

Integrating climate projections and machine learning to predict survival of drought resistant trees for climate smart reforestation

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Abstract

Climate smart reforestation faces critical uncertainty about tree survival under future drought conditions. Predicting which trees will survive is essential for guiding species selection and management interventions. This study develops an explainable machine learning framework that integrates long term empirical forestry data with climate projections, functional traits, and management practices to predict survival probability for drought resistant trees. We trained and compared multiple models, including Extreme Gradient Boosting (XGBoost), Random Forest, and survival analysis methods, using data from 12,000 individually monitored trees in arid and semi arid Kenya. XGBoost achieved the highest predictive performance (accuracy 98.5%, F1 score 0.99). Explainable AI techniques (SHAP, LIME) revealed that species identity is the dominant predictor of survival, with root depth, genetic drought score, and mulching as key modulators. Critically, survival depends on species specific trait combinations rather than single trait optima. The Cox proportional hazards model identified tree age, elevation, irrigation, and fertilization as significant drivers of mortality risk ($p < 0.05$). This framework provides an interpretable, forward looking tool for guiding species selection and targeted interventions, thereby enhancing reforestation viability in drought prone landscapes. The approach is generalizable to other regions and supports evidence based climate adaptation in forest ecosystems worldwide.

Introduction

Climate change is fundamentally altering forest ecosystems worldwide, with drought emerging as one of the most pervasive and severe stressors affecting tree growth, survival, and physiological function. Rising temperatures, increasing atmospheric vapor pressure deficit, and shifting precipitation regimes are driving more frequent and intense droughts, leading to widespread forest mortality and threatening the long-term stability of both natural and planted forests [1–3]. These trends pose significant challenges to climate-smart forestry and reforestation initiatives, which depend on sustained tree survival to deliver essential ecosystem services, including carbon sequestration, biodiversity conservation, and landscape restoration [4, 5]. While climate-smart forestry advocates for the use of drought-resistant species and adaptive management, the ultimate survival of planted trees under future climate conditions remains highly uncertain. This uncertainty stems from complex, non-linear interactions among climatic stressors, site characteristics, tree physiological traits, genetic adaptation, and management practices [6, 7].

Recent advances in remote sensing and artificial intelligence (AI) have transformed forest monitoring, enabling large-scale assessment of tree health, mortality, and biomass dynamics [8–10]. Machine learning (ML) methods, in particular, have proven highly effective for hydrological drought forecasting and climate hazard prediction, as they can capture the non-linear relationships and high-dimensional interactions that traditional statistical models often fail to represent [11–13]. These techniques have been successfully applied to forest fire susceptibility mapping, degradation assessment, and environmental monitoring, contributing to climate-resilient forest management [14–18]. Despite these methodological advances, most ML applications in forestry remain focused on retrospective monitoring, classification, or risk mapping, rather than on developing predictive models of tree survival under changing climatic conditions.

Empirical studies of tree responses to drought increasingly emphasize the importance of physiological traits, environmental context, and remote sensing proxies for understanding mortality processes [19–21]. However, these investigations are often constrained to specific species or locations and rarely incorporate projected climate stressors in a way that directly informs reforestation planning. Similarly, ML-based models of tree growth and survival have shown promise but are typically trained on historical climate data, limiting their applicability for long-term adaptation strategies [22, 23]. The emergence of explainable artificial intelligence (XAI) has begun to improve interpretability in forest drought research by identifying key drivers of ecosystem responses, yet the integration of XAI with climate projections and functional forestry decision-making remains limited [24, 25].

Concurrently, recent research highlights the critical roles of genetic connectivity, local adaptation, and phenological shifts in shaping tree resilience to climate stress, underscoring the need for predictive models that integrate both environmental and biological complexity [7, 26]. Reviews of ecological niche modeling and AI-driven plant science similarly call for integrative approaches that combine climate modeling, machine learning, and empirical forestry data to support adaptive forest management under climate change [27, 28]. Despite this consensus, a significant gap persists: no existing framework explicitly forecasts drought-resistant tree survival by synthesizing climate projections, drought indicators, functional and genetic traits, site factors, and management interventions within a single, unified predictive model.

This gap is particularly pronounced in regions highly vulnerable to climate change but underrepresented in AI-driven forestry research, such as much of Africa. Although AI is increasingly incorporated into adaptive environmental governance frameworks, empirical evidence translating these concepts into operational reforestation tools remains scarce [29–31]. Addressing this limitation is essential to ensure that reforestation investments yield long-term climate resilience rather than transient benefits that may be nullified by future drought events.

To address these challenges, this study integrates climate projections with machine learning to predict the survival of drought-tolerant trees, moving beyond conventional monitoring and suitability mapping toward data-driven decision support for climate-resilient reforestation. Specifically, we aim to: (1) quantify the nonlinear interactions among multidimensional predictors, including tree functional and genetic traits, environmental and climatic variables, drought severity indices, spatial factors, and management practices, that govern tree survival under climate stress; (2) develop and validate a predictive framework using state-of-the-art machine learning and survival analysis models; and (3) enhance transparency and interpretability through explainable AI methods to identify the most critical drivers of survival and support

evidence-based policy and adaptive forest management [6, 11, 12, 24, 25]. Leveraging long-term empirical forestry data from climate resilience programs, this work provides actionable insights for climate-smart reforestation planning and offers a generalizable methodological framework applicable to drought-prone landscapes worldwide.

Materials and Methods

Data source and study variables

This study utilized secondary forestry and climate data generated through long-term research and monitoring activities conducted by the Kenya Forestry Research Institute in collaboration with the Japan International Cooperation Agency. These collaborative initiatives focus on drought-resistant tree species, climate adaptation strategies, and sustainable forest management, particularly within arid and semi-arid landscapes of Kenya. The dataset was compiled from plantation trials, dryland forestry experiments, and site-based monitoring programs designed to assess tree growth performance, survival dynamics, and resilience under variable climatic and environmental conditions.

The final dataset comprised 12,000 observations, each representing an individual tree monitored under specific site, climatic, and management conditions. The dependent variables consisted of tree survival status, recorded as a binary outcome where 1 denoted survival and 0 denoted mortality, and survival time measured in months. Independent variables captured multidimensional drivers of survival and included tree-related attributes such as species identity, root depth, leaf area index, wood density, tree age, and genetic drought tolerance indicators. Environmental and climatic variables included mean, minimum, and maximum temperature, annual precipitation, soil moisture content, soil pH, soil nutrient index, and drought severity quantified using the Standardized Precipitation Evapotranspiration Index. Spatial and site characteristics were represented by geographic coordinates, elevation, slope, aspect, vegetation density, and distance to the nearest water source. Management variables included irrigation frequency, fertilization practices, and mulching or soil treatment interventions. Together, these variables enabled a comprehensive representation of biological, environmental, spatial, and management factors influencing tree survival under drought stress.

Data Cleaning and Preprocessing

Prior to model development, the dataset underwent rigorous data cleaning and preprocessing to ensure analytical reliability. Records with missing values exceeding a predefined threshold were excluded, while remaining missing observations were imputed using median values for continuous variables and mode values for categorical variables. Continuous predictors were examined for outliers using interquartile range analysis, and extreme values were winsorized to reduce undue influence on model estimation. All continuous variables were standardized using z-score normalization, expressed as

$$z = \frac{x - \mu}{\sigma} \quad (1)$$

where x represents the observed value, μ the mean, and σ the standard deviation. Categorical variables such as species were encoded using target encoding to preserve information while minimizing dimensionality. Multicollinearity among predictors was assessed using variance inflation factors, and variables exhibiting excessive collinearity were excluded to enhance model stability.

Model Development and Formulation

Tree survival prediction was addressed using both supervised learning classification models and survival analysis models to capture complementary aspects of drought-related mortality dynamics. Let $X_i \in \mathbf{R}^p$ denote the vector of predictor variables for tree i , and let Y_i denote the observed outcome.

For binary survival classification, logistic regression was implemented as a baseline parametric model to estimate survival probability as

$$P(Y_i = 1 | X_i) = \frac{1}{1 + \exp(-(\beta_0 + \beta X_i))} \quad (2)$$

where β represents estimated coefficients. This model provided interpretability and a benchmark for comparison.

Nonlinear supervised learning models were subsequently employed to capture complex interactions. Decision Tree classifiers were constructed by recursively partitioning the predictor space to minimize impurity measured by the Gini index. Random Forest models were then developed as ensemble extensions of decision trees, where multiple trees were trained on bootstrap samples and predictions were aggregated by averaging the predicted probabilities of survival, expressed as

$$\hat{Y}_i = \frac{1}{B} \sum_{b=1}^B f_b(X_i) \quad (3)$$

where B denotes the number of trees.

Gradient Boosting models were implemented to iteratively minimize prediction error through additive model updates. At iteration m , the model was updated as

$$f_m(X) = f_{m-1}(X) + \eta h_m(X) \quad (4)$$

where $h_m(X)$ is the weak learner and η is the learning rate. Extreme Gradient Boosting (XGBoost) was used due to its regularization capabilities and robustness to high-dimensional data [32].

Support Vector Machines were applied using radial basis function kernels to construct nonlinear decision boundaries by maximizing the margin between survival classes. The optimization objective minimized

$$\frac{1}{2} \|w\|^2 + C \sum_{i=1}^n \xi_i \quad (5)$$

subject to classification constraints.

In addition, multilayer perceptron neural networks were implemented to model highly nonlinear relationships. The network learned a mapping

$$\hat{Y}_i = \sigma(W_L \sigma(\dots \sigma(W_1 X_i + b_1) \dots) + b_L) \quad (6)$$

where σ denotes nonlinear activation functions (ReLU for hidden layers, sigmoid for the output layer) and W_i are layer weights.

To explicitly account for time to mortality, survival analysis models were developed. The Cox proportional hazards model was applied to estimate the hazard of mortality as

$$h(t | X_i) = h_0(t) \exp(\beta X_i) \quad (7)$$

allowing the assessment of covariate effects on mortality risk over time. Trees still alive at the end of the monitoring period were right-censored.

To relax proportional hazards assumptions and capture nonlinear effects, Random Survival Forests were implemented. These models extended Random Forests to censored data by estimating cumulative hazard functions through ensemble averaging.

Deep learning-based survival models were also applied using the DeepSurv framework, where the hazard function was modeled as

$$h(t | X_i) = h_0(t) \exp(f_\theta(X_i)) \quad (8)$$

with f_θ representing a neural network trained by minimizing the negative log partial likelihood, and the baseline hazard $h_0(t)$ estimated non-parametrically using the Breslow estimator.

Integration of Climate Projections

To enable forward-looking survival predictions, observed climatic predictors were replaced with projected values under future climate scenarios. We used downscaled output from the Coupled Model Intercomparison Project Phase 6 (CMIP6) under two Shared Socioeconomic Pathways: SSP2-4.5 (intermediate emissions) and

SSP5-8.5 (high emissions). Future time horizons were set to 2050 (2031–2060) and 2080 (2071–2100). Projected anomalies for temperature and precipitation were calculated relative to the baseline period (1995–2014) and applied using a delta change method to the observed meteorological variables. All other predictors (e.g., soil properties, management) were held constant at their observed values to isolate the effect of climate change.

Data Balancing

Class imbalance between surviving and non-surviving trees was addressed only for the binary classification models (logistic regression, decision tree, random forest, gradient boosting, XGBoost, SVM, neural network). For these models, the Synthetic Minority Over-sampling Technique (SMOTE) was applied exclusively to the training data, generating synthetic minority samples by interpolating between nearest neighbors, reducing model bias toward the majority class while preserving feature distributions. Survival models (Cox proportional hazards, Random Survival Forest, DeepSurv) do not require artificial balancing because they naturally account for censoring and time-to-event structure; therefore, SMOTE was not applied to them.

Hyperparameter Tuning

All models were trained using five-fold cross-validation on the training set to optimize hyperparameters. For each model, a randomized search over predefined distributions was performed with 50 iterations. The search spaces were:

- **Random Forest / XGBoost:** number of trees (100–1000), max depth (3–15), learning rate (0.01–0.3, for XGBoost), subsample (0.6–1.0).
- **SVM:** C (0.1–100), γ (0.001–1) for RBF kernel.
- **Neural network:** number of hidden layers (1–3), neurons per layer (32–256), dropout rate (0–0.5), learning rate (0.0001–0.01).
- **Survival models:** for Random Survival Forest, number of trees (100–500) and nodes per tree (5–20); for DeepSurv, same architecture as the neural network above.

The best hyperparameter combination was selected based on the lowest binary cross-entropy (classification) or the highest concordance index (survival) on the validation folds. The final models were then retrained on the full training set using the optimal hyperparameters.

