harvesting systems such as the SMS. Such approaches provide useful operational

guidance, but they offer limited means of systematically evaluating and comparing the long-term ecological consequences of alternative decisions [22], [25]. Evaluation of different harvesting strategies is therefore usually accomplished through retrospective analysis or manual assessment rather than structured simulation.

Counterfactual reasoning has become an increasingly important tool for analysing decision scenarios systematically by evaluating alternative outcomes under differing assumptions. In its formal definition, counterfactual reasoning originates in the causal inference literature [9] and estimates the potential outcomes of interventions that could have been made. Implementing full causal counterfactual models in complex ecological systems is difficult, however, because of limited data and high uncertainty.

This study therefore employs a scenario simulation method that uses predictive modelling and simulation to estimate potential futures under alternative management strategies. Rather than attempting to identify causal effects, the method allows what-if scenarios to be explored by changing inputs, such as the set of selected trees or the harvesting regime and projecting the resulting forest condition. Simulation of this kind has also been used in AI to analyse decision making in complex environments [26].

By combining scenario-based reasoning with simulation, decision makers can evaluate multiple alternative scenarios while maintaining consistency through a shared baseline condition. Management recommendations can therefore be implemented virtually and their potential effects examined before they are applied in practice. The method provides analytical support for managing complex systems in which uncertainty and dynamic interactions make formal causal models impractical. Table III summarises the key differences between traditional forest management practice and the proposed scenario simulation approach.

TABLE III. TRADITIONAL FOREST MANAGEMENT PRACTICE AND THE SCENARIO SIMULATION APPROACH

Aspect	Traditional forest management	Scenario simulation approach
Decision paradigm	Rule-based prescriptions derived from silvicultural guidelines and expert judgment.	Scenario based reasoning that evaluates alternative harvesting decisions through simulation.
Use of forest inventory data	Primarily used to describe current forest conditions and determine cutting limits.	Used as the baseline forest state for generating and evaluating alternative harvesting scenarios.
Evaluation of harvesting options	Limited exploration of alternatives; decisions typically follow predefined harvesting regimes.	Multiple harvesting scenarios can be generated and evaluated through scenario simulation.
Exploration of what-if scenarios	Typically performed manually and relies heavily on expert interpretation.	Systematically simulated by modifying tree selection sets and projecting future forest states.
Integration with growth prediction	Growth models often used separately for forecasting.	Growth prediction models are integrated with harvesting simulation to project post-harvest forest dynamics.

Aspect	Traditional forest management	Scenario simulation approach
Decision transparency	Decision logic may rely on tacit expert knowledge.	Explicit decision process in which assumptions and outcomes can be examined and compared.
Decision support capability	Provides static recommendations based on rules or thresholds.	Provides interactive decision support enabling comparison of alternative strategies.
Outcome analysis	Focuses mainly on short-term operational decisions.	Evaluates long-term impacts on forest structure, biomass, carbon stock, and biodiversity indicators.

Recent advances in AI have further expanded the use of simulation-based environments for decision making. AI-driven world models simulate complex systems and allow decision makers to test actions within virtual environments without real-world risk, supporting reasoning, planning, and evaluation by representing how systems evolve under different conditions [26]. Despite these developments, the integration of simulation-based AI and counterfactual reasoning within forest management DSS remains limited, and most existing forestry tools focus on predictive modelling rather than on systematic exploration of alternative interventions.

E. Evaluation of Decision Support Systems and Analytical Dashboards

Interactive dashboards are the most common interface to a DSS because they consolidate visualisation, analytics, and interaction within a single environment, allowing users to explore complex datasets, identify patterns, and interpret analytical output more effectively than a static report permits [27]. A growing body of research shows that dashboard design and usability substantially influence the ability of users to extract insight and to support organisational decision making [28].

Evaluating a DSS is essential to ensure that analytical tools genuinely support users in interpreting information and making informed decisions. Beyond technical performance, usability and practical value must be assessed from a user-centred perspective. Earlier research highlights the need to evaluate a DSS in terms of how easily users can engage with the system, whether it aids the interpretation of analytical results, and whether it adds value to the decision process [24], [29].

User-centred evaluation methodologies have been established for analytical dashboards and measure concepts including usability, perceived usefulness, and analytical value [30], [31]. The SUS has become the most widely adopted instrument for measuring usability across digital systems because of its reliability and the simplicity with which it captures user interaction [32]. Dashboard evaluations frequently supplement usability with criteria that capture how users perceive analytical features in terms of relevance, insightfulness, and importance, representing how useful the presented information is judged to be within a decision-support environment.

Although a growing number of studies have evaluated analytical dashboards and DSS, few have investigated user-centred evaluation of AI-enabled DSS for forest management.

There remains a need to evaluate such systems on both predictive performance and the extent to which they allow users to interact with and interpret the analytical output on which their decisions rest.

F. Research Gaps

Considerable progress has been made in forest growth modelling, in machine learning for growth prediction, and in the development of forestry DSS, yet several important limitations persist.

First, most forest growth models are concerned with predicting stand development, such as diameter growth or stand productivity, and their output is used for forecasting rather than for evaluating alternative harvesting strategies. Although valuable for characterising growth dynamics, these models offer limited capability for the interactive evaluation of alternatives, so their contribution to decisions is indirect and managers must process the results further before acting.

Second, many existing forestry DSS rely on static growth tables, rule-based recommendations, or predetermined harvesting regimes. Although informative, they offer little ability to explore how different tree selection choices affect future forest conditions, and the evaluation of harvesting options consequently depends almost entirely on expert judgement and manual analysis.

Third, although recent studies have applied machine learning to improve growth prediction, few couple these predictive models with a simulation environment in which decision makers can test and evaluate management scenarios. In the absence of this connection, predictive modelling and decision support are rarely implemented together.

Fourth, counterfactual reasoning is well established in causal inference, policy analysis, and AI-supported decision systems, but is largely absent from the forest management literature. Implementing formal causal counterfactual methods in complex ecological systems is demanding, which motivates deterministic scenario simulation methods that allow users to explore hypothetical what-if scenarios through predictive models and interactive visualisation.

Finally, the existing literature does not adequately address human-centred design of AI-based decision support, particularly with respect to interpretability, usability, and decision effectiveness. Until these aspects are addressed, analytically advanced tools are likely to remain underused in practical forest management.

Closing these gaps requires a human-guided AI decision support system that integrates tree growth prediction with scenario simulation, so that forest managers can systematically evaluate alternative tree selection strategies and understand their potential effects on future forest structure and biodiversity.

III. MATERIALS AND METHODS

A. Dataset

The study uses long-term forest inventory data collected by the Forest Research Institute Malaysia (FRIM) in the Pasoh Forest Reserve, Negeri Sembilan, Malaysia, a lowland dipterocarp reserve that supports more than 800 tree species. The

inventory consists of repeated censuses capturing tree level information over time and comprises 436,591 tree records drawn from two permanent compartments of 2 hectares and 50 hectares. Trees are assigned to five species groups (Dipterocarp, Non-dipterocarp, Chengal, Palm, and Pioneer), and the recorded variables include DBH, species code, tag identifier, and spatial location. The grouping is not derived in this study; it follows the operational classification used by FRIM and embedded in the SMS, under which cutting limits are set per group rather than per species. The groups therefore correspond to the units in which harvesting decisions are regulated. Because the groups are inherited rather than fitted, the sensitivity of the results to alternative groupings has not been assessed, and this is noted as a limitation in Section V. These records provide the forest state representation and the candidate tree pool used by the stand prescription and simulation modules.

