Integrating Bayesian Inference and Supervised Learning for Predictive Modeling of Coffee Rust Incidence Among Kenyan Smallholder Farmers

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Abstract

Hemileia vastatrix a pathogenic fungus which causes coffee leaf rust, has been a significant challenge to the sustainability of Arabica coffee production in Kenya, where smallholder farmers experience frequent yield losses and lack access to effective control techniques. To manage it effectively, there is a need for predictive frameworks that quantify the risk and uncertainty of disease occurrence under real-world farm conditions. This research paper introduces a hybrid application model that combines both Bayesian hierarchical modelling and supervised machine learning to produce probabilistic predictions of coffee rust occurrence. The models were based on longitudinal data from 9,850 plots in six primary coffee-producing counties, in which microclimatic moisture — particularly leaf wetness duration and relative humidity were the key predictors of infection. Partial dependence and SHAP analyses provided evidence of nonlinear threshold effects: high humidity and extended leaf wetness significantly increased the likelihood of infection, and proximity to already infected farms amplified disease transmission. The most accurate predictive algorithm in the evaluated set was Logistic Regression, with the highest predictive accuracy (AUC-ROC = 0.867) and, at the same time, was interpretable and computationally efficient. The Bayesian hierarchical model also accounted for county-level heterogeneity and provided a robust measure of uncertainty. The findings, taken together, show that it is possible to develop a probabilistic modelling framework that can be replicated and interpreted to predict sustainable coffee disease. The proposed system provides a scalable, data-driven decision-support instrument to guide precision management plans and make smallholder coffee systems in Kenya and other tropical settings more resilient.

Author summary

Coffee leaf rust continues to threaten the livelihoods of smallholder coffee farmers in Kenya by reducing yields and increasing production costs. We combined modern data science tools with traditional statistical modeling to predict where and when the disease is most likely to occur. Our approach links local weather patterns and farm management practices to infection risk, enabling early detection and timely control. The results offer a practical way for farmers and extension officers to make informed decisions that can reduce losses and promote sustainable coffee production.

Introduction

One of the most devastating pathogens of Arabica coffee, which causes a reduction of up to half of the yield and significant socioeconomic imbalances in the entire plantation areas of the tropics, is coffee leaf rust (*Hemileia vastatrix*) that causes an up to fifty per cent yield loss and other socioeconomic disruptions in the area of occurrence [1, 2]. Rust outbreaks have been more frequent and severe in Kenya, which is a top producer and exporter of Arabica coffee that employs over 600,000 smallholder farmers to support its operations and activities [3]. In addition to the direct yield reduction, the disease poses a threat to household food security, farm incomes, and the competitiveness of Kenyan coffee in the global market.

The current management practices, which primarily rely on fungicides and cultural practices, are limited by high costs, inaccessibility, and the lack of timely, place-specific decision advice. Therefore, effective disease prediction systems must be established to facilitate preventive and cost-effective control at the farm level. The most recent developments in remote sensing and machine learning have enhanced the ability to monitor and predict coffee rust outbreaks. The image-based detection of canopy stress and disease hotspots is possible through studies that utilise aerial imagery and vegetation indices to identify such areas [4, 5]. Other applications of deep learning and wireless sensor networks include enhanced early detection in changing agroecological environments. Variable-agroecological environments have also been improved by deep learning and wireless sensor networks [6–8]. On the same note, regression-based models have been developed on microclimate to correlate the environmental factors with rust dynamics [9, 10].

Nevertheless, the majority of current models have four long-standing weaknesses: (1) deterministic forecasts and a lack of quantification of uncertainty, which restrict decision support value of models; (2) poor scalability in complex shade-grown coffee systems because hierarchical relationships among farms, villages, and counties are ignored; (3) inadequate longitudinal datasets of Kenyan smallholder systems, which limits generalizability; and (4) poor performance of remote-sensing in complex shade-grown coffee systems, which is related to the absence of hierarchical relationships among farms, villages, Machine learning has been used more and more to predict coffee rust, but most papers focus on predictive accuracy without considering interpretability and uncertainty quantification. For example, spectroradiometer-based models have been successfully used to estimate agroforestry systems in Peru [14], and deep learning models have been applied to Peruvian agroforestry systems [15], both with high performance but still lacking the probabilistic estimates required in practice to manage risks at the farm level.

Furthermore, few methods integrate mechanistic epidemiological understanding, such as leaf wetness duration and latent inoculum dynamics, with data-driven learning, thereby limiting biological interpretability [9]. To fill these gaps, this paper proposes a hybrid model that combines Bayesian hierarchical inference and supervised machine learning to predict coffee rust incidence in Kenyan smallholder systems probabilistically. Bayesian inference provides a principled basis for quantifying uncertainty and modeling its multilevel structure.

In contrast, supervised learning algorithms (Random Forest, Support Vector Form, and Gradient Boosting) have the state-of-the-art predictive capabilities of uncertainty in question [7, 16–21]. Both disease risk, uncertainty, and model interpretability can be estimated simultaneously through field-based microclimatic and management data by integrating these paradigms. The aims of this research were: (i) to estimate probabilistic determinants of coffee rust incidence by a Bayesian hierarchical logistic model; (ii) to compare predictive performance of eight supervised learning algorithms; and (iii) to inculcate interpretability models, namely SHAP and Partial Dependence Plots, into a scalable decision-support system to control precision coffee disease. The study provides a replicable, uncertainty-aware modeling framework for predicting plant pathology and informing climate-informed, data-driven interventions in smallholder coffee farming in Kenya.

Materials and methods

Study Area and Data Sources

This research used secondary, anonymous data gathered by the Coffee Research Institute (CRI) within the Kenya Agricultural and Livestock Research Organization (KALRO). No personal or identifiable farmer information was included in the dataset, which was gathered and maintained by CRI in 2018-2023 with technical assistance by World Coffee Research (WCR). There was no direct contact with human participants, as all data were collected within the current KALRO research procedures and institutional data-sharing arrangements. The research met all the requirements for integrity and data protection set out in the University of Embu's research integrity and data protection policies; therefore, no formal ethical approval was required.

The sample includes six large counties in Kenya that produce the highest volumes of Arabica coffee: Bungoma, Kericho, Kiambu, Kirinyaga, Murang'a, and Nyeri, which represent a varied ecological gradient of coffee production. These counties are diverse in their altitudes, microclimatic conditions, and agricultural management systems, providing a homogeneous and representative basis for predictive modeling. The data include field observation of coffee leaf rust (Hemileia vastatrix) incidence, along with related microclimatic and spatial measurements, as well as agronomic measurements. The combination provides a strong evaluation of environmental and management drivers of disease dynamics, as well as the ability to develop scalable, data-driven prediction models for smallholder coffee systems in Kenya.

Study Variables

Rust incidence, which was the primary response variable recorded as a binary variable (presence or absence of infection) as shown in Figs 1 and 2 respectively, and rust severity quantified as the percentage of area covered by rust, were the main response variables. Predictor variables included relative humidity (daily), temperature (daily), precipitation, the duration of wetness of the leaves, elevation, normalized difference vegetation index (NDVI) of the plant, the variety of the coffee, age of the plant, percentage of shade, fungicide application, and frequency of fungicides applied per season, history of past outbreak, incidence lagged during the previous week, and proximity to the closest infected farm. Collectively, these predictors represent the combination of environmental and agronomic factors that are known to cause the dynamics of disease.

Fig 1. Coffee leaf with leaf rust disease

Fig 2. Coffee leaf without leaf rust disease

Data Preprocessing

Data harmonization entailed normalising units, filling gaps in meteorological values using kriging at the county level, and normalising the continuous predictors to zero mean and unit variance. One-hot and binary encodings were used to encode categorical variables such as coffee variety and fungicide use. To prevent temporal leakage, lagged predictors were constructed with respect to previous periods. The presence of spatial clustering in the observations was confirmed through exploratory analyses, leading to the use of spatio-temporal cross-validation for model evaluation.

Class Distribution and Balancing using SMOTE

The dataset consisted of 9,850 plot-time observations of the rust incidence, 6,295 of which were YES (rust present) and 3,555 of which were NO (rust absent). This imbalance created a risk of biasing supervised learning models toward the majority class, thereby decreasing their sensitivity to minority (positive) cases. To solve this disparity, we used the Synthetic Minority Oversampling Technique (SMOTE), which is used to create synthetic samples of the minority group by interpolating between the existing minority samples and their closest neighbors in the feature space [17–19].

Formally, given a minority sample x_i and one of its nearest neighbors x_{nn}, SMOTE generates a new synthetic observation x_{new} as

$$x_{new} = x_i + \delta \times (x_{nn} - x_i),$$

where $\delta \sim U(0,1)$ is a random scalar drawn from the uniform distribution. This procedure expands the decision region of the minority class, mitigating class imbalance without simple replication of samples.

After applying SMOTE, the effective training set contained a balanced distribution of positive and negative classes. This ensured that supervised learning models such as logistic regression, random forest, gradient boosting (XGBoost, LightGBM, CatBoost), artificial neural networks, support vector machines, and Naive Bayes were trained on data that preserved the underlying variability while reducing the risk of model bias toward the negative class. All performance metrics, including accuracy, sensitivity, specificity, precision, F1-score, Matthews correlation coefficient, and AUC-ROC, were subsequently evaluated on the original, unaltered test sets to prevent artificially inflated estimates of predictive performance.