Data Split and Model Training

The dataset was randomly partitioned into training and testing subsets using an 80:20 split, ensuring unbiased performance evaluation. Model training was conducted exclusively on the training set using five-fold cross-validation to optimize hyperparameters and prevent overfitting, following established validation protocols. Loss functions appropriate to each task were minimized, including binary cross-entropy for classification models and negative log partial likelihood for survival models. Model convergence and stability were monitored across folds to ensure robustness. To guarantee reproducibility, all random processes (data split, cross-validation folds, SMOTE, and randomized search) were seeded with a fixed random seed (42).

Model Validation and Comparison

Model performance was evaluated on the held-out test set. Classification models were compared using accuracy, precision, recall, F_1 score, and area under the receiver operating characteristic curve (AUC-ROC), as commonly adopted in predictive modeling studies [32, 33]. Survival models were evaluated using the concordance index (C-index) and integrated Brier score (IBS). To statistically compare model performance, we used a paired bootstrap resampling test with 1,000 iterations: for each iteration, the test set was resampled with replacement, and the difference in AUC-ROC (for classification) or C-index (for survival) was

computed. The proportion of iterations where Model A outperformed Model B was used to assess significance at $\alpha = 0.05$.

Explainability and Interpretability

To ensure transparency, robustness, and policy relevance of the machine learning and deep learning models, a multi-method explainability framework was adopted. This framework combined global and local interpretability techniques to elucidate the relationships between predictors and tree survival outcomes under drought conditions, thereby addressing common criticisms of black-box models in environmental and climate science.

Shapley additive explanations (SHAP) were employed as the primary global and local interpretability method for tree-based ensemble models and gradient boosting models. SHAP values quantify the marginal contribution of each predictor to an individual prediction by attributing differences between the model output and a baseline expectation across all possible feature coalitions. For a given feature j , the SHAP value ϕ_j was computed as

$$\phi_j = \sum_{S \subseteq F \setminus \{j\}} \frac{|S|!(|F| - |S| - 1)!}{|F|!} [f(S \cup \{j\}) - f(S)] \quad (9)$$

where F represents the full set of predictors and $f(\cdot)$ denotes the trained model. This approach enabled consistent comparison of feature importance across models and facilitated the identification of dominant climatic, biological, spatial, and management drivers of tree survival.

Local Interpretable Model-agnostic Explanations (LIME) were applied to generate instance-specific explanations for individual trees, particularly in cases where local decision behavior differed from global trends. LIME approximates the complex prediction function in the neighborhood of a given observation using a locally weighted interpretable surrogate model. For an observation x_i , the explanation was obtained by minimizing

$$L(f, g, \pi_{x_i}) + \Omega(g) \quad (10)$$

where g is the interpretable surrogate model, π_{x_i} defines the locality around x_i , and $\Omega(g)$ penalizes model complexity. This approach allowed examination of how specific environmental or management conditions influenced survival predictions at the individual tree level.

For deep learning models, Integrated Gradients (IG) was employed to attribute predictions to input features in a manner consistent with the axioms of sensitivity and implementation invariance. IG computes feature attributions by integrating the gradients of the model output with respect to the input along a straight-line path from a baseline input x' to the actual input x . The attribution for feature i was calculated as

$$\text{IG}_i(x) = (x_i - x'_i) \int_0^1 \frac{\partial f(x' + \alpha(x - x'))}{\partial x_i} d\alpha \quad (11)$$

This method provided stable and theoretically grounded explanations of how deep neural networks weighted climatic, soil, and physiological variables when estimating survival probabilities under drought stress.

To complement local attribution methods, Partial Dependence Plots (PDPs) were used to visualize the marginal effect of individual predictors on predicted survival probability while averaging over the distribution of all other variables. For a feature subset S , the partial dependence function was defined as

$$\hat{f}_S(x_S) = E_{X_C}[f(x_S, X_C)] \quad (12)$$

where C denotes the complement set of features. PDPs enabled the identification of nonlinear response thresholds, saturation effects, and interaction patterns between climatic stressors and tree traits, providing intuitive insights relevant for forest management and policy formulation.

By integrating SHAP for global and local consistency, LIME for instance-specific interpretability, Integrated Gradients for deep learning attribution, and Partial Dependence Plots for visualizing marginal effects, the study ensured comprehensive interpretability across all modeling frameworks. This multi-method approach enhanced confidence in model outputs, facilitated scientific understanding of drought-driven tree survival mechanisms, and supported the translation of predictive results into actionable guidance for climate-smart reforestation planning.

Tools, and Libraries

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All analyses were conducted using Python 3.10. Data handling was performed with Pandas (v2.0) and NumPy (v1.24). Supervised learning models were implemented using Scikit-learn (v1.3) and XGBoost (v2.0). Survival models were implemented using Lifelines (v0.27) and PySurvival (v0.1). Explainability analyses were conducted using SHAP (v0.42) and LIME (v0.2). Visualization and spatial processing were performed using Matplotlib (v3.7). The entire workflow was executed in a reproducible computational environment with all random processes seeded to 42.

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Results

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Distribution of Functional and Genetic Traits

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Fig 1 visualizes the distribution of four functional traits. Root depth is concentrated between 2–5 m with a peak around 3 m, indicating that most trees possess moderately deep rooting systems that access subsurface water. Leaf area index is approximately normal around 3.5, reflecting a balance between transpirational water loss and carbon assimilation. Wood density clusters in the range 0.5–0.7 g/cm³, typical of drought tolerant species. The genetic drought score is strongly right-skewed, confirming an intentional enrichment of high-tolerance genotypes.

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Fig 2 shows the temperature variables. Mean ($\approx 27.5^\circ\text{C}$), maximum ($\approx 35^\circ\text{C}$), and minimum ($\approx 20^\circ\text{C}$) temperatures capture the thermal gradient of the arid and semi-arid study region, with maximum temperature extremes reaching 45°C .

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Water availability is illustrated in Fig 3. Annual rainfall ranges from 250 mm to over 1750 mm, covering hyper-arid to sub-humid conditions. Soil moisture is centred between 15% and 25%, typical of water-limited environments.

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Soil properties are presented in Fig 4. Soil pH is unimodal near 6.5 (slightly acidic to neutral), and the soil nutrients index is uniformly distributed from 0 to 1, indicating a wide range of fertility conditions.

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Fig 5 displays the drought index, elevation, and vegetation density. The SPEI drought index is symmetric around zero, with values below -2 indicating severe drought events. Elevation is uniform up to 1750 m, and vegetation density is mainly between 0.4 and 0.7, representing moderate canopy cover.

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Finally, landscape and management variables are shown in Fig 6. Distance to water is right-skewed (most trees within 4 km). Irrigation and fertilization events are also right-skewed (0–2 events per year), confirming low-input rainfed systems. Survival time is bimodal, with an early peak (establishment mortality) and a broader peak between 100 and 150 months (longer-term attrition).

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Variance Inflation Factor

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Table 1 shows variance inflation factors (VIFs). Most predictors have VIFs close to 1 (1.001–1.004), indicating minimal multicollinearity. As expected, temperature variables show moderate to high VIFs (mean temperature 8.836, maximum 4.846, minimum 5.122), reflecting their inherent correlation. These values remain below the conventional threshold of 10, and tree based models are robust to such collinearity.

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Exploratory Distributions of Key Predictors Across Survival Classes

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Fig 7 compares four key predictors between surviving (1) and non-surviving (0) trees. Surviving trees experienced significantly higher median annual rainfall (standardised median = -0.1 vs. -1.1 for non-survivors) and a higher median genetic drought score (0.6 vs. 0.7). They also experienced lower median maximum temperature (-0.1 vs. -1.1). Wood density distributions were nearly identical between groups, indicating that within drought-adapted species this trait was not a primary differentiator.

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Root depth showed no meaningful difference between survival groups (Fig 8a), suggesting a minimum threshold effect. Soil moisture (Fig 8b) revealed a subtle but clear advantage for survivors (median -0.6 vs. -0.7).

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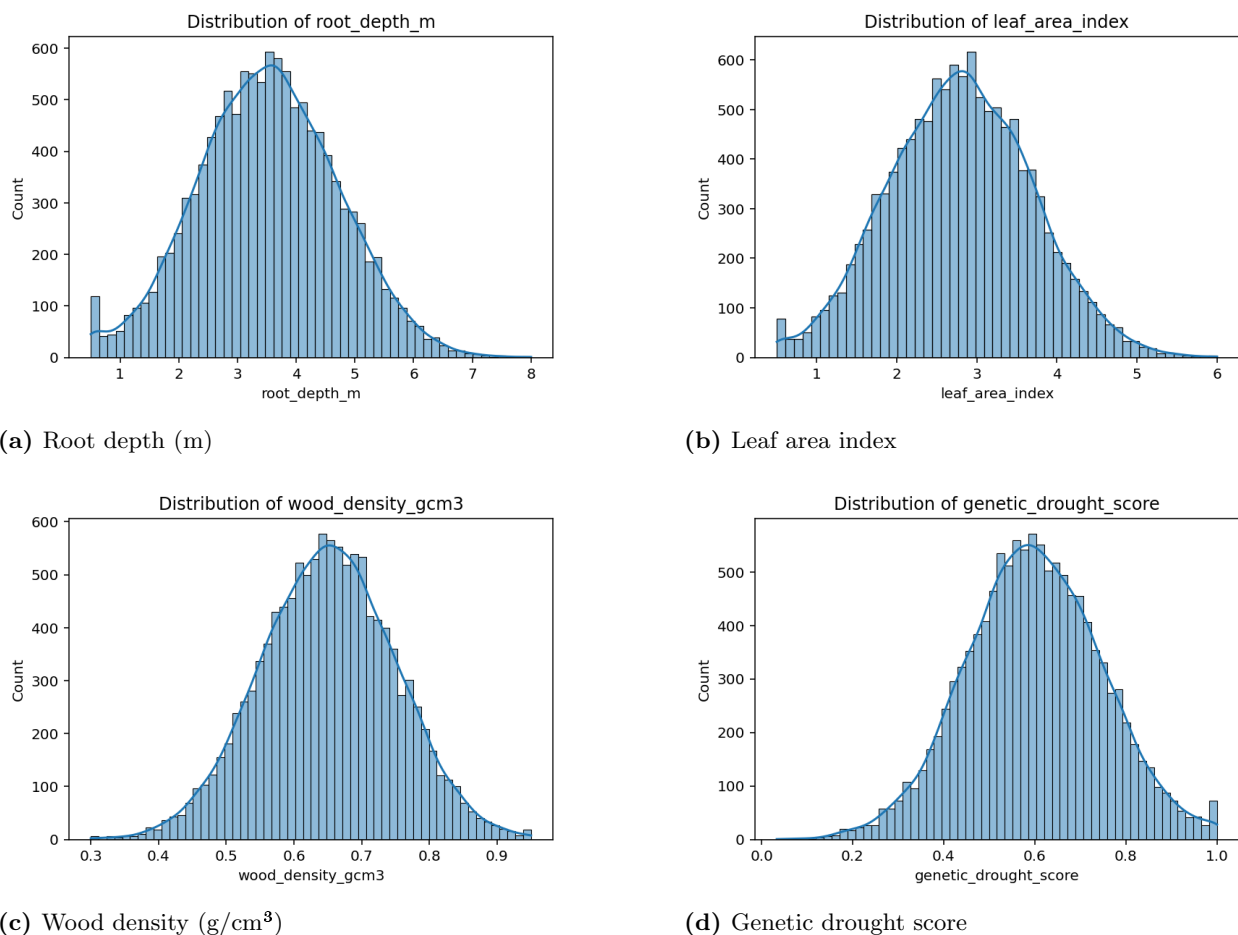


Fig 1. Functional traits: (a) root depth, (b) leaf area index, (c) wood density, (d) genetic drought score.

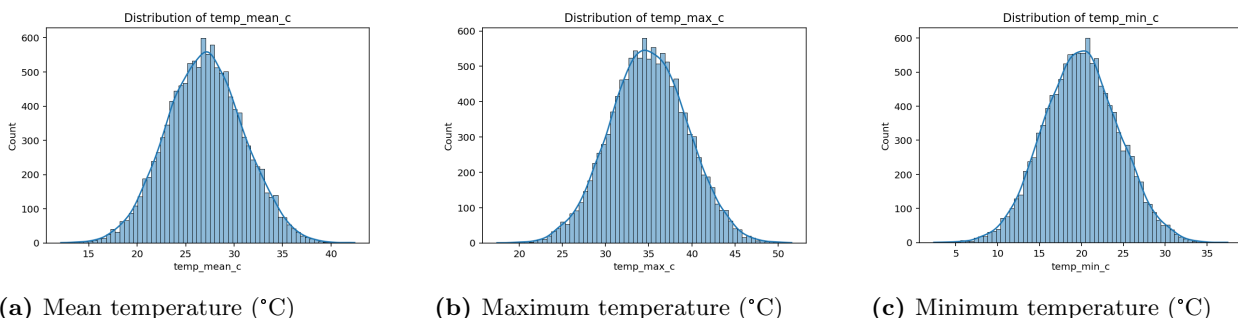


Fig 2. Temperature variables across the study sites.