The DBH prediction module was developed in earlier work on a subset of this inventory, namely the 2-hectare permanent ecological plot, which has been censused since 1971 at intervals of two to nine years. Censuses before 2003 were excluded because of incomplete measurement coverage, and the analysis therefore uses the 2013, 2015, 2017, 2019, and 2021 censuses. Trees with missing or zero DBH in the target census were removed, leaving 1,944 stems with complete measurements across all five censuses. The stem population of this plot is dominated by small trees, with the modal diameter class falling between 5.1 cm and 10.0 cm. Preprocessing followed a fixed protocol. For the two-hectare plot, censuses before 2003 were excluded because measurement coverage is incomplete, leaving the 2013, 2015, 2017, 2019, and 2021 censuses. Stems with a missing or non-positive DBH in the target census were removed, as were stems without a complete measurement series across the retained censuses, leaving 1,944 records from an initial pool of tagged stems. Species and quadrant were label-encoded, growth variables were derived as differences between consecutive censuses, and all predictors were standardised by a z-score transformation whose mean and variance were estimated on the training partition alone. Partitions were drawn at 70:30 and 80:20 with a fixed random seed so that every reported comparison uses the same split. For the 50-hectare compartment, the same census-consistency rule retained 22,874 stems recorded as alive with a positive diameter in all six censuses, from 44,002 tagged stems. No imputation was applied at any stage, and no duplicate tag identifiers were found. The

two compartments therefore serve different roles in this study. The prediction module is fitted on the 2-hectare plot, where the census interval is short and the measurement series complete for individual stems, while the harvesting scenario experiment reported uses the 50-hectare compartment, which is large enough for the density of commercial-sized stems to be estimated at an operational scale. Because the two compartments differ in census interval and in stem size distribution, results derived from them are reported separately throughout and are not pooled.

B. Proposed Framework

This study proposes a human-guided AI decision-support framework for forest management that integrates stand prescription, tree selection, and predictive forest growth modelling to support scenario exploration. The framework allows managers to examine how alternative harvesting decisions influence several projected forest outcomes simultaneously, enabling comparison, trade-off assessment, and iterative refinement of tree selections before implementation.

The system was implemented by combining a machine learning pipeline with dashboard technology in Power BI. The predictive component was developed in Python using scikit-learn and XGBoost, libraries that are widely used in decision support and ecological modelling and that provide robust and interpretable results. Five algorithms were evaluated for tree growth prediction: Linear Regression (LR), Random Forest (RF), Decision Tree (DT), Long Short-Term Memory (LSTM), and XGBoost (XGB). Models were assessed using standard regression metrics, namely, Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and the coefficient of determination, and the model with the lowest RMSE was selected for integration into the simulation module of the dashboard.

The system was evaluated on three dimensions: usability, insightfulness, and acceptance. Usability was assessed with the SUS [33], an extensively validated instrument. Analytical insight and value were assessed to establish whether the dashboard generates sufficient insight to assist experts in making management intervention decisions [34]. User acceptance was examined by asking respondents to compare the two dashboard designs directly. Fig. 1 presents the proposed framework.

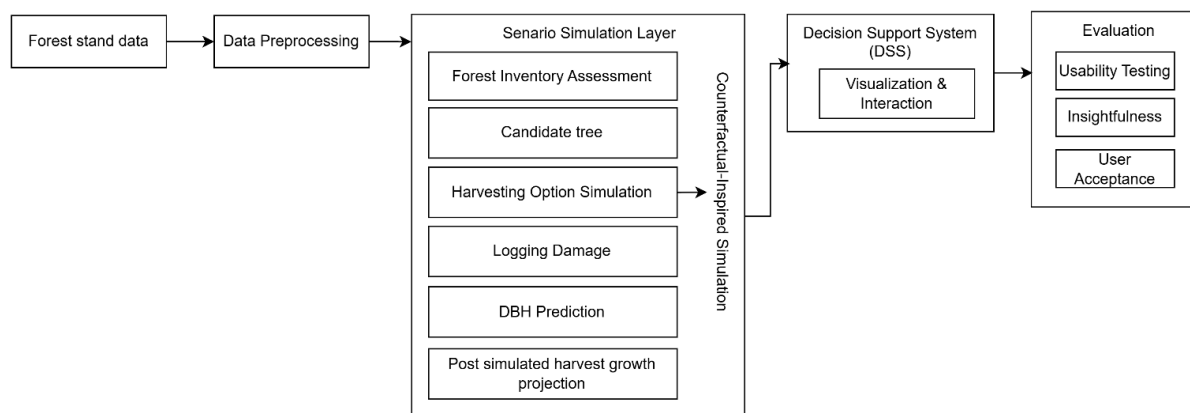


Fig. 1. Proposed human-guided AI decision support framework.

The framework begins with an assessment of the forest inventory using the long-term census dataset. Five structural indicators (basal area, volume, stand density, biomass, and carbon) represent the condition of the stand at a given time step t . The forest state is defined as:

$$f_t = \{N_{t,g,c}, D_{t,g,c}, BA_{t,g,c}, V_{t,g,c}, B_{t,g,c}, C_{t,g,c}\} \quad (1)$$

where,

$g \in G$ = species group {Dipterocarp, Non-dipterocarp, Chengal, Pioneer, Palm};

$c \in C$ = DBH size class {15–30, 30–45, 45–60, 60–75, 75–90, 90+ cm};

$N_{t,g,c}$ = tree density per hectare in group g and class c ;

$D_{t,g,c}$ = representative DBH for class c ;

$BA_{t,g,c}$, $V_{t,g,c}$, $B_{t,g,c}$, $C_{t,g,c}$ = forest basal area, volume, biomass, and carbon.

Starting from the observed forest state, the system evaluates harvesting options through a stand prescription mechanism based on scenario simulation. This mechanism generates alternative tree selection scenarios representing different harvesting strategies, including selections generated automatically from predefined harvesting regimes and selections specified manually by the user. Fig. 2 shows the pre-felling inventory assessment for trees above 30 cm diameter that determines which trees are harvestable.

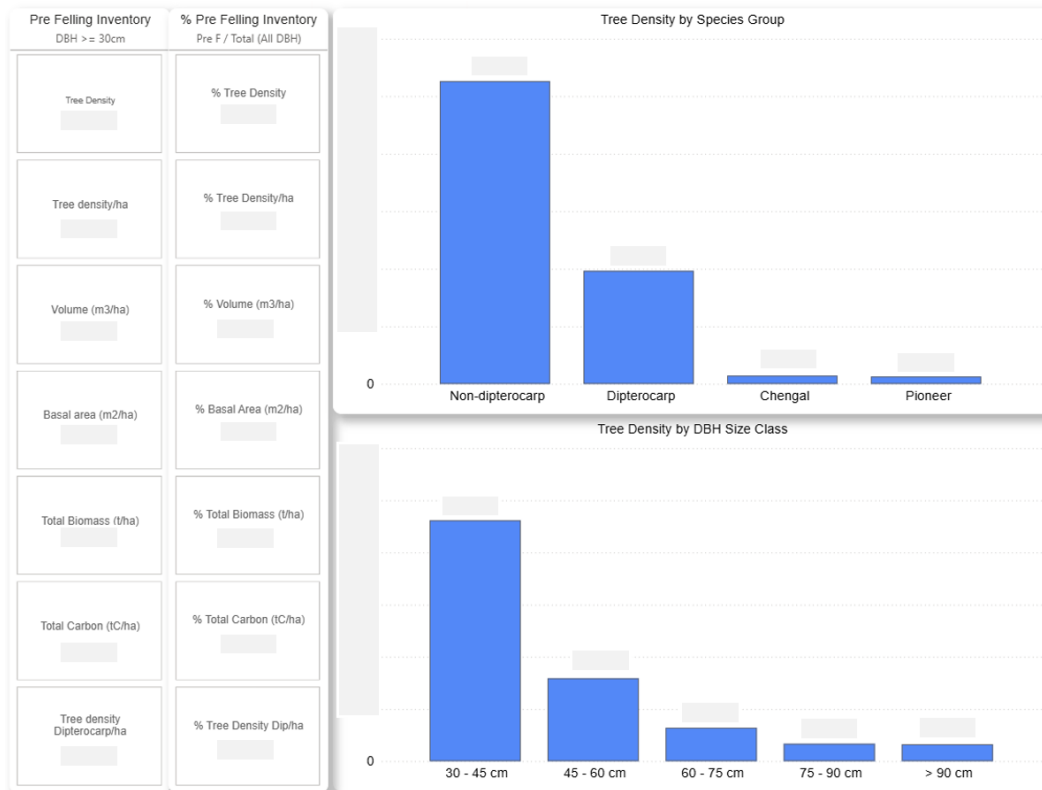


Fig. 2. Pre-felling inventory assessment.

Several factors are considered when identifying candidate trees, including species group, tree diameter, cutting limits, and operational constraints. Dipterocarp species, for example, become candidates for harvesting once their DBH reaches 65 cm, while the cutting limits for most non-Dipterocarp species and for Chengal are 55 cm and 70 cm respectively. A tree is considered damaged if it sustains moderate to severe stem or crown damage during logging operations [35]. Neighbouring trees are susceptible to such damage when trees are felled and extracted, which affects forest structure and post-logging regeneration. The likelihood of damage varies by diameter class, with smaller trees more likely to be damaged than larger ones because they are closer to the operation and more exposed to mechanical disturbance. Logging damage is therefore computed by the system according to the rates in Table IV.

TABLE IV. ASSUMED LOGGING DAMAGE RATE BY DBH CLASS

DBH (cm)	Logging damage
Above 60	20%
45–60	30%
30–45	40%
15–30	50%

C. Stand Prescription and Tree Selection

Stand prescription forms the decision layer that determines which trees are to be harvested from the stand. Two modes are provided: automatic and manual.

Rather than applying a single predetermined harvesting rule, the automatic stand prescription generates and evaluates alternative harvesting regime scenarios together with their projected future outcomes. The mechanism is a deterministic ranking rather than an optimisation: candidate trees are ordered by diameter and selected in descending order until the regime limit is reached. No objective function is defined, no constraints beyond the cutting limits and the regime cap are imposed, and no search over alternative selections is performed. The system therefore supports the comparison of scenarios a manager specifies and does not identify an optimal selection. Formal multi-criteria optimisation over the five structural indicators is identified as future work. This enables managers to examine how different tree selection strategies may influence future forest conditions. Trees are first ranked by DBH, after which the

system assembles the harvest set for each regime. Three regimes are defined, namely light, medium, and heavy, with a maximum of 12, 16, and 20 trees per hectare, respectively, in accordance with the SMS guideline. The automatic stand prescription is expressed as:

$$SP_a = \pi R(s_i) \quad (2)$$

where:

$R \in \{\text{heavy, medium, light}\};$

$\pi R =$ operator that ranks trees by DBH size.

Fig. 3 illustrates the output of the automatic stand prescription. Users can interactively examine the generated selection and customise it as required.



Fig. 3. Example of automatic stand prescription.

In the manual stand prescription, users select trees directly through the interactive interface. This allows forest managers to incorporate expert knowledge or specific management objectives when defining a harvesting strategy. Trees may be selected by clicking on the list of candidate trees or by their spatial location. The manual stand prescription is expressed as:

$$SP_m = \{u_{i,c}^m\}, i = 1, \dots, n_t \quad (3)$$

where:

$U_{candidate} \subseteq \{1, \dots, n_c\};$

$u_{i,c} = 1$ if tree i is selected by the user, and 0 otherwise.

Fig. 4 shows an example of the manual stand prescription. In this module, users interactively select trees to harvest according to species group, location, and the list of candidate trees. The system responds by computing the total tree count, price, volume, basal area, biomass, and carbon of the selection, and alerts the user when a selection conflicts with the SMS policy.

D. Post-Harvest State and DBH Prediction

The next step derives the immediate post-harvest forest state. The system computes the remaining trees by excluding both the trees chosen by the stand prescription and the trees lost to logging damage, producing an immediate simulated post-harvest state. DBH prediction is then applied to this state to

derive updated structural indicators, enabling estimation of future post-harvest forest conditions at horizon $t + k$.

The prediction task is formulated as a supervised regression problem in which the target is the DBH of an individual tree at the next census, that is DBH2021, and the predictors are the four preceding DBH observations together with species, spatial, and derived growth variables. The remaining components of the framework, namely the forest state representation, the stand prescription mechanism, the harvesting simulation, and the dashboard, are contributed by the present study and operate on the full inventory. The DBH prediction model uses species, spatial, historical DBH, and derived growth variables. Species and spatial variables provide ecological and environmental context for tree growth, while historical DBH and derived growth variables reconstruct the growth of individual trees over time. Table V summarises the predictor variables used in the modelling process. Categorical variables for species and quadrant were label-encoded before training, and all predictors were standardised with a z-score transformation fitted on the training partition only. Additional features were derived from the census data to express the increment in DBH between successive censuses; these encode past growth behaviour and therefore assist in predicting future growth. The result of pre-processing is an ordered array of tree records combining tree characteristics, spatial position, and historical growth pattern.

Tree growth dynamics are influenced by many ecological drivers. The model incorporates species, spatial, and temporal information to capture three of the most significant: species behaviour, local environment, and previous growth history. To improve predictive performance, a hyperparameter tuning procedure was carried out for each algorithm. Hyperparameters govern aspects of the learning process and can have a substantial effect on predictive accuracy and generalisation, and default settings frequently give sub-optimal performance on complex ecological datasets.

This research used GridSearchCV, which evaluates all combinations within a predefined hyperparameter space. Each combination was assessed by training the model and validating

it, and the configuration with the lowest validation RMSE was retained as the final model for that algorithm. The hyperparameter search grids for RF, DT, LSTM, XGB, and LR are listed in Table VI, and the meaning of each hyperparameter is summarised in Table VII. Table VI reproduces the grids as they were executed. Several entries in those grids control execution rather than model fit, namely verbosity and thread for XGBoost and copy_X and n_jobs for linear regression, and these cannot alter predictive accuracy. They are therefore excluded from Table VII and were not treated as tuning parameters. The effective search space is smaller than the grids suggest, and for linear regression it reduces to fit_intercept and positive.

TABLE VI. HYPERPARAMETER SEARCH GRID

Algorithm	Hyperparameter grid
Random forest	{'n_estimators': [int(x) for x in np.linspace(start = 200, stop = 2000, num = 10)], 'max_features': ['auto', 'sqrt'], 'max_depth': [int(x) for x in np.linspace(10, 110, num = 11)] + [None], 'min_samples_split': [2, 5, 10], 'min_samples_leaf': [1, 2, 4]}
Decision tree	{'criterion': ['absolute_error', 'friedman_mse', 'squared_error', 'poisson']}
Long short-term memory	{'units': min_value = 32, max_value = 128, step = 32, 'activation': ['relu', 'tanh', 'sigmoid'], 'optimizer': ['adam', 'rmsprop', 'sgd']}
XGBoost	{'booster': ['gbtree', 'gblinear', 'dart'], 'verbosity': [0, 1, 2, 3], 'nthread': [1, 2, 4, 8]}
Linear regression	{'copy_X': [True, False], 'fit_intercept': [True, False], 'n_jobs': [1, 2, 3], 'positive': [True, False]}

TABLE VII. EXPLANATION OF HYPERPARAMETERS

Hyperparameter	Explanation	Algorithm
n_estimators	Number of trees in the forest.	RF
max_features	Number of features to consider when looking for the best split.	RF
max_depth	Maximum depth of the tree.	RF
min_samples_split	Minimum number of samples required to split a node.	RF
min_samples_leaf	Minimum number of samples required to be at a leaf node.	RF
criterion	Function used to measure the quality of a split.	DT
units	Number of hidden units in the LSTM cell.	LSTM
activation	Activation function used in the LSTM cell.	LSTM
optimizer	Algorithm used to update the weights of the model.	LSTM
booster	Specifies which booster is used.	XGB
fit_intercept	Whether to calculate the intercept for the model. If set to False, no intercept is used in the calculation.	LR
positive	When set to True, forces the coefficients to be positive.	LR

The model with the lowest RMSE was integrated into the simulation module of the dashboard for scenario-specific prediction. The system displays the projected forest state across the five structural indicators for 30 years ahead, reported at five-year intervals, so that the user can judge the implications of the

simulated management strategy (Fig. 5). By comparing projected outcomes across harvesting alternatives, the system enables managers to evaluate systematically the ecological consequences of different stand prescriptions.

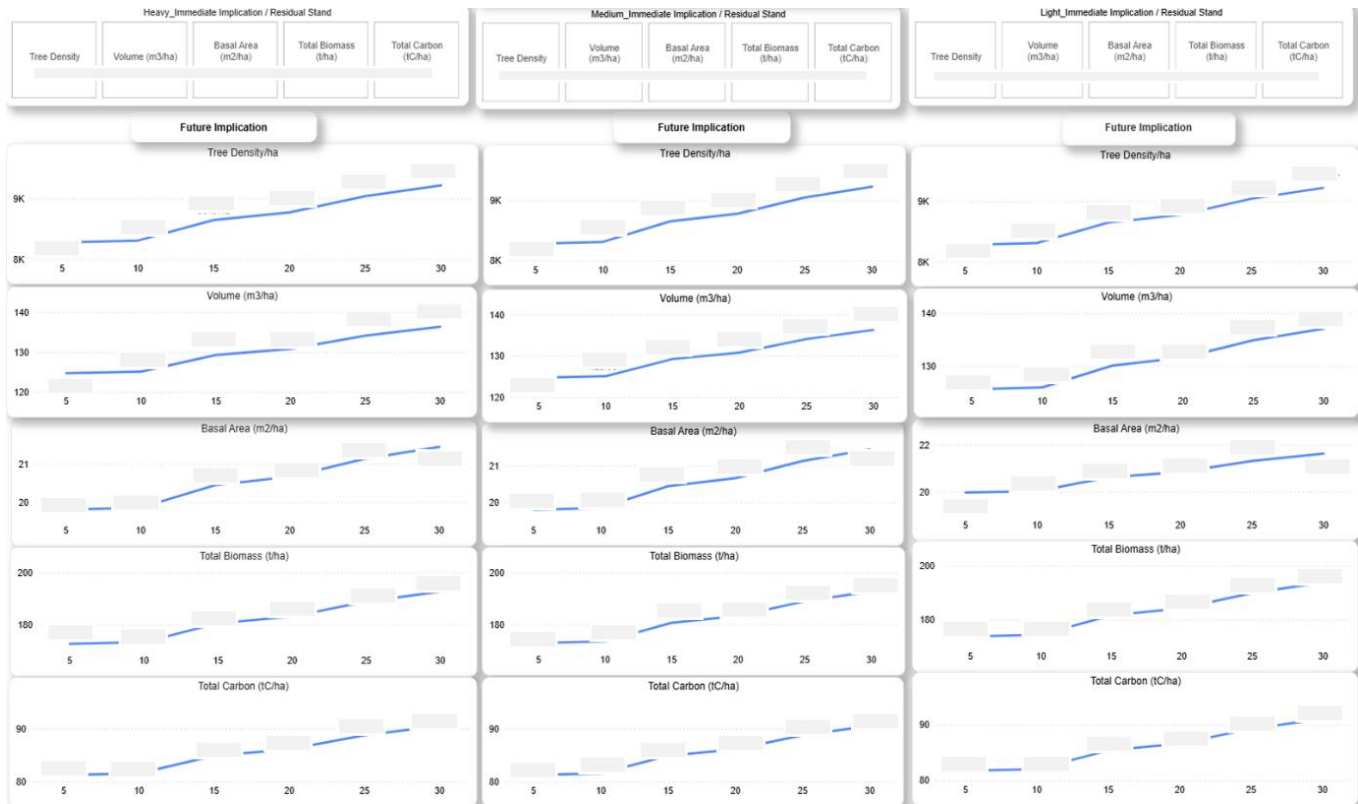


Fig. 5. Example of immediate and future forest state.

E. Experimental Design for Feature Ablation

To identify the most suitable model for predicting tree diameter growth, the five algorithms were compared across four feature ablation designs, using RMSE, MAE, and the coefficient of determination as evaluation criteria. RMSE is expected to exceed the corresponding MAE where outliers or extreme values are present in the data.

The experimental design shown in Table VIII evaluates the contribution of each predictor group to DBH prediction performance, beginning from the complete feature set in

experiment E1, which includes species identity, spatial attributes, historical DBH, and derived growth rates. Each subsequent experiment removes one group of predictors to measure its effect. Experiment E2 removes quadrant identity to assess whether coarse spatial grouping improves growth estimates. Experiment E3 removes the X and Y coordinates to evaluate the contribution of explicit spatial position. Experiment E4 removes the derived growth variables to evaluate the contribution of growth history. This design makes it possible to establish how far each predictor type contributes to the estimation of tree diameter growth.

TABLE VIII. FEATURE ABLATION EXPERIMENT DESIGN

Experiment	Features used	Analytical purpose
E1 (full model)	SPECIES, QUAD, XCO, YCO, DBH2013, DBH2015, DBH2017, DBH2019, GROWTH1315, GROWTH1517, GROWTH1719	Establishes the baseline prediction model using the complete feature set, incorporating species identity, spatial location, historical DBH measurements, and derived growth rates.
E2 (without quadrant grouping)	SPECIES, XCO, YCO, DBH2013, DBH2015, DBH2017, DBH2019, GROWTH1315, GROWTH1517, GROWTH1719	Examines the influence of quadrant-based spatial grouping by excluding the QUAD variable from the baseline configuration.
E3 (without spatial coordinates)	SPECIES, QUAD, DBH2013, DBH2015, DBH2017, DBH2019, GROWTH1315, GROWTH1517, GROWTH1719	Evaluates the contribution of explicit spatial coordinates (XCO and YCO) to DBH prediction performance.
E4 (without growth history variables)	SPECIES, QUAD, XCO, YCO, DBH2013, DBH2015, DBH2017, DBH2019	Investigates the importance of derived growth-rate variables by removing GROWTH1315, GROWTH1517, and GROWTH1719 from the baseline configuration.

For each of the four experiments, models were trained and independently cross-validated under two training and test split ratios to evaluate the stability of predictive performance under different training set sizes. Data splitting divides the data into

training and testing subsets used to fit and to evaluate the model respectively. In this study, two splits were applied: 70% training with 30% testing, and 80% training with 20% testing.

F. Harvesting Scenario Experiment

A separate experiment was carried out to establish what the stand prescription and simulation layer produces on a stand of operational size. The 50-hectare permanent plot was used, taking the most recent census as the baseline forest state. Candidate trees were identified by applying the SMS cutting limits of 65 cm for Dipterocarp, 70 cm for Chengal, and 55 cm for the remaining commercial groups. Candidates were ranked by DBH and selected in descending order, and the five structural indicators were recomputed on the residual stand and expressed per hectare.

Two selection rules were compared. The first applies the three SMS regimes directly, capping the harvest at 12, 16, and 20 trees per hectare for the light, medium, and heavy prescriptions, respectively. The second retains the light, medium, and heavy labels but redefines their intensity as a proportion of the candidate pool, at 40, 70, and 100 per cent respectively, which allows the three prescriptions to be distinguished even where the absolute per-hectare caps cannot be reached. Logging damage was applied to residual trees lying within 10 m of a felled stem, at the class-dependent rates given in Table IV. A no-harvest control was included so that every scenario is compared against the unharvested baseline.

G. Evaluation Methodology

An A/B testing design was used to determine how dashboard design affects usability and the effectiveness of decision support. Two dashboards were developed and evaluated, referred to as DSS A and DSS B. Both were built on the same forest simulation and analytical framework but differ in how forest information and analytical capability are exposed to the user.

DSS A is a baseline dashboard designed around conventional forest management practice. It focuses on the traditional structural indicators used in forest assessment, such as stand condition and spatial information. Users can view the current condition of the forest by year and location and examine the structural indicators derived from DBH. DSS A also supports scenario analysis, allowing the user to evaluate the potential impact of harvesting based on manual tree selection, and presents results in a form that mirrors the analytical workflow of a traditional forest management decision process.

DSS B builds on the design of DSS A and adds analytical capabilities that further support decision making. In addition to

displaying current forest condition, DSS B integrates further ecological information and adds a forecasting module in which users can project the condition of the forest over a 30-year period. DSS B also supports both automatic and manual tree selection within the simulation module and evaluates the implications of each selection. The enhanced design is intended to give users a more thorough understanding of forest dynamics and to increase their ability to interpret management scenarios.

Both dashboards implement the same analytical framework developed in this study, comprising four components: assessment of forest condition, stand prescription through scenario-based harvesting simulation, projection of post-harvest growth, and visualisation of decision outcomes. The only difference between the two dashboards is the extent to which these components are exposed to the user. DSS A serves principally as a visualisation tool for the structural indicators produced by the forest condition assessment module, with manual tree selection used to construct harvesting scenarios. DSS B additionally exposes the forecasting and automatic simulation components, allowing stand prescription options to be evaluated through both manual and automated selection, with the resulting prescriptions passed to the growth projection module so that immediate and long-term effects are simulated. Because these additional components are present, DSS B operationalises the scenario simulation approach advocated in this study more fully than DSS A.

The A/B design therefore isolates the effect of increased analytical transparency and additional decision-support features on the usability and acceptance of the two dashboards, and on the ability of forest experts to interpret forest condition and evaluate management strategies.

Usability was assessed using the SUS. Twelve forest domain experts completed a SUS questionnaire after using both dashboards. The sample is small, which may limit the generalisability of the results; however, all participants were forestry experts affiliated with the Alliance for Precision Biodiversity under Akademi Sains Malaysia (ASM), which ensured that participants held domain knowledge directly relevant to the study. Participation was voluntary. All participants were informed of the purpose of the evaluation and of the intended use of their responses before taking part, no personally identifying information was collected, and all responses are reported in aggregate. Fig. 6 shows the current positions held by the participants.

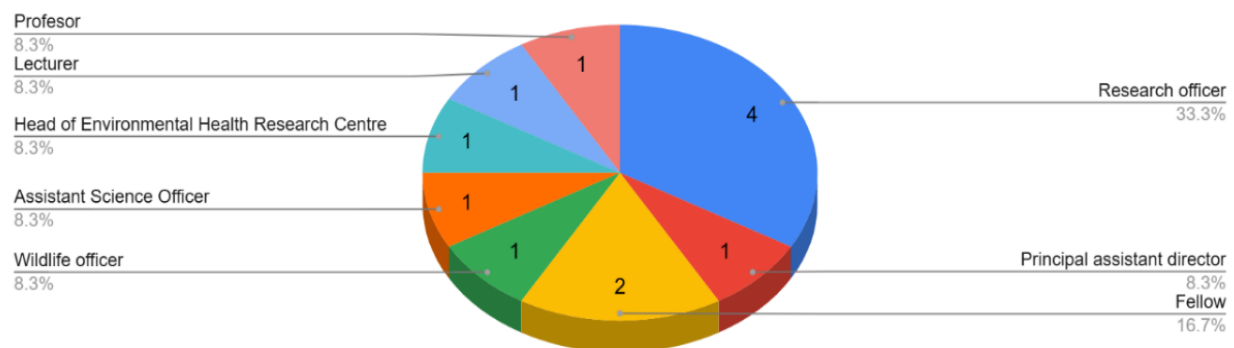


Fig. 6. Current positions of the evaluation participants.

SUS scores range from 0 to 100, with higher scores representing a more favourable perception of usability. Large-scale empirical studies report an average SUS score of 68 across software systems, which is accepted as the benchmark for interpreting usability [33]. Table IX lists the SUS items used, and Table X lists the comparative user evaluation items used for the A/B comparison of the two dashboards.

In addition to usability, the analytical value of each dashboard was assessed on three criteria: relevance, defined as the degree to which the analytical information supports forest management tasks; insightfulness, defined as the degree to which the dashboard provides meaningful knowledge about forest condition and dynamics; and importance, defined as the perceived weight of the analytical dimension for decision making.

TABLE IX. SYSTEM USABILITY SCALE ITEMS

No.	Question
Q1	I think that I would like to use this dashboard frequently.
Q2	I found the dashboard unnecessarily complex.
Q3	I thought the dashboard was easy to use.
Q4	I think that I would need the support of a technical person to be able to use this dashboard.
Q5	I found the various functions in this dashboard were well integrated.
Q6	I thought there was too much inconsistency in this dashboard.
Q7	I would imagine that most people would learn to use this dashboard very quickly.
Q8	I found the dashboard very cumbersome to use.
Q9	I felt very confident using the dashboard.
Q10	I needed to learn a lot of things before I could use this dashboard.

TABLE X. COMPARATIVE USER EVALUATION ITEMS FOR A/B TESTING OF THE DASHBOARDS

No.	Question
Q1	The dashboard in Round 2 is more relevant to the forest manager than the dashboard in Round 1.
Q2	The dashboard in Round 2 provides more insightful information than the dashboard in Round 1.
Q3	The dashboard in Round 2 presents information in a more useful way than the dashboard in Round 1.
Q4	The dashboard in Round 2 helps me understand forest structure better than the dashboard in Round 1.
Q5	The dashboard in Round 2 is easier to use than the dashboard in Round 1.
Q6	I prefer using the dashboard in Round 2 over the dashboard in Round 1.
Q7	The improvements made in the dashboard in Round 2 address the weaknesses in the dashboard in Round 1.
Q8	The changes in the dashboard in Round 2 positively enhanced the user experience.

IV. RESULTS AND DISCUSSION

A. Prediction Model Performance

Table XI reports RMSE, MAE, and the coefficient of determination obtained by each algorithm under its default

configuration, across the four ablation experiments and the two training and test splits. Table XII then reports the performance of the same algorithms after hyperparameter tuning. The two tables are therefore not directly comparable; the figures in Table XI establish an untuned reference point, while those in Table XII reflect the configurations selected for deployment.

TABLE XI. PREDICTION PERFORMANCE ACROSS ABLATION EXPERIMENTS AND TRAINING TEST SPLITS

Exp.	Features	Algorithm	70/30 split			80/20 split		
			RMSE	MAE	R ²	RMSE	MAE	R ²
1	SPECIES, QUAD, XCO, YCO, DBH2013, DBH2015, DBH2017, DBH2019, GROWTH1315, GROWTH1517, GROWTH1719	RF	2.159	0.845	0.982	1.647	0.733	0.989
		DT	2.608	1.103	0.974	2.616	0.982	0.972

Exp.	Features	Algorithm	70/30 split			80/20 split		
			RMSE	MAE	R ²	RMSE	MAE	R ²
2	SPECIES, XCO, YCO, DBH2013, DBH2015, DBH2017, DBH2019, GROWTH1315, GROWTH1517, GROWTH1719	LSTM	1.675	1.068	0.989	1.777	1.011	0.988
		XGB	2.363	1.010	0.978	1.925	0.882	0.985
		LR	1.267	0.631	0.994	1.381	0.627	0.992
		RF	2.140	0.842	0.982	1.689	0.733	0.988
		DT	2.484	1.035	0.976	2.766	1.010	0.969
3	SPECIES, QUAD, DBH2013, DBH2015, DBH2017, DBH2019, GROWTH1315, GROWTH1517, GROWTH1719	LSTM	1.733	1.048	0.988	1.727	0.979	0.988
		XGB	2.361	1.003	0.978	1.932	0.882	0.985
		LR	1.269	0.634	0.994	1.380	0.628	0.992
		RF	2.072	0.826	0.983	1.690	0.720	0.988
		DT	2.398	1.061	0.978	2.753	1.044	0.969
4	SPECIES, QUAD, XCO, YCO, DBH2013, DBH2015, DBH2017, DBH2019	LSTM	1.668	1.069	0.989	1.717	1.019	0.988
		XGB	2.348	1.005	0.979	1.969	0.914	0.984
		LR	1.267	0.631	0.994	1.381	0.628	0.992
		RF	2.163	0.859	0.982	1.643	0.729	0.989
		DT	2.510	1.076	0.976	2.835	1.117	0.967

Table XII reports the best hyperparameter configuration identified by GridSearchCV for each algorithm and experiment, together with the RMSE achieved by that configuration on the 70/30 split. Linear regression obtained the lowest RMSE in every experimental setup, indicating the highest predictive accuracy among the algorithms tested. In the baseline configuration (experiment 1), tuning reduced the RMSE of LR

from 1.267 cm to 0.988 cm using the full predictor set of species, spatial attributes, historical DBH, and derived growth variables, compared with 1.334 for LSTM, 1.381 for XGB, 1.660 for RF, and 2.283 for DT. Tuning improved LSTM, XGB, and RF relative to their default configurations as well, but did not change the ordering of the algorithms.

TABLE XII. BEST HYPERPARAMETER CONFIGURATION AND CORRESPONDING RMSE

Experiment	Algorithm	Best hyperparameters	RMSE
1	RF	{'n_estimators': 400, 'min_samples_split': 2, 'min_samples_leaf': 2, 'max_features': 'auto', 'max_depth': None}	1.660
	DT	{'criterion': 'friedman_mse'}	2.283
	LSTM	{'units': 64, 'activation': 'relu', 'optimizer': 'sgd'}	1.334
	XGB	{'booster': 'gblinear', 'nthread': 8, 'verbosity': 2}	1.381
	LR	{'copy_X': True, 'fit_intercept': True, 'n_jobs': 1, 'positive': True}	0.988
2	RF	{'n_estimators': 200, 'min_samples_split': 5, 'min_samples_leaf': 1, 'max_features': 'auto', 'max_depth': None}	1.880
	DT	{'criterion': 'friedman_mse'}	1.927
	LSTM	{'units': 128, 'activation': 'tanh', 'optimizer': 'adam'}	1.523
	XGB	{'booster': 'gbtree', 'nthread': 4, 'verbosity': 1}	1.395
	LR	{'copy_X': True, 'fit_intercept': True, 'n_jobs': 1, 'positive': True}	0.989
3	RF	{'n_estimators': 500, 'min_samples_split': 10, 'min_samples_leaf': 4, 'max_features': 'auto', 'max_depth': None}	1.821
	DT	{'criterion': 'friedman_mse'}	1.949

Experiment	Algorithm	Best hyperparameters	RMSE
	LSTM	{'units': 32, 'activation': 'relu', 'optimizer': 'rmsprop'}	1.421
	XGB	{'booster': 'dart', 'nthread': 8, 'verbosity': 2}	1.402
	LR	{'copy_X': True, 'fit_intercept': True, 'n_jobs': 1, 'positive': True}	0.989
4	RF	{'n_estimators': 300, 'min_samples_split': 2, 'min_samples_leaf': 2, 'max_features': 'auto', 'max_depth': None}	1.682
	DT	{'criterion': 'friedman_mse'}	2.088
	LSTM	{'units': 64, 'activation': 'tanh', 'optimizer': 'sgd'}	1.778
	XGB	{'booster': 'gblinear', 'nthread': 4, 'verbosity': 1}	1.388
	LR	{'copy_X': True, 'fit_intercept': True, 'n_jobs': 1, 'positive': True}	0.989

These results suggest that a linear or near-linear relationship exists between past DBH measurements and future growth in this dataset, so that future tree growth is represented adequately by a simple regression model. More complex models such as RF or LSTM did not improve accuracy on this data.

The ablation study quantifies the contribution of each predictor group, and the pattern differs sharply between model families. For the tree-based and recurrent models, removing the derived growth variables (experiment 4) produced the largest deterioration, with LSTM rising from 1.675 to 2.381 and DT from 2.398 to 2.510 on the 70/30 split; this indicates that these models draw substantially on the temporal dynamics of growth from prior census periods. Spatial information contributed more modestly: removing quadrant grouping (experiment 2) or the explicit coordinates (experiment 3) changed RMSE by less than 0.1 for most models, and in the case of RF the error fell slightly when the coordinates were removed, which is consistent with the coordinates acting partly as noise at this plot scale.

Linear regression behaves differently and the difference is material, because LR is the model deployed in the DSS. Its error is effectively invariant across the four experiments, at 1.267, 1.269, 1.267, and 1.267 on the 70/30 split, and 0.988, 0.989, 0.989, and 0.989 after tuning. Removing the spatial variables, the quadrant grouping, or the entire growth-history block leaves the fitted model essentially unchanged. The implication is that the linear model draws almost all its predictive signal from the most recent diameter observation, and that the remaining predictor groups add little once that observation is present. This is consistent with the strong serial dependence between successive DBH measurements of the same stem over a two-year census interval, and it means that the ablation evidence for the importance of growth history applies to the tree-based and recurrent models rather than to the model selected for deployment.

Overall, historical DBH is the dominant source of predictive information, with derived growth history contributing materially for the tree-based and recurrent models and spatial attributes contributing marginally. The LR model configured as in experiment 1 was selected as the DBH prediction module of the DSS, since it produced the lowest RMSE after hyperparameter tuning and is fast and transparent enough for interactive use. Within the simulation module this model projects post-harvest stand development, and the predicted DBH is used to update forest metrics such as basal area, biomass, volume, and carbon

stock, giving the DSS the capacity to simulate the long-term consequences of alternative harvesting strategies.

Because successive diameter measurements of the same stem are strongly serially dependent, accuracy on absolute DBH is not by itself evidence that growth has been modelled. To quantify this, the models were re-estimated on the 50-hectare plot, predicting diameter at the most recent census from the five preceding censuses, and benchmarked against a persistence rule that predicts no change in diameter. The persistence rule alone attains an RMSE of 1.124 cm and a coefficient of determination of 0.974 on the absolute scale, while linear regression attains 0.952 cm and 0.981. The margin by which the fitted model improves on doing nothing is therefore approximately 15% in RMSE. Evaluated on the increment scale, which is the quantity the simulation layer propagates, LR attains a coefficient of determination of 0.174 and RF 0.180. These values are consistent with the difficulty of predicting individual-tree diameter increment in a species-rich tropical stand, and they indicate that the high coefficients of determination in Table XI and Table XII should be read as measures of fit to absolute diameter rather than as explained growth variation.

B. Harvesting Scenario Analysis

Applying the SMS cutting limits to the baseline stand yields a candidate pool of 10.2 stems per hectare. This density falls below the cap of the lightest prescribed regime, which permits 12 trees per hectare. The consequence is that the light, medium, and heavy prescriptions all select the entire candidate pool and therefore produce identical residual stands. In a stand of this condition the regime caps are not binding, and the operative constraint on harvest planning is the availability of stems above the cutting limits rather than the prescription itself. This is a substantive finding rather than a limitation of the simulation: a prescription framework calibrated for production forest does not discriminate between strategies when applied to a stand whose commercial stock has not recovered to that level, and a decision support system that reports only the regime label would conceal this from the user.

To obtain scenarios that do differ, harvest intensity was expressed as a proportion of the candidate pool. Table XIII reports the residual stand condition under the no-harvest control and under the light, medium, and heavy prescriptions, with intensity defined as a proportion of the candidate pool.

TABLE XIII. PROJECTED STAND CONDITION UNDER ALTERNATIVE
HARVEST INTENSITIES

Scenario	Trees/ha	Basal area (m ² /ha)	Volume (m ³ /ha)	Biomass (t/ha)	Carbon (tC/ha)	Harvested volume (m ³ /ha)
No harvest (control)	4911	31.32	142.4	426.6	200.5	0.00
Light (40% of pool)	4677	26.86	96.9	335.0	157.5	42.13
Medium (70% of pool)	4490	24.55	81.1	295.3	138.8	53.98
Heavy (100% of pool)	4316	22.98	72.5	271.0	127.4	60.83

Expressed relative to the unharvested control, residual basal area falls by 14.2%, 21.6%, and 26.6% under the light, medium, and heavy prescriptions respectively; standing volume by 32.0%, 43.1%, and 49.1%, and biomass and carbon stock by 21.5%, 30.8%, and 36.5%. Harvested volume rises from 42.13 to 60.83 m³ per hectare over the same range. The reduction in residual stock is consistently larger than the harvested volume alone accounts for, because collateral damage to residual stems contributes an appreciable share of the loss; this is the trade-off that the dashboard is intended to make visible at the point of tree selection, and it is not apparent from the harvested volume that a conventional prescription would report.

Two qualifications apply to these figures. The damage model assigns exposure to residual stems within 10 m of a felled tree, which is an assumption adopted for this experiment rather

than a calibrated felling-gap model, so the absolute magnitude of the damage component should be treated as indicative. The indicators are also computed on the immediate post-harvest state and do not yet incorporate the growth projection, so they describe the instantaneous cost of each strategy rather than its long-term trajectory.

C. Usability Evaluation

The usability of DSS B, reported in Table XV, reached an average SUS score of 69.17, compared with 61.88 for DSS A in Table XIV. The score for DSS B exceeds the accepted benchmark of 68, indicating an improvement in usability relative to DSS A. The score for DSS A corresponds to an adjective rating of "OK", suggesting that the functionality is present but that moderate usability problems remain. The redesigned interface and expanded analytical capability of DSS B raised the rating to "Good".

For DSS A, the average rating on the ease-of-use item (Q3) was 3.92 on a five-point scale, with 67% positive responses, suggesting that the system is usable but not highly intuitive. Some respondents reported that they would need technical assistance to operate the dashboard (Q4) and that additional training would be required to use it effectively (Q10). For DSS B, the ease-of-use rating rose to 4.08 with 83% positive responses, a clear improvement. Respondents reported better integration between functions, easier learning, and greater confidence in using the dashboard, although a few indicated that further learning would still be needed to exploit the analytical features fully.

TABLE XIV. SYSTEM USABILITY SCALE RESPONSES FOR DSS A

Respondent	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10	SUS raw score	SUS final score
1	3	4	3	4	3	3	4	3	3	4	18	45
2	4	2	3	3	4	3	4	2	4	2	27	67.5
3	3	1	5	2	5	1	5	1	5	3	35	87.5
4	4	2	5	1	5	4	4	1	4	3	31	77.5
5	4	2	4	3	5	2	3	2	4	4	27	67.5
6	3	3	3	4	3	3	4	3	3	4	19	47.5
7	4	4	4	2	4	2	4	2	4	2	28	70
8	4	3	4	4	4	2	4	3	4	4	24	60
9	5	4	5	3	5	3	4	2	3	5	25	62.5
10	5	5	4	4	5	3	4	3	4	3	24	60
11	3	3	4	4	2	3	4	3	3	2	21	52.5
12	4	4	3	4	2	4	4	3	4	4	18	45
Mean SUS score												61.88
Adjective rating												OK

TABLE XV. SYSTEM USABILITY SCALE RESPONSES FOR DSS B

Respondent	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10	SUS raw score	SUS final score
1	4	3	4	3	4	2	4	2	4	3	27	67.5
2	5	1	5	1	4	2	5	2	5	2	36	90
3	5	5	5	2	5	3	5	3	5	3	29	72.5
4	5	1	4	4	5	2	5	2	4	4	30	75
5	3	3	4	2	4	3	4	2	4	2	27	67.5
6	3	1	4	2	4	1	4	1	3	3	30	75
7	3	3	3	3	3	3	3	3	3	3	20	50
8	4	3	3	4	3	2	3	2	3	4	21	52.5
9	5	4	4	2	4	2	4	2	4	1	30	75
10	4	4	4	1	3	4	4	3	4	1	26	65
11	5	2	4	3	2	4	4	3	5	3	25	62.5
12	5	3	5	3	5	2	5	3	5	3	31	77.5
Mean SUS score											69.17	
Adjective rating											Good	

The evaluation reported here is formative. All twelve respondents used DSS A before DSS B, so interface design is confounded with order of exposure; DSS B is a superset of DSS A rather than an independent alternative; and the comparative items in Table X are worded in a single direction, which may have encouraged agreement. The results below should therefore be read as indicating where the design merits further testing, not as establishing that one interface supports decisions better than the other. A paired-sample t-test was conducted using the SUS scores of the same twelve respondents. The scores were 61.88 (SD = 13.15) for DSS A and 69.17 (SD = 10.99) for DSS B. The difference was not statistically significant at the 0.05 level, $t(11) = 1.49$, $p = 0.164$. The effect size, however, was moderate

(Cohen's $d = 0.43$), indicating a practically meaningful improvement in user experience despite the small sample.

D. Insightfulness and Analytical Value

Beyond ease of interaction, a DSS must be assessed on whether it provides adequate analytical insight to support management intervention decisions. A dashboard needs not only to display structural indicators but also to provide a basis for interpreting ecological patterns, spatial relationships, and management scenarios. Each analytical function was therefore rated on relevance, insightfulness, and importance. Table XVI reports the results.

TABLE XVI. EXPERT RATINGS OF THE ANALYTICAL FUNCTIONS OF BOTH DASHBOARDS

Analytical function	Relevance		Insightfulness		Importance	
	DSS A	DSS B	DSS A	DSS B	DSS A	DSS B
Monitoring forest inventory	4.42	4.50	4.42	4.58	4.58	4.58
Forest structure analysis	4.58	4.50	4.58	4.50	4.58	4.67
Species-specific analysis	4.58	4.58	4.67	4.58	4.67	4.58
Estimation of forest indicators	4.67	4.58	4.67	4.58	4.67	4.75
Spatial exploration	4.50	4.58	4.42	4.67	4.50	4.67
Simulation / scenario analysis	4.67	4.50	4.67	4.58	4.67	4.58
Overall average	4.55	4.52	4.55	4.57	4.60	4.60

The results in Table XVI and Fig. 7 indicate that both dashboards deliver high analytical value, with every evaluation dimension achieving an average above 4.5 on a five-point scale. This suggests that the analytical modules implemented in the system align closely with the needs of forest management and biodiversity monitoring.

The estimation and simulation modules received some of the highest ratings across both dashboards, showing that respondents placed considerable value on the ability to assess key indicators of forest structure and to use simulation to inform management decisions. Species-specific analysis was also rated highly in both dashboards, indicating that users regarded species-level data as critical for managing forests in a way that

supports biodiversity, since such data allow the ecological continuity of a proposed harvest to be evaluated.

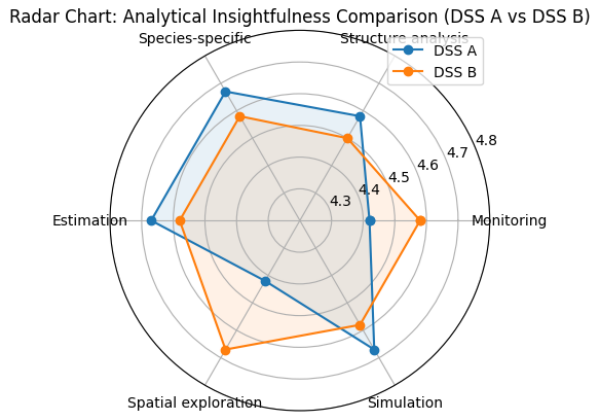


Fig. 7. Radar chart comparing perceived analytical insightfulness between DSS A and DSS B.

The two dashboards differ in where their analytical strengths lie. In DSS A, monitoring and spatial exploration received somewhat lower insightfulness ratings than the other modules;

although the underlying forest data were considered usable, users had to interpret relationships between separate views manually rather than being supported directly by the system. In DSS B, by contrast, spatial exploration attained one of the highest insightfulness ratings (4.67 out of 5), indicating that improved visualisation of patterns across the landscape helped users comprehend the distribution of forest attributes. Estimation of forest indicators was rated highest on importance (4.75 out of 5), indicating that examining the relationships between structural indicators assists users in evaluating management options.

Taken together, the enhancements in DSS B to spatial analysis, relationship analysis, and scenario simulation support the identification of alternative management options and make the immediate and long-term consequences of those options easier to visualise.

E. User Acceptance

To evaluate the perceived analytical value of DSS B further, respondents were asked to compare DSS B directly with DSS A using the items listed in Table X. The responses are reported in Table XVII.

TABLE XVII. USER ACCEPTANCE OF THE ANALYTICAL IMPROVEMENTS IN DSS B

Item	Respondent												Mean	Positive (%)
	1	2	3	4	5	6	7	8	9	10	11	12		
Q1	3	5	5	4	4	5	4	4	4	4	4	5	4.25	92
Q2	5	5	5	4	4	5	5	4	5	5	5	5	4.75	100
Q3	5	4	5	4	4	5	4	4	4	5	4	5	4.42	100
Q4	5	5	5	4	4	5	4	4	4	5	4	5	4.50	100
Q5	5	5	5	4	3	5	4	3	2	5	3	5	4.08	67
Q6	5	5	5	5	3	5	5	3	4	5	5	5	4.58	83
Q7	5	4	5	3	4	5	4	3	2	5	4	5	4.08	75
Q8	5	5	5	4	4	5	5	3	4	5	5	5	4.58	92

The results in Table XVII show a high level of consensus among participants that DSS B offers greater analytical insight than DSS A. On several items every respondent agreed that DSS B produced a greater level of analytical insight, indicating that the enhancements generate greater perceived value as a decision-making tool. To examine the difference in analytical insightfulness further, a paired t-test was conducted on the module-level insightfulness scores. The mean difference between DSS B and DSS A was 0.01, with $t = 0.159$ and an effect size of Cohen's $d = 0.065$.

The difference between the two dashboards on this measure is therefore small and not statistically significant, which is unsurprising given that both were built on the same underlying analytical framework. The limited statistical support reflects both the small sample size and the expert-driven nature of the study. Nonetheless, the slightly higher mean for DSS B suggests that the improved interface and tighter analytical integration

enhanced the perceived interpretability of the analytical output even though the underlying models were identical.

F. Discussion

The LR model from experiment 1 was adopted as the DBH prediction component because it achieved the lowest RMSE (0.988 cm) after hyperparameter tuning. That a simple regression model outperformed ensemble and recurrent alternatives is itself informative: within a permanent plot monitored at regular intervals, successive diameter measurements of the same stem are strongly serially dependent, and the mapping from recent diameter to next-census diameter is close to linear. The practical consequence is a prediction module that is fast enough for interactive use and transparent enough for practitioners to interrogate, both of which matter for a system whose purpose is to support rather than replace expert judgement.

This same property qualifies how the accuracy figures should be read. Because the target is absolute diameter at the next census rather than the diameter increment, and because increments over a two-year interval in this stand are small relative to stem diameter, a substantial part of the reported accuracy reflects the persistence of diameter between censuses rather than the modelling of growth as such. The coefficient of determination of 0.994 should therefore not be interpreted as evidence that 99% of growth variation is explained. A more informative benchmark is the error of a persistence rule that predicts no change in diameter between censuses, and the value of the model lies in the margin by which it improves on that rule. Reporting this margin, and refitting the models to predict the increment directly, would place the prediction module on firmer ground; both are addressed in Section V.

The usability evaluation revealed clear differences between the two dashboard designs and demonstrates how important iterative, user-focused development is for a forestry DSS. The SUS score of 61.88 obtained by DSS A indicates a system that works but leaves room for improvement; participants identified problems related to overall complexity and to the need for technical support, which are common in analytical dashboards that combine rich visualisation with decision-support functionality. Exposing the forecasting and automatic simulation components in DSS B raised the SUS score to 69.17, above the accepted benchmark for analytical dashboards. Notably, adding analytical capability did not reduce usability, which is the outcome a human-centred design would predict when additional capability is introduced through a clearer interface.

The acceptance results support this interpretation. Participants rated the enhanced dashboard as more relevant, more insightful, and more helpful for understanding forest structure and biodiversity data. Since both dashboards share the same analytical framework, the difference is attributable to how the analytical capability is surfaced rather than to the models themselves; this reinforces the argument that interface design is a substantive component of decision support, not a presentational afterthought. Taken together, the findings show that an interactive DSS can convert complex forest inventory data into representations that allow users to assess biodiversity patterns, understand how forest ecosystems respond to intervention, and ground management decisions in evidence.

V. CONCLUSION AND FUTURE WORK

This study presented a human-guided decision support system that couples DBH growth prediction with scenario simulation for selective harvesting and an interactive multi-criteria dashboard for tropical forest management. Four contributions were reported. First, the simulation framework projects the consequences of a stand prescription across five structural indicators, and residual basal area, volume, biomass, and carbon were reported for a no-harvest control and three harvest intensities on a 50-hectare permanent plot. Second, the candidate pool meeting the SMS cutting limits was found to be 10.2 stems per hectare, below the lightest prescribed regime of 12 trees per hectare, so that the regime caps do not discriminate in a stand of this condition and harvest intensity must be expressed relative to the available pool; recognising this

constraint is necessary for the prescription layer to behave meaningfully outside production forest. Third, the prediction module was benchmarked through a feature ablation study and against a persistence baseline, which showed that accuracy on absolute diameter substantially overstates the modelling of growth and that increment-scale performance is the appropriate measure. Fourth, a formative evaluation with twelve forest management professionals found a higher mean usability score for the interface that exposes the simulation and forecasting components (SUS 69.17 against 61.88), although the difference did not reach significance and the analytical value ratings were indistinguishable. A counterbalanced, task-based study is in progress to test whether the difference holds under a design that separates interface from order of exposure.

The results indicate that the system offers a workable basis for data-driven decision making in forest biodiversity monitoring, and that further refinement of dashboard usability and design would strengthen its contribution to forest management and biodiversity conservation. Throughout, the system is positioned as a means of extending practitioner expertise rather than replacing it: the manager retains control of the tree selection, and the system supplies the projected consequences of that selection.

Several limitations qualify these findings. The first concerns the formulation of the prediction task. Because the model predicts absolute diameter at the next census rather than the diameter increment, its reported error and coefficient of determination are inflated by the serial dependence between successive measurements of the same stem, and no persistence baseline was reported against which that inflation could be quantified. A second limitation is that the prediction cohort contains only stems alive in every census, so mortality and recruitment are absent from the model. Because the projections of biomass and carbon over 30 years are built by iterating that model, they implicitly assume that no tree dies and that no tree is recruited, which will bias the projected stocks upward. The inventory does record mortality, and the number of stems recorded as alive in the 50-hectare compartment falls from 44,000 at the first census to 26,941 at the sixth, so the magnitude of the omission is substantial. A third limitation follows from the training data: the prediction module was fitted on a 2-hectare plot of 1,944 stems dominated by trees in the 5-10 cm diameter classes, whereas the harvesting simulation operates on commercial-sized stems above the 55-70 cm cutting limits. The growth behaviour of large canopy trees is therefore extrapolated from a sample in which they are sparsely represented. A fourth limitation is that the 30-year projection is produced by iterating a model calibrated on two-year census intervals, so prediction error compounds across successive steps and the uncertainty of the later projection points is not quantified. A fifth limitation concerns the harvesting scenario experiment: the collateral damage component rests on an assumed 10 m exposure radius rather than a calibrated felling-gap model, and the reported indicators describe the immediate post-harvest state without the growth projection applied, so they quantify the instantaneous cost of each strategy rather than its recovery trajectory. A further limitation is the absence of back-testing against observed post-harvest data, and no uncertainty bounds are attached to the iterated trajectory, so the outcomes reported in Table XIII reflect

the assumed damage parameters as much as the fitted growth model. The five species groups are inherited from the SMS classification rather than derived, and the sensitivity of the results to alternative groupings has not been tested. The outcome set is also restricted to five structural indicators, so biodiversity and species composition, which the paper identifies as management objectives, are not among the quantities the simulation reports. The predictive component was evaluated with standard statistical performance measures, but the projected post-selection outcomes were not validated against independent observations of stand development after harvesting. The simulator output should therefore be interpreted as decision-support scenarios rather than as a validated long-term predictive model. In addition, the modelling architecture uses DBH as the basis for projecting growth and does not explicitly represent ecological processes such as mortality, recruitment, or inter-tree competition, all of which contribute to long-term forest dynamics. In its present form the system is a tool for data-informed decision making rather than an ecological simulator. The evaluation sample of twelve experts, although drawn from a relevant professional population, is small enough to limit the statistical power of the comparisons reported here. Finally, all participants used DSS A before DSS B, so dashboard design is confounded with order of exposure, and part of the observed improvement may reflect growing familiarity with the task; the comparative acceptance items were also phrased in a single direction, which may have encouraged agreement.

Future work will address these limitations in six directions. The first is to reformulate the prediction task in terms of the diameter increment and to report performance against a persistence baseline, so that the contribution of the model is separated from the contribution of diameter persistence, and to refit the models on the larger 50-hectare compartment so that commercial-sized stems are better represented. The second is to incorporate process-based components that represent mortality, recruitment, and competition explicitly, to improve the ecological realism of the projections and to attach uncertainty bounds to the iterated 30-year trajectories. The third is to back-test the projections against observed post-harvest census data, which would allow the reliability of the simulated trajectories to be quantified for real management applications. The fourth is to extend the expert evaluation to a larger and more varied group of practitioners under a counterbalanced design in which half the participants encounter each interface first, with neutrally worded instruments and task-based measures of decision quality in place of preference ratings; this study is in progress. The fifth is to model mortality and recruitment explicitly, so that projected biomass and carbon are not conditioned on the survival of every stem, and to back-test the projections against the later censuses already held so that the iterated trajectory can be given uncertainty bounds. The sixth is to replace the diameter ranking in the automatic prescription with formal multi-criteria optimisation over the structural indicators, and to extend the outcome set with a biodiversity measure such as a species diversity index computed on the residual stand, so that composition can be traded off against yield rather than reported separately.

DATA AND CODE AVAILABILITY

The forest inventory data used in this study were provided by the FRIM and are not redistributable by the authors; access may be requested directly from FRIM. The analysis scripts that implement the growth models, the persistence baseline, and the harvesting scenario experiment are available from the corresponding author on reasonable request. The dashboard is implemented in Power BI and depends on that platform; the underlying prescription, damage, and projection logic is specified in sufficient detail to be reimplemented independently.

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