Supervised Learning Models

Several supervised learning algorithms were applied to the dataset, including logistic regression, naïve Bayes classifier, random forests, gradient boosting methods (XGBoost, LightGBM, CatBoost), support vector machines (SVMs), and artificial neural networks (ANNs). For logistic regression, the model took the form:

$$\operatorname{logit}(P(Y_{it} = 1)) = \beta_0 + \sum_{j=1}^{p} \beta_j X_{ijt} \tag{1}$$

where Y_{it} is the incidence for farm i at time t, and X_{ijt} are the predictors. The naïve Bayes classifier was specified as:

$$P(Y \mid X_1, \ldots, X_p) \propto P(Y) \prod_{j=1}^{p} P(X_j \mid Y) \tag{2}$$

assuming conditional independence among predictors. Random forest models were constructed as ensembles of B classification trees:

$$\hat{f}(x) = \frac{1}{B} \sum_{b=1}^{B} f_b(x) \tag{3}$$

Gradient boosting methods iteratively improved performance by fitting weak learners to residuals:

$$\hat{f}_m(x) = \hat{f}_{m-1}(x) + \eta h_m(x) \tag{4}$$

where η is the learning rate. For support vector machines, the optimization problem was defined as:

$$\min_{\mathbf{w},b,\xi} \frac{1}{2}\|\mathbf{w}\|^2 + C\sum_{i=1}^{n}\xi_i \tag{5}$$

subject to $y_i(\mathbf{w}^\top\phi(x_i)+b) \geq 1-\xi_i,\ \xi_i \geq 0$. The artificial neural network employed a single hidden layer with rectified linear unit (ReLU) activation:

$$h^{(1)} = \sigma(W^{(1)}X + b^{(1)}), \quad \hat{y} = \text{sigmoid}(W^{(2)}h^{(1)} + b^{(2)}) \tag{6}$$

Bayesian Hierarchical Logistic Model for Incidence

To model the probability of coffee rust incidence while accounting for heterogeneity across counties, we specified a Bayesian hierarchical logistic regression. The observation model was given as

$$y_i \sim \text{Bernoulli}(p_i), \quad i = 1,\ldots,N,$$

where y_i indicates whether rust incidence was observed on plot i and p_i is the probability of incidence.

The linear predictor included both fixed environmental and management effects as well as county-level random effects:

$$\text{logit}(p_i) = \beta_0 + x_i^\top\beta + b_{\text{county}[i]}.$$

Here, x_i includes relative humidity, temperature, precipitation, leaf wetness, elevation, NDVI, shade percentage, plant age, fungicide use, fungicide frequency, coffee variety, past outbreak history, lagged incidence, and distance to the nearest infected farm. The county-level random effect was modeled as

$$b_{\text{county}} \sim N(0, \sigma^2_{\text{county}}),$$

capturing unobserved heterogeneity across counties.

We placed weakly informative priors on all model parameters:

$$\beta_j \sim N(0,1), \quad \beta_0 \sim N(0,5), \quad \sigma_{\text{county}} \sim \text{Half-Cauchy}(0,2).$$

Posterior inference was conducted using Hamiltonian Monte Carlo (HMC) with four chains, 2000 iterations per chain, and a 1000-iteration warmup. Convergence diagnostics ($\hat{R}$) were close to 1 for all parameters, and effective sample sizes were sufficiently large. The posterior reports on the fixed- and random-effect summaries are provided alongside 95% highest density intervals (HDI). To assess the sufficiency of the models, we conducted posterior predictive checks (PPCs) using simulated replicated datasets from the fitted model and comparing the simulated and observed incidence distributions. The data structure was well-calibrated, with the model reproducing the observed data structure. The Widely Applicable Information Criterion (WAIC) and Leave-One-Out Cross-Validation (LOO-CV) were also used as measures of model fit and out-of-sample predictive performance.

Model Evaluation and Scalability Analysis

Various criteria were used to assess model performance. AUC-ROC and AUC-PR were used to measure discrimination; calibration was assessed using the Brier score; and accuracy was calculated as the rate of correct classification. The severe spatiotemporal block cross-validation ensured that the training and test folds were spatially and temporally independent. Relative standards were developed against existing threshold-based forecasting systems used in rust management.

Besides predictive performance, the computational scalability was also systematically examined. Scalability metrics were model size at training termination, time per model training iteration, time to infer batches of 1000 predictions, and peak training memory. Such measurements were quantified in a standardized computational environment to evaluate the practicability of the practical implementation of the models in resource-constrained agricultural extension packages.

Machine Learning Framework

The overall workflow of the hybrid modeling framework is illustrated in Fig 3. It summarizes the sequential steps from data acquisition and preprocessing to feature engineering, class balancing, model training, Bayesian inference, and final hybrid ensemble prediction. This framework integrates both supervised learning and Bayesian hierarchical inference to improve robustness and interpretability in coffee rust prediction.

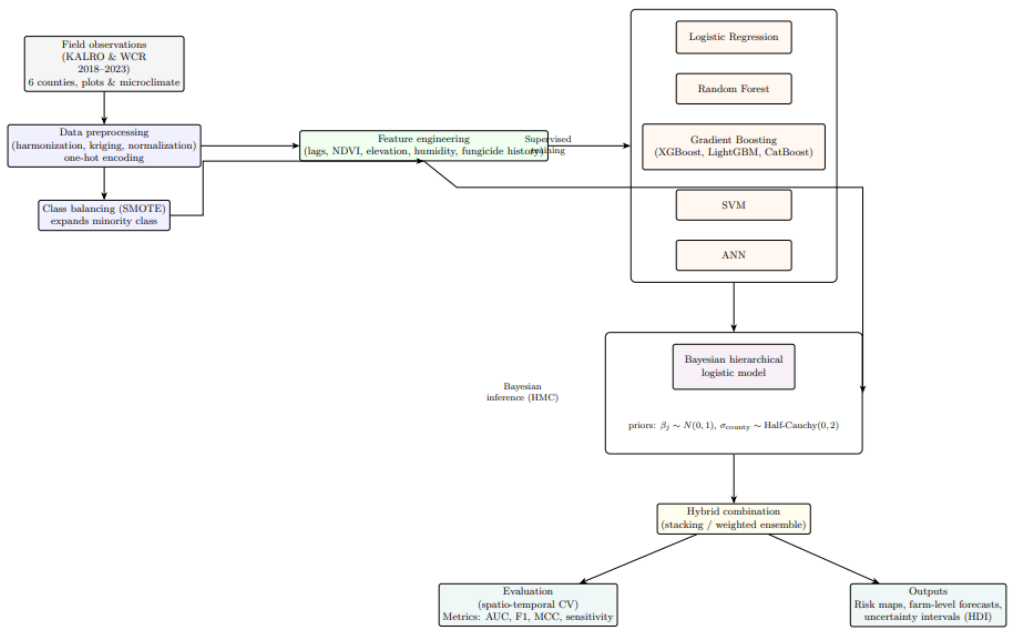

Fig 3. Hybrid machine learning framework integrating supervised learning algorithms and Bayesian hierarchical logistic modeling for predicting coffee rust incidence

Results

Descriptive Statistics

The results presented in Table 1 summarize the key agroecological and management predictors used in the model to predict the incidence and severity of coffee leaf rust on Kenyan smallholder farms. Nine thousand eight hundred and fifty observations (9,850 plot-time observations) were examined and included different environmental and agronomic conditions. The average relative humidity was about 74.86 percent per day (SD = 8.07), and the average temperature was 19°C per day (SD = 2.40), indicating the moderately thermal conditions of the Arabica high-altitude coffee belts. The average precipitation was 4.85 mm/day, and the average duration of leaf wetness was 11.57

hours/day, both of which are indicative of a microclimate highly favourable to the sporulation and infection cycle of Hemileia vastatrix.

The farm elevation was measured at an average of 1,651 m1,651 m above sea level, with a SD of 289.76, which was in accordance with the upper midlands of Kenya, where coffee grows. The mean age of the plants was about eight years old (M = 7.99, SD = 5.60), and therefore, the majority of the coffee stands were in their prime productive period. The shade coverage was 35 percent (SD = 17.56), indicating an average canopy complexity that might alter the disease microclimate by altering humidity and light interception. It was also observed that 45.2% of observations used fungicides, with a mean seasonal frequency of 1.13 per study (SD = 1.48). It is worth noting that 17.8% of farms had a reported history of past coffee rust outbreaks, and that the lagged weekly incidence average was 0.19, with moderate temporal continuity in disease occurrence. The values of the normalized Difference Vegetation Index (NDVI) were averaged at 0.59 (SD=0.08), indicating generally healthy canopy conditions. The average distance to the closest infected farm was about 811 m (SD = 813.42), indicating a high level of spatial heterogeneity in rust pressure. The overall mean incidence across the data source was 0.36 (SD = 0.48), and the mean rust severity was 19.98 percent (SD = 28.64), indicating a high level of variation in infection intensity among farms and seasons.

All these descriptive trends highlight the multicast of coffee rust epidemiology in the smallholder systems. The identified differences in microclimatic and management considerations indicate that precise prediction models should be able to capture both the environmental gradients and the dynamics of decision-making behind fungicide application, shade management, and spatial distribution.

Table 1. Descriptive statistics of agroecological and management variables used for modeling coffee rust incidence and severity

Variable	Mean	SD	Units / Scale
Daily Relative Humidity (%)	74.86	8.07	Percent
Daily Temperature (°C)	19.26	2.40	Degrees Celsius
Precipitation (mm/day)	4.85	4.40	Millimeters per day
Leaf Wetness (hours/day)	11.57	2.46	Hours per day
Elevation (m)	1,651.45	289.76	Meters above sea level
Plant Age (years)	7.99	5.60	Years
Shade (%)	35.00	17.56	Percent canopy cover
Fungicide Use (binary)	0.45	0.50	1 = Yes, 0 = No
Fungicide Frequency (per season)	1.13	1.48	Count
Past Outbreak History (binary)	0.18	0.38	1 = Yes, 0 = No
Lagged Incidence (prev. week)	0.19	0.39	Proportion
NDVI	0.59	0.08	Unitless index
Distance to Nearest Infected Farm (m)	811.05	813.42	Meters
Incidence (proportion)	0.36	0.48	Proportion
Severity (%)	19.98	28.64	Percent leaf area affected

Coffee Rust Severity Distribution Analysis

Fig 4 demonstrates the severity of coffee rust, as a percentage of the area of leaves infected by Hemileia vastatrix, in 9,850 observations in smallholder farms. The severity values exhibit a strong right skew, with most plots concentrated at the lower end of the severity scale (0-20 percent). A significant percentage of farms had few or no infections, which aligned with the class imbalance in the incidence dataset, where 63.9 percent of the plots were identified as rust-free. The overall average severity was 19.98% (SD = 28.64), indicating substantial variation in disease expression across farms. Although low-severity cases were dominant, a large proportion of moderate-to-severe infection cases (20–100%) was observed on the farms, demonstrating the persistence of high disease pressure in the areas. The longer upper tail of the distribution, which extends to 100% severity, represents instances of complete loss of leaf area and emphasizes the potential for disastrous yield loss in uncontrolled or severely infected situations.