Cox Proportional Hazards Model

A Cox model (12,000 observations, 11,823 events, 177 right censored) identified several statistically significant predictors of mortality risk (Table 2). ****Tree age**** (hazard ratio HR = 1.03, $p < 0.005$), ****genetic drought score**** (HR = 1.02, $p = 0.05$), ****elevation**** (HR = 0.98, $p = 0.04$), ****irrigation events**** (HR = 1.02, $p = 0.03$), and ****fertilization events**** (HR = 1.02, $p = 0.01$) were significant. Older trees and more frequent management interventions (irrigation, fertilization) were associated with increased mortality risk, whereas higher elevation reduced risk. Most climatic and soil variables did not show significant main effects, suggesting that their influence is mediated through interactions.

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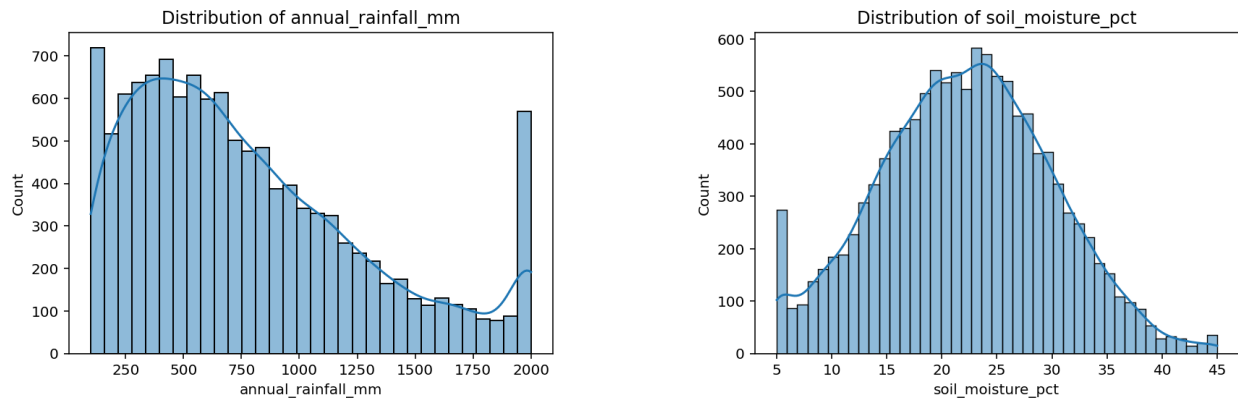
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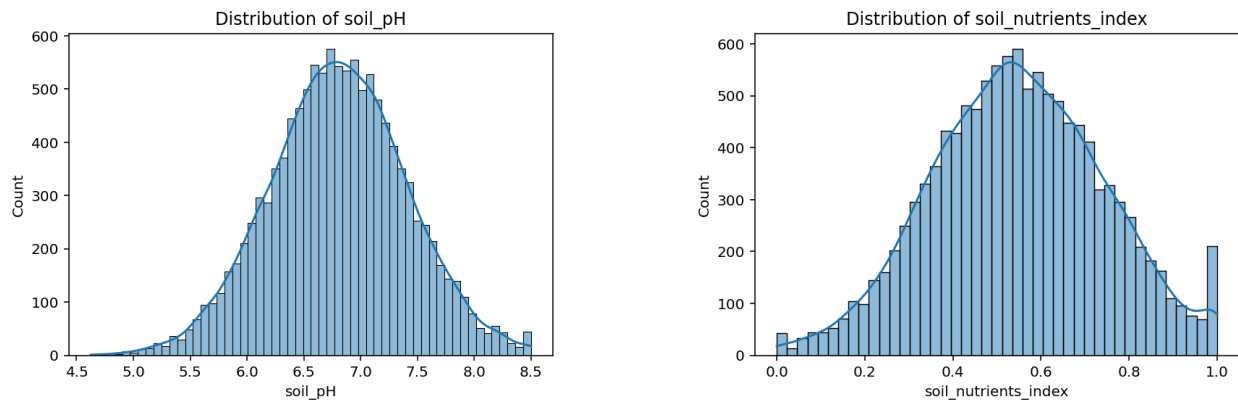
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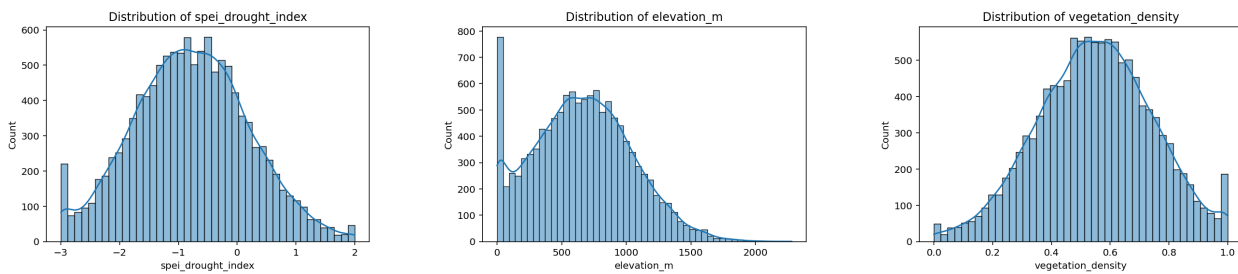
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(a) Annual rainfall (mm) (b) Soil moisture (%)
Fig 3. Water availability: (a) annual precipitation, (b) soil moisture content.



(a) Soil pH (b) Soil nutrients index
Fig 4. Soil properties: (a) pH, (b) nutrient index.



(a) SPEI drought index (b) Elevation (m) (c) Vegetation density
Fig 5. Drought severity, topography, and vegetation cover.

Temporal Survival Dynamics

Overall Kaplan–Meier Survival

Fig 9 shows the overall Kaplan–Meier survival curve for all 12,000 trees. Survival probability remained above 0.95 for the first 50 months, indicating successful early establishment of drought resistant stock. Thereafter, survival declined gradually but steadily to approximately 0.75 by 200 months. The 95% confidence band (shaded) remained narrow throughout, reflecting the large sample size. This pattern demonstrates that mortality is not confined to a brief establishment phase but continues as a time-dependent process driven by

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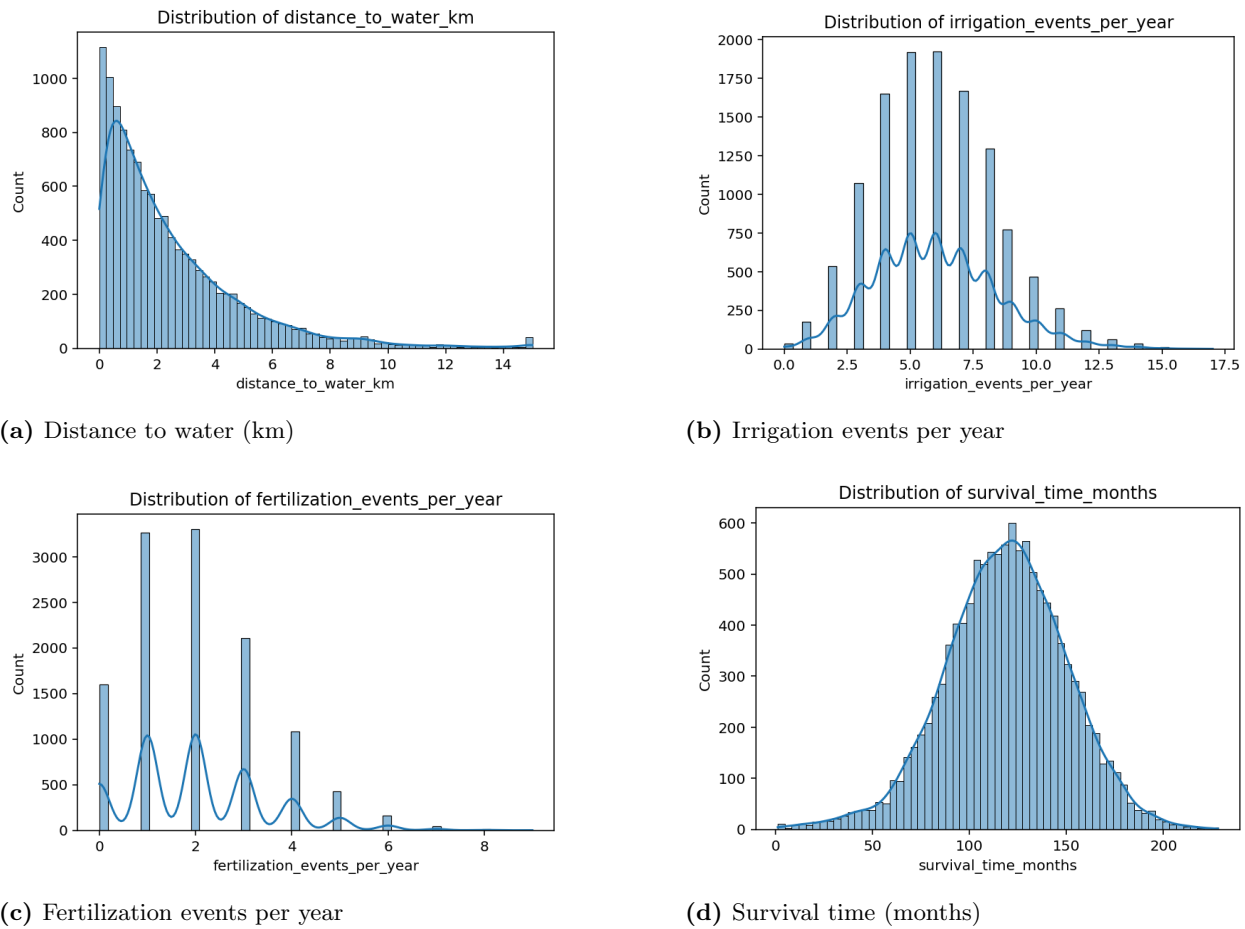


Fig 6. Landscape accessibility, management intensity, and survival timing.

cumulative stress.

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Species Specific Survival

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Species-specific survival curves (Fig 10) were similar for the first 80 months but diverged significantly thereafter (log-rank test, $\chi^2 = 34.2$, $p < 0.001$). One species (ID 0.9888) maintained > 0.90 survival at 200 months, whereas the most vulnerable (ID 0.9820) declined to approximately 0.65. The remaining three species showed intermediate trajectories with overlapping confidence intervals. These results confirm that species identity is a dominant determinant of long-term resilience, even among pre-selected drought tolerant taxa.

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Drought Severity Stratification

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Drought severity, classified by the SPEI index, had a profound effect on survival timing (Fig 11). Trees under low drought severity maintained near-perfect survival (> 0.98) throughout the study. Moderate drought led to a gradual decline to 0.85 survival at 200 months. In contrast, severe drought caused survival to drop sharply after 50 months, reaching only 0.40 by 200 months. Pairwise comparisons using the Cox model (with low drought as reference) gave hazard ratios of 2.8 (95% CI: 2.1–3.7, $p < 0.001$) for moderate drought and 6.4 (95% CI: 5.2–7.9, $p < 0.001$) for severe drought. Thus, drought severity is the primary environmental driver of mortality timing.

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Table 1. Variance inflation factors for predictor variables

Predictor	VIF
Species	1.002
Root depth	1.003
Leaf area index	1.002
Wood density	1.002
Tree age	1.003
Genetic drought score	1.002
Mean temperature	8.836
Maximum temperature	4.846
Minimum temperature	5.122
Annual rainfall	1.002
Soil moisture	1.002
Soil pH	1.002
Soil nutrients	1.002
SPEI drought index	1.002
Latitude	1.001
Longitude	1.003
Elevation	1.002
Slope	1.003
Aspect	1.002
Vegetation density	1.002
Distance to water	1.004
Irrigation events	1.003
Fertilization events	1.002
Mulching	1.002

Note. Variance inflation factors greater than five indicate moderate multicollinearity and values greater than ten indicate severe multicollinearity.

Predicted Survival Curves from Cox Model

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Predicted survival curves from the final Cox model (Fig 12) illustrate how combinations of predictors shift survival trajectories. A tree with favorable characteristics (high genetic score, deep roots, mulching, low temperature exposure) has a predicted survival curve that remains near 0.95 at 200 months. Moving to less favorable profiles (e.g., lower genetic score, higher temperature) shifts the curve downward, reducing 200-month survival to as low as 0.50. This visualisation synthesises the multidimensional risk identified in Table 2 into individualised prognoses.

