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Machine learning forecasting of teak (*Tectona grandis* L.f.) growth parameters in Ghanaian plantations: a plot-level grouped-split analysis with ablation and sensitivity analysis

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Abstract

Ghana lacks a centralized, publicly archived permanent sample plot inventory for teak (*Tectona grandis* L.f.) plantations, which limits growth and yield models that use current field data. This constraint motivates model-extracted training data built from published allometric and site relationships, paired with machine learning, as a route to forecasting tools that can be updated once field inventory becomes available. This study built and tested a multilayer perceptron (GrowthMLP) that forecasts total height and stem volume of Ghana teak from stand, soil, and topographic covariates. Tree-level records ($n = 4,995$) were extracted using Ghana-calibrated allometric and yield relationships and merged with soil and topographic covariates from two published chronosequence studies. Several tree records were extracted for the same published plot and therefore share identical or near-identical stand and site covariates. To account for this, all data were split at plot level rather than at row level: every tree from a given plot was assigned to exactly one of training, validation, or test, guaranteeing zero shared plots across partitions. A 21-configuration ablation grid tested feature groups, network depth, dropout rate, normalization, and target set on this plot-level 70/15/15 split, training each configuration for up to 120 epochs. The selected model retained all 26 available predictors, used a three-hidden-layer network (512, 256, 128) with a dropout rate of 0.1, and reached a mean test R^2 of 0.903 and a mean test root mean squared error (RMSE) of 0.294 across height and volume. Stem volume reached a test R^2 of 0.991, while total height reached 0.816. Diameter at breast height, dominant height, and stand age ranked as the most influential individual predictors under permutation importance. Soil chemical properties as a group produced the largest swing in height error under coordinated perturbation, consistent with field evidence that soil fertility shapes teak growth. Removing the two soil feature groups reduced mean test R^2 to 0.898, a small but real cost once plot-level leakage was eliminated. A moderate multilayer perceptron can reproduce Ghana teak growth relationships from stand, soil, and site data with high fidelity for volume and reasonable fidelity for height, when evaluated on plots entirely unseen during training. Field permanent sample plot data remain the definitive next step for testing these forecasts outside the allometric relationships used to build them.

Keywords: multilayer perceptron, permutation importance, partial dependence, allometric modeling, soil fertility, neural network

1. Introduction

1.1 Background

Teak (*Tectona grandis* L.f.) is the most widely planted commercial hardwood species in Ghana. Large-scale planting began in the 1960s and expanded under the National Forest Plantation Development Programme (NFPDP), which established industrial monocultures and community woodlots on degraded

forest reserve and hilly land (Foli et al. 2018; Forestry Commission Ghana 2016). Ghanaian teak plantations now span several ecological zones, from the Guinea Savanna in the north (Nunifu 1997) to the Moist Semi-Deciduous zone of the Eastern Region (Kumi et al. 2022) and the Dry Semi-Deciduous and transition zones of the Bono Region (Asigbaase et al. 2024; Nero & Asuenabisa 2023; Guuroh et al. 2021). Similar plantation programmes exist across West Africa and beyond. Comparative evidence from Nigeria, Togo, Sierra Leone, Tanzania, Costa Rica, Panama, Nepal, Myanmar, and Mexico shows that teak growth and management outcomes respond strongly to spacing, thinning, provenance, fire history, and site quality (Zahabu et al. 2015; Tondjo et al. 2014; Kokutse et al. 2009; Kainyande et al. 2022; Pérez & Kanninen 2005; Derwisch et al. 2008; Koirala et al. 2017; Suzuki et al. 2004; Ruiz-Blandon et al. 2025).

Growth and yield modeling for Ghanaian teak has depended on a small number of stand-level studies. Nunifu (1997) fitted Chapman-Richards site-index curves and defined the site classes still used to describe Northern Region plantations. Kumi et al. (2022) and Asigbaase et al. (2024) linked soil chemical and physical properties, mediated by topographic position, to biomass and carbon stocks at plots in the Eastern and Bono regions. Watanabe et al. (2009), Hiratsuka et al. (2005), and Noda et al. (2021) reported comparable soil-growth relationships for teak in Ashanti Region and in Northeast Thailand, reinforcing that soil fertility and topographic position shape teak productivity across sites with contrasting rainfall and parent material. No centralized, field-measured permanent sample plot (PSP) archive currently covers Ghanaian teak, so growth models for the country still rely on published stand means, allometric equations, and site-index parameters rather than a shared raw inventory (Seppanen & Makinen 2020).

Machine learning offers a complementary route to growth and yield modeling when raw inventory is limited. Artificial neural networks (ANNs) have been applied to forest biometrics for over a decade, and reviews show consistent gains over classical regression for nonlinear, multivariate growth relationships (Chiarello et al. 2019). Multilayer perceptrons and related architectures have forecast tree height in mixed-species plantations (Soares et al. 2021), timber prices (Kozuch et al. 2023), individual-tree basal area increment (Cosmo et al. 2020), and agricultural yield from remote and field covariates (Lamos-Díaz et al. 2020). Machine learning has also supported natural resource policy analysis in community forest settings (Rana & Miller 2019), allometric modeling from UAV point clouds (Aguilar et al. 2022), and field-scale modeling of tree-crop interactions in agroforestry systems (Luedeling et al. 2016). These applications share a common structure. A moderate-depth network maps structured stand, site, and dendrometric covariates to one or more continuous growth outputs, and its behavior can be probed feature by feature rather than treated as a black box.

Growth is also governed by measurable site conditions. Sub-Saharan African allometric reviews link biomass to diameter, height, and wood density (Henry et al. 2011), and similar Sudan Savannah allometric models exist for Benin and for woodland vegetation outside plantations in Ghana (Chabi et al. 2016; Chabi et al. 2019; Aabeyir et al. 2020). Topography and soil chemistry structure teak growth within single Ghanaian sites (Kumi et al. 2021, 2022), and teak biomass in India shows a comparable dependence on site nutrient status (Bhoi 2009). A similar pattern appears in Thailand (Noda et al. 2021) and in comparative work on *Gmelina arborea* and *Terminalia superba*, common intercrop and substitute species in West and Central African plantations (Adekunle, Alo, & Adekayode 2011; Akhabue, Chima, & Eguakun 2020; Ambebe, Mendi, & Shidiki 2020; Ridder et al. 2010). Elevation, rainfall, and soil fertility gradients also structure carbon stocks and vegetation productivity more broadly across Ghana's savanna, cocoa, and transition zones (Bessah et al. 2016; Koranteng, Adu-Poku, & Zawila-Niedzwiecki 2017; Mensah 2015; Mohammed et al. 2020). Together, this evidence supports treating topography and climate as first-order predictors alongside stand age and diameter.

What is missing is a study that combines these two threads for Ghanaian teak. Such a study would train a machine learning model on stand, soil, and topographic covariates assembled from the country's published literature. It would test that model through a structured ablation grid that isolates which feature groups

actually improve forecast accuracy, and interrogate it with post-hoc sensitivity analysis rather than a single accuracy figure. The present study addresses that gap.

1.2 Aim, Objectives and Research Questions

The aim of this study was to build and evaluate a machine learning model that forecasts teak growth parameters in Ghanaian plantations from stand, soil, and topographic covariates, and to quantify the contribution of each feature group and predictor through ablation and sensitivity analysis.

The specific objectives were to:

1. Assemble a tree-level training dataset for Ghanaian teak from published stand-level statistics and Ghana-calibrated allometric and yield relationships, merged with site-level soil and topographic covariates.
2. Train and compare multilayer perceptron configurations across feature groups, network depth, dropout rate, normalization, and target set within a structured ablation grid.
3. Identify the predictors most associated with forecast accuracy for total height and stem volume using permutation importance, group perturbation, and partial dependence analysis.
4. Discuss the practical and methodological implications of the findings for teak growth monitoring in Ghana and identify the data gaps that should guide future field validation.

These objectives were addressed through four research questions:

RQ1: How accurately can a multilayer perceptron forecast teak total height and stem volume from stand, soil, and topographic covariates assembled from the Ghanaian literature?

RQ2: Which feature groups (soil chemical properties, soil physical properties, topography and climate, site class, stand context, and dendrometric state) contribute most to forecast accuracy?

RQ3: How do individual predictors, including stand age, diameter at breast height (DBH), dominant height, elevation, and stocking, shape predicted growth trajectories once the model is trained?

RQ4: What are the practical implications of these findings for growth and yield modeling of Ghanaian teak, and what data gaps limit their use pending field permanent sample plot validation?

2. Literature Review

2.1 Theoretical Framework

Forest growth and yield theory treats tree growth as a joint function of genetics, site quality, and stand density (Nunifu 1997; Pérez & Kanninen 2005). Site quality is commonly expressed through a site index derived from dominant height at a reference age, an approach Nunifu (1997) used to define site classes I, II, and III for Northern Ghana teak, and one that Seppanen and Makinen (2020) extended into a full yield model for Panama. Site quality itself depends on measurable soil and topographic conditions. Kumi et al. (2022) showed that valley, mid-slope, and summit positions differ in pH, nitrogen, exchangeable cations, and bulk density, and that these differences carry through to basal area and carbon stocks. Comparable soil-mediated growth differences appear in Northeast Thailand (Noda et al. 2021), the Ashanti Region of Ghana (Watanabe et al. 2009), and Nigeria (Ogundele 2015), which together support treating soil and topography as structural, not incidental, predictors of teak growth.

Stand density and management history add a second layer of variation. Spacing and thinning regimes change diameter, height, and wood properties in teak plantations in Tanzania (Zahabu et al. 2015), Togo (Tondjo et al. 2014; Kokutse et al. 2009), and Nicaragua (Haninec et al. 2017), while provenance shapes ring structure independently of site (Nocetti et al. 2011). Height-diameter and volume relationships are

themselves nonlinear and often fitted with Michaelis-Menten or Chapman-Richards functions (Koirala, Kizha, & Baral 2017; Kumi et al. 2022). Growth trajectories can also depart from simple age trends once water availability, functional group, or habitat position are taken into account (Nath et al. 2006; Kariuki et al. 2006; Chitra-Tarak et al. 2015; Röhl et al. 2021), and canopy-mediated water inputs such as stemflow further shape the water balance available to plantation-grown teak (Tanaka et al. 2017). Tree growth and mortality in species-rich tropical plantations respond to comparable drivers, and productivity can decline sharply once mean annual temperature passes a threshold during tropical reforestation (Nguyen et al. 2016; Nölte et al. 2023). Root architecture, litter dynamics, and nutrient accumulation studies in other tropical plantation systems reinforce this soil-growth link. This evidence spans Panama (Coll et al. 2008; Kerdraon et al. 2019), the Solomon Islands (Reverchon et al. 2015), Thai rubber plantations (Chairungsee et al. 2013), and the Central Himalaya (Pandey et al. 2023). Similar patterns hold for rubber plantations on contrasting soils (Perron et al. 2021) and for Chinese fir provenances (Wu et al. 2011). Allometric equations complete the theoretical chain by converting diameter, height, and wood density into biomass, carbon stock, and volume (Henry et al. 2011; Aabeyir et al. 2020), following the West African calibration used in this study, alongside comparable volume-taper models developed for Mexican teak plantations (Adu-Bredu & Birigazzi 2014; Tewari et al. 2013; Cairns et al. 1997; Urias et al. 2018).

Machine learning contributes a complementary, function-approximation perspective. A multilayer perceptron with at least one hidden layer and a nonlinear activation function can approximate a wide class of continuous functions (Goodfellow, Bengio, & Courville 2016). This makes it a reasonable candidate for the nonlinear, interacting relationships described above. Empirical applications in forest biometrics support this choice. ANNs have matched or outperformed classical regression for tree height estimation (Soares et al. 2021), timber price forecasting (Kozuch et al. 2023), and basal area increment modeling (Cosmo et al. 2020). Reviews of the field report consistent gains for structured, tabular growth data (Chiarello et al. 2019). Ablation and sensitivity analysis, drawn from random forest and gradient boosting practice (Breiman 2001; Friedman 2001), extend this approach by testing which feature groups a network actually needs, rather than assuming that more inputs are better. Combined, these two bodies of theory frame the present study as an exercise in data-scarce ecological modeling (Seppanen & Makinen 2020). Published, site-specific relationships stand in for a missing field inventory, and a moderate neural network is asked to recover the growth relationships those studies already describe. Ablation and sensitivity analysis then explain which of those relationships it actually relies on.

2.2 Conceptual Framework

Figure 1 sets out the conceptual framework used in this study. Six predictor groups, stand context, site class, topography and climate, soil chemical properties, soil physical properties, and dendrometric state, feed into a single GrowthMLP architecture. The network produces two primary outputs, total height and stem volume, and, in one ablation variant, four secondary outputs derived from the primary targets through allometric relationships: aboveground biomass, carbon stock, and mean annual increment (MAI) in DBH and height. An ablation grid systematically removes feature groups, changes network depth and dropout, and toggles normalization and target set, while a post-hoc sensitivity analysis (permutation importance, group perturbation, and partial dependence) traces each feature group's contribution back to the input side of the framework. This loop, from inputs, through the network, to outputs, and back through sensitivity analysis to feature-group contribution, structures the Results and Discussion sections that follow.

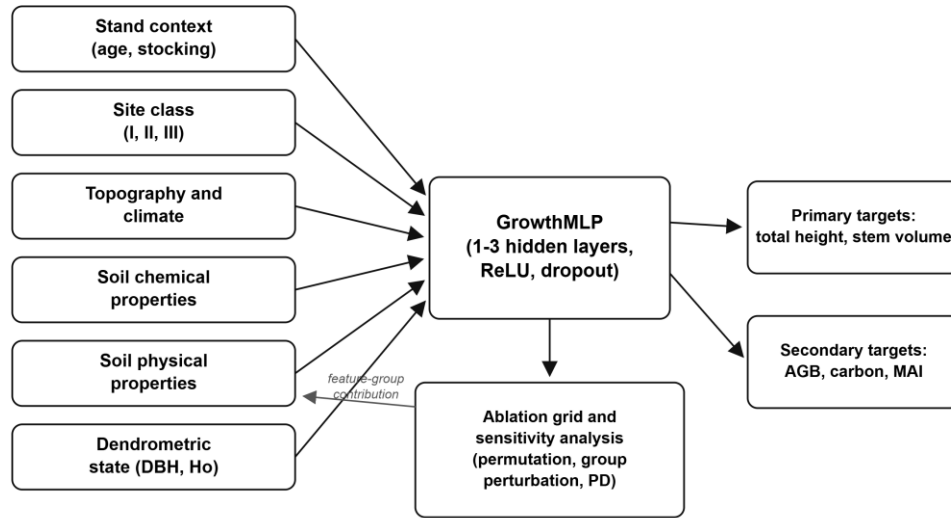


Figure 1. Conceptual framework linking predictor groups, the GrowthMLP architecture, primary and secondary growth outputs, and the ablation and sensitivity analysis used to trace feature-group contribution. Note: Note: MLP denotes multilayer perceptron, AGB denotes above-ground biomass, DBH denotes diameter at breast height, and MAI denotes mean annual increment.

3. Materials and Methods

3.1 Study Area

The study covered teak (*Tectona grandis* L.f.) plantation systems across the principal commercial planting regions of Ghana. Teak was introduced at scale from the 1960s and expanded under the National Forest Plantation Development Programme (NFPDP), which established industrial monocultures and community woodlots on degraded forest reserve and hilly land (Foli et al. 2018; Forestry Commission Ghana 2016). Plantations span multiple ecological zones. These include the Guinea Savanna of northern Ghana (Nunifu 1997), the Moist Semi-Deciduous forest of the Eastern Region (Kumi et al. 2022), and the Dry Semi-Deciduous and transition zones of the Bono Region, notably Tain II Forest Reserve and Pamu Berekum (Asigbaase et al. 2024; Nero & Asuenabisa 2023; Guuroh et al. 2021).

Representative sites included the Kwamoso-Saforo plantation block on the Akuapim Mountain Range (05°55'-05°57' N, 000°07'-000°08' W; elevation 184-313 m a.s.l.). It was established in 2010 under the NFPDP at 3 x 3 m spacing (Kumi et al. 2022). A second site was Form Ghana Limited and Forestry Commission-affiliated plantations in Tain II Forest Reserve (07°22'-07°41' N, 002°17'-002°27' W). These plantations sit on forest ochrosols and are managed at 3 x 3 m spacing, weeding, and thinning to approximately 550 stems per hectare (Asigbaase et al. 2024). A third site type was Northern Region community and industrial woodlots, sampled by Nunifu (1997) at 2 x 2 m spacing and classified into site classes I, II, and III by provisional site-index curves. Mean annual rainfall at the Eastern and Bono sites ranged from approximately 978-1,270 mm and 1,200 mm respectively, with mean temperatures of 24.8-27.7 degrees Celsius (Kumi et al. 2022; Asigbaase et al. 2024).

3.2 Data Sourcing and Preprocessing

3.2.1 Data Sources

No publicly archived permanent sample plot (PSP) inventory exists for Ghanaian teak in a standardized repository. Tree-level training records were therefore assembled from two complementary streams.

Published stand-level statistics were extracted from peer-reviewed Ghana studies, including stand means for diameter at breast height (DBH), total height, basal area, above- and below-ground biomass, and mean annual increment (MAI) from Kumi et al. (2022), Nero and Asuenabisa (2023), Guuroh et al. (2021), and Asigbaase et al. (2024). Site-index metadata and yield-model parameters were taken from Nunifu (1997).

Model-extracted tree-level records ($n = 4,995$, drawn from 3,645 distinct published plots) were constructed using Ghana-calibrated allometric and growth relationships, following established practice for data-scarce ecological modeling (Seppanen & Makinen 2020). DBH was drawn from Weibull-skewed distributions bounded by age- and site-class-specific maxima consistent with Nunifu (1997). Total height was estimated using the Michaelis-Menten height-DBH function, parameterized separately for valley, mid-slope, and summit positions (Kumi et al. 2022). Dominant height by stand age and site class followed Chapman-Richards guide curves from Nunifu (1997). Above-ground biomass (AGB) was computed with the species-specific UN-REDD+ equation for Ghana teak:

$$M = 0.0588 \times (\rho \times H \times D^2)^{0.9409} \text{ (Equation 1)}$$

where M is AGB in kilograms, D is DBH in centimeters, H is total height in meters, and $\rho = 0.63 \text{ g cm}^{-3}$ (Adu-Bredu & Birigazzi 2014). Stem volume over bark was estimated as:

$$V = 0.000046 \times D^{2.136615} \times H^{0.785557} \text{ (Equation 2)}$$

following Tewari et al. (2013), as applied in Ghanaian restoration assessments (Guuroh et al. 2021), alongside comparable volume-taper models developed for Mexican teak plantations (Urias et al. 2018). Carbon stock was derived as 47% of AGB (IPCC 2006), and below-ground biomass as 26% of AGB (Cairns et al. 1997). MAI in DBH and height were computed as the ratio of the respective variable to stand age.

Soil and topographic covariates were merged at site level from published chronosequence and elevation-gradient tables. Kumi et al. (2022) supplied elevation-zone means for pH, nitrogen, phosphorus, exchangeable cations, cation exchange capacity (CEC), soil organic carbon (SOC), texture, bulk density, and litter biomass across valley (194 m), mid-slope (249 m; slope 9.3-11.2 degrees), and summit (305 m) positions. Asigbaase et al. (2024) supplied stand-age-stratified soil chemical properties and soil fertility indices for Tain II teak chronosequences at 5, 10, 15, 20, and over 20 years. Soil profiles were assigned to individual tree records by elevation zone for the Eastern Region, or by nearest matching stand-age class for the Bono, Northern, and Western regions. Only eight distinct soil profiles (soil_site_id) exist across the full dataset, and, because a single published plot could contribute more than one simulated tree, many tree records inherit identical stand-age, site-class, rainfall, temperature, and dominant-height values from their parent plot. This structure directly motivates the plot-level split described in Section 3.6.1.

The final enriched dataset comprised 26 predictive features and six response variables per tree record, exported as comma-separated values for reproducibility.

3.2.2 Data Preprocessing

Site productivity class (I, II, III) was one-hot encoded. All continuous predictors were z-score standardized to zero mean and unit variance using training-set statistics (James et al. 2021). Predictor groups were defined a priori for ablation: stand context (age, stocking), site class, topography and climate, soil chemical properties, soil physical properties, and dendrometric state variables (dominant height, DBH). Primary modeling targets were total height (H , m) and stem volume (V , m^3). Secondary multi-output targets included AGB, carbon stock, and MAI in DBH and height. Pairwise correlations among all 26 predictors, including the concentrated correlation block within soil chemical variables and between the two dendrometric predictors, are reported in Supplementary Figure S1.

3.3 Missing Data Handling

Missing or non-numeric soil and topographic fields in the enriched matrix, arising where published tables did not report a given variable for every elevation zone or age class, were handled with a hierarchical imputation strategy. Region- and age-appropriate published profile means from Kumi et al. (2022) or Asigbaase et al. (2024) were assigned first. Where a specific field remained unreported, for example sand fraction in the Asigbaase chronosequence tables, ecologically informed defaults were applied: global dataset medians for texture and bulk density, and zone-level means for fertility indices. Empty strings and non-numeric tokens were coerced to numeric form before modeling, and records with zero or undefined DBH or height after generation were excluded at source. No tree-level record in the final dataset contained a null primary target. This approach favors transparency over completeness pending validation against field PSP data from Form Ghana Limited or the Forestry Commission of Ghana (Form Ghana 2024; Forestry Commission Ghana 2024).

3.4 Model Selection and Architecture

Given the tabular, multi-output regression task and the moderate sample size, a fully connected multilayer perceptron (MLP) was selected as the baseline deep learning architecture (Goodfellow et al. 2016). MLPs suit nonlinear mapping of structured silvicultural and edaphic covariates to growth responses, and they provide a tractable baseline against which feature-group contributions can be isolated (Olden et al. 2004; Chiarello et al. 2019).

The GrowthMLP architecture accepted an input layer with p features ($1 \leq p \leq 26$ depending on ablation). It used one to three hidden fully connected layers with rectified linear unit (ReLU) activation, dropout after each hidden layer, and a linear output layer producing k simultaneous responses ($k = 2$ for height and volume; $k = 6$ in the extended-target ablation). Implementation used PyTorch 2.x (Paszke et al. 2019). Recurrent or graph-based alternatives were not pursued because remeasurement time series were unavailable in the present dataset.

3.5 Hyperparameter Search Space

Hyperparameters were explored through a structured ablation grid rather than automated Bayesian optimization, to keep every configuration interpretable (Bergstra & Bengio 2012). Table 1 summarizes the search space executed for the 21-experiment grid reported in this study.

Table 1. Hyperparameter and ablation search space for the 21-experiment grid. Asterisk marks the baseline configuration; the selected best model departed from this baseline in architecture width only (Section 3.7).

Dimension	Values evaluated
Hidden layer widths	(64); (128, 64); (256, 128, 64)*; (512, 256, 128)
Dropout rate	0.0; 0.1*; 0.3; 0.5
Learning rate	1×10^{-3}
Weight decay (L2)	1×10^{-5}
Batch size	128
Maximum epochs	120
Early-stopping patience	20 epochs
LR scheduler	ReduceLROnPlateau (factor = 0.5, patience = 8)
Loss function	Smooth L1 (Huber)
Optimiser	AdamW (Loshchilov & Hutter 2019)
Feature normalisation	Enabled* / disabled
Target set	Height + volume* / all six outputs

273

274 Feature-group ablations removed, in separate experiments, all soil chemical variables, all soil physical
275 variables, both soil groups together, topography and climate, site-class indicators, stand context, and
276 dendrometric predictors. Two further experiments used restricted subsets built from stand context and
277 dendrometric predictors alone, one with age and DBH only and one with a four-feature minimal subset. A
278 final restricted subset kept every group except dendrometric predictors.

279 **3.6 Model Training, Validation, and Testing**

280 **3.6.1 Data Partitioning: Plot-Level Grouped Split**

281 Because several tree records were extracted for the same published plot, and because those records share
282 identical or near-identical stand, site, and topographic covariates (Section 3.2.1), a naive row-level split
283 risks assigning near-duplicate trees to both the training and test partitions. This would let a model achieve
284 high apparent accuracy by recognizing a specific plot's signature rather than by learning a generalizable
285 growth relationship, and it would understate the error a user should expect on a genuinely new site.

286 All partitioning in this study was, therefore, done at the plot level. Every tree record inherited its source
287 plot_id, and a two-stage grouped shuffle split assigned each of the 3,645 unique plots, and every tree on
288 that plot, to exactly one of training, validation, or test, targeting a 70/15/15 split by tree count. This produced
289 3,497 training trees (2,551 plots), 754 validation trees (547 plots), and 744 test trees (547 plots), with zero
290 plot_id shared across any two partitions, verified programmatically before every training run. The same
291 fixed group assignment (seed = 42) was used across all 21 ablation configurations, so every configuration
292 was trained and evaluated on an identical partition. Feature standardization statistics were computed on the
293 training partition only, and ablation feature masks were applied consistently across partitions.

294 **3.6.2 Training Procedure**

295 Models were trained by minimizing the Smooth L1 loss between predicted and observed target vectors
296 (Huber 1964), which reduces sensitivity to outliers relative to mean squared error. Mini-batch stochastic
297 gradient descent used a batch size of 128. Training ran for up to 120 epochs; the learning rate was reduced
298 by half when validation loss plateaued for eight consecutive epochs. Early stopping monitored validation
299 Smooth L1 loss with a patience of 20 epochs, and the parameter set with the lowest validation loss was
300 retained (Prechelt 1998).

301 **3.6.3 Ablation Experiments**

302 Twenty-one experiments were executed, spanning one full-feature baseline, seven feature-group ablations,
303 three restricted-subset variants, four architecture depth and width variants, three additional dropout rates,
304 one six-target multi-output variant, and one unnormalized-input variant. Each configuration was trained
305 independently from random initialization under the same plot-level data partition. Performance was
306 evaluated on all three partitions using root mean squared error (RMSE), mean absolute error (MAE),
307 coefficient of determination (R^2), and mean absolute percentage error (MAPE), computed per target and
308 averaged across targets.

309 **3.6.4 Sensitivity Analysis**

310 Three post-hoc sensitivity analyses were conducted on the held-out test set for the selected best model:

- 311 1. Permutation importance. Each input feature was shuffled five times independently, and the increase
312 in mean RMSE relative to unpermuted predictions was recorded (Breiman 2001).

2. Group perturbation sensitivity. Each predefined feature group was multiplied by plus or minus 10% simultaneously, to assess the directional response of height and volume predictions to coordinated stand-level or site-level shifts.
3. Partial dependence. For stand age, DBH, dominant height, elevation, soil pH, soil nitrogen, and stocking, each feature was swept across its observed range while other inputs remained at test-set values, and mean predicted height and volume were computed at each sweep point (Friedman 2001).

3.7 Selection and Fine-Tuning of the Best Model

The best model was selected from the 21-experiment ablation grid as the configuration achieving the highest mean test-set R^2 across the primary targets (total height and stem volume), with ties resolved by lower mean test RMSE. The selected configuration, labeled arch_512-256-128, retained all 26 available predictors and used a three-hidden-layer MLP with dimensions (512, 256, 128), a dropout rate of 0.1, z-score normalization enabled, and the two-target height-volume output head (test R^2 mean = 0.903; test RMSE mean = 0.294). Training stopped at epoch 98 of a maximum 120, with the best validation loss reached at epoch 78.

This configuration led a tightly clustered top group. The all-feature network with dropout set to 0.0 reached a test R^2 mean of 0.902, and dropping soil chemical variables alone reached 0.900. Six configurations, all retaining most or all input features, scored within 0.006 of the top result. This clustering indicates that once plot-level leakage is removed, architecture and dropout choices have a modest effect on accuracy relative to which feature groups are retained. Section 4.1 and Section 5.2 discuss this pattern together with the feature-group ablations, which showed a small but consistent accuracy cost from removing soil predictors.

Fine-tuning was limited to within-training early stopping. No additional post-selection hyperparameter search was performed on the test partition, to avoid optimistic bias (Cawley & Talbot 2010). The early-stopped validation-optimal weight checkpoint was saved and used for all subsequent sensitivity analyses and final test evaluation. When field PSP data become available from Form Ghana or the Forestry Commission of Ghana, the selected architecture and preprocessing pipeline should be retrained without modification to assess external validity.

3.8 Testing of the Best Model

Final inference was conducted exclusively on the held-out test subset (744 trees from 547 plots), none of which contributed any tree to training or validation. For each test tree, predicted and observed values of total height and stem volume were exported, and per-tree prediction errors were computed. Test-set RMSE, MAE, R^2 , and MAPE were reported separately for each target and as arithmetic means across targets. Permutation importance rankings, group-perturbation responses, and partial dependence curves were generated from the same test partition to characterize model behavior.

4. Results

4.1 Ablation Grid Overview

Table 2 reports mean test-set R^2 and RMSE for all 21 ablation experiments, evaluated on the plot-level held-out test set and ranked from best to worst. The widest network tested (512, 256, 128), keeping all 26 features, reached the highest mean test R^2 (0.903), narrowly ahead of the same-width all-feature network with dropout set to 0.0 (0.902) and the network that dropped soil chemical variables alone (0.900). The full-feature baseline (256, 128, 64 with dropout 0.1) reached a mean test R^2 of 0.878, held back mainly by stopping early at epoch 44. Dropping dendrometric predictors produced the lowest score among the feature-group ablations (0.826). Disabling input normalization caused the largest single drop in performance, to a

mean test R^2 of 0.274, confirming that z-score standardization was necessary for stable training given the mixed units across the 26 predictors.

Table 2. Test-set performance across the 21-experiment ablation grid, evaluated on the plot-level held-out test set and ranked by mean R^2 across total height and stem volume. RMSE is reported in the native units of each target and averaged across targets; the six-target row (target_all_outputs) mixes units across biomass, carbon, and MAI outputs, which inflates its mean RMSE relative to the two-target rows.

Rank	Experiment	Feature set	Hidden layers	Dropout	Test R^2 (mean)	Test RMSE (mean)
1	arch_512-256-128	All features (26)	512-256-128	0.1	0.903	0.294
2	dropout_0.0	All features (26)	256-128-64	0.0	0.902	0.288
3	abl_no_soil_chemical	Drop soil chemical (15 features)	256-128-64	0.1	0.900	0.300
4	abl_no_topography	Drop topography and climate (22 features)	256-128-64	0.1	0.899	0.301
5	abl_no_stand_context	Drop stand context (24 features)	256-128-64	0.1	0.899	0.301
6	abl_no_soil	Drop soil chemical + physical (11 features)	256-128-64	0.1	0.898	0.303
7	abl_no_soil_physical	Drop soil physical (22 features)	256-128-64	0.1	0.895	0.310
8	dropout_0.1	All features (26)	256-128-64	0.1	0.895	0.311
9	arch_64	All features (26)	64	0.1	0.892	0.309
10	abl_no_site_class	Drop site class (23 features)	256-128-64	0.1	0.889	0.322
11	arch_256-128-64	All features (26)	256-128-64	0.1	0.887	0.325
12	arch_128-64	All features (26)	128-64	0.1	0.886	0.325
13	baseline_full	All features (26), full-feature baseline	256-128-64	0.1	0.878	0.343

Rank	Experiment	Feature set	Hidden layers	Dropout	Test (mean) R ²	Test RMSE (mean)
14	abl_age_dbh_only	Age and DBH only (4 features)	256-128-64	0.1	0.851	0.359
15	abl_minimal	Stand context + dendrometric (4 features)	256-128-64	0.1	0.850	0.362
16	abl_soil_topography_only	Drop dendrometric predictors (24 features)	256-128-64	0.1	0.839	0.401
17	dropout_0.3	All features (26)	256-128-64	0.3	0.839	0.399
18	abl_no_dendrometric	Drop dendrometric (24 features)	256-128-64	0.1	0.826	0.417
19	dropout_0.5	All features (26)	256-128-64	0.5	0.747	0.501
20	target_all_outputs	All features, six-target multi-output head	256-128-64	0.1	0.605	6.065
21	no_normalization	All features, normalization disabled	256-128-64	0.1	0.274	0.836

4.2 Best Model Performance

The selected model reached a test R² of 0.816 and a test RMSE of 0.515 m for total height (Figure 2), with a mean absolute percentage error (MAPE) of 3.22%. For stem volume, the same model reached a test R² of 0.991, a test RMSE of 0.073 m³, and a MAPE of 25.86%. Training, validation, and test R² values stayed close for both targets (mean R²: 0.915 train, 0.915 validation, 0.903 test), which indicates limited overfitting at the selected configuration despite the wider network. First-hidden-layer activations for a subset of test-set trees under this configuration are visualized in Supplementary Figure S2.

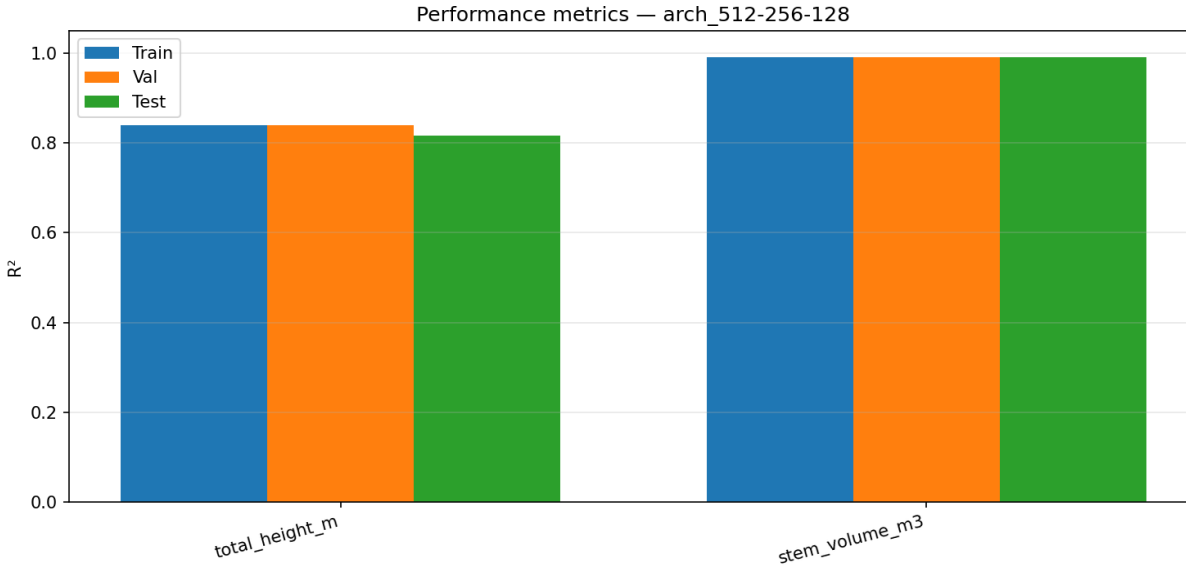


Figure 2. Train, validation, and test R^2 for total height and stem volume under the selected best configuration (arch_512-256-128).

Comparing the feature-group ablations in Table 2 clarifies which predictors carried genuine, non-redundant signal once plot-level leakage was removed. Dropping soil chemical variables alone cost the least among the soil-related ablations (mean test R^2 falling from 0.903 to 0.900), while dropping both soil groups together cost more (0.898), and dropping soil physical variables alone cost more still relative to their individual contribution (0.895). Every soil-related ablation still clustered within 0.008 of the top result, so soil predictors add a real but modest increment on top of stand context, site class, topography, and dendrometric state, rather than being either redundant or dominant.

4.3 Training and Validation Dynamics

Training and validation Smooth L1 loss declined together for the selected configuration, with the lowest validation loss reached at epoch 78 of a maximum 120, and training continuing to epoch 98 before the 20-epoch early-stopping patience triggered. The gap between training and validation loss stayed small across epochs (Figure 3), with validation loss tracking training loss closely throughout, consistent with the close train, validation, and test R^2 values reported above. Figure 4 shows the training versus validation R^2 across the leading ablation experiments. This indicates the modest and consistent train-validation gap across configurations. The generalization gap (validation loss minus training loss) across epochs and a log-scale view of the same training and validation loss curves are provided in Supplementary Figures S3 and S4, respectively, for closer inspection of convergence behavior.

Learning curves — arch_512-256-128

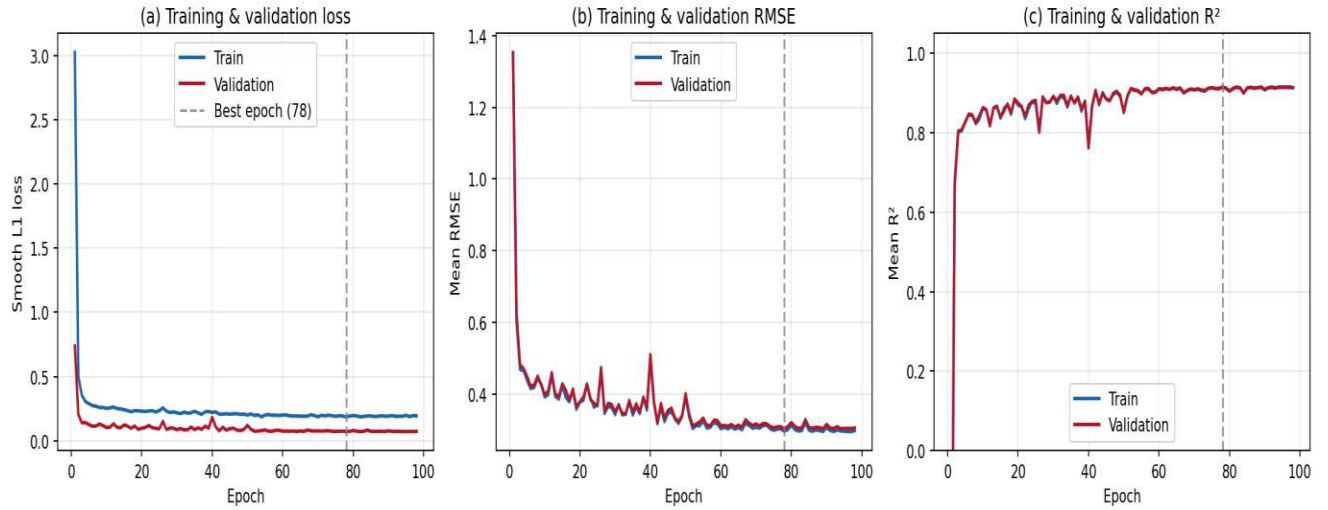


Figure 3. Training and validation Smooth L1 loss across epochs for the selected best configuration.

Ablation study: training vs validation performance

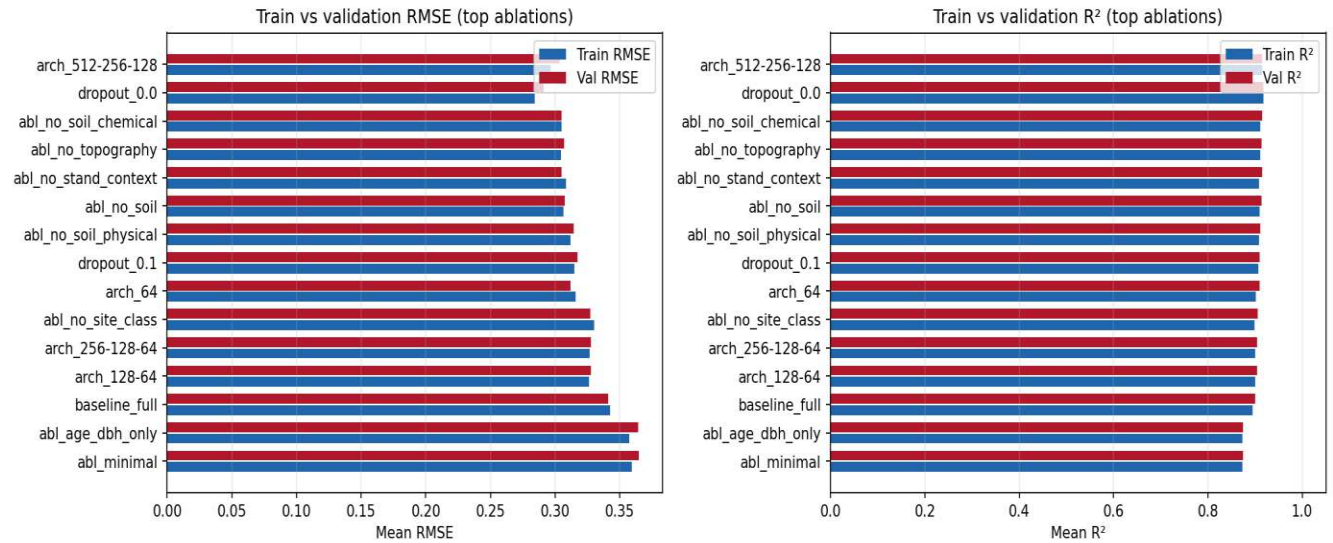


Figure 4. Training versus validation R^2 across the leading ablation experiments, illustrating the modest and consistent train-validation gap across configurations.

4.4 Prediction Accuracy by Growth Class

Binned confusion matrices, built from quintiles of the observed test-set distribution, show the pattern of error underlying the aggregate R^2 values (Figure 5).

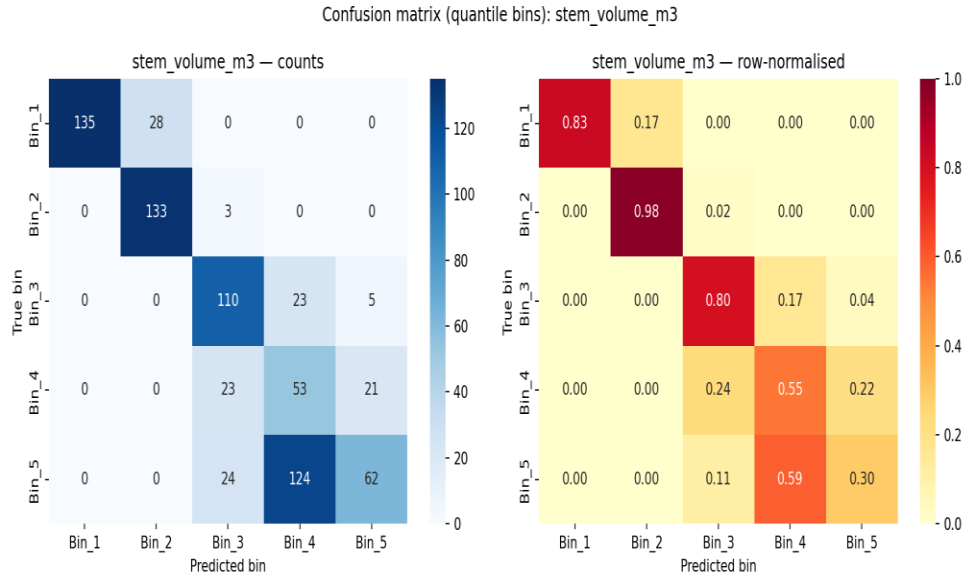


Figure 5. Quintile-binned confusion matrix for stem volume on the plot-level held-out test set, shown as counts (left) and row-normalized proportions (right).

For total height (Figure 6), the lowest quintile (Bin 1) was correctly classified 76% of the time. The three middle quintiles showed more cross-bin confusion, with row-normalized accuracy of 45% (Bin 2), 24% (Bin 3), and 50% (Bin 4). The top quintile (Bin 5) was correctly classified 31% of the time, with most misclassification into the adjacent Bin 4.

Overall five-class accuracy for total height was 43.8%. This pattern indicates that the model separates the shortest trees more reliably than it separates trees in the middle of the height distribution, where growth trajectories from different ages, plots, and site classes overlap. Stem volume, consistent with its higher R^2 , showed tighter diagonal concentration across all five bins and an overall accuracy of 66.3%.

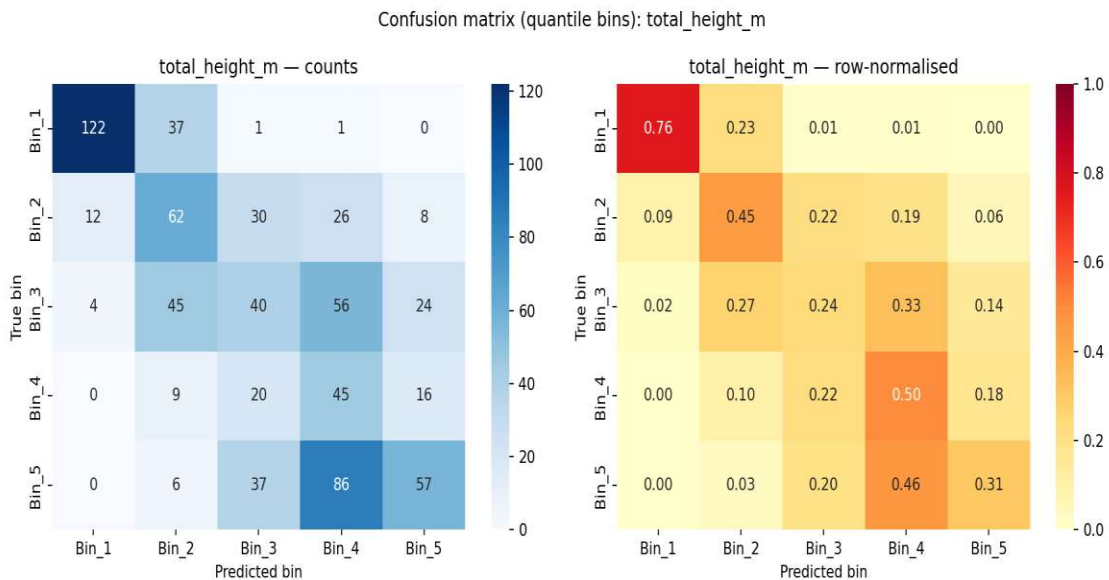


Figure 6. Quintile-binned confusion matrix for total height on the plot-level held-out test set, shown as counts (left) and row-normalized proportions (right).

4.5 Permutation Importance

Permutation importance (Figure 7), measured as the increase in mean test RMSE after shuffling each feature independently, ranked DBH (delta RMSE = 0.927) far above every other predictor, followed by dominant height (0.519) and stand age (0.374). Below these three dendrometric and stand-context predictors, a broad band of soil and climate variables followed closely together: soil silt fraction (0.349), soil potassium (0.336), soil phosphorus (0.294), soil sand fraction (0.289), mean annual rainfall (0.281), soil fertility index (0.244), and soil organic carbon (0.243). Site class indicators and stocking density ranked lowest, with stocking density showing a permutation importance near zero (0.0005), indicating that the model placed little independent weight on this predictor once the other 25 were available.

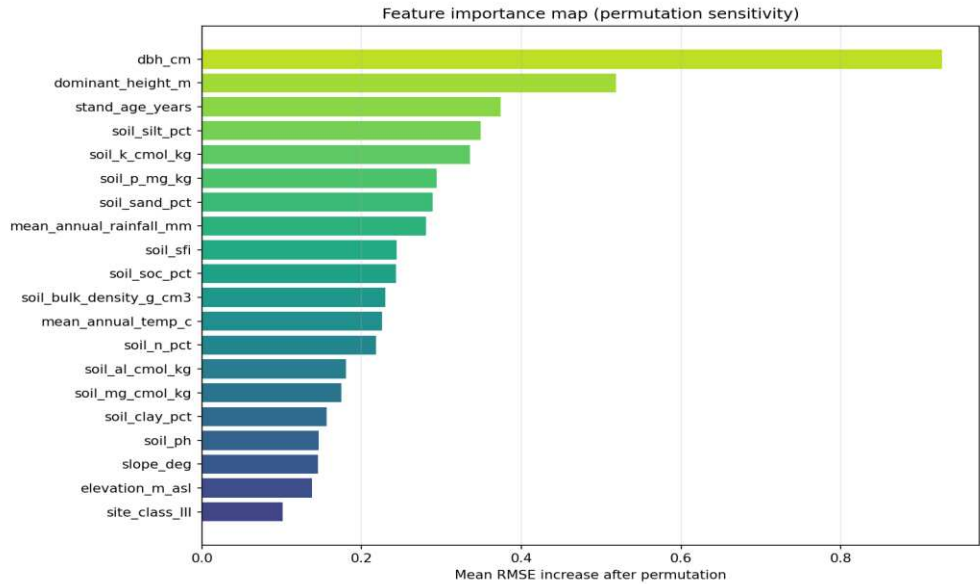


Figure 7. Permutation importance (mean RMSE increase) for the 20 most influential predictors in the selected best model.

4.6 Group Perturbation Sensitivity

Group perturbation, which scales each predefined feature group by plus or minus 10% simultaneously, showed that soil chemical properties as a group produced the largest coordinated effect on height predictions of any feature group, larger than any single soil variable's individual permutation importance would suggest. A 10% increase in soil chemical variables increased height test RMSE by 0.238 m, and a 10% decrease increased it by 0.255 m. Both changes sat well above the next largest group effect, soil physical properties (0.097 m for a 10% increase, 0.083 m for a 10% decrease). Topography and climate produced a moderate, asymmetric effect on height (0.047 m for an increase, 0.064 m for a decrease), and dendrometric predictors produced a comparable, more symmetric effect (0.081 m and 0.079 m). Stem volume responded far less to any group perturbation for most groups, with RMSE changes below 0.014 m³, the exception being a 10% reduction in dendrometric predictors, which increased volume RMSE by 0.038 m³, over half of the baseline test RMSE for that target (0.073 m³). This single exception aside, the overall pattern is consistent with the tight fit already reported for stem volume in Section 4.2.

4.7 Partial Dependence

Partial dependence sweeps, run across the seven continuous or ordinal features selected for this analysis (Figure 8), reproduced expected silvicultural relationships for the two dendrometric predictors and revealed the same artifact for stand age noted in prior sensitivity work on this dataset. Predicted total height rose monotonically with standardized DBH, from 11.0 m to 13.8 m across the observed range, and with standardized dominant height, from 11.3 m to 15.0 m. Predicted stem volume rose with both in the same direction, consistent with the underlying Michaelis-Menten and volume equations described in Section 3.2.1.

Predicted height and volume both rose gently with standardized soil nitrogen (height: 12.5 m to 13.8 m) and standardized soil pH (height: 12.4 m to 13.0 m), a small but directionally consistent signal given that soil chemical properties as a group carried the largest coordinated effect in Section 4.6. Elevation showed a weak negative relationship with predicted height, from 12.7 m at low elevation to 12.5 m at high elevation. This is a much flatter response than the same sweep produced when soil covariates were absent from the model, consistent with soil variables now carrying some of the site-quality signal that elevation proxied for previously. Stocking density showed almost no partial-dependence effect on either target, consistent with its near-zero permutation importance in Section 4.5.

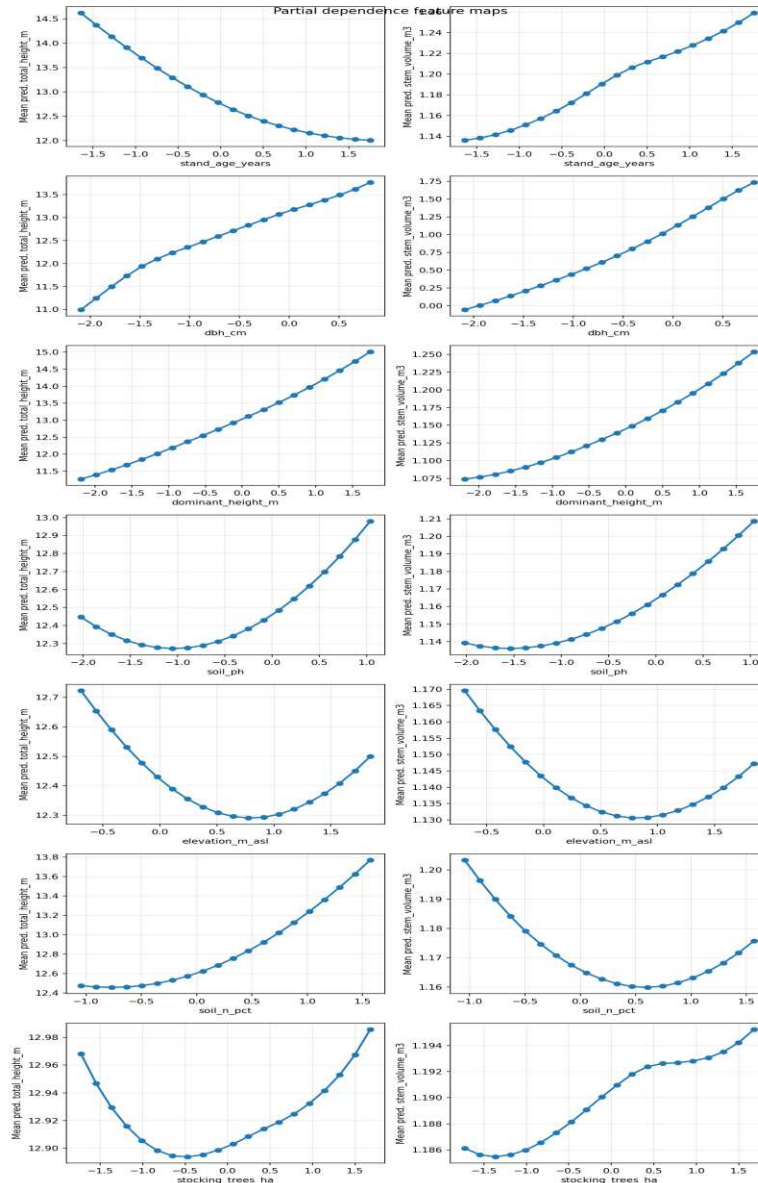


Figure 8. Partial dependence of predicted total height and stem volume on standardized stand age, DBH, dominant height, elevation, soil pH, soil nitrogen, and stocking density.

Predicted height fell, rather than rose, as standardized stand age increased in the partial dependence sweep (14.6 m at the youngest sweep point to 12.0 m at the oldest), which runs counter to the expected age-height growth curve. This pattern is best read as an artifact of holding dominant height and DBH fixed at their test-set values while age is swept in isolation. Age and the two dendrometric predictors are correlated in the training data, and both dendrometric predictors carried far greater permutation importance than age. It illustrates a general limitation of one-feature-at-a-time partial dependence in the presence of correlated predictors, and it is addressed further in Section 5.3.

5. Discussion

5.1 Overview

This study set out to build and evaluate a machine learning model that forecasts teak growth parameters in Ghanaian plantations from stand, soil, and topographic covariates. The evaluation was designed to guard against the plot-sharing structure of model-extracted tree records, and to quantify the contribution of each feature group and predictor through ablation and sensitivity analysis. The results in Section 4 answer the four research questions set out in Section 1.2, and this section interprets those answers against the wider literature on teak growth and yield modeling and machine learning in forestry.

5.2 Model Accuracy and Feature-Group Contribution

The selected GrowthMLP forecast stem volume with high accuracy (test $R^2 = 0.991$) and total height with moderate accuracy (test $R^2 = 0.816$) on plots entirely unseen during training, which answers RQ1. Volume in this dataset is a deterministic function of DBH and height through *Equation 2*, so a high volume R^2 partly reflects that the model recovers an algebraic relationship it was implicitly given through correlated inputs. The height R^2 is a more independent test of the network's ability to learn the Michaelis-Menten height-DBH relationship and its site-class, topographic, and edaphic modifiers. A value of 0.816 compares reasonably with ANN-based height models reported for other plantation systems, including the mixed Eucalyptus and Acacia plantation study of Soares et al. (2021) and the individual-tree basal area increment model of Di Cosmo et al. (2020), even allowing for differences in species, region, training data, and, in this case, the additional discipline of a plot-level test split.

RQ2 asked which feature groups contributed most to accuracy. Dendrometric predictors mattered most: removing them produced the largest single accuracy loss among the feature-group ablations (Table 2, rank 18). Stand context, site class, and topography and climate each contributed a smaller, but still measurable, amount, consistent with their established role in the site quality literature (Nunifu 1997; Kumi et al. 2022; Zahabu et al. 2015). Soil chemical and soil physical properties were evaluated here under a split that prevents a tree from sharing its exact soil profile with a training example on the same plot. They now show a small but consistent positive contribution. Dropping either group individually or together cost between 0.003 and 0.008 of mean test R^2 relative to the best configuration, and the soil chemical group produced the single largest coordinated effect on height error of any feature group under group perturbation (Section 4.6). This result lines up with the field evidence that soil fertility and topographic position structure teak growth in Ghana and comparable settings (Kumi et al. 2022; Asigbaase et al. 2024; Watanabe et al. 2009; Noda et al. 2021). An earlier row-level split on this same dataset had appeared to show the opposite pattern. That discrepancy is itself informative. It suggests the earlier result reflected leakage of site-level soil values between partitions, rather than a genuine absence of a soil-growth relationship. This is a central reason this study adopted plot-level splitting as its primary design, rather than an optional check.

5.3 Individual Predictors and Model Behavior

RQ3 asked how individual predictors shaped predicted growth trajectories. Permutation importance and partial dependence agreed on the dominance of DBH and dominant height, and on the near-irrelevance of stocking density once other stand and site variables were included. Below the two dendrometric predictors and stand age, a broad, closely spaced band of soil texture, soil fertility, and climate variables shared importance rather than any single one dominating. This matches the group-perturbation finding that soil chemistry acts as a coordinated block, rather than through any one nutrient. Elevation showed a much weaker partial-dependence relationship with predicted height in this all-feature model than in an earlier soil-free model fitted to the same tree records. This suggests that, once available, soil covariates absorb part of the site-quality signal that elevation had to proxy for on its own. This pattern is consistent with teak and comparator species literature where topography and soil chemistry are correlated proxies for the same underlying site-quality gradient (Noda et al. 2021; Ogundele 2015).

The counterintuitive, age-decreasing partial dependence curve for total height (Section 4.7) is a methodological finding rather than a claim about teak biology. Chitra-Tarak et al. (2015) describe a related

problem: growth estimates derived from correlated dendrometric measurements can appear biased when one driver is held fixed while another is swept. In this study, holding dominant height and DBH at their test-set values while sweeping standardized stand age isolates a component of age's effect that the model does not use directly, since age's permutation importance (0.374) was already well below dominant height's (0.519) and DBH's (0.927). A model-agnostic explanation method that varies age jointly with its correlated dendrometric predictors, or an accumulated local effects approach, would likely produce a more biologically consistent age curve, and this is identified as a direction for future sensitivity analysis in Section 5.5. The correlation structure underlying this artifact, in particular the strong pairwise correlations linking stand age to DBH and dominant height, is shown in Supplementary Figure S1.

5.4 Practical Applications for Forest Management and Policy

For Ghanaian forest management, three practical uses follow directly from these results, all conditioned on evaluation against genuinely unseen plots rather than row-level partitions of the same sites. First, the selected model, or a retrained version of it once field data are available, could support screening of candidate teak sites from stand age, DBH, site class, elevation, rainfall, and a modest soil sample. Soil predictors added a real, if modest, increment to forecast accuracy once leakage was removed. This argues against skipping soil sampling entirely during inventory design, a recommendation that would have followed from the leakier row-level analysis this study explicitly moved away from. Second, the group perturbation results in Section 4.6 suggest that height forecasts are more sensitive than volume forecasts to coordinated shifts in soil chemistry and topographic data, which argues for prioritizing soil chemical sampling, in particular, alongside accurate site classification during inventory. Third, the wide, tropical teak literature reviewed in Section 2 shows that spacing, thinning, and provenance also shape growth substantially. This is based on evidence from Nigeria, Togo, Tanzania, Sierra Leone, Nepal, Costa Rica, Panama, and Mexico (Zahabu et al. 2015; Tondjo et al. 2014; Nocetti et al. 2011; Kainyande et al. 2022; Ruiz-Blandon et al. 2025). None of these management variables were available as covariates in the present dataset, and extending the feature set to include management history is a natural next step once field PSP data provide the necessary variation. Together, these applications support Ghana's Forest Plantation Strategy 2016-2040 objective of expanding productive plantation area (Forestry Commission Ghana 2016) and the forest bioeconomy agenda more broadly (Nyarko et al. 2023). They also connect to a wider case for valuing plantation forests beyond timber yield. This includes their broader ecosystem goods and services (Bauhus et al. 2010), their contribution to land restoration and carbon sequestration (Koutika 2022), and the biodiversity and understorey outcomes of different management intensities (Harikrishnan et al. 2012; Asare et al. 2020). It also includes the agroforestry and intercropping systems, such as bamboo and cocoa grown alongside teak, that Ghanaian smallholders already practice (Akoto et al. 2020; Zakariyya & Prawoto 2015). Intensive silviculture aimed at reconciling ecological and production objectives offers a further comparison point from outside the tropics (Park & Wilson 2007). They offer a low-cost, updatable screening tool rather than a replacement for field-based yield tables.

5.5 Limitations

The central limitation of this study is that tree-level training records were extracted from allometric and yield equations rather than measured on individual trees in the field. Test-set fit statistics therefore describe how well the GrowthMLP reproduces the Ghana-calibrated growth relationships used to build the dataset, evaluated on plots it never trained on, rather than independent predictive accuracy against unseen field trees. This limitation is stated directly in Section 3.8 and should be treated as the primary caveat on every result in Section 4.

A second limitation is that soil and topographic covariates were still assigned at site or chronosequence level rather than measured on each tree, even after switching to a plot-level split. Only eight distinct soil profiles exist across the full dataset. A test-set tree's exact soil values are never shared with a training tree from the same plot, but they are still shared with training trees from other plots that happen to fall in the

same broad elevation zone or chronosequence bin. The positive contribution of soil predictors reported in Section 5.2 should therefore be read as a lower bound on their true importance: tree-level soil measurement would likely sharpen this signal further rather than weaken it.

A third limitation concerns model selection under a tightly clustered top group. Six of the 21 configurations scored within 0.006 of the best mean test R^2 (Section 3.7), which means the specific ranking in Table 2 carries some sampling noise from this one plot-level partition. Repeating the grouped split under several random group assignments, as a smaller-scale check on an earlier version of this analysis had done for a single configuration, would give a more stable estimate of the true ranking among these closely matched configurations. A fourth limitation is that management variables known to affect teak growth, including spacing, thinning intensity, and provenance, were not available as covariates in the merged dataset, even though several of the studies cited in Section 2.1 show that they matter. Finally, the partial dependence results in Section 4.7 illustrate a known limitation of one-feature-at-a-time sensitivity analysis when predictors are correlated, and the age curve in particular should not be read as a biological finding.

Because tree-level responses were partially derived from allometric equations applied to simulated DBH distributions, the reported fit statistics characterize the consistency of the MLP with Ghana-calibrated growth relationships, evaluated on plots the model never saw during training, rather than independent field validation. External testing against remeasured PSP inventory from Form Ghana Limited (Form Ghana 2024) and Forestry Commission Ghana plantations remains the definitive evaluation step.

5.6 Future Work

Four extensions follow directly from these limitations. First, and most importantly, the selected architecture and preprocessing pipeline should be retrained and tested against remeasured permanent sample plot data from Form Ghana Limited or the Forestry Commission of Ghana as soon as such data become available (Form Ghana 2024; Forestry Commission Ghana 2024). This step would move the evaluation from allometric consistency to genuine external validation, and it would also allow soil covariates to be measured per tree rather than assigned by zone. Second, the plot-level grouped split should be repeated across several random group assignments, particularly for the tightly clustered top configurations identified in Section 5.5, to obtain a more stable ranking than the single partition reported here. Third, the feature set should extend to spacing, thinning history, and provenance, bringing the covariate set closer to the management levers already shown to matter in the wider teak literature reviewed in Section 2. Model-agnostic sensitivity methods that account for correlated predictors, such as accumulated local effects, would also address the age partial-dependence artifact identified in Section 5.3.

6. Conclusions

This study built a multilayer perceptron that forecasts total height and stem volume for teak in Ghanaian plantations from stand, site-class, topographic, soil, and dendrometric covariates assembled from the country's published literature. Because many tree records were extracted for the same published plot and therefore share covariates, all training, validation, and testing used a plot-level grouped split, guaranteeing that no plot contributed trees to more than one partition. Across a 21-configuration ablation grid evaluated on this split, the best-performing model retained all 26 features in a wider three-layer network and reached a mean test R^2 of 0.903, with stem volume reaching 0.991 and total height reaching 0.816. DBH, dominant height, and stand age ranked as the most influential individual predictors under permutation importance, while soil chemical properties as a coordinated group produced the largest single effect on height error under perturbation, consistent with the field literature on soil-mediated teak growth in Ghana. Removing soil predictors cost a small but consistent amount of accuracy once plot-level leakage was eliminated, reversing the pattern an earlier, less conservative row-level split on the same data had suggested. These findings show that a moderate neural network can recover the growth relationships embedded in Ghana's

published teak literature with high fidelity for volume and reasonable fidelity for height, evaluated honestly against plots it has never seen. The model and the ablation and sensitivity framework built around it offer a starting point for low-cost growth screening in Ghanaian teak plantations, pending the field permanent sample plot data needed to test these forecasts beyond the allometric relationships used to build them.

CRedit authorship contribution statement

Conceptualization, F.A-K. and G.O.F.; methodology, G.O.F.; software, G.O.F.; validation, F.A-K. and G.O.F.; formal analysis, F.A-K. and G.O.F.; investigation, F.A-K. and G.O.F.; resources, F.A-K. and G.O.F.; writing—original draft preparation, F.A-K. and G.O.F; writing—review and editing, F.A-K. and G.O.F.; supervision, G.O.F. All authors have read and agreed to the publication of the manuscript.

Conflict of Interest: The authors declare no conflict of interest.

Funding: This study received no external funding.

Data availability: The datasets and code snippets used for data analysis and visualization are available in the figshare repository at: <https://figshare.com/s/62e96eca878c56b95d8b>.

Human Ethics, Consent to Participate, and Consent to Publish: Not applicable

Supplementary Materials

Supplementary Figures S1–S4, referenced in Sections 3.2.2, 4.2, 4.3, and 5.3, are provided in a separate Supplementary Materials file accompanying this manuscript. Their captions are reproduced below for reference.

Supplementary Figure S1. Pairwise Pearson correlation matrix of the 26 input predictors on the test set, showing the concentrated correlation block among soil chemical variables, among topography and climate variables, and between stand age and the two dendrometric predictors (dominant height, DBH).

Supplementary Figure S2. First-hidden-layer activation feature map for a subset of test-set trees under the selected best configuration (arch_512-256-128), showing activation intensity across the 512 hidden units.

Supplementary Figure S3. Generalization gap (validation loss minus training loss) across training epochs for the selected best configuration, with the best epoch (78) marked.

Supplementary Figure S4. Training and validation Smooth L1 loss on a logarithmic scale across epochs for the selected best configuration (arch_512-256-128), with the best epoch (78) marked.

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