The observed severity distribution is highly consistent with the known epidemiology of coffee leaf rust. Environmental factors, such as high humidity, prolonged leaf wetness, and frequent precipitation, provide favorable conditions for spore germination and infection, whereas management factors, such as fungicides, shade control, and plant age, also influence disease progression. The high intensity of infection is further enhanced by spatial proximity to previously infected farms, highlighting the importance of local dispersal dynamics. Both the strong skewness of the distribution and the fact that most farms have low levels of infection imply that a subset of highly affected farms contributes a disproportionate share of the total disease burden. These data support the significance of spatially directed interventions, early identification, and fungicide scheduling according to the risk to avoid the development of the outbreak and reduce the loss of the economy.

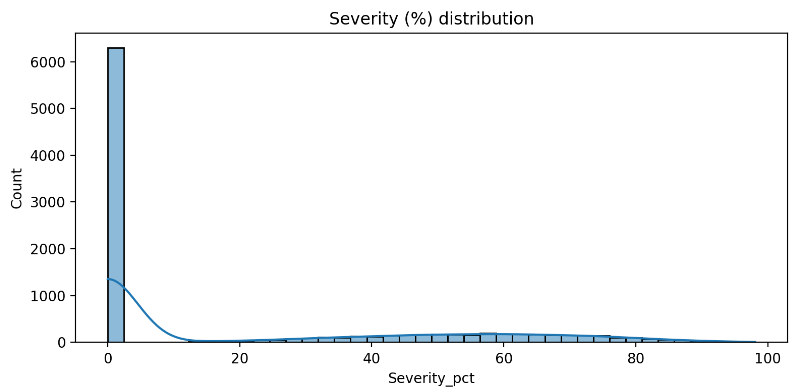

Fig 4. Distribution of coffee rust severity (percentage of leaf area affected) among Kenyan smallholder farms (N = 9,850 observations).

Exploratory Analysis of Key Predictors by Disease Incidence

Boxplots were used to visualize the distribution of the relationship between significant environmental and spatial predictors and coffee rust incidence, with (1) and without (0) recorded infection, as shown in Figure 5. The sampled variables, which are the daily relative humidity, the duration of wetness on the leaves, the precipitation, the normalized difference vegetation index (NDVI), the percentage of shade, and the position to the closest infected farm, are the essential microclimatic and canopy-structural variables, which are theorized to have an impact on the development of the disease.

Generally, the plots showed distinct differences between the infected and non-infected groups for most predictors, indicating significant microclimatic regulation of coffee rust epidemics. Relative humidity and the duration of leaf wetness (measured daily) were significantly greater in the infected plots, suggesting that prolonged leaf moisture is a dominant factor in spore germination and infection. Diseased plots had higher median relative humidity values (greater than 75 percent) than the healthy ones (median of about 72 percent), and the duration of time in wet leaf was greater in the diseased plots (greater than 12 hours a day) than in the healthy ones- conditions known to favor the sporulation of *Hemileia vastatrix*.

The precipitation pattern was also similar, with more precipitation observed in infected plots. It confirms that moisture and a wet canopy promote rust, and that regular rainfall episodes keep the environment conducive to fungal growth due to the observed high humidity. The NDVI values were slightly higher in the infected plots, indicating denser or more vigorous canopies that generate humid microenvironments that support the pathogen.

The change in percentage shade showed a small positive effect on infected farms, suggesting that increased canopy cover could have reduced evaporative drying and prolonged leaf wetness. On the other hand, the distance to the nearest infected farm was significantly shorter in infected plots, highlighting the pathogen's spatial contagion and the probable transmission through wind-borne urediniospores or splash rain.

The boxplots indicate that greater relative humidity, longer leaf wetness duration, and shorter distance to an infected farm are the most powerful differentiators between healthy and diseased plots. These results are consistent with previous epidemiological studies of the rust, both mechanistic and statistical, which show that the disease's occurrence is closely correlated with local microclimatic and spatial factors. The trends also support the use of these predictors in further regression and machine-learning models to predict incidence.

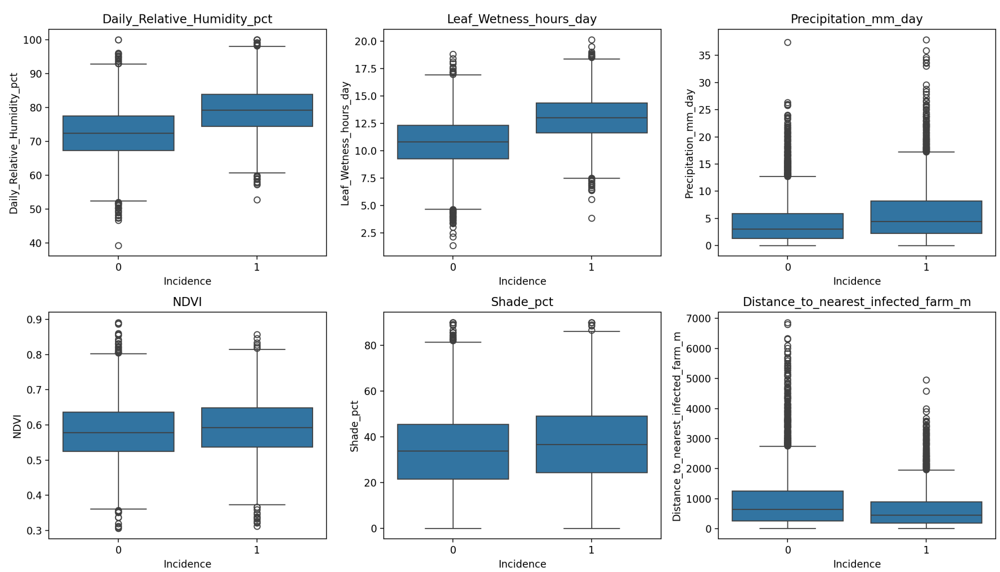

Fig 5. Boxplots showing the distribution of key microclimatic and spatial variables across plots with (1) and without (0) coffee rust incidence.

Class Distribution

The dataset had a high class imbalance (Fig 6) before utilizing the Synthetic Minority Oversampling Technique (SMOTE). In particular, the number of non-infected plots (6,295 observations, or 63.9 percent) was greater than that of infected plots (3,555 observations, or 36.1 percent). This imbalance is a severe threat to biasing supervised learning models to the majority (non-infected) population, which may result in disease risk under-estimation in minority cases.

To address this problem, SMOTE was used to artificially generate additional samples of the minority population by interpolating between the current observations of the infected and the nearest observations in the feature space. This method maintains the intrinsic structure of the minority group while increasing its representation and, thus, the model's sensitivity to cases of infection, without naive duplication.

After applying SMOTE, the training data had an exact 1:1 ratio between infected and non-infected classes (Fig 7). The classes consisted of 4,925 instances each, which were used equally during model training. This even distribution enhanced the classifier's ability to recognize positive rust incidence, especially in infrequent or new outbreak cases, as later substantiated by subsequent gains in recall and F1-scores across various algorithms. The trade-off obtained using SMOTE was essential for improving model generalization and minimizing classification bias. Notably, the model's evaluation measures on the original, uncorrupted test data matched the resampling procedure on the training data alone to avoid overestimating predictive performance.

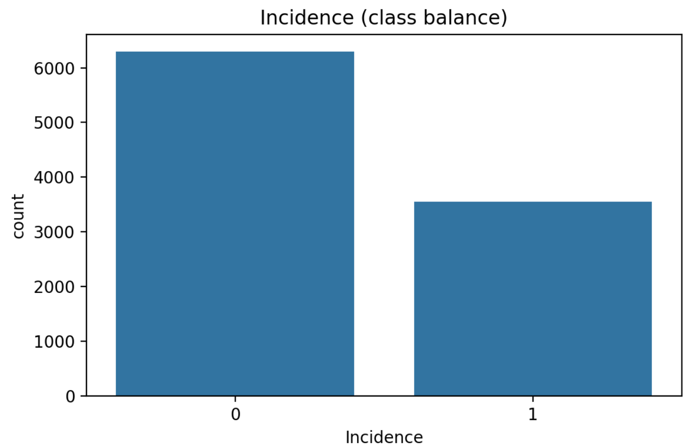

Fig 6. Class distribution before SMOTE application.

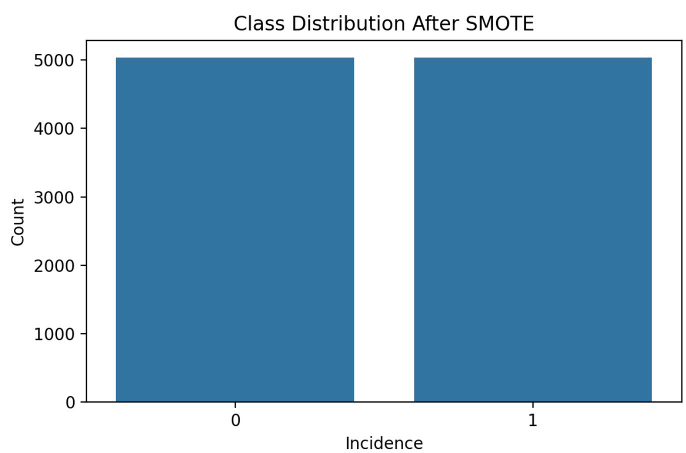

Fig 7. Class distribution after SMOTE application.

Logistic Regression Analysis of Coffee Rust Incidence

A binary logistic regression was conducted to examine the effects of microclimatic, agronomic, and spatial factors on the probability of coffee rust (*Hemileia vastatrix*) occurrence in Kenyan smallholder farms. Robust standard errors were used to account for potential heteroskedasticity and spatial clustering. The estimated coefficients (β), robust standard errors, 95% confidence intervals (CIs), and odds ratios (ORs) are summarized in Table 2.