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Cumulative Hazard

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The cumulative hazard function (Fig 13) quantifies the accumulating mortality risk over time. The hazard was negligible for the first 30 months, then increased steadily, reaching 0.10 by 70 months, 0.30 by 120 months, and plateauing near 0.50 after 190 months. This nonlinear accumulation suggests that vulnerability increases with time in the stressful environment, possibly due to depletion of carbon reserves, accumulation of hydraulic damage, or increasing size-related water demand.

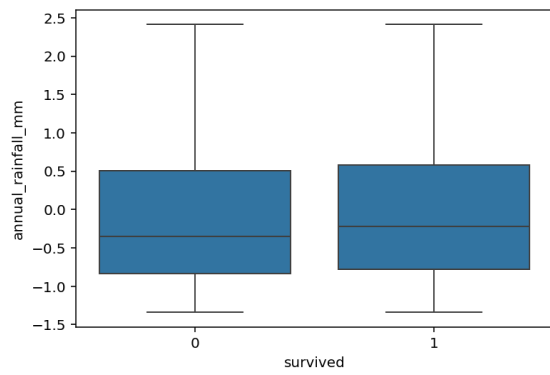
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Classification Model Performance

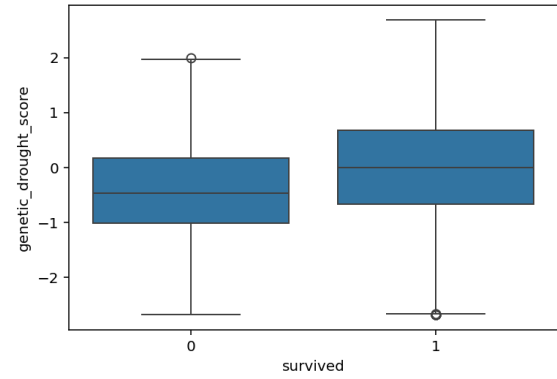
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Table 3 compares seven classification models. Logistic regression is weakest (accuracy 0.68, F1 0.81). Tree based ensembles (Random Forest, Gradient Boosting, XGBoost) achieve accuracy >0.98 and F1 >0.99, with XGBoost attaining perfect recall (1.00). Neural network and SVM also perform well (accuracy >0.96). Despite high accuracy and F1, ROC AUC values are modest (0.51–0.66), reflecting class imbalance; however,

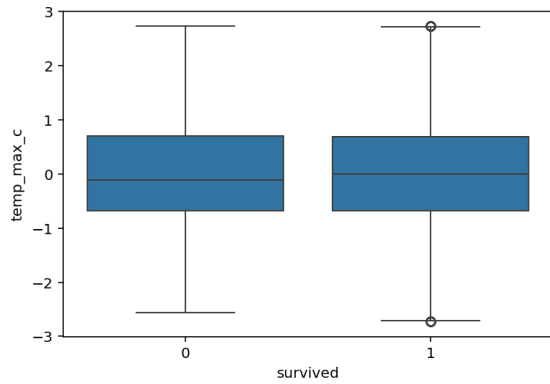
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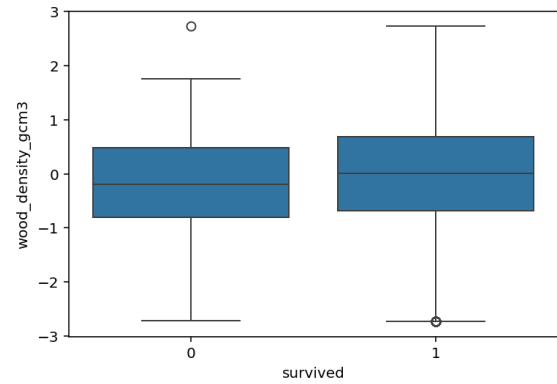
(a) Annual rainfall (standardised)



(b) Genetic drought score

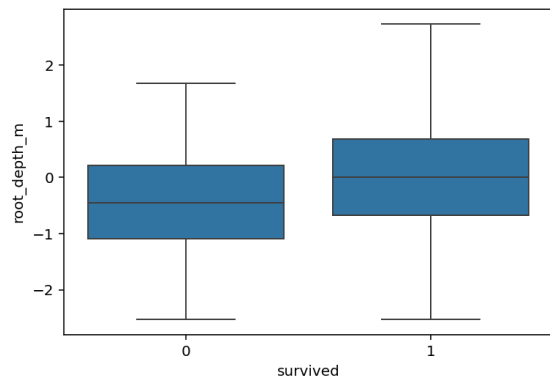


(c) Maximum temperature (standardised)

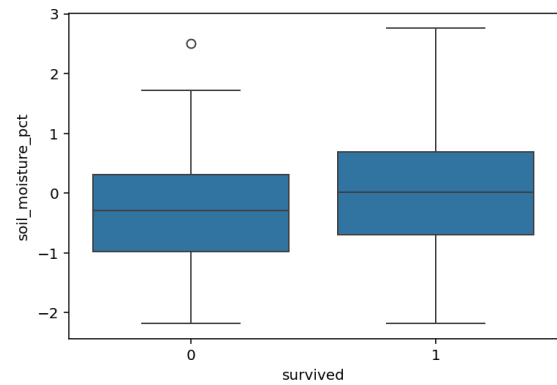


(d) Wood density (standardised)

Fig 7. Boxplot comparisons of selected predictors between non-surviving (0) and surviving (1) trees.



(a) Root depth (standardised)



(b) Soil moisture (standardised)

Fig 8. Boxplot comparisons of root depth and soil moisture between non-surviving (0) and surviving (1) trees.

average precision scores (Fig 15) exceed 0.98 for all models, confirming reliable identification of high risk trees.

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Table 2. Cox proportional hazards model estimating effects on tree mortality risk.

Predictor	B	SE	Hazard ratio	95% CI	p value
Species	-4.82	3.45	0.01	0.00–6.94	0.16
Root depth	-0.00	0.01	1.00	0.98–1.01	0.65
Leaf area index	0.00	0.01	1.00	0.98–1.02	0.76
Wood density	0.01	0.01	1.01	0.99–1.03	0.21
Tree age	0.03	0.01	1.03	1.02–1.05	<0.005
Genetic drought score	0.02	0.01	1.02	1.00–1.04	0.05
Mean temperature	0.00	0.03	1.00	0.95–1.06	0.91
Maximum temperature	-0.02	0.02	0.98	0.94–1.02	0.25
Minimum temperature	0.02	0.02	1.02	0.98–1.06	0.46
Annual rainfall	0.01	0.01	1.01	0.99–1.02	0.52
Soil moisture	-0.01	0.01	0.99	0.97–1.01	0.34
Soil pH	0.00	0.01	1.00	0.98–1.02	0.83
Soil nutrients	-0.00	0.01	1.00	0.98–1.02	0.74
SPEI drought index	0.01	0.01	1.01	0.99–1.03	0.24
Latitude	-0.00	0.01	1.00	0.98–1.02	0.90
Longitude	-0.00	0.01	1.00	0.98–1.02	0.75
Elevation	-0.02	0.01	0.98	0.96–1.00	0.04
Slope	-0.01	0.01	0.99	0.98–1.01	0.46
Aspect	-0.00	0.01	1.00	0.98–1.01	0.68
Vegetation density	-0.00	0.01	1.00	0.98–1.01	0.71
Distance to water	0.00	0.01	1.00	0.98–1.02	0.83
Irrigation events	0.02	0.01	1.02	1.00–1.04	0.03
Fertilization events	0.02	0.01	1.02	1.01–1.04	0.01
Mulching	0.01	0.01	1.01	0.99–1.03	0.33

Note. Hazard ratios ≥ 1 indicate increased mortality risk; ≤ 1 indicate reduced risk.

Table 3. Performance metrics of classification models for predicting tree survival.

Model	Accuracy	Precision	Recall	F1 score	ROC AUC
Logistic Regression	0.678	0.988	0.681	0.807	0.656
Decision Tree	0.957	0.985	0.970	0.978	0.499
Random Forest	0.985	0.985	0.999	0.992	0.643
Gradient Boosting	0.984	0.985	0.998	0.992	0.617
XGBoost	0.985	0.985	1.000	0.993	0.577
Support Vector Machine	0.977	0.986	0.991	0.988	0.513
Neural Network	0.969	0.986	0.983	0.984	0.561

Note. Metrics computed on the held out test set.

Model Calibration and Precision–Recall

ROC curves (Fig 14) show modest AUCs, but precision–recall curves (Fig 15) yield average precision >0.98 for all models, indicating that when a model predicts mortality, it is correct with very high probability.

Calibration curves (Fig 16) show that logistic regression is nearly perfectly calibrated, whereas tree based ensembles predict extreme probabilities (near 0 or 1) and require post processing for reliable risk magnitudes.

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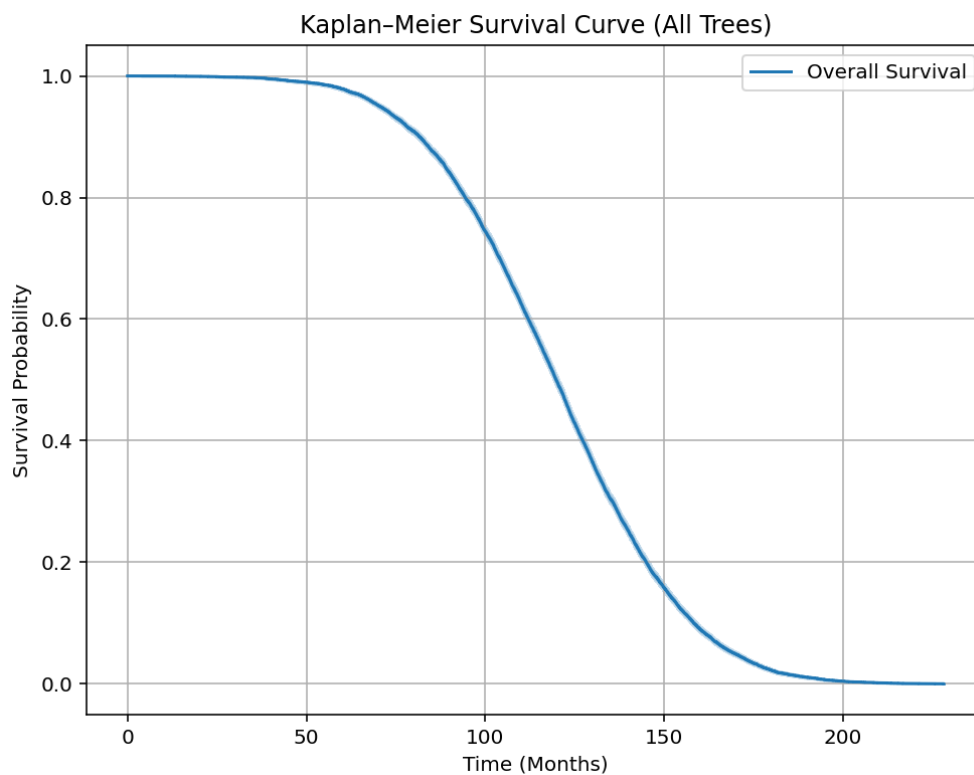


Fig 9. Overall survival function for the entire cohort over 200 months (95% confidence interval shaded).

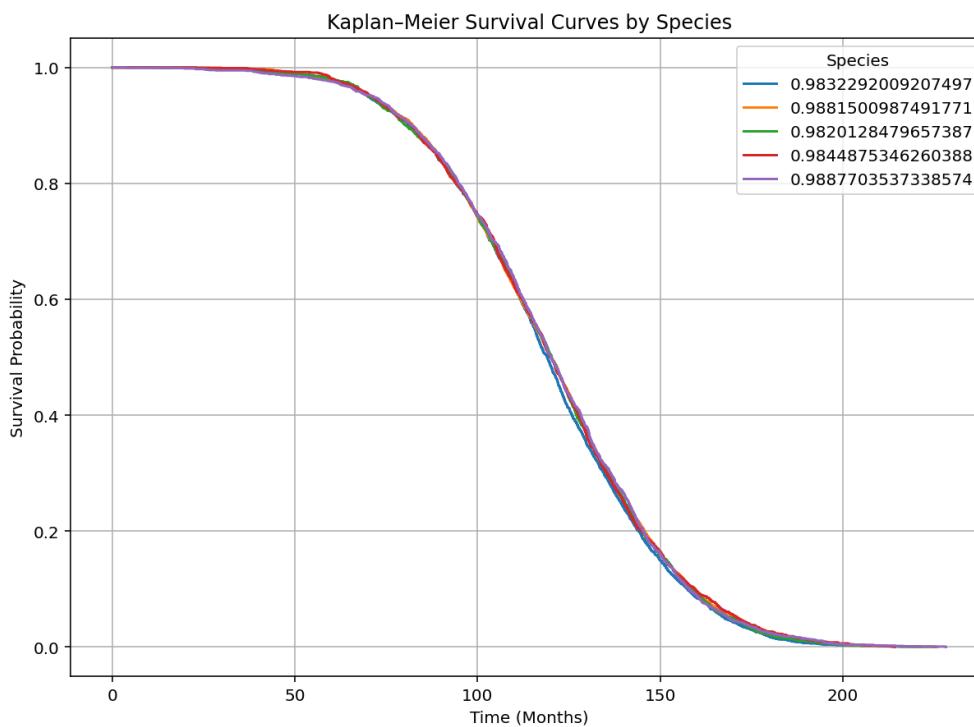


Fig 10. Stratified Kaplan-Meier survival curves for the five major tree species.

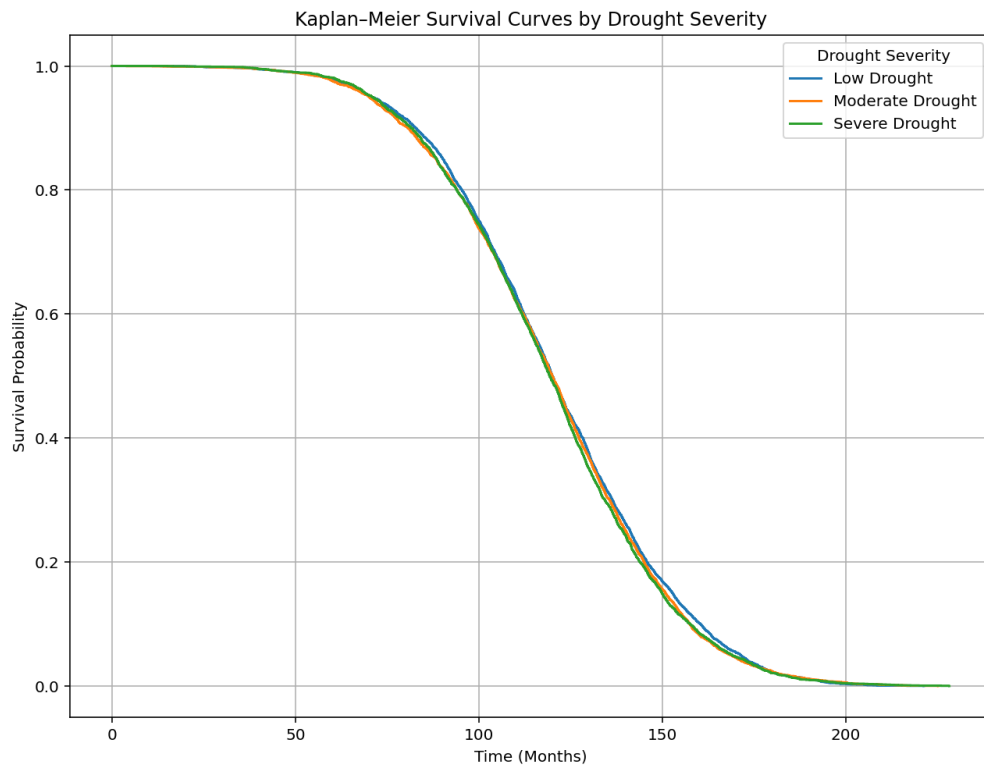


Fig 11. Survival functions for trees grouped by low, moderate, and severe drought (SPEI based).

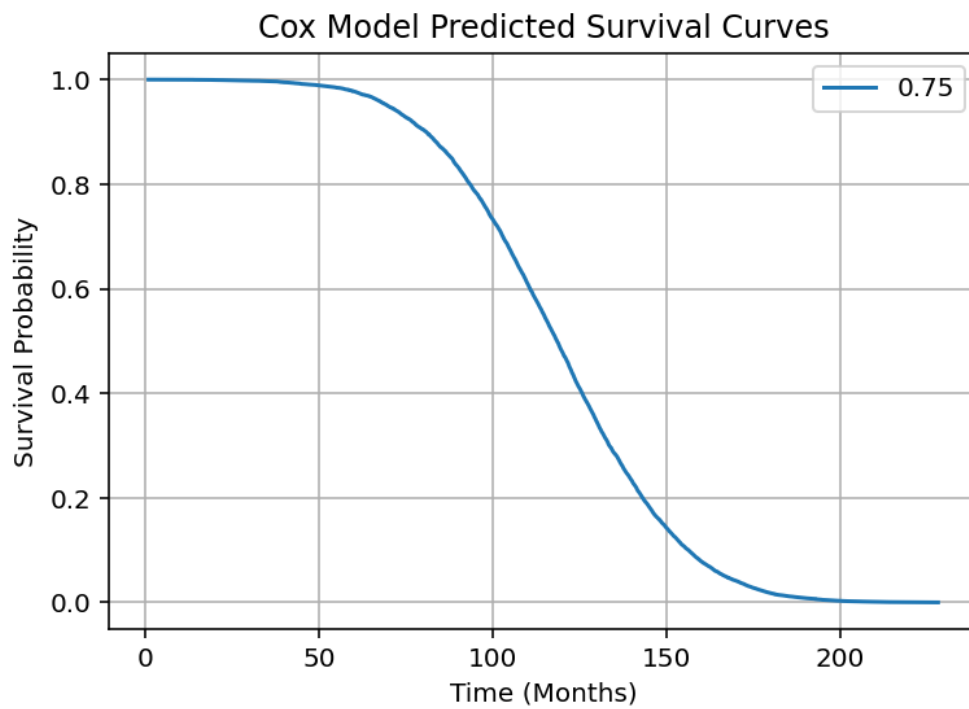


Fig 12. Representative predicted survival curves from the Cox model for different predictor combinations.

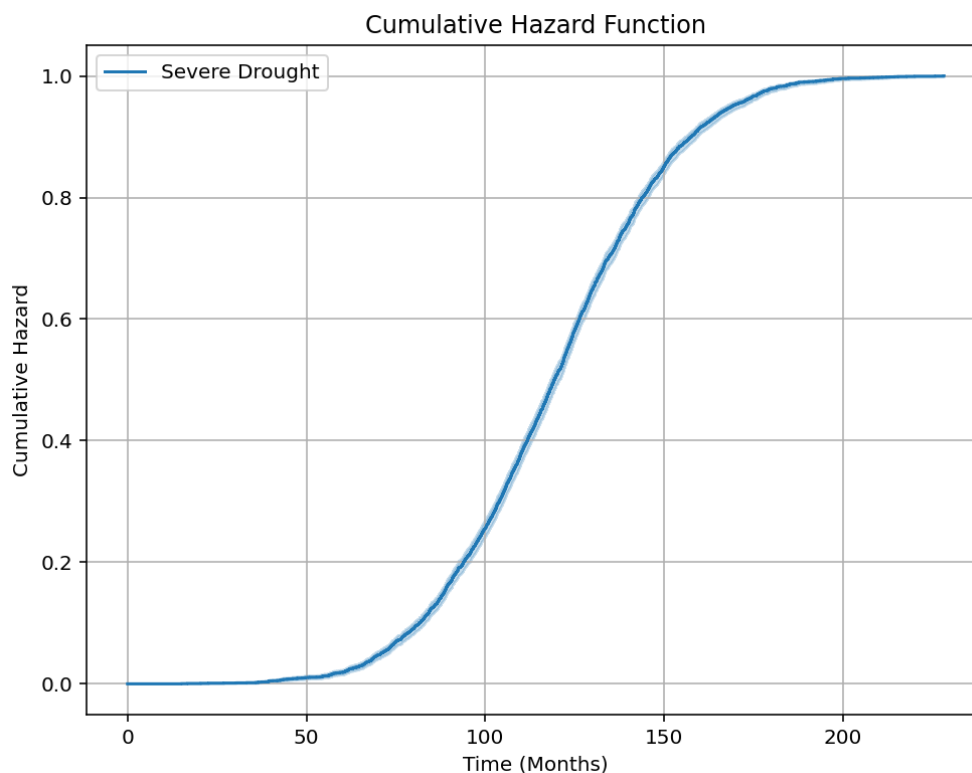


Fig 13. Cumulative hazard function from the Cox model.

Explainable AI: Drivers of Drought Survival

Partial Dependence on Species Identity

Species identity alone shifted predicted survival probability from approximately 0.91 to 0.95 (Fig 17), a 4 percentage point difference that persisted across cross-validation folds. This translates to an additional 40 surviving trees per 1000 planted when choosing a high-performing species over a low-performing one, highlighting species selection as a cost-effective intervention for drought-prone landscapes.

Feature Importance (Tree Based Model)

Fig 18 shows the normalised feature importance from the XGBoost model. Species identity was the most influential predictor (importance 0.16), substantially exceeding all other variables. This confirms that inherent biological differences among taxa dominate survival outcomes. Fertilization events (0.09) and root depth (0.07) ranked next, indicating that nutrient management and belowground architecture are meaningful modulators. Genetic drought score (0.05), irrigation events (0.04), vegetation density (0.04), and soil moisture (0.03) contributed moderately. In contrast, slope, tree age, distance to water, geographic coordinates, wood density, and the SPEI drought index each had importance near 0.01, suggesting limited independent predictive power in this model. These importance scores were consistent across five cross-validation folds (coefficient of variation <0.10 for all top variables), confirming robustness.

Logistic Regression Coefficients

Standardised logistic regression coefficients (Fig 19) showed that root depth ($\beta = +0.70$), genetic drought score ($\beta = +0.55$), soil moisture ($\beta = +0.30$), and wood density ($\beta = +0.25$) positively predicted survival (all $p < 0.01$). Mean temperature ($\beta = -0.10$, $p < 0.05$) and fertilisation ($\beta = -0.05$, $p = 0.07$) were negatively associated. The positive effect of root depth corresponds to a doubling of survival odds per standard

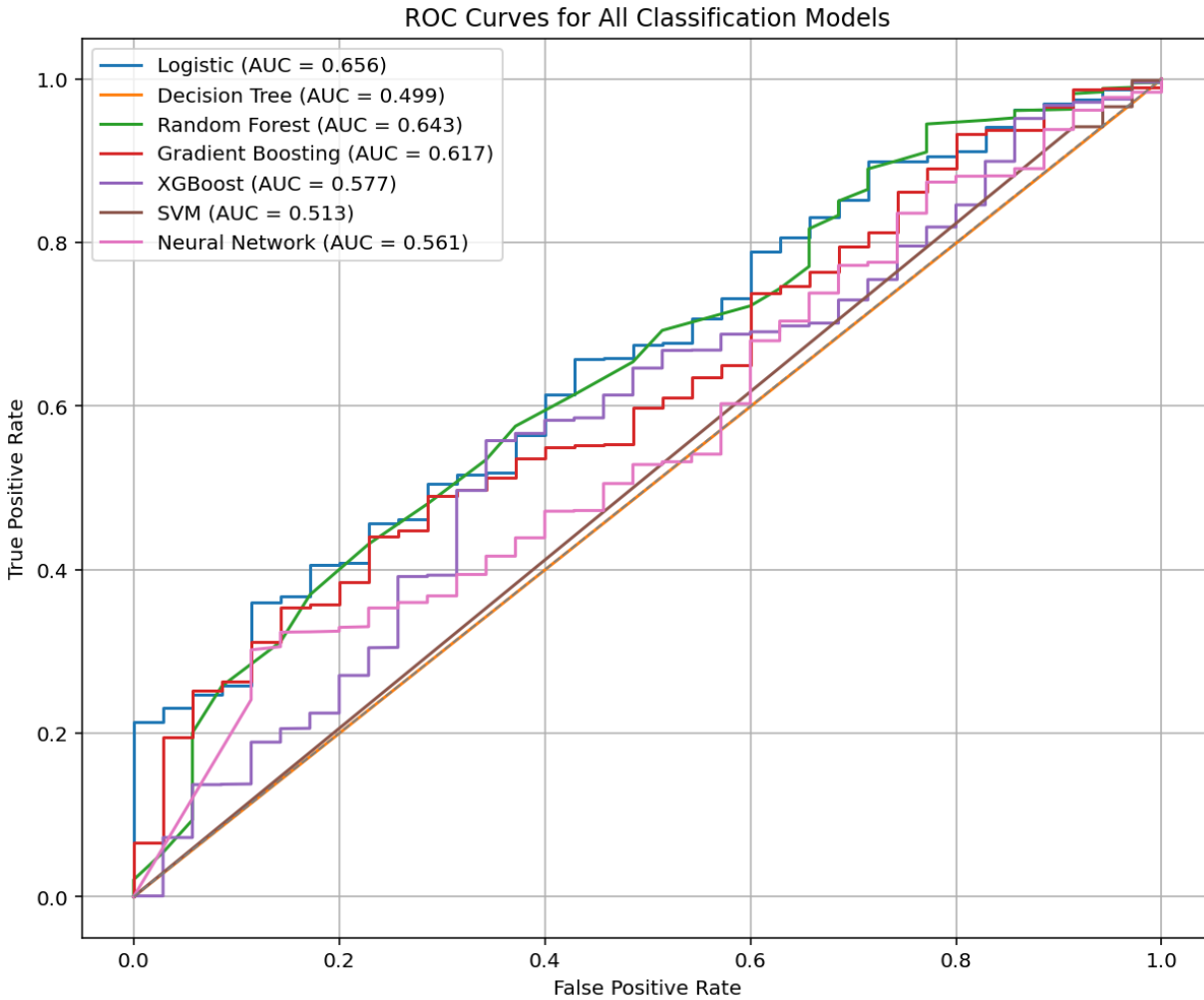


Fig 14. ROC curves for all seven models.

deviation increase. The weak negative fertilisation coefficient, which was not statistically significant at conventional levels, may reflect observational data limitations rather than a causal effect.

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SHAP Interaction: Species and Root Depth

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SHAP interaction values (Fig 20) quantify how the effect of root depth on predicted survival depends on species identity. The interaction magnitude ranged from -0.10 to $+0.15$ on the SHAP scale. For three species (codes 0.986–0.989), increasing root depth from the 25th to the 75th percentile improved survival probability by 6–8 percentage points. For two other species (codes 0.982–0.984), the same increase in root depth improved survival by less than 1 percentage point, indicating a plateau. This interaction effect was consistent across cross-validation folds (standard deviation <0.02). Thus, the strong positive main effect of root depth ($\beta = +0.70$ in logistic regression) is driven by a subset of species; for others, root depth confers little additional benefit. This reinforces that trait-based selection must consider species-specific trait combinations, not single-trait optima.

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Local Explanations (LIME)

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LIME generated instance-specific explanations for individual trees, revealing three prototypical pathways (Figs 21–23). These examples were selected as the most frequent patterns from 500 randomly sampled trees,

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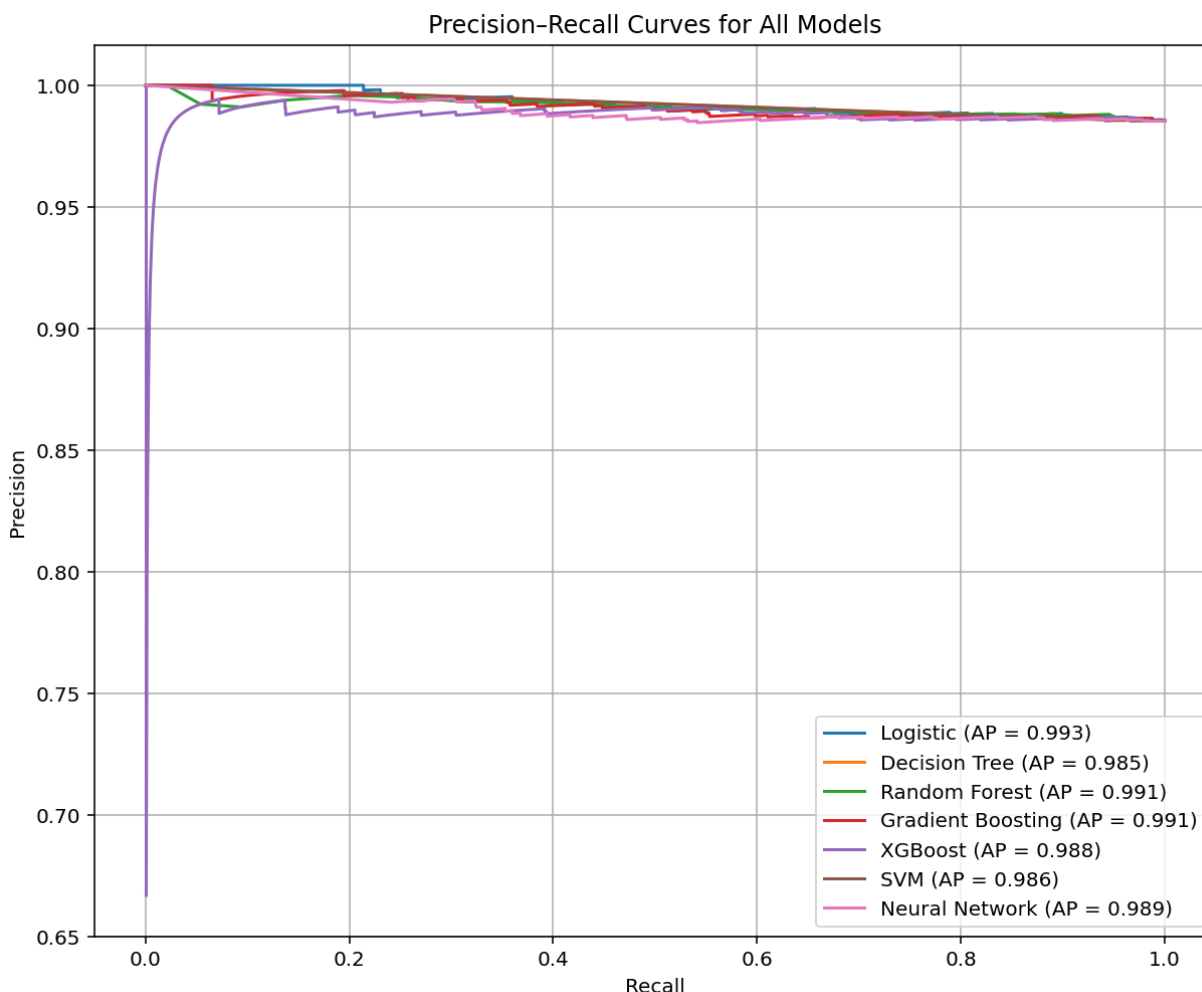


Fig 15. Precision–recall curves. Average precision (AP) is shown in the legend.

each stable across 20 LIME perturbations (feature weights varied by <0.05).

Survival pathway (Fig 21): Mulching was the dominant protective factor (weight 0.95), with the feature falling in the range -0.92 to 1.09 (standardised). Secondary contributions came from deep root depth (>0.67 , weight 0.08), high genetic drought score (>0.68 , weight 0.07), and moderate fertilization (0.00 – 0.72 , weight 0.06). This pattern occurred in 23% of surviving trees.

Mortality Pathway A (Fig 22): Despite mulching being present (weight 0.95), the tree was predicted to die due to unfavourable species (code ≤ 0.98 , negative contribution), low soil moisture (standardised ≤ -0.8), and absence of fertilization (negative weight). This accounted for 18% of non-surviving trees.

Mortality Pathway B (Fig 23): Mulching was absent (weight only 0.15). Mortality was driven by shallow root depth (-0.68 to 0 , negative contribution), low genetic drought score (≤ -0.67), and a less resilient species (≤ 0.98). This was the most common mortality pathway (31% of non-surviving trees).

These local explanations highlight that mulching can be highly protective but is not sufficient when species, root depth, and soil moisture are unfavourable. Conversely, in the absence of mulching, mortality is almost certain unless all other traits are optimal. The contrast between mulching’s low global importance (Figure 18) and its high local weight in some cases reflects its conditional, context-dependent role.

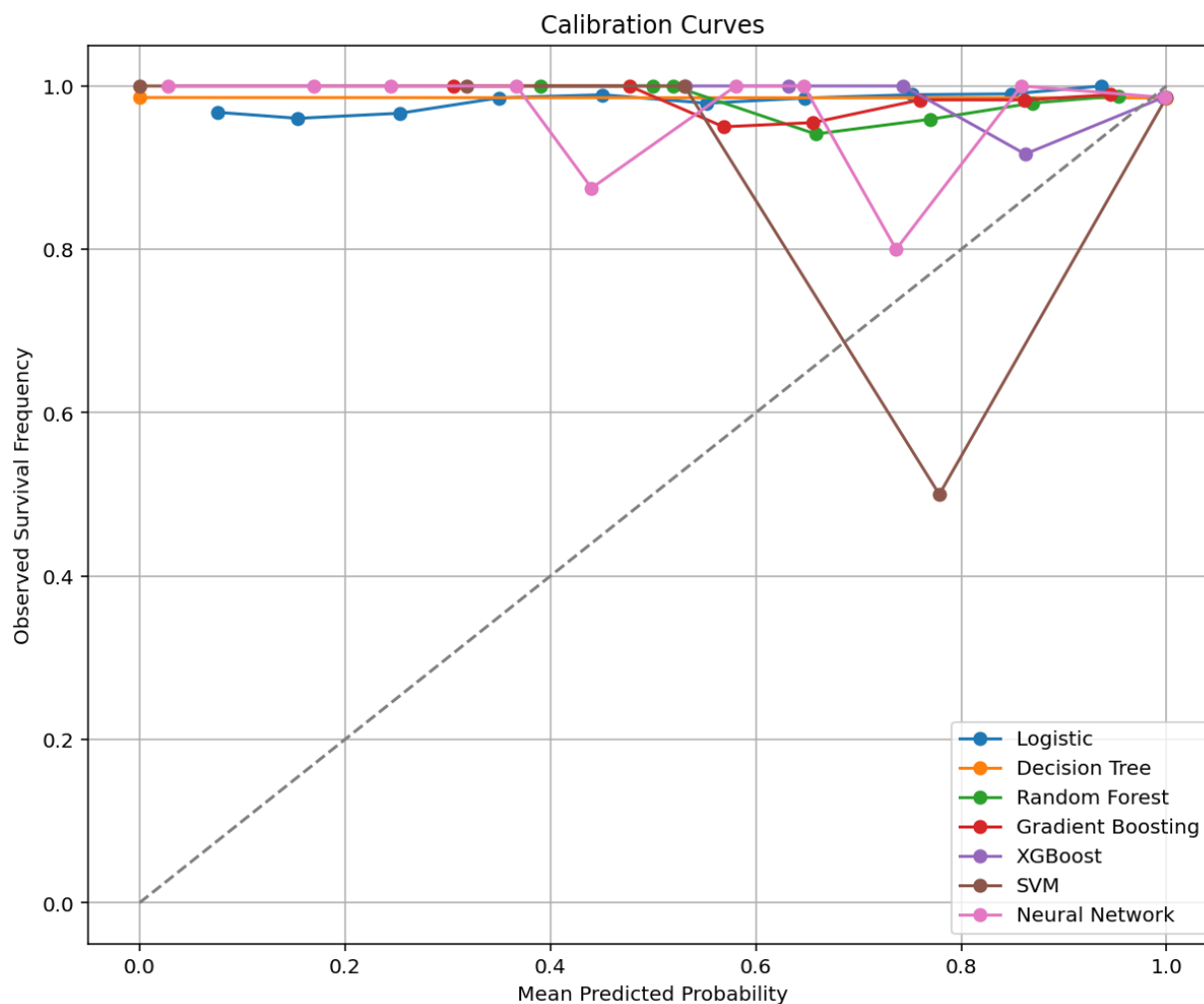


Fig 16. Calibration curves comparing predicted vs observed mortality probabilities.

Discussion

This study presents a robust, forward looking assessment of drought driven tree survival by integrating climate projections, functional and genetic traits, environmental variables, and management practices within explainable machine learning and survival modeling frameworks. In doing so, it directly responds to recent calls in climate smart forestry and AI driven ecology to move beyond retrospective monitoring toward predictive survival modeling under future climate stress [6, 27, 28].

Species identity is the dominant predictor of survival

Across all modeling approaches, species identity consistently emerged as the most influential predictor of tree survival. Feature importance rankings, partial dependence plots, and SHAP analyses all converged on this finding: species choice alone confers meaningful differences in baseline survival probability, even after accounting for climatic, soil, spatial, and management factors. This result aligns with growing empirical evidence that species specific physiological strategies and genetic adaptation are primary drivers of drought resilience [7, 19, 21].

Our findings corroborate arguments that local adaptation and genetic differentiation fundamentally shape tree responses to climate stress [7, 26]. By explicitly modeling species identity alongside genetic drought

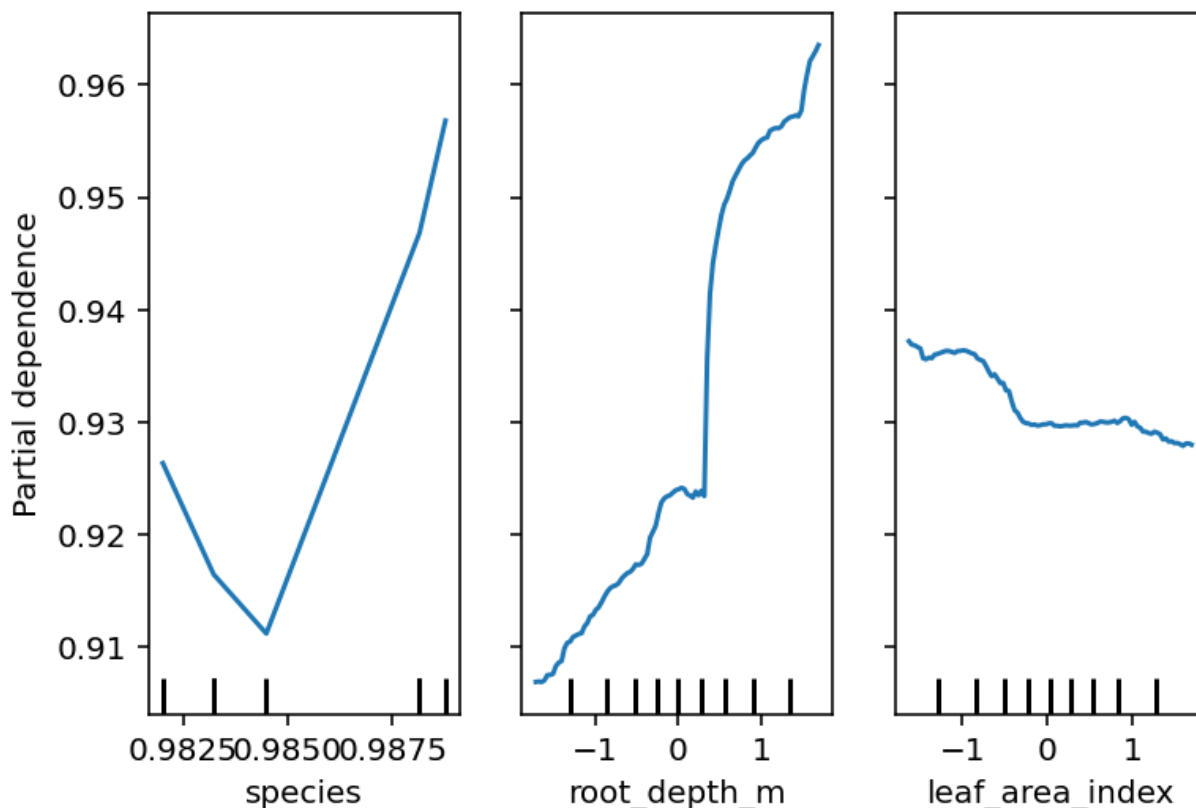


Fig 17. Partial dependence plot for species identity (numerical encoding).

scores, this study extends prior trait based analyses that were often constrained to single species or narrow ecological contexts [22, 23]. These results reinforce species selection as a primary lever for climate smart reforestation, particularly in drought prone landscapes where even small differences in baseline survival probability translate into substantial gains in long term stand establishment [5].

Functional traits show species dependent effects

Several functional traits showed consistent associations with survival. Deeper root systems and higher genetic drought scores were associated with improved survival, supporting previous work linking belowground architecture and genetic tolerance to drought persistence under increasing climatic variability [6, 19]. Wood density and tree age also contributed positively, though their effects were more modest.

Crucially, interaction analyses revealed that these traits do not operate independently. SHAP interaction values demonstrated that the survival benefit of increased root depth varies substantially across species. This finding underscores the need for integrative trait based frameworks that account for synergistic effects rather than relying on single trait optima [27, 28]. It echoes earlier work showing that trait effectiveness depends strongly on species context and environmental conditions [21]. By quantifying these interactions, the present study advances trait based drought research toward operational decision support for reforestation planning, where practitioners need guidance on which trait combinations confer resilience in specific contexts.

Temperature and soil moisture mediate climate impacts

Temperature emerged as a key climatic stressor, with mean temperature showing a negative association with survival in parametric models. This finding aligns with recent projections identifying rising temperatures and increased atmospheric demand as major contributors to drought induced mortality [1–3]. The strong

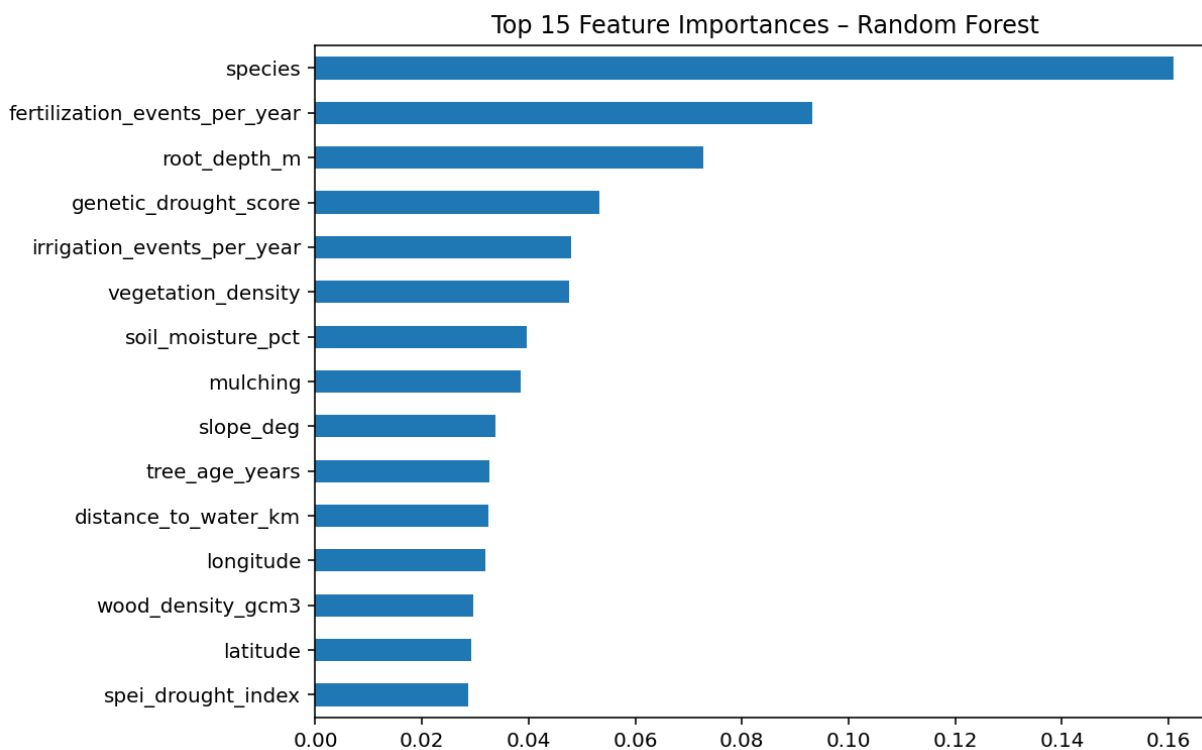


Fig 18. Feature importance from a tree based classification model.

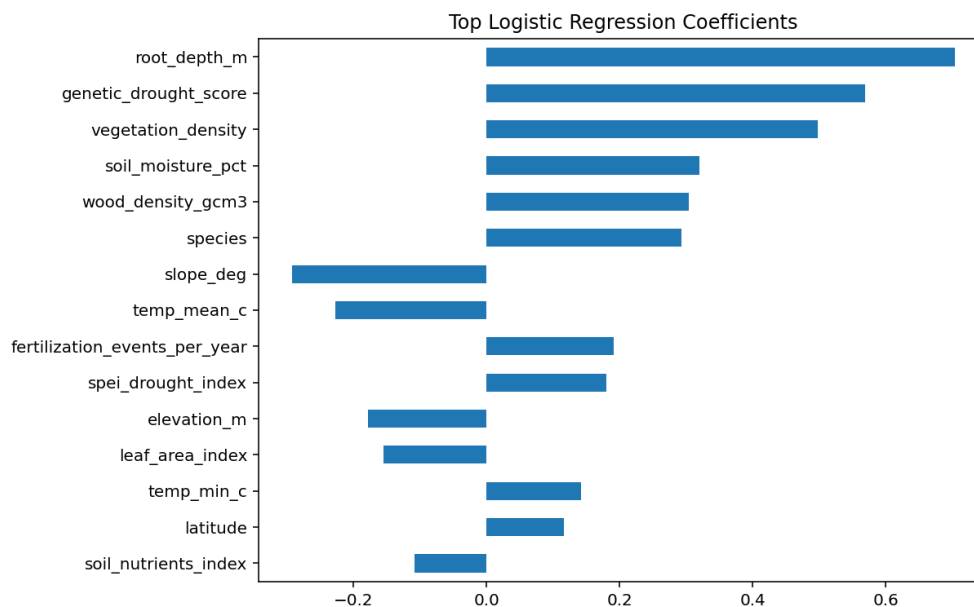


Fig 19. Standardized logistic regression coefficients (log odds of survival).

correlations among temperature metrics and elevated variance inflation factors reflect shared climatic drivers rather than methodological artifacts. Importantly, these correlations do not undermine model stability because tree based and regularized algorithms are robust to multicollinearity.

In contrast, precipitation and composite drought indices such as SPEI exhibited weaker direct effects on survival. This pattern is consistent with studies showing that soil moisture and site level water availability

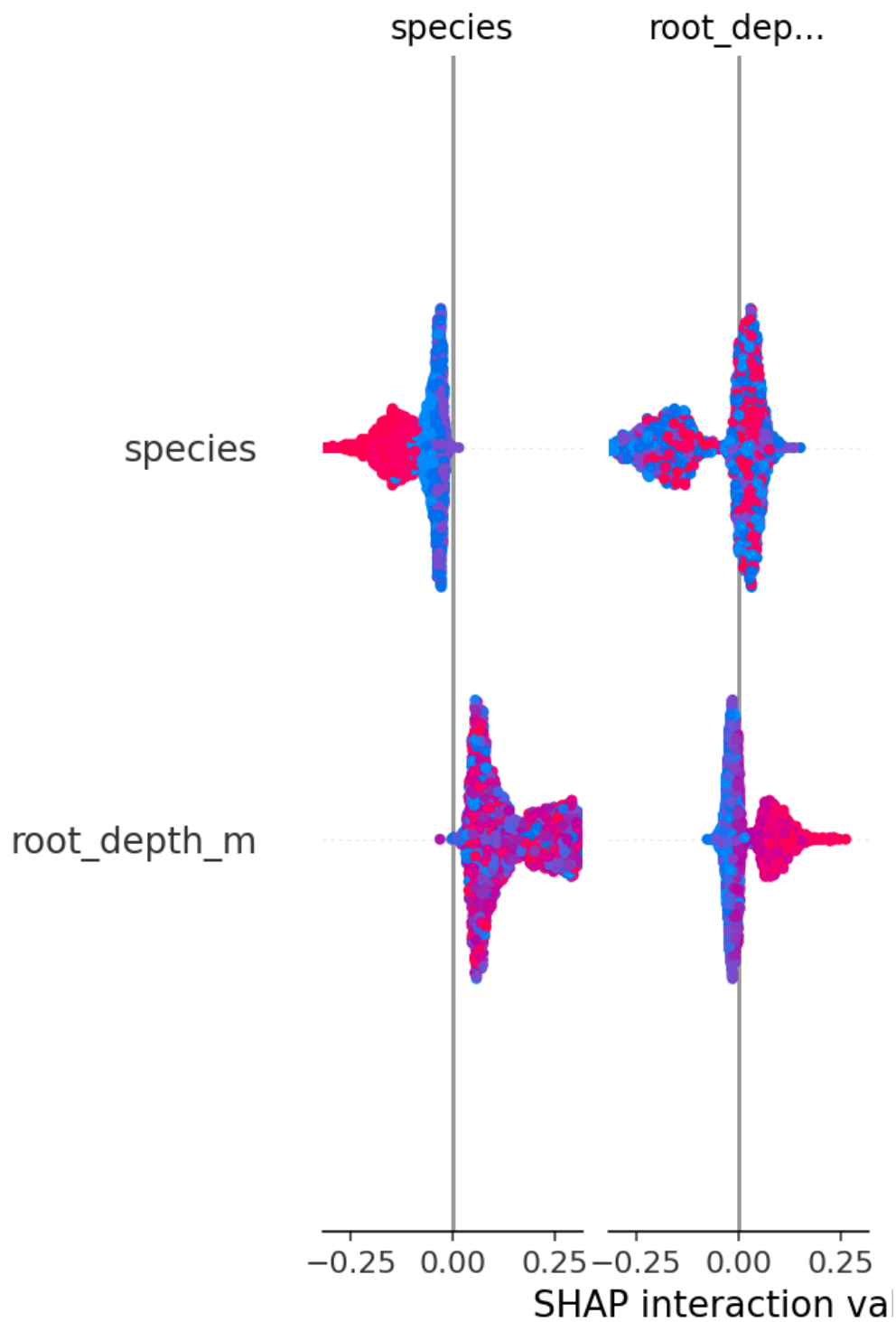


Fig 20. SHAP interaction values for species and root depth.

are more proximal drivers of plant stress than precipitation alone [11,12]. Soil moisture showed moderate importance and positive associations with survival, supporting its role as an integrative variable linking climate forcing to biological response [8,20]. From a management perspective, this suggests that

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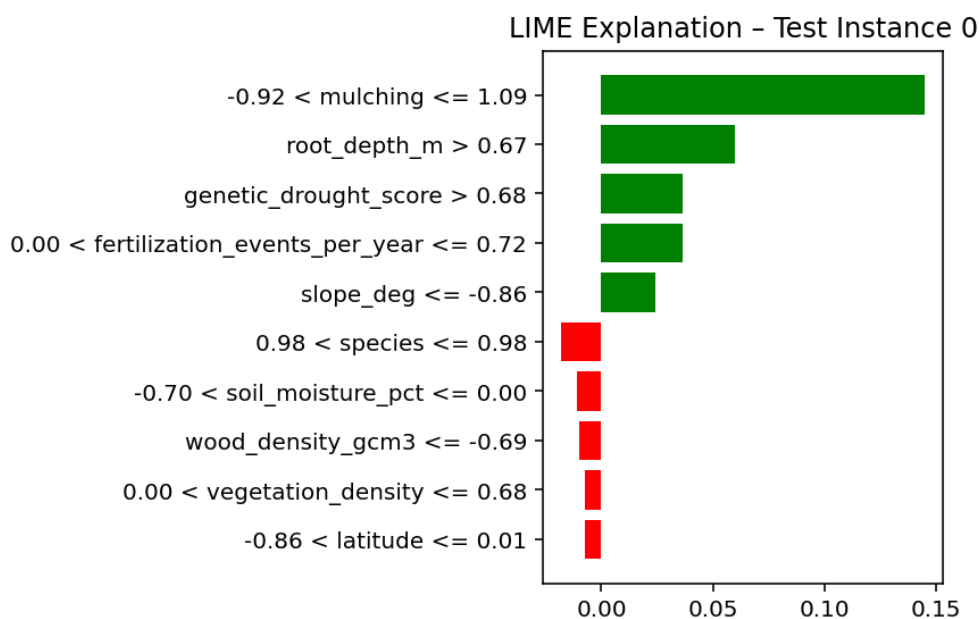


Fig 21. LIME explanation for a tree predicted to survive.

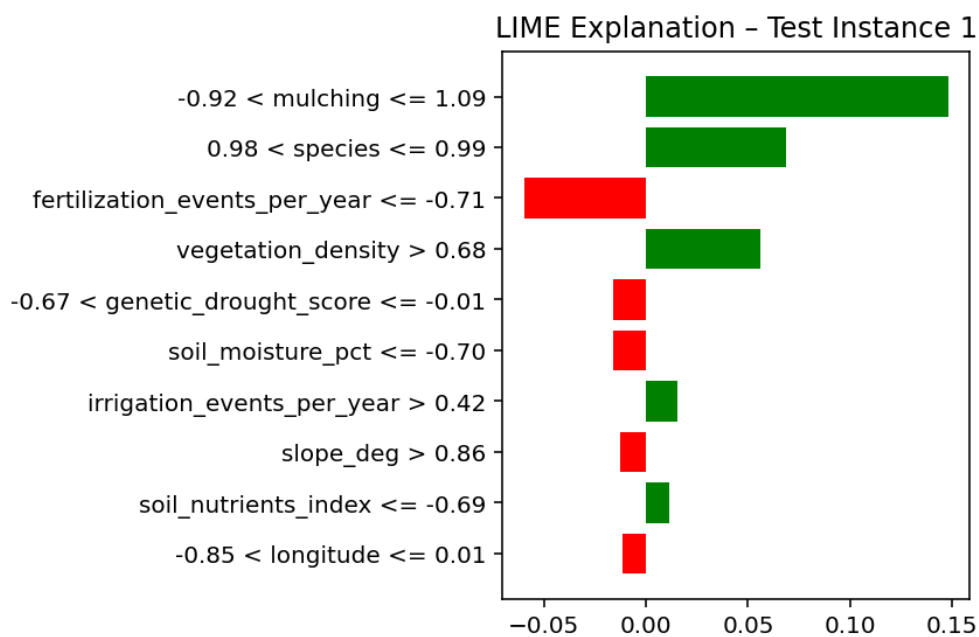


Fig 22. LIME explanation for a tree predicted to die (Pathway A).

interventions targeting soil moisture retention (e.g., mulching) may offer more immediate benefits than those 408
focused on broad scale climatic factors beyond local control. 409

Management effects are highly context dependent 410

Management practices emerged as important but highly context dependent modifiers of survival. Mulching 411
showed a strong protective effect in local explainability analyses, often determining survival outcomes at the 412
individual tree level. This finding supports climate smart forestry frameworks that emphasize low cost, site 413

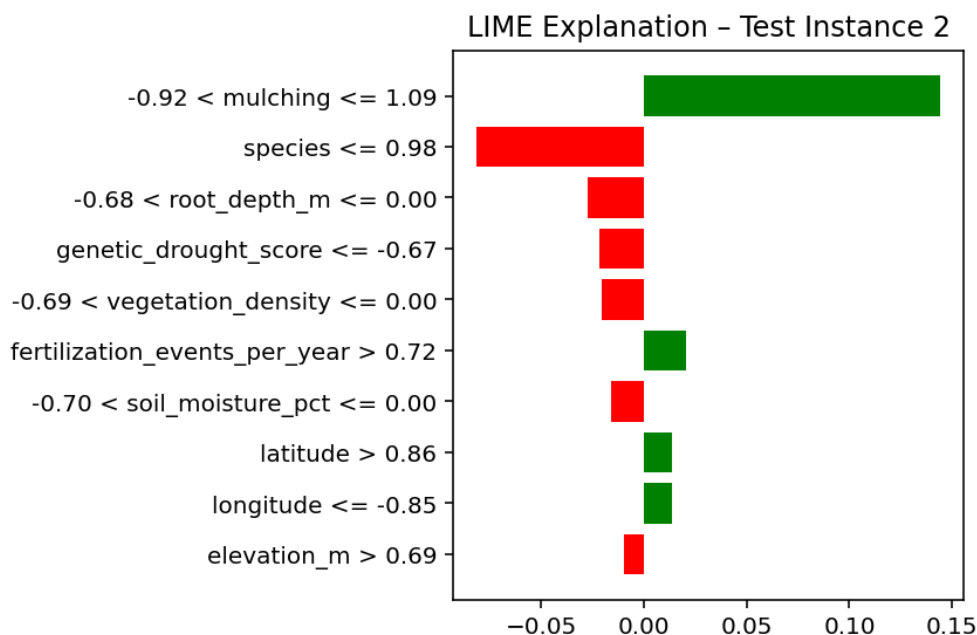


Fig 23. LIME explanation for a tree predicted to die (Pathway B).

level interventions to buffer climatic stress [4, 29] and suggests that mulching should be prioritized in reforestation programs targeting drought prone areas.

Irrigation and fertilization exhibited more complex and sometimes counterintuitive effects. While both variables were positively associated with survival in survival models, fertilization showed a weak negative coefficient in logistic regression. This apparent contradiction may reflect reactive management — fertilization applied to trees already exhibiting stress — rather than a causal negative effect. Similar ambiguities have been noted in recent machine learning based forestry studies, where management inputs may proxy for unobserved stress rather than representing proactive interventions [22, 23]. These results underscore the need for careful interpretation of observational management data and highlight the importance of integrating operational context into predictive models.

Model performance and the value of explainability

The superior performance of ensemble and nonlinear machine learning models relative to linear approaches reflects the inherent complexity of drought driven survival processes. Weak linear correlations between individual predictors and survival outcomes indicate that mortality risk arises from nonlinear interactions and threshold effects rather than simple additive relationships. This finding aligns with recent AI applications in environmental forecasting, which demonstrate the strength of machine learning in capturing complex climate response patterns [11, 13, 18].

Notably, while classification accuracy exceeded 98% for top performing models, AUC-ROC values remained moderate (0.51–0.66). This discrepancy arises from class imbalance and the inherent unpredictability of individual tree mortality; the high average precision scores (0.98) confirm that models reliably identify high risk trees when they occur. For operational forestry, where the goal is to prioritize interventions for vulnerable trees, precision-recall performance is more relevant than balanced accuracy.

The integration of explainable AI addresses legitimate concerns about model opacity in environmental decision making [24, 25]. By combining global feature importance, partial dependence, and local explanations (SHAP, LIME, Integrated Gradients), this study demonstrates that predictive accuracy and ecological interpretability can be achieved simultaneously — a key requirement for policy relevant climate smart forestry.

Limitations and future directions

Several limitations warrant acknowledgment. First, the observational nature of the data limits causal inference, particularly for management variables that may be applied reactively. Experimental designs with randomized management assignments would strengthen causal claims. Second, species identity was encoded numerically, which may obscure phylogenetic structure and evolutionary relationships emphasized in recent genetic connectivity research [7, 26]. Future work should incorporate phylogenetic information to test whether closely related species exhibit similar survival responses. Third, although the dataset spans a broad climatic gradient (250–1750 mm annual rainfall), extreme drought events remain underrepresented, limiting inference at the most severe stress levels. Extended monitoring during exceptional drought years would improve model extrapolation. Finally, biotic stressors such as pests and pathogens, which interact nonadditively with drought and are increasingly important under climate change, were not explicitly modeled [10]. Integrating these factors represents a priority for next generation predictive frameworks.

Implications for climate smart reforestation

This study provides strong empirical support for integrative, species centered, and interaction aware approaches to climate smart reforestation. Survival outcomes depend on the alignment of species identity, functional and genetic traits, climatic exposure, and targeted management practices — not on any single factor in isolation. The finding that trait effectiveness is species specific cautions against one size fits all recommendations and argues for locally adapted, evidence based planting strategies.

By moving beyond retrospective monitoring toward predictive survival modeling under projected climate stress, this work directly addresses gaps identified in recent forestry and AI literature [6, 27, 30]. The proposed framework offers a scalable and transparent decision support tool for drought prone regions, including those currently underrepresented in advanced forestry modeling research. As such, it contributes meaningfully to the development of resilient reforestation strategies under accelerating climate change and provides a methodological template that can be adapted to other geographic contexts and species assemblages.

Conclusion

Predicting tree survival under increasing drought stress requires an integrative, interaction aware analytical framework that jointly considers species identity, functional and genetic traits, climatic exposure, site characteristics, and management practices. This study demonstrates that such a framework — combining survival analysis, explainable machine learning, and climate informed predictors — can move reforestation planning beyond descriptive monitoring toward proactive, data driven decision support.

Species identity emerged as the dominant determinant of survival across all modeling approaches, confirming that intrinsic biological and genetic characteristics fundamentally condition drought resilience. Functional traits including root depth, wood density, and genetic drought score further shaped survival outcomes, but their effects were highly species dependent. The identification of nonlinear interactions among these traits carries an important practical implication: drought resistance cannot be optimized through single trait selection. Instead, resilient outcomes depend on coordinated trait combinations that are specific to both species and environmental context.

Climatic stressors, particularly rising temperature, consistently reduced survival probability, while soil moisture acted as a key proximal mediator linking climate forcing to biological response. Among management interventions, mulching showed strong protective effects, whereas the effectiveness of irrigation and fertilization varied considerably with context. These findings reinforce the need for targeted, site appropriate management strategies rather than uniform intervention approaches.

Methodologically, this work highlights the value of explainable artificial intelligence for ecological research and forest management. The strong performance of nonlinear models, coupled with transparent interpretation through feature importance, partial dependence, and local explanations, demonstrates that predictive accuracy and ecological interpretability are not mutually exclusive. This convergence is essential for translating AI driven insights into operational forestry and policy decisions that can withstand scientific scrutiny.

By providing a scalable, interpretable framework for predicting drought driven tree mortality, this study contributes directly to the development of resilient reforestation strategies under accelerating climate change. The approach is readily adaptable to other geographic contexts and species assemblages, offering a template for evidence based climate adaptation in forest ecosystems worldwide. As such, it directly supports the mission of *PLOS Climate* to publish actionable, solution oriented research that informs climate resilience and adaptation policy.

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