

Predicting African timber strength from density: accuracy and robustness of simple models.

Abstract:

Density is a readily measurable property that can support preliminary estimates of wood strength. Its practical value depends on the accuracy obtained beyond model fitting. This study evaluates the predictive information supplied by density for African timber reference means and examines how stable that information remains when the composition of a small documentary corpus changes.

Thirteen African timber references from Tropix (CIRAD, 2023–2026), spanning 380–1060 kg/m³ at 12% moisture content, were analysed for bending and compression parallel to grain. Proportional, affine and power models were compared with a mean-only baseline using internal leave-one-out and leave-one-genus-out validation. Influence diagnostics and twelve genus-deletion scenarios assessed sensitivity.

The proportional model achieved genus-out root mean square errors of 8.96 MPa in bending and 2.97 MPa in compression, reducing baseline errors by 73.2% and 84.4%, respectively. Mean absolute percentage errors were 8.00% and 4.74%. Across composition scenarios, proportional-model coefficients had descriptive coefficients of variation of 0.93% and 0.53%. The predictive advantage of density persisted, whereas the ranking of model forms could reverse.

Density supplied substantial and comparatively stable information for estimating mean reference strengths in this corpus. A one-coefficient relation captured most of the observed predictive benefit, offering a useful basis for documentary screening and planning timber tests in Guinea and West Africa. The reported accuracy concerns reference means; independent measurements are required to establish performance for individual pieces and regional lots.

Keywords: wood density; African timbers; bending strength; compression parallel to grain; internal cross-validation; predictive sensitivity.

1 Introduction

Estimating wood strength from density offers a practical route from a simple physical measurement to a first assessment of mechanical performance. Mass and volume measurements are more accessible than destructive strength testing, making density an attractive input when information must be gathered before committing resources to a mechanical testing programme. Previous studies have established associations between apparent density and wood strength, including analyses of multiple properties across forty Brazilian timbers and longitudinal compression across seventy-two hardwood species (Dias and Lahr, 2004; Lahr et al., 2021). The useful scientific question is therefore how much predictive information density supplies, with what error, and at which material scale.

Density reflects the amount of material within an apparent volume, while mechanical behaviour also depends on anatomical organisation, grain direction, moisture and defects. These additional factors explain why density does not uniquely determine strength (Senalik and Farber, 2021). Bending and compression parallel to grain must be considered separately: the response mechanisms differ, and predictive accuracy for one property cannot simply be assigned to the other. Moisture must also be specified because changes in water content affect both mass and dimensions (Glass and Zelinka, 2021).

Published timber reference means provide an accessible basis for evaluating predictive relationships. Their statistical interpretation is nevertheless specific. A relationship among mean densities and mean strengths describes differences between references; it does not directly describe differences between pieces within a species. The present corpus contains thirteen documentary means, including commercial groups that may encompass several species, without associated sample sizes or variances (CIRAD, 2023–2026). Defining the reference mean as the prediction target allows these data to be used productively without attributing specimen-level accuracy to them.

A second consideration is evaluation beyond fitting. Comparing density models with a mean-only baseline reveals the information gained by measuring density. Predicting references excluded from fitting then provides an internal assessment of predictive error. Group-aware validation can address identifiable dependencies, although it does not remove dependencies that are absent from the source metadata (Roberts et al., 2017). With a small corpus, the stability of both performance and model ranking is as informative as the minimum error obtained from a single comparison.

The study asks how accurately density at 12% moisture content can estimate documentary mean bending and parallel-to-grain compressive strengths for selected African timber references. Its objectives are to quantify improvement over a predictor-free baseline, compare simple functional forms, evaluate individual errors and composition sensitivity, and define the conditions for preliminary use. The contribution is a joint assessment of predictive benefit and stability: it identifies what a readily measured input contributes while distinguishing stable information from uncertain preferences among model forms.

This distinction is particularly useful for developing timber research in Guinea and West Africa. Some species associated with the selected references occur in Guinea (Gosline et al., 2023), providing a concrete reason to investigate these relationships with locally sourced material. Documentary estimates can help organise an initial test programme and formulate expectations across a density range. Establishing their accuracy for regional supplies remains a separate empirical question. Figure 1 sets out this progression from reference data to internal assessment and subsequent field-relevant validation.

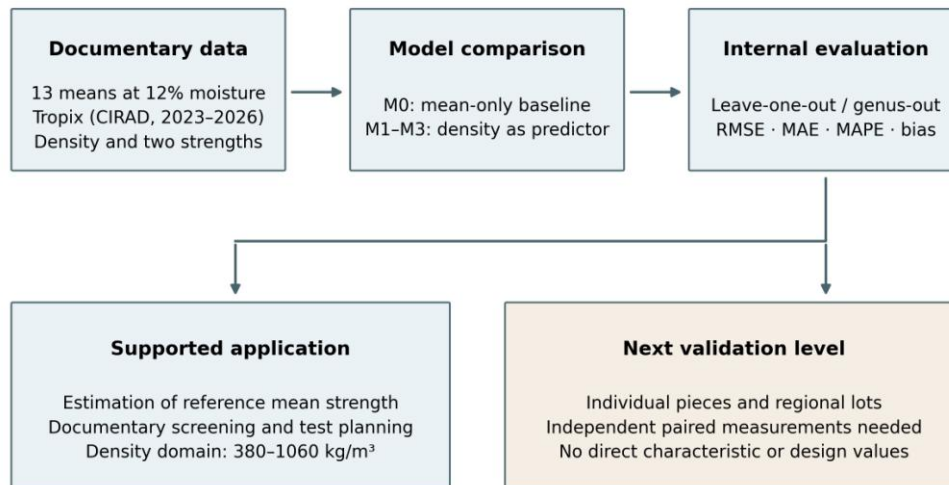


Figure 1. Analytical framework and scope. All inputs are published reference means. M0 is the mean-only baseline; M1–M3 use density. Independent measurements are needed before transferring the reported accuracy to pieces or regional lots.

2 Materials and Methods

2.1 Documentary corpus and selection

The analysis used thirteen technical sheets from the African timber section of Tropix (CIRAD, 2023–2026): African mahogany, afrormosia, avodiré, ayous, azobé, bilinga, bubinga, ilomba, iroko, limba, okoumé, ovengkol and sapelli. The selection linked commercial designations in the African scope of Table 5–5a of the Wood Handbook (Senalik and Farber, 2021) to sheets providing all three required properties. Ayous, bilinga, ovengkol and sapelli correspond commercially to obeche, opepe, ovangkol and sapele in that scope. These naming correspondences define the selection and do not establish identical underlying populations.

All numerical observations came from CIRAD sheets; Wood Handbook strength values were neither pooled with them nor treated as independent validation data. Angelin, Benge, Cypress Mexican and Ekop were not retained in the defined documentary selection. This intersection is an auditable convenience sample, not an exhaustive survey of African timber properties. References were not selected according to model residuals. The results therefore characterise this specified case study rather than an estimated probability sample of all African timbers.

Table 1 gives the complete analytical dataset. The published values refer to mature wood and a stated moisture content of 12%. Individual sample counts, dispersions and complete experimental provenance are not available for the extracted means. A common moisture reference does not establish identical testing protocols. Each row was assigned equal weight. Thirteen references represent twelve genera, with two entries for Guibourtia; commercial references, genera and biological species are not interchangeable sampling units. Exact sheet URLs, botanical names and content dates are supplied with the data.

88 **Table 1. Documentary mean properties at 12% moisture content from Tropix (CIRAD, 2023–2026).**

Reference	Genus	ρ_{12} (kg/m ³)	f_m (MPa)	$f_{c,0}$ (MPa)
African mahogany	Khaya	570	77	46
Afromosia	Pericopsis	740	93	64
Avodiré	Turraeanthus	580	94	52
Ayous	Triplochiton	380	52	30
Azobé	Lophira	1060	162	96
Bilinga	Nauclea	760	95	63
Bubinga	Guibourtia	920	137	76
Ilomba	Pycnanthus	490	63	38
Iroko	Milicia	640	87	54
Limba	Terminalia	540	80	47
Okoumé	Aucoumea	440	62	36
Ovengkol	Guibourtia	820	127	69
Sapelli	Entandrophragma	690	102	62

89

90 Note: f_m denotes bending strength; $f_{c,0}$ denotes compression parallel to grain. African mahogany corresponds
 91 to “Acajou d’Afrique” in the source. Entries may represent multiple species.

92 **2.2 Density and prediction targets**

93 Apparent density is the ratio of mass to volume at the same moisture state. Moisture content u is expressed
 94 relative to oven-dry mass; $u = 0.12$ represents 12% (Glass and Zelinka, 2021). The symbols m_u , V_u and m_0
 95 denote mass and volume at u and oven-dry mass, respectively.

$$\rho_u = \frac{m_u}{V_u} ; \quad u = \frac{m_u - m_0}{m_0} \quad (1)$$

96 The dimensionless density d_{12} reported in Tropix (CIRAD, 2023–2026) was expressed as mass density using
 97 the convention $\rho_w = 1000$ kg/m³. This density at 12% must not be confused with basic density, which relates
 98 oven-dry mass to green volume.

$$\rho_{12} = d_{12}\rho_w = 1000d_{12} \text{ kg/m}^3 \quad (2)$$

99 Bending strength f_m and compressive strength parallel to grain $f_{c,0}$ were modelled separately in MPa. The
 100 target is the published mean for a reference, not the failure load of a structural element. Density measured at an
 101 unknown moisture content is not directly compatible with these equations. No moisture-correction relationship
 102 was inferred from this dataset.

103 **2.3 Models and fitting**

104 Four models were fitted independently for each response. M0 predicts the training-set mean; M1 is
 105 proportional; M2 is affine; M3 is a power function normalised by $\rho_0 = 700$ kg/m³. Throughout the model
 106 equations, ρ denotes ρ_{12} and A denotes the training set.

$$M0: \hat{f} = \frac{\sum_{j \in A} f_j}{n_A}; \quad M1: \hat{f} = c\rho \quad (3)$$

$$M2: \hat{f} = \alpha + \beta\rho; \quad M3: \hat{f} = a(\rho/\rho_0)^b \quad (4)$$

The coefficients c and β have units $\text{MPa} \cdot \text{m}^3/\text{kg}$, α and a are in MPa , and b is dimensionless. M1 has one fitted coefficient; M2 and M3 have two. Parameters minimise equally weighted squared errors on the original MPa scale. Linear least squares were used for M1 and M2. M3 was fitted by nonlinear least squares with positive amplitude and exponent starting values of 0.5, 1 and 2; the converged solution with the lowest sum of squares was retained. No logarithmic transformation changed the fitting criterion.

The zero intercept in M1 is a parsimonious empirical constraint within 380–1060 kg/m^3 , not evidence for a constitutive law extending to zero density. M1 is used as an illustrative simple relationship rather than declared the intrinsically best model. No arbitrary percentage threshold was used to select a winner. Small performance differences were interpreted alongside composition sensitivity.

2.4 Internal cross-validation and error measures

Leave-one-out (LOO) validation fitted each model to twelve references and predicted the omitted reference. Leave-one-genus-out (LOGO) validation removed all references belonging to a genus and re-estimated the model before predicting them. Because only *Guibourtia* contains two references, LOGO adds limited grouping beyond LOO. Both procedures are internal to the same documentary compilation; neither evaluates a new laboratory, provenance or independent regional lot (Roberts et al., 2017).

Every coefficient, including the M0 mean, was re-estimated in every fold. Scores give equal weight to the thirteen held-out predictions. Prediction error is defined as predicted minus published strength, so positive errors denote overestimation. Root mean square error (RMSE), mean absolute error (MAE), bias and mean absolute percentage error (MAPE) summarise complementary aspects of performance.

$$e_i = \hat{f}_i - f_i; \quad RMSE = \sqrt{\frac{\sum_i e_i^2}{n}}; \quad MAE = \frac{\sum_i |e_i|}{n} \quad (5)$$

$$Bias = \frac{\sum_i e_i}{n}; \quad MAPE = \frac{100}{n} \sum_i \left| \frac{e_i}{f_i} \right| \quad (6)$$

We also report counts within $\pm 10\%$ and $\pm 20\%$, the maximum absolute error, and the empirical 90th percentile of absolute errors using the upper-rank convention: rank $\lceil 0.90n \rceil$, or the twelfth ordered error for $n = 13$. These are descriptive error summaries, not regulatory acceptance criteria or probabilistic prediction limits.

2.5 Composition sensitivity and influence diagnostics

Each of the twelve genera was then removed from the corpus in turn, and the complete LOGO procedure was repeated on the remaining eleven or twelve references for every model. Within each scenario, models were compared on the same retained references. Across scenarios, the test population changes. Minimum–maximum ranges therefore describe deterministic sensitivity to composition, not confidence intervals from independent samples. The paired difference $RMSE(M1) - RMSE(M3)$ was used to examine ranking reversals.

Proportional coefficients were also fitted to each reduced corpus. Their descriptive coefficient of variation was calculated as 100 times the standard deviation divided by the mean coefficient, using divisor 11 for the standard deviation across twelve scenarios. Because scenarios overlap, this dispersion is not a coefficient standard error. Additional fits excluded azobé, ayous, or both density extremes.

For M1 and M2, leverage, internally studentised residuals and Cook's distance were computed on the full-corpus fit, following standard regression diagnostics (NIST, n.d.). With design matrix X , leverage h_i is the diagonal of $X(X^T X)^{-1} X^T$; the residual variance is $SSE/(n - p)$, with $p = 1$ for M1 and $p = 2$ for M2. Internally studentised residuals use $e_i/[s\sqrt{(1 - h_i)}]$, retaining the prediction-minus-observation sign convention. Cook's distance is $e_i^2 h_i/[ps^2(1 - h_i)^2]$. No observation was removed automatically because of a diagnostic threshold. Residual plots were examined for systematic patterns and changing dispersion (NIST/SEMATECH, n.d.).

3 Results

3.1 Predictive information supplied by density

Density provided a substantial improvement over the mean-only baseline for both responses (Table 2). Under LOGO, the proportional model reduced RMSE from 33.49 to 8.96 MPa in bending and from 19.03 to 2.97 MPa in compression. These correspond to reductions of 73.2% and 84.4%. Thus, even a one-coefficient relationship captured a large share of the between-reference information available in the corpus.

Table 2. Internal validation RMSE for all models, in MPa.

Model	Bending LOO	Bending LOGO	Compression LOO	Compression LOGO
M0	32.78	33.49	18.80	19.03
M1	8.78	8.96	2.94	2.97
M2	8.60	8.75	2.90	3.06
M3	8.44	8.57	2.97	3.11

Note: M0, mean-only; M1, proportional; M2, affine; M3, power. All coefficients are re-estimated within each fold. LOGO is internal genus-out validation.

3.2 Model forms and an illustrative simple relationship

In bending, LOGO RMSE decreased from 8.96 MPa for M1 to 8.75 MPa for M2 and 8.57 MPa for M3. The 0.40 MPa difference between M1 and M3 is small compared with the overall predictive gain from density. In compression, M1 had the lowest observed RMSE, 2.97 MPa, compared with 3.06 and 3.11 MPa. Figures 2 and 3 show the fitted relationships and held-out predictions. These comparisons support the usefulness of simple equations without identifying a unique functional form.

Table 3. Coefficients estimated using all thirteen references.

Response	M1: c	M2: α ; β	M3: a ; b
Bending	0.14367	-9.272 ; 0.15661	99.859 ; 1.1114
Compression	0.08545	-4.649 ; 0.09194	59.510 ; 1.0822

Note: density in kg/m^3 and strength in MPa; c and β in $\text{MPa} \cdot \text{m}^3/\text{kg}$, α and a in MPa, b dimensionless. M3 uses $\rho_0 = 700 \text{ kg/m}^3$. These full-corpus coefficients differ from fold-specific coefficients used to calculate validation errors.

$$\widehat{f}_m = 0.14367\rho_{12} \quad (7)$$

$$\widehat{f}_{c,0} = 0.08545\rho_{12} \quad (8)$$

Bending strength

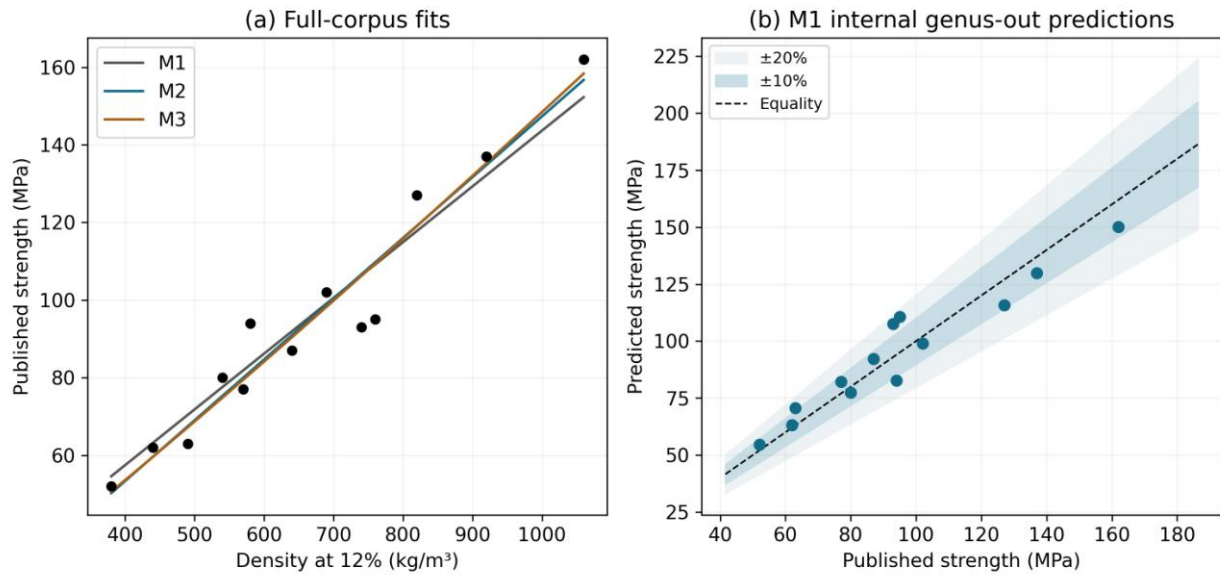


Figure 2. Bending strength. (a) Fits on all thirteen references. (b) M1 predictions from internal LOGO validation versus published means. Shaded $\pm 10\%$ and $\pm 20\%$ bands are descriptive, with no probabilistic coverage implied.

Compression parallel to grain

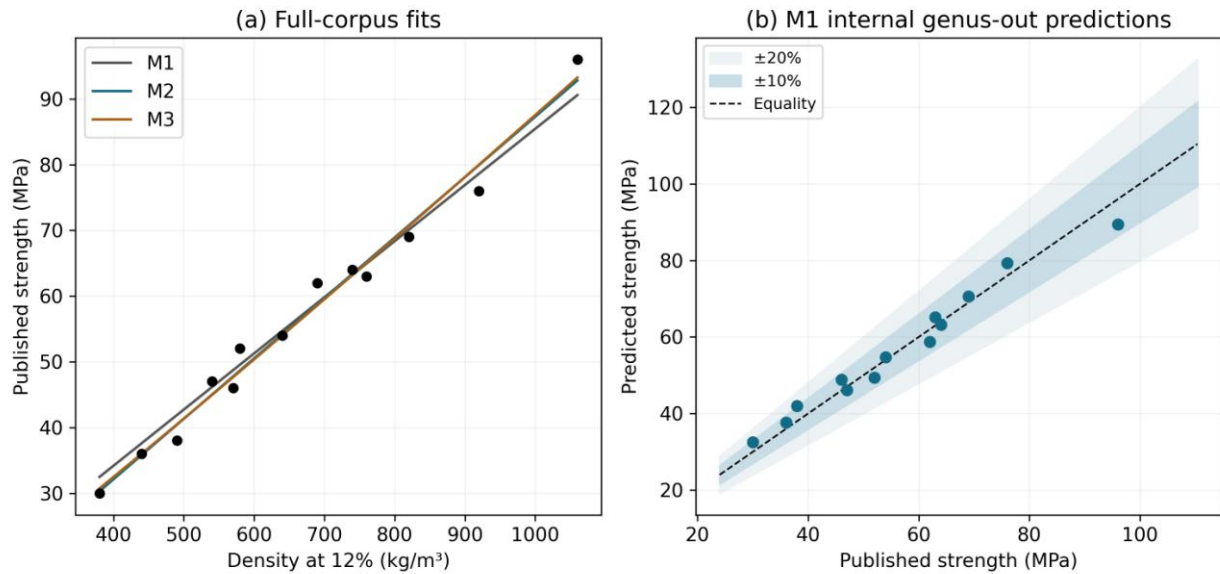


Figure 3. Compression parallel to grain. (a) Full-corpus fits. (b) M1 internal LOGO predictions. The equality line and percentage bands provide visual reference points, not specimen-level prediction intervals.

3.3 Magnitude and distribution of prediction errors

Table 4 characterises the errors of M1. MAPE was 8.00% in bending and 4.74% in compression, with mean biases below 0.40 MPa. Nine bending predictions and twelve compression predictions were within $\pm 10\%$; all thirteen were within $\pm 20\%$ for both responses. Compression therefore had lower relative errors in this corpus.

The maximum errors, 15.65 and 6.62 MPa, also show why an average error should not be interpreted as a bound applying to every reference.

Table 4. Internal LOGO errors for the illustrative proportional model.

Metric	Bending	Compression
RMSE (MPa)	8.96	2.97
MAE (MPa)	7.66	2.55
Bias (MPa)	0.39	0.36
MAPE (%)	8.00	4.74
90th percentile absolute error (MPa)	14.61	4.03
Maximum absolute error (MPa)	15.65	6.62
References within $\pm 10\%$	9	12
References within $\pm 20\%$	13	13

Note: positive bias indicates overestimation. Counts are out of thirteen; the percentile uses upper rank 12. These statistics describe held-out documentary means.

3.4 Stability across composition scenarios

The predictive benefit of density persisted throughout the twelve genus-deletion scenarios. For M1, recomputed LOGO RMSE ranged from 7.95 to 9.43 MPa in bending and from 2.29 to 3.13 MPa in compression (Table 5; Figure 4). These ranges remained well below those of M0. The result is encouraging because the main conclusion does not depend on one exact selection of the thirteen references.

Table 5. Range of internal LOGO RMSE after removing each genus and repeating validation, in MPa.

Model	Bending range	Compression range
M0	27.75–35.18	15.34–19.95
M1	7.95–9.43	2.29–3.13
M2	7.33–10.91	2.27–3.29
M3	7.20–11.67	2.19–3.34

Note: twelve overlapping deterministic scenarios; ranges are sensitivity summaries, not confidence intervals.

By contrast, the paired difference $RMSE(M1) - RMSE(M3)$ ranged from -2.54 to $+1.09$ MPa in bending and from -0.53 to $+0.88$ MPa in compression. Its sign reversal shows that the preference between proportional and power forms depends on composition. The robust finding is the information gained from density; the exact shape of the relationship remains less firmly identified.

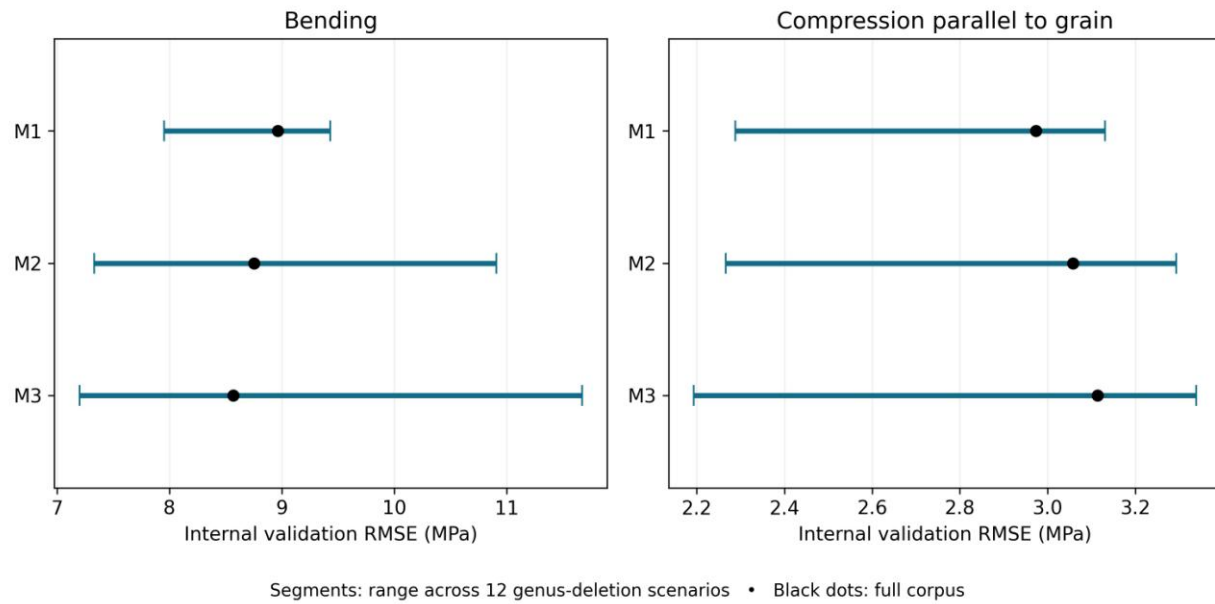


Figure 4. Sensitivity of model performance to corpus composition. Segments span minimum to maximum RMSE over twelve genus-deletion scenarios; black dots show full-corpus internal LOGO RMSE. The displayed ranges have no confidence-level interpretation.

3.5 Coefficient stability and influence of extreme references

The proportional coefficients were comparatively stable. Across the twelve genus deletions, the bending coefficient ranged from 0.14110 to 0.14559 MPa·m³/kg, with descriptive CV 0.93%. The compression coefficient ranged from 0.08432 to 0.08616 MPa·m³/kg, with CV 0.53%. These small scenario dispersions complement the performance analysis by showing that the illustrative equations do not change sharply under the examined perturbations.

Table 6. Proportional coefficients following deletion of density extremes, in MPa·m³/kg.

Corpus	Bending c	Compression c
Full corpus	0.14367	0.08545
Without azobé	0.14164	0.08432
Without ayous	0.14383	0.08561
Without both	0.14178	0.08447

Note: coefficients are fitted to retained references. They are distinct from errors obtained by repeating internal validation within a reduced corpus.

Removing azobé reduced the coefficients by 1.42% in bending and 1.33% in compression; removing ayous increased them by 0.11% and 0.18% (Table 6). This asymmetry is consistent with the squared-density leverage of a proportional fit without an intercept. Azobé had leverage 0.182 under M1 and 0.422 under M2. Its M1 Cook's distance in compression was 1.074, identifying meaningful influence but not invalidating the observation. The modest coefficient changes show that the global relationship was not determined by this reference alone.

Table 7. Full-fit influence diagnostics for the density extremes.

Model	Reference	Leverage	r bending	D bending	r compression	D compression
M1	Azobé	0.182	-1.30	0.374	-2.20	1.074
M1	Ayous	0.023	0.32	0.002	0.92	0.020
M2	Azobé	0.422	-0.85	0.261	-1.68	1.033
M2	Ayous	0.254	-0.25	0.011	0.13	0.003

Note: r, internally studentised residual with prediction-minus-observation sign; D, Cook’s distance. No automatic exclusion threshold was used.

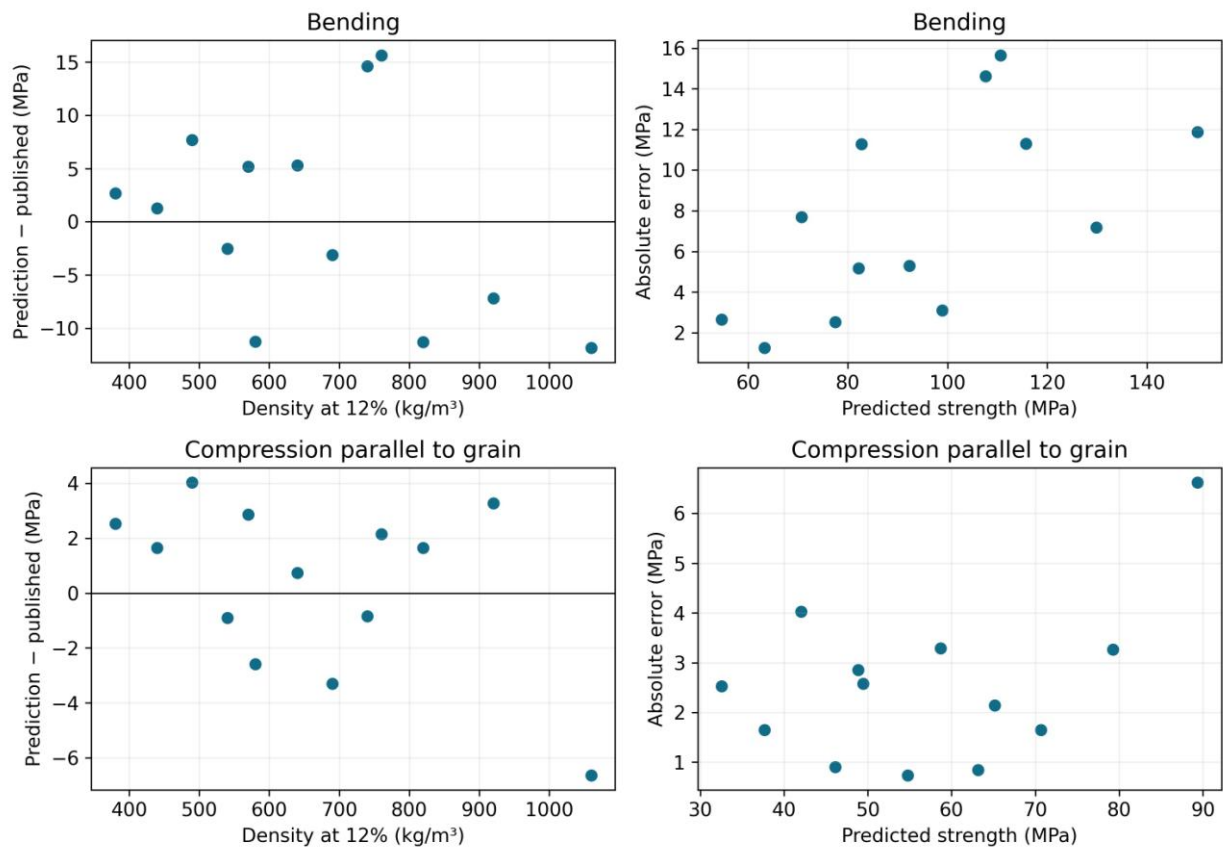


Figure 5. M1 internal LOGO residuals against density and absolute errors against predicted strength. Patterns describe errors among reference means; thirteen observations do not establish a reliable variance model.

Residuals changed sign at similar densities. In compression, azobé produced the largest absolute held-out error. The plots do not provide enough evidence to specify a stable heteroscedastic error model, and no additional response-dependent weighting was imposed.

4 Discussion

4.1 What the results add

The clearest finding is the scale of improvement delivered by density relative to a predictor-free estimate. Reductions of 73.2% and 84.4% in internal RMSE demonstrate that this simple physical variable is informative for the analysed reference means. The contribution extends established density–strength

229 associations (Dias and Lahr, 2004; Lahr et al., 2021) by quantifying held-out accuracy, documenting
 230 individual error magnitudes and testing how the conclusion changes with corpus composition.

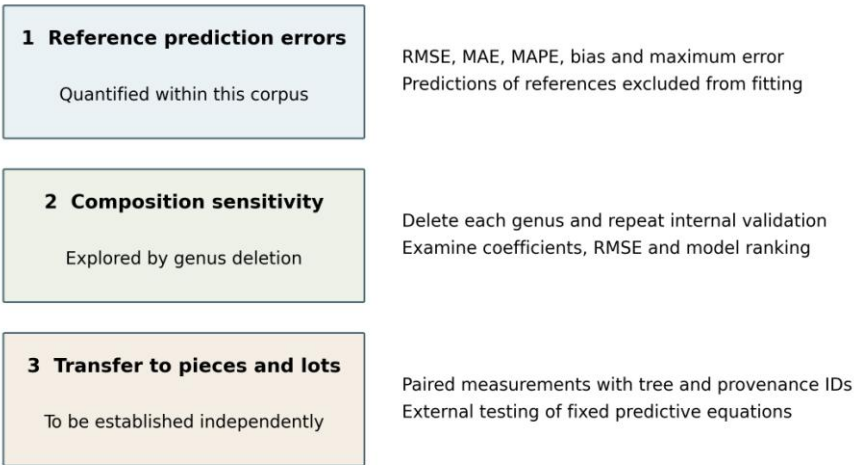
231 The distinction between predictor usefulness and model-form preference is particularly valuable. Density
 232 retained a large predictive advantage across all examined deletions, and proportional coefficients showed small
 233 descriptive variation. At the same time, ranking reversals caution against treating the small full-corpus RMSE
 234 differences as evidence of an exact underlying law. A single-coefficient equation captured most of the
 235 observed predictive benefit while remaining straightforward to interpret and reproduce. This makes it a useful
 236 starting point for independent testing.

237 The two responses also yield complementary information. Compression had lower relative errors here,
 238 including a MAPE of 4.74%, compared with 8.00% in bending. This comparison is a finding about the present
 239 corpus rather than a universal statement that compression must always be more predictable. Differences in
 240 source populations, measurement protocols or aggregation could alter the relationship in another dataset.

241 **4.2 Aggregation and the three levels of interpretation**

242 The fitted relation concerns reference means , expressed conceptually as $\bar{f}_j = g(\bar{\rho}_j) + \epsilon_j$. A specimen-level
 243 relation would instead link f_{ij} to ρ_{ij} , with additional within-reference variation. Without individual paired
 244 measurements, these between- and within-reference components cannot be separated. Averaging can smooth
 245 variability and contribute to apparently favourable errors. Consequently, the compression MAPE of 4.74% is
 246 not an expected error for a randomly selected piece of iroko, azobé or another timber.

247 Figure 6 separates three questions. Documentary error is quantified by held-out residuals. Composition
 248 sensitivity is explored by overlapping deterministic deletions. Transfer to pieces, trees, lots and provenances
 249 remains to be measured. Neither the empirical error percentiles nor the min–max sensitivity ranges have
 250 guaranteed probabilistic coverage. Making these distinctions explicit gives the equations a clear and useful
 251 domain rather than an unspecified claim of reliability.



252
 253 **Figure 6. Three distinct levels of interpretation. Observed documentary errors and composition sensitivity are evaluated here;**
 254 **predictive accuracy for individual pieces and independent regional lots requires new data.**

4.3 Preliminary use and a worked example

Consider an illustrative piece conditioned to 12% moisture content, with mass 0.700 kg and apparent volume 1000 cm³, equivalent to 0.001 m³. This is a constructed example, not an experiment performed in the study.

$$\rho_{12} = \frac{0.700 \text{ kg}}{0.001 \text{ m}^3} = 700 \text{ kg/m}^3 \quad (9)$$

Equations (7) and (8) give central estimates of 100.6 MPa in bending and 59.8 MPa in compression. These values express what the between-reference relationship predicts at that density; they do not certify the piece used for the mass and volume measurements. Table 8 provides comparable reference estimates within the fitted domain.

Table 8. Illustrative central strength estimates from the full-corpus proportional equations.

ρ_{12} (kg/m ³)	Bending (MPa)	Compression (MPa)
400	57.5	34.2
500	71.8	42.7
600	86.2	51.3
700	100.6	59.8
800	114.9	68.4
900	129.3	76.9
1000	143.7	85.5

Note: estimates apply to the reference-mean relationship and are not characteristic or design strengths. The fitted density domain is 380–1060 kg/m³.

Input quality remains important. For a proportional equation, a density perturbation $\Delta\rho$ changes the estimate by $c\Delta\rho$. An illustrative ± 20 kg/m³ perturbation therefore produces approximately ± 2.87 MPa in bending and ± 1.71 MPa in compression. These are arithmetic sensitivity values, not measured instrument uncertainties. They cannot be combined with validation RMSE as independent random components without an appropriate error model. Moisture state, specimen geometry and any deterioration should be checked before using a mass-to-volume ratio as the input.

4.4 Relevance to Guinea and West Africa

For Guinea, the immediate opportunity is to use density as an organised entry point to timber evaluation. *Lophira alata*, *Triplochiton scleroxylon* and *Terminalia superba*, associated with references in this analysis, are documented in the Guinean flora (Gosline et al., 2023). This botanical overlap makes a targeted local investigation relevant. It does not establish that the CIRAD means were measured on Guinean material or that all thirteen references represent local commercial supplies.

A practical application is to use documentary estimates to plan which density ranges and materials to include in a mechanical testing programme. Researchers can compare anticipated mean strengths across candidate references, identify materials for which direct evidence is sparse, and reserve independent lots to assess prediction errors. In this role, the present equations provide quantitative expectations and an explicit benchmark against which a local validation can be judged. The same approach can support comparable work in other West African countries when material identity and moisture conditions are verified.

The next empirical step is paired measurement of density and strength on traceable pieces, with tree, lot and provenance identifiers. Fixed equations should first be evaluated on independent lots before any local recalibration. Separate training and reserved validation lots would then permit a defensible assessment of regional prediction error. Sample size should be based on expected variability and the precision sought, rather than a universal number of specimens. This extension directly serves the original objective: determining how much useful information about wood strength can be obtained from density alone.

4.5 Relation to structural design and remaining limitations

A predicted reference mean is distinct from both characteristic strength and design strength. For example, EN 1995-1-1:2004+A1:2008, clause 2.4.1(1)P, equation (2.14), expresses the relationship between a characteristic property and its design value as follows (CEN, 2008; see also Swedish Wood, 2022). The cited edition defines this distinction and is not asserted to be the automatically applicable edition for any current project.

$$f_d = \frac{k_{mod} f_k}{\gamma_M} \quad (10)$$

Here, f_k is characteristic strength, k_{mod} accounts for load duration and moisture conditions, and γ_M is the material partial factor. The documentary mean prediction cannot replace f_k . Subtracting the observed RMSE from a predicted mean would also not establish a valid lower characteristic fractile. Structural application requires the relevant product assessment and design framework.

The principal limitation remains the evidence base: thirteen selected documentary means without source sample sizes, within-reference variances or a fully independent validation set. Some references aggregate several species, and source-campaign dependencies cannot be reconstructed. Internal genus-out validation provides only a modest addition to LOO because one genus contains two references. These conditions limit population-wide interpretation and probabilistic uncertainty estimation.

Within that scope, the analysis offers a reproducible and practically interpretable result. Additional statistical complexity would not resolve the missing specimen-level evidence. The most productive improvement is independent data collection that separates within-species variation from differences among species and tests whether the observed predictive advantage persists for local timber lots.

5 Conclusion

Density at 12% moisture content supplied substantial predictive information for the mean strengths of thirteen African timber references. The proportional equations $\hat{f}_m = 0.14367\rho_{12}$ and $\hat{f}_{c,0} = 0.08545\rho_{12}$, with density in kg/m^3 and strength in MPa, achieved internal genus-out RMSE values of 8.96 and 2.97 MPa. These represent improvements of 73.2% and 84.4% over a mean-only baseline, with lower relative errors for compression in this corpus.

The principal result was stable under the examined changes in composition. Proportional-model coefficients had descriptive variation below 1%, and density retained a clear advantage over the baseline across all twelve deletion scenarios. Ranking reversals between functional forms nevertheless showed that the data do not robustly identify one superior shape. A simple relation therefore provides an informative and transparent starting point.

The study establishes a quantitative basis for documentary screening and the design of timber testing programmes in Guinea and West Africa. Its next step is independent validation using paired density and strength measurements on traceable local material. An informative relationship among reference means is a promising foundation, but it is not yet a validated method for characterising individual timber pieces.

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