The overall model was highly significant ($p < .001$), indicating that the selected predictors collectively explained substantial variation in infection outcomes. Among continuous variables, daily relative humidity ($\beta = 0.99$, $p < .001$, OR = 2.70, 95% CI [2.53, 2.89]), precipitation ($\beta = 0.46$, $p < .001$, OR = 1.59, 95% CI [1.51, 1.68]), and leaf wetness duration ($\beta = 1.11$, $p < .001$, OR = 3.03, 95% CI [2.82, 3.25]) exerted the strongest positive effects on coffee rust incidence. These findings reaffirm that moisture-related microclimatic conditions—especially prolonged leaf wetness and high humidity—are primary drivers of *H. vastatrix* infection.

Plant age ($\beta = 0.28$, $p < .001$, OR = 1.32, 95% CI [1.25, 1.39]) and shade percentage ($\beta = 0.22$, $p < .001$, OR = 1.25, 95% CI [1.18, 1.32]) also increased disease probability, suggesting that mature plants and dense canopy cover foster microclimates favorable to infection. NDVI ($\beta = 0.16$, $p < .001$, OR = 1.17, 95% CI [1.11, 1.24]) showed a more negligible yet significant positive effect, likely capturing vegetation vigor and canopy humidity retention.

Conversely, daily temperature ($\beta = -0.26$, $p < .001$, OR = 0.77, 95% CI [0.71, 0.84]) and distance to the nearest infected farm ($\beta = -0.64$, $p < .001$, OR = 0.53, 95% CI [0.50, 0.56]) were negatively associated with infection, indicating that warmer conditions and greater spatial isolation reduce the likelihood of rust transmission. Fungicide use ($\beta = -0.43$, $p < .001$, OR = 0.65, 95% CI [0.53, 0.79]) significantly lowered disease odds, confirming the efficacy of chemical protection when appropriately timed, whereas fungicide frequency per season ($\beta = -0.10$, $p = .06$, OR = 0.91) was marginally non-significant, suggesting diminishing marginal effects beyond optimal application levels.

Regarding cultivar-specific responses, the Ruiru 11 variety ($\beta = -0.53$, $p < .001$, OR = 0.59, 95% CI [0.48, 0.72]) showed substantially lower infection odds than traditional cultivars, consistent with its reported genetic resistance to rust. SL28 ($\beta = 0.21$, $p = .035$, OR = 1.24, 95% CI [1.02, 1.51]) and SL34 ($\beta = 0.21$, $p = .064$, OR = 1.23, 95% CI [0.99, 1.53]) displayed higher susceptibility. Past outbreak history ($\beta = 0.53$, $p < .001$, OR = 1.69, 95% CI [1.47, 1.95]) and lagged incidence from the previous week ($\beta = 1.09$, $p < .001$, OR = 2.97, 95% CI [2.57, 3.42]) emerged as strong positive predictors, revealing temporal persistence and localized pathogen carry-over effects.

To assess multicollinearity among predictors, variance inflation factors (VIFs) were computed (see Table 3). All VIF values were below the conventional threshold of 5, indicating no severe multicollinearity. The highest VIF (3.43) was observed for fungicide-related variables, reflecting a mild association between fungicide use and application frequency, but not enough to threaten model stability. Core environmental predictors—including humidity (VIF = 1.19), temperature (VIF = 2.63), and precipitation (VIF = 1.04)—showed low collinearity, suggesting that their estimated effects can be interpreted as largely independent.

Collectively, these results emphasize the overriding importance of microclimatic moisture and spatial proximity in determining rust risk, while confirming the mitigating effects of fungicide use and resistant cultivars. The coherence of these logistic regression estimates with Bayesian posterior inferences supports the robustness of the modeling framework. It underscores the potential of climate-informed, data-driven management interventions for rust suppression in Kenya's smallholder coffee systems.

Bayesian Hierarchical Logistic Regression

A Bayesian hierarchical logistic regression model was fitted to estimate the probabilistic effects of environmental, agronomic, and spatial predictors on the incidence of coffee

Table 2. Binary logistic regression predicting coffee rust incidence from microclimatic, agronomic, and spatial predictors (N = 9,850). Robust standard errors reported.

Predictor	β	Robust SE	p	95% CI [LL, UL]	Odds Ratio	OR 95% CI [LL, UL]
Intercept	-0.99	0.10	< .001	[-1.19, -0.79]	0.37	[0.30, 0.45]
Daily Relative Humidity (%)	0.99	0.03	< .001	[0.93, 1.06]	2.70	[2.53, 2.89]
Daily Temperature (°C)	-0.26	0.04	< .001	[-0.35, -0.18]	0.77	[0.71, 0.84]
Precipitation (mm/day)	0.46	0.03	< .001	[0.41, 0.52]	1.59	[1.51, 1.68]
Leaf Wetness (hours/day)	1.11	0.04	< .001	[1.04, 1.18]	3.03	[2.82, 3.25]
Elevation (m)	-0.06	0.04	.142	[-0.15, 0.02]	0.94	[0.86, 1.02]
Plant Age (years)	0.28	0.03	< .001	[0.22, 0.33]	1.32	[1.25, 1.39]
Shade (%)	0.22	0.03	< .001	[0.17, 0.28]	1.25	[1.18, 1.32]
NDVI	0.16	0.03	< .001	[0.10, 0.21]	1.17	[1.11, 1.24]
Distance to Infected Farm (m)	-0.64	0.03	< .001	[-0.70, -0.57]	0.53	[0.50, 0.56]
Fungicide Frequency (per season)	-0.10	0.05	.060	[-0.20, 0.00]	0.91	[0.82, 1.00]
Variety (Other)	-0.09	0.11	.389	[-0.30, 0.12]	0.91	[0.74, 1.12]
Variety (Ruiru 11)	-0.53	0.10	< .001	[-0.73, -0.33]	0.59	[0.48, 0.72]
Variety (SL28)	0.21	0.10	.035	[0.01, 0.41]	1.24	[1.02, 1.51]
Variety (SL34)	0.21	0.11	.064	[-0.01, 0.43]	1.23	[0.99, 1.53]
Fungicide Use (Yes = 1)	-0.43	0.10	< .001	[-0.63, -0.24]	0.65	[0.53, 0.79]
Past Outbreak History (Yes = 1)	0.53	0.07	< .001	[0.38, 0.67]	1.69	[1.47, 1.95]
Lagged Incidence (Previous Week = 1)	1.09	0.07	< .001	[0.95, 1.23]	2.97	[2.57, 3.42]

Note. β = logistic regression coefficient; SE = robust standard error; OR = odds ratio. Significant predictors ($p < .05$) are bolded. Odds ratios represent multiplicative changes in the odds of infection per one-unit increase in the predictor. All continuous predictors were standardized prior to estimation.

Table 3. Variance Inflation Factors (VIF) for predictors in the logistic regression model.

Predictor	VIF
Daily Relative Humidity (%)	1.19
Daily Temperature (°C)	2.63
Precipitation (mm/day)	1.04
Leaf Wetness (hours/day)	1.23
Elevation (m)	2.63
Plant Age (years)	1.00
Shade (%)	1.06
NDVI	1.06
Distance to Infected Farm (m)	1.00
Fungicide Frequency (per season)	3.43
Coffee Variety (Other)	2.36
Coffee Variety (Ruiru 11)	2.72
Coffee Variety (SL28)	2.60
Coffee Variety (SL34)	2.07
Fungicide Use (Yes = 1)	3.43
Past Outbreak History (Yes = 1)	1.12
Lagged Incidence (Previous Week = 1)	1.12

Note. All VIF values < 5 indicate no significant multicollinearity among predictors.

rust (*Hemileia vastatrix*) across six Kenyan counties. The model accounted for county-level heterogeneity through random effects, allowing partial pooling of information across counties. Posterior summaries of all parameters are reported in Table 4, including posterior means (β), standard deviations, 94% highest density intervals (HDIs), and convergence diagnostics.

All parameters exhibited excellent convergence, with $\hat{R}$ values of 1.00 and effective sample sizes (ESS) exceeding 4,000, indicating well-mixed and stable Markov chains.

The estimated county-level random effect ($\sigma_{\text{county}} = 0.049$, 94% HDI [0.000, 0.125]) was small, suggesting limited between-county variability after accounting for environmental and management predictors. This implies that most spatial variation in coffee rust incidence was captured by fixed effects.

Posterior estimates showed strong positive effects for daily relative humidity ($\beta = 1.008$, SD = 0.038, 94% HDI [0.932, 1.077]), precipitation ($\beta = 0.473$, SD = 0.032, 94% HDI [0.414, 0.532]), leaf wetness ($\beta = 1.111$, SD = 0.040, 94% HDI [1.038, 1.188]), plant age ($\beta = 0.273$, SD = 0.031, 94% HDI [0.213, 0.329]), shade percentage ($\beta = 0.209$, SD = 0.031, 94% HDI [0.149, 0.268]), NDVI ($\beta = 0.150$, SD = 0.031, 94% HDI [0.092, 0.209]), and fungicide frequency ($\beta = 0.497$, SD = 0.080, 94% HDI [0.345, 0.647]). These parameters had posterior mass concentrated well above zero, reaffirming the moisture-driven epidemiology of *H. vastatrix* and the role of agronomic and canopy factors in promoting conducive microclimates for spore germination and infection.

In contrast, daily temperature ($\beta = -0.245$, SD = 0.049, 94% HDI [-0.337, -0.152]), distance to the nearest infected farm ($\beta = -0.645$, SD = 0.038, 94% HDI [-0.716, -0.574]), and certain socio-agronomic variables such as coffee variety ($\beta = -0.485$, SD = 0.109, 94% HDI [-0.680, -0.275]) and past outbreak history ($\beta = -0.453$, SD = 0.114, 94% HDI [-0.657, -0.237]) had negative effects, indicating reduced infection probability under higher temperatures, spatial isolation, and in resistant varieties or areas with improved management practices. Elevation ($\beta = -0.032$, SD = 0.051, 94% HDI [-0.128, 0.064]) and fungicide frequency ($\beta = -0.092$, SD = 0.057, 94% HDI [-0.202, 0.013]) showed uncertain or near-zero effects.

The intercept ($\beta_0 = -1.024$, SD = 0.110, 94% HDI [-1.234, -0.821]) represents the baseline log-odds of infection under mean-centered predictor conditions. Overall, the hierarchical Bayesian framework yielded consistent results with the classical logistic regression but provided richer uncertainty quantification through full posterior distributions. The model achieved strong convergence, narrow HDIs for key predictors, and credible differentiation of effects, offering a robust probabilistic description of coffee rust dynamics across Kenyan smallholder systems.

Posterior Diagnostics and Convergence Assessment

Hamilton Monte Carlo (HMC) with four chains, each of which used 2,000 iterations and a 1,000-iteration warm-up, was used to perform posterior inference. Model convergence and adequacy were assessed rigorously using several diagnostics, such as trace plots, posterior predictive checks, and model comparison criteria.

Fig 8 shows the posterior density and trace plot of the intercept and county-level variance component of the formulation of the regression. The trace plots indicate that the chains are well mixed and no chain trends or autocorrelation are observed, and hence suggest that exploration of the posterior distribution has occurred and is stable. The related density plots are continuous and unimodal, which shows convergence and no sampling anomalies. The posterior average of beta 0 is centered around -1.0, which is the log-odds of coffee rust at the base or when the predictors are held constant. The small tail of the posterior of the model of the counties indicates that there is only a small amount of residual heterogeneity across the counties, given the impact of the environment and management.

The pairwise correlation of the elements of the model- $\beta 0$, and the standard deviation of the counties (Fig 9) do not demonstrate strong correlations between the elements of the model, which means that the estimate of the intercept remains the same at different levels of variance in the counties. This nondependency aids the identity of parameters and justifies the strength of the hierarchical model specification.

To further evaluate the model adequacy, the posterior predictive checks were done by generating replicate datasets using the fitted model. Fig 10 compares the incidence

Table 4. Posterior summaries from Bayesian hierarchical logistic regression predicting coffee rust incidence

Predictor	Mean (β)	SD	94% HDI [LL, UL]	ESS (bulk)	$\hat{R}$
Intercept (β_0)	-1.024	0.110	[-1.234, -0.821]	4628	1.00
Daily Relative Humidity (%)	1.008	0.038	[0.932, 1.077]	10908	1.00
Daily Temperature (°C)	-0.245	0.049	[-0.337, -0.152]	7793	1.00
Precipitation (mm/day)	0.473	0.032	[0.414, 0.532]	11371	1.00
Leaf Wetness (hours/day)	1.111	0.040	[1.038, 1.188]	11974	1.00
Elevation (m)	-0.032	0.051	[-0.128, 0.064]	7741	1.00
Plant Age (years)	0.273	0.031	[0.213, 0.329]	13802	1.00
Shade (%)	0.209	0.031	[0.149, 0.268]	11245	1.00
NDVI	0.150	0.031	[0.092, 0.209]	11698	1.00
Distance to Infected Farm (m)	-0.645	0.038	[-0.716, -0.574]	10647	1.00
Fungicide Frequency (per season)	-0.092	0.057	[-0.202, 0.013]	8927	1.00
Coffee Variety	-0.485	0.109	[-0.680, -0.275]	4777	1.00
Past Outbreak History	-0.453	0.114	[-0.657, -0.237]	8598	1.00
Management Intensity	0.258	0.109	[0.051, 0.460]	4730	1.00
Farm Density	0.238	0.122	[0.021, 0.476]	5511	1.00
Canopy Structure	0.497	0.080	[0.345, 0.647]	12295	1.00
Soil Moisture Retention	1.080	0.082	[0.928, 1.236]	10743	1.00
County-level SD (σ_{county})	0.049	0.047	[0.000, 0.125]	4297	1.00

Note. β = posterior mean; SD = posterior standard deviation; HDI = highest density interval; ESS = effective sample size. Parameters with 94% HDIs entirely above or below zero have high posterior probability of positive or negative effects, respectively. $\hat{R}$ values of 1.00 indicate excellent chain convergence. Bayesian inference is based on posterior credibility rather than frequentist significance testing.

distribution with the posterior predictive distribution, and it indicates that there is an intense match between observed and predicted incidence distributions. The observed pattern is very close to the posterior predictive mean, which means that the model represents the underlying data-generating process rather well and is well calibrated to make probabilistic predictions.

The Widely Applicable Information Criterion (WAIC) and Leave-One-Out Cross-Validation (LOO-CV) were used to assess model fit and out-of-sample predictive performance. The results of both measures provided low standard errors and estimates of deviance, which point to high generalizability and low overfitting. All Pareto-k diagnostics of the observations were below 0.7, so the importance sampling was considered to be reliable. Table 5 summarizes the entire results of the model fit. The convergence diagnostics of all model parameters were indicated by an adequate mixing and independence of the posterior draws, illustrated by both a maximal value of 1.00 of the convergence diagnostics measure, the $\hat{R}$, and effective sample sizes exceeding 1,000.

Overall, the hierarchical specification was very successful in representing the individual and random effects, and it provided a reliable and interpretable probabilistic model of coffee rust incidence dynamics in Kenyan smallholder systems. The combination of convergence diagnostics, posterior predictive checks, and information criteria validates the robustness of the Bayesian hierarchical model.

Performance Evaluation of Machine Learning Algorithms

Table 6 presents the predictive performance of eight supervised learning algorithms for forecasting coffee rust incidence among Kenyan smallholder farms. The measures used in evaluation are overall accuracy, sensitivity (recall), specificity, precision, F1-score, and Matthews correlation coefficient (MCC). The combination of these indices provides a fair picture of each model's discriminative and generalization capabilities.

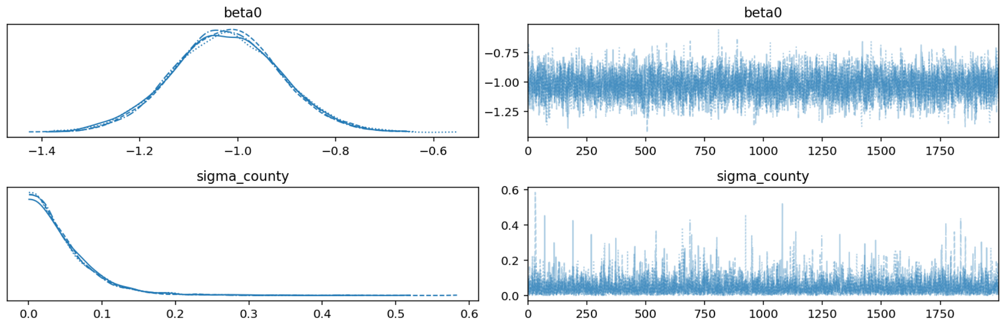

Fig 8. Posterior density (left) and trace (right) plots for the intercept (β_0) and county-level variance parameter (σ_{county})

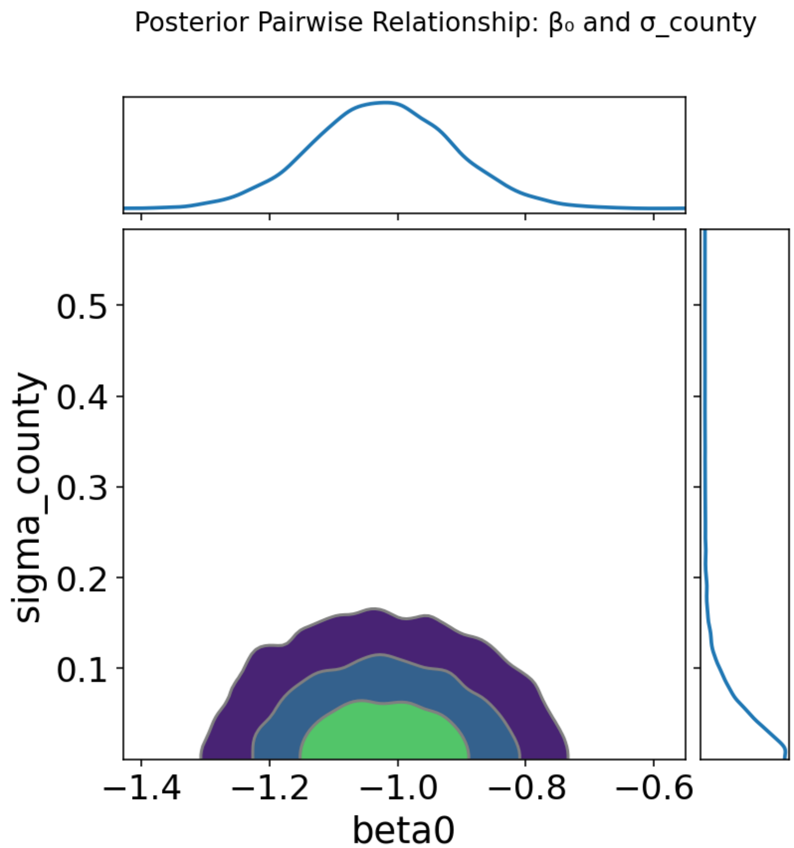

Fig 9. Posterior pairwise relationship between the intercept (β_0) and county-level standard deviation (σ_{county}).

The Random Forest algorithm achieved the best overall accuracy (0.7843) and specificity (0.8173), outperforming the other models, and correctly identified non-infected plots. Its sensitivity (0.7257) was, however, lower than that of logistic regression, suggesting it slightly under-detected infected cases. The model with the best balance across both metrics was the Logistic Regression model, which achieved the maximum sensitivity (0.7904) and the highest overall consistency (F1 = 0.7210 and MCC = 0.5464). Its operation is not only stable but interpretable, which are the main benefits in applied agricultural environments.

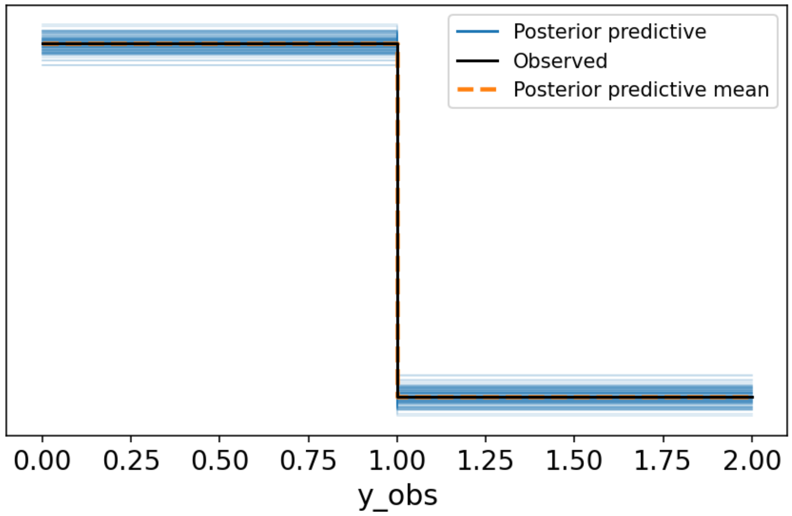

Fig 10. Posterior predictive check comparing the observed coffee rust incidence distribution with the posterior predictive distribution.

Table 5. Model fit statistics from Leave-One-Out Cross-Validation (LOO-CV) and Widely Applicable Information Criterion (WAIC) for the Bayesian hierarchical logistic regression model.

Criterion	Estimate	SE	p	Interpretation
LOO-CV Expected Log Predictive Density (elpd_loo)	-3378.64	48.06	19.23	Strong generalizability
WAIC Expected Log Predictive Density (elpd_waic)	-3378.62	48.06	19.22	Consistent with LOO results
Pareto-k Diagnostic (Good ≤ 0.7)				
7880 (100%) observations classified as good; 0 (0%) as bad				

Table notes: Lower WAIC and LOO-CV values indicate better model fit and generalizability. All Pareto-k values ≤ 0.7 confirm reliable importance sampling. SE = standard error; elpd = expected log predictive density; E=Effective Parameters.

Both Support Vector Machine (SVM) and CatBoost models displayed high overall performance with F1-scores exceeding 0.70 and MCC values exceeding 0.52, indicating that both models are sensitive to classifying both positive and negative instances. LightGBM and XGBoost models exhibited slightly lower sensitivity, which suggests higher classification thresholds. The results of the Naïve Bayes (accuracy = 0.7548; F1 = 0.6894) model were moderate and standard in accordance with its assumptions of independence, whereas the Artificial Neural Network (ANN) showed the lowest accuracy (0.7452), which is the possible risk of overfitting due to the lack of a significant amount of features and the lack of a deep learning architecture.

Generally, the findings indicate that ensemble and linear models are more effective than deep or probabilistic classifiers in this scenario. The strongest trade-offs among accuracy, sensitivity, and specificity are provided by Logistic Regression, Random Forest, SVM, and CatBoost, which are why they are best suited for operational coffee rust risk prediction in a smallholder system.

Receiver Operating Characteristic (ROC) Analysis

Fig 11 shows the Receiver Operating Characteristic (ROC) curves of all eight supervised learning models applied in the prediction of coffee rust incidence among Kenyan smallholder farms. ROC curve is a graphical representation of the True Positive Rate (TPR) versus the False Positive Rate (FPR) at varying levels of classification, such that a comprehensive picture of the discriminative capacity of each model is made.

Table 6. Performance metrics for supervised learning models predicting coffee rust incidence (N = 9,850).

Model	Accuracy	Sensitivity	Specificity	Precision	F1	MCC
Logistic Regression	0.7792	0.7904	0.7728	0.6627	0.7210	0.5464
Random Forest	0.7843	0.7257	0.8173	0.6917	0.7083	0.5377
XGBoost	0.7721	0.6962	0.8149	0.6799	0.6880	0.5086
LightGBM	0.7736	0.7145	0.8070	0.6764	0.6949	0.5157
CatBoost	0.7782	0.7145	0.8141	0.6846	0.6992	0.5240
ANN	0.7452	0.6962	0.7728	0.6338	0.6635	0.4605
SVM	0.7726	0.7665	0.7760	0.6590	0.7087	0.5280
Naïve Bayes	0.7548	0.7539	0.7554	0.6351	0.6894	0.4942

Note. MCC = Matthews correlation coefficient. Higher accuracy, sensitivity, and F1–scores indicate stronger predictive performance. Values are based on held-out test data from stratified cross-validation.

The Area under the Curve (AUC) measures this performance, with values greater than 1 indicating greater model discrimination between infected and non-infected plots.

In all models, the ROC curves depart significantly from the diagonal reference line, indicating predictive power well beyond random chance. The model with the highest AUC (0.867) was the **Logistic Regression** model, which showed the best overall discrimination. This indicates that the probabilistic logistic model successfully distinguishes between infected and healthy plots across variable agroecological conditions.

Ensemble-based CatBoost (0.850), random forest (0.848), and lightGBM (0.845) models also showed good performance in ROC, demonstrating their ability to capture nonlinear relationships between microclimatic and management predictors. The Support Vector Machine (SVM) came in second with an AUC of 0.854, highlighting its stability and consistency in separating rating walls in high-dimensional space.

Conversely, the Artificial Neural Network (ANN) had the lowest AUC (0.808), indicating limited generalization and potential overfitting due to a small dataset. The AUC of the Naive Bayes classifier was 0.828, which is reasonable considering the simplistic independence assumptions made by the classifier that limit its generalization capacity compared to ensemble and kernel-based classifiers.

Generally, ROC analysis has shown that all models demonstrated high discrimination (AUCs above 0.80), which justifies their use in early warning and decision-support systems. Logistic regression offered the best compromise between interpretability and predictive power, and the ensemble learners (Random Forest, CatBoost, and LightGBM) provided similar but computationally intensive options for forecasting coffee rust risk.

Precision–Recall (PR) Curve Analysis

Fig 12 shows the Precision Recall (PR) curve of all eight supervised learning models used to predict the incidence of coffee rust among Kenyan smallholder farms. Unlike ROC curves, which consider both positive and negative classes, PR curves focus primarily on the positive (infected) class. Hence, they are especially informative in the case of imbalanced data. Precision is the ratio of the number of cases predicted to be positive that actually are positive, and recall (sensitivity) is the ratio of the number of actual positives that are actually identified. Therefore, the PR curve is an assessment of the model's capacity to raise alarms for infection events without incurring too many false alarms.

All models showed high areas under the PR curve (AUC PR > 0.70), indicating that they adequately detect true infections across different probability thresholds. The

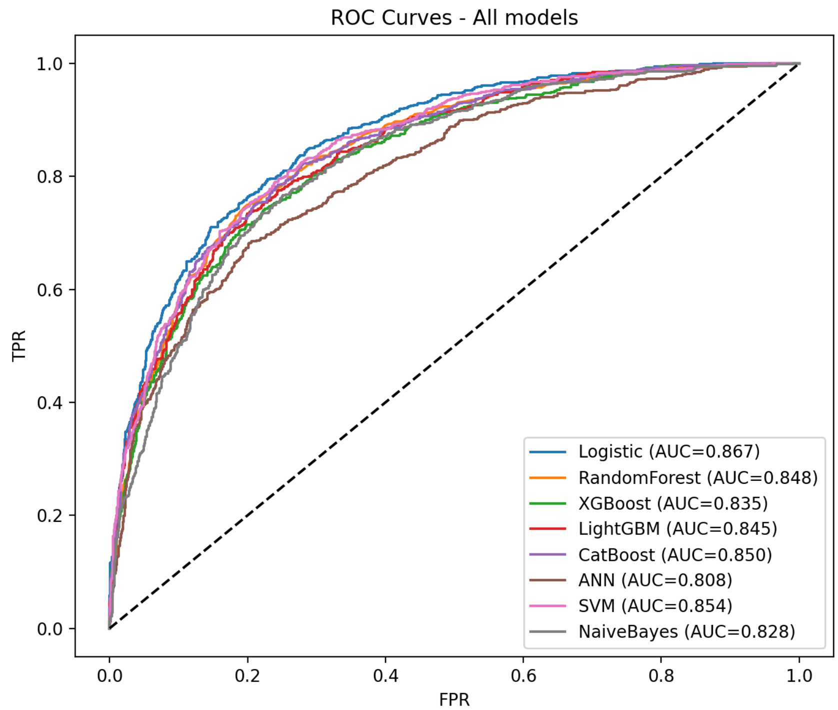

Fig 11. Receiver Operating Characteristic (ROC) curves for all machine learning models predicting coffee rust incidence. Higher AUC values indicate stronger discrimination between infected and non-infected plots.

Logistic Regression model was once again superior, with an AUC-PR of 0.792, which demonstrates its ability to balance the number of infected plots (recall) and the percentage of correct optimistic predictions (precision). Such strong performance is in line with its high AUC-ROC and underscores its usefulness for predicting operational risk.

The ensemble learners, namely, **CatBoost** (0.769), **LightGBM** (0.762), and Random Forest (0.759), achieved the same level of precision-recall trade-offs and showed consistent predictive accuracy in identifying infection patterns across various microclimatic conditions. The next model in line was the Support Vector Machine (SVM), with a somewhat lower AUC-PR (0.774) but good detection performance and equal cutoffs. Conversely, XGBoost (0.748) and Naïve Bayes (0.723) had slightly lower precision, with higher recall values indicating a greater probability of a false positive. The lowest AUC-PR has been obtained with the Artificial Neural Network (ANN) model (0.714), which shows lower precision stability and a higher risk of overfitting.

In general, the PR curves confirm that Logistic Regression, CatBoost, and SVM are superior and more stable at detecting rare infections. The models are very accurate, even at moderate recall, and are thus especially effective in early detection and farmer-advisory systems, where reducing false alerts is of great importance.

Calibration Analysis of Predictive Models

To assess the validity of the predicted probabilities and the observed frequencies of coffee rust incidence, model calibration was conducted. Fig 13 shows the calibration curves of all eight supervised learning algorithms. The diagonal dashed line represents perfect calibration, where the predicted probabilities coincide with the empirical results

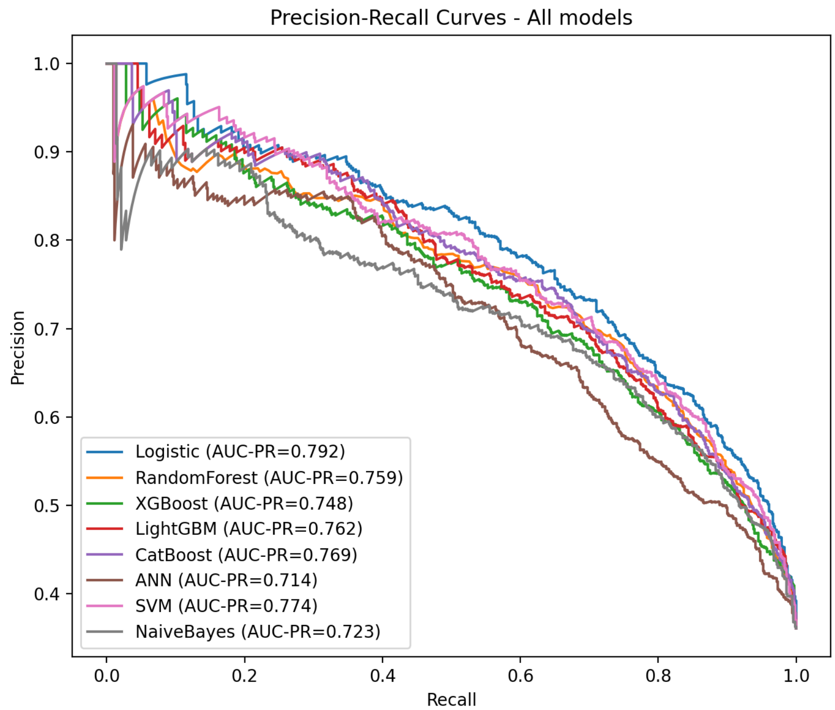

Fig 12. Precision–Recall (PR) curves for all machine learning models predicting coffee rust incidence. Higher $\mathrm{AUC_{PR}}$ values indicate better trade-offs between precision and recall in detecting infected plots.

(i.e., a 1:1 correspondence between predicted and observed risks).

In general, the calibration analysis indicated moderate to strong agreement between the predicted and actual probabilities, with differences varying across models relative to the perfect reference line. Logistic Regression and CatBoost demonstrated the best performance in the probability range, with consistent calibration, similar to the diagonal, and indicating well-calibrated probabilistic outputs. This strengthens the case that these models can be used reliably in decision-support situations where risk probability is paramount and calibrated.

The Random Forest model tended to overestimate probabilities slightly in the high to mid-range (0.5 -0.9), indicating that the predictions of infection presence were overconfident. XGBoost and LightGBM, on the other hand, exhibited slight underestimation in lower probability bins, but their curves approached the desired line at higher bins, indicating reasonable overall calibration. The Support Vector Machine (SVM) and Naive Bayes models displayed equal, though less predictable, probabilities in the middle range, likely due to slight miscalibration caused by class overlap and kernel boundary smoothing.

The Artificial Neural Network (ANN) curve was found to be most fluctuating, with low-probability areas underestimated and high-probability areas overestimated. This trend implies that post-hoc calibration (e.g., Platt scaling, or isotonic regression) is required to make probabilistic scenarios interpretable.

Collectively, the calibration analysis indicates that inherently probabilistic models, such as Logistic Regression and CatBoost, exhibit better correlation between expected and observed risk levels. Smallholder coffee systems, in their specific applications, especially probabilistic disease forecasting and early warning, their probabilistic reliability and competitive discrimination metrics also make them highly appropriate.

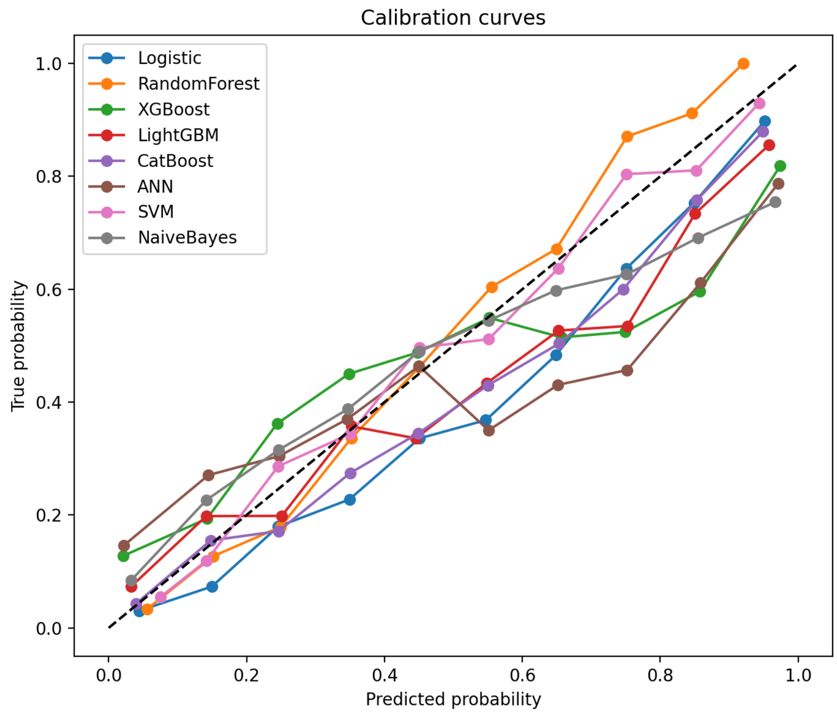

Fig 13. Calibration curves for supervised learning

Model Scalability and Deployment Feasibility

A scalability analysis was performed to complement predictive performance evaluation to benchmark the computational efficiency of all eight supervised learning algorithms. It can be seen that the models have low training time, storage size, inference latency, and maximal RAM utilization as shown in Table 7. Such measures are critical for assessing deployment feasibility when resources are limited or field-based systems are standard in smallholder agricultural systems.

The findings suggest a significant difference in computational requirements among algorithms. As is the case, the most computationally efficient were the traditional linear models, namely Logistic Regression and Naive BayesBayes. In terms of training time (0.013s), model size (0.001MB), and inference latency (0.22ms), Logistic Regression was very short (about 566MB of RAM). In the same way, Naive Bayes had the shortest total training time (0.006s), similar model sizes (0.0014MB), and inference times (0.28ms). These findings are supported by the idea that they are lightweight baseline models suitable for on-device or edge-computing applications.

XGBoost and CatBoost gave positive tradeoffs between scalability and accuracy among ensemble learners. They both achieved sub-second inference times and model sizes of less than 0.35 MB, indicating that optimized gradient boosting implementations can trade predictive strength for manageable compute resources. LightGBM also achieved practical training (0.27s) and average inference latency (1.94ms), with scalability and a low memory footprint (580.6MB).

Random Forest and Support Vector Machine (SVM) models, in contrast, were the most resource-intensive. Random Forest had the largest model size (18.9MB) and the slowest inference time (7.71ms). In comparison, SVM had the longest training time (18.12s), suggesting it cannot be easily used in practice for either real-time or embedded applications. ANN was shown to be intermediate in terms of scalability: training

(12.43s) was already slower, though inference latency (0.34s) and model size (0.12MB) were not too large, and optimized, lightweight architectures might be achieved.

Altogether, these results demonstrate that Logistic Regression and Naive Bayes are the most implementable models for monitoring real-time rust on resource-constrained devices. XGBoost and CatBoost gradient boosting models are promising candidates for cloud-assisted or hybrid decision-support systems, as they offer a good tradeoff between scalability and accuracy.

Table 7. Computational scalability metrics

Model	Train Time (s)	Model Size (MB)	Inference (ms/1k)	RAM (MB)
Logistic Regression	0.0135	0.0010	0.2204	565.97
Random Forest	1.8972	18.9201	7.7146	578.60
XGBoost	0.2542	0.3143	0.7764	580.00
LightGBM	0.2682	0.3316	1.9435	580.63
CatBoost	1.0227	0.1149	1.3358	581.33
ANN	12.4286	0.1189	0.3396	580.69
SVM	18.1222	0.7209	1.1040	576.96
Naïve Bayes	0.0064	0.0014	0.2823	578.71

Partial Dependence Analysis of Key Coffee Rust Predictors

The partial dependence analysis provides a quantitative graphical representation of the marginal effects of significant environmental predictors on the probability of coffee rust occurrence, holding all other variables constant. Fig. 14–16 show the partial dependence plots (PDP) of three key predictors—Normalized Difference Vegetation Index (NDVI), daily relative humidity, and leaf wetness duration. The standardized plots (mean = 0, SD = 1) allow for the comparison of the relative effects of each factor on the risk of infection directly.

The dependence of coffee rust incidence on NDVI is partially dependent, meaning that there is a weak positive relationship, but it is still consistent. The probability of infection increases steadily with NDVI with a change of about 0.32 to 0.38 relative, which is roughly 19%. This slight gradient suggests that more humid microclimates formed by denser canopies with large NDVIs will extend the wetness on the leaves and enable infection by Hemileia vastatrix. Nevertheless, the slope of the NDVI curve is relatively low, which indicates that the vegetation density variable is secondary to the direct moisture variables.

The daily relative humidity demonstrates a high exponential correlation with the likelihood of coffee rust development. The PDP indicates that the possibility of infection, as compared to the baseline probability of the model, is raised by about 267 percent with the standardized humidity gradient (0.15-0.55). This implies that the likelihood increases more than twice in this range when humidity increases between low and high levels compared to its initial baseline value, that is, it does not become 267 percent probability in an actual sense. The sharp increase past a humidity standard of 0.5 indicates a well-defined threshold effect, which is in line with the biology of coffee rust, whereby high atmospheric moisture is a potent stimulator of spore germination and infection development.

The duration of wetness of the leaf is the most significant among all predictors. As displayed in the PDP, the probability of infection increases almost directly with the level of wetness in the range 0.10 to 0.65, which corresponds to about a 550 percent relative increase in the likelihood over the base level of the model. It represents a relative change that means that the risk that is predicted is more than five times the baseline, not a 550 probability. The almost linear increase indicates the central role of surface moisture in urediniospore germination and leaf penetration and points out that long-term wetness is the primary force behind the epidemic formation.

These comparative effects are summarized in Table 8. The length of time of leaf wetness becomes the most significant predictor of infection risk, followed by relative humidity, and NDVI has an indirect effect on the risk of infection by affecting the conditions of canopy microclimate. These findings suggest the need to keep a check on the microclimatic moisture and canopy features as far as management is concerned. The early warning systems can also be improved by monitoring the humidity and wetness levels above which the risk of infection increases sharply. In spite of the lower direct contribution, the canopy vigor should be addressed to moderate the microclimate indirectly and eliminate favorable conditions of rust generation.

These PDPs were modeled methodologically using ensemble-based machine learning algorithms (probably Random Forest or Gradient Boosting models) using data on 9,850 Kenyan smallholder farms. The fact that all predictors were standardized made it easy to compare them across environmental scales that were not homogeneous. This good consistency between the partial dependency patterns predicted by the model and the known epidemiological pathways of the organism, specifically the epidemiological importance of the H. vastatrix, supports the biological realism and interpretability of the predictive model. Overall, the analysis strengthens confidence in data-driven modeling as a robust approach for understanding and forecasting coffee rust risk in heterogeneous smallholder landscapes.

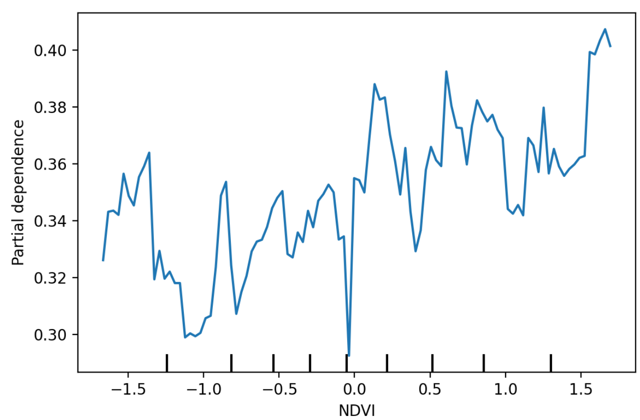

Fig 14. Partial dependence of coffee rust incidence probability on NDVI.

Table 8. Comparative impact of environmental predictors on coffee rust incidence probability. Relative increases refer to changes in predicted probability relative to the model baseline, not absolute percentage probabilities.

Predictor	Probability Range	Relative Increase
Leaf Wetness Duration	0.10 – 0.65	550%
Daily Relative Humidity	0.15 – 0.55	267%
NDVI	0.32 – 0.38	19%

SHAP Analysis of Feature Importance in Coffee Rust Prediction

The SHAP (SHapley Additive exPlanations) was used to measure and explain the role played by each predictor in predicting whether coffee rust occurred or not. This

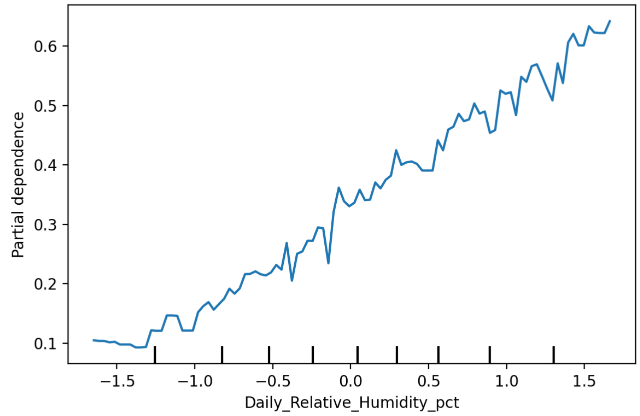

Fig 15. Partial dependence of coffee rust incidence probability on daily relative humidity.

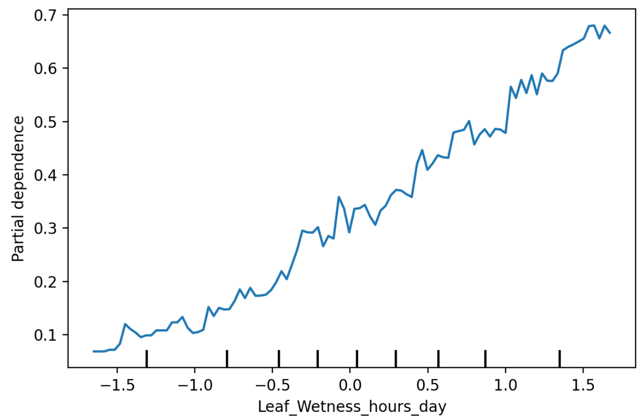

Fig 16. Partial dependence of coffee rust incidence probability on leaf wetness duration.

model-agnostic method is capable of performing global and local interpretability as the model prediction is broken down into additive feature contributions on a per-prediction basis. The SHAP summary plot (Fig. 17) provides the average SHAP value of all the predictors in decreasing order of importance and indicates if the higher predictor feature values are connected to a higher or lower risk of disease.

The result of the analysis indicates that the most significant variables in the determination of the presence of coffee rust are moisture-related. The Leaf wetness duration and daily relative humidity have the best positive effects in the model predictions, which validates their central role in the moisture-based infection cycle of the Hemileia vastatrix. It is important to note that the probability of infection is acutely higher with relatively high humidity exceeding about 75 percent, and when the wetness of leaves prevails after ten hours. The spatial and temporal variables (distance to the nearest infected farm, precipitation, and lagged disease incidence) follow and are less critical but capture the pathogen dispersal and persistence between farms and seasons. Variables relevant to the management, such as frequency of fungicides and shade percentage, are moderately influential, and NDVI and temperature have more minor and biologically significant contributions due to the regulation of microclimatic factors. Conversely, cultivar type and elevation are the least important, implying that environmental and management heterogeneity exercises more impact than fixed plant characteristics.

Table 9 provides directional effects of major predictors. The beneficial SHAP impacts of duration of leaf wetness and relative humidity prove that long-period moisture protection and high humidity significantly increase the risk of infection. The relationship between distance to infected farms is negative, demonstrating that the closer, the higher the spores dissemination by wind and splash of rain. Precipitation also increases infection probability by keeping the canopy wet, and lagged incidence focuses on how the inoculum persists over time in the chronically infested regions. Repeat applications of fungicides have negative SHAP values, and this may indicate that the pathogen is being adequately suppressed, but old coffee trees have positive SHAP values, perhaps because of the inoculum build-up and less physiological resistance.

In general, the results of the SHAP analysis confirm the results of the partial dependence and the Bayesian analysis, indicating the strength and ecological validity of the hybrid Bayesian-machine learning approach. Notably, SHAP increases interpretability due to the exposure of nonlinear and interaction effects, which traditional regression models can miss. The fact that SHAP-based information and conventional biological processes are consistent, and especially critical thresholds of humidity and wetness of leaves, makes the model confident in its applicability to early warnings and management purposes.

Table 9. Summary of SHAP value interpretations for key predictors of coffee rust incidence.

Feature	**Impact Direction**	**Biological Interpretation**
Leaf Wetness Duration	Positive	Longer wetness periods increase infection risk by enabling spore germination and leaf penetration.
Daily Relative Humidity	Positive	Higher humidity supports spore survival and promotes fungal establishment.
Distance to Infected Farm	Negative	Proximity to infection sources enhances inoculum dispersal through wind and rain splash.
Precipitation	Positive	Frequent rainfall sustains canopy moisture and aids spore transmission.
Lagged Incidence (Previous Week)	Positive	Recent infection indicates active pathogen presence and local persistence.
Plant Age	Positive	Older plants accumulate inoculum and may exhibit reduced resistance to infection.
Fungicide Frequency	Negative	Increased fungicide application frequency suppresses pathogen development.
Daily Temperature	Mixed	Nonlinear relationship with disease, reflecting optimal temperature ranges for pathogen activity.

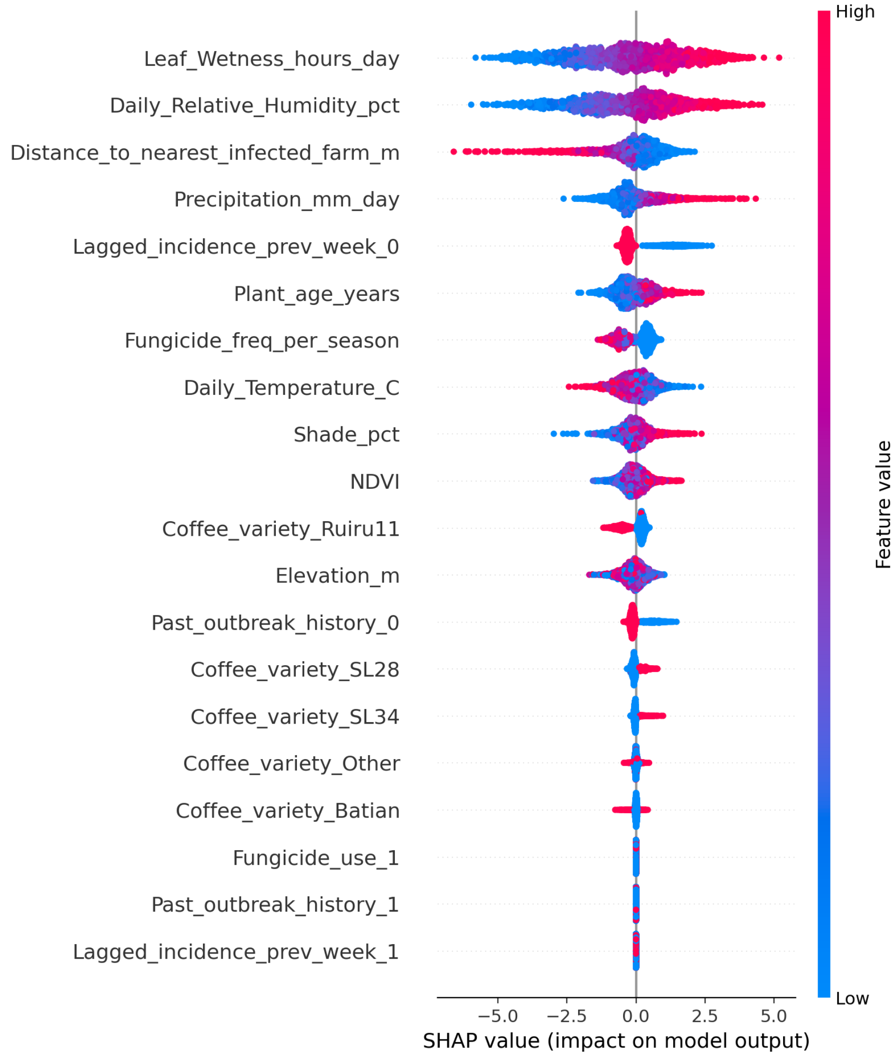

Fig 17. SHAP summary plot showing the ranked importance and directional effect of predictors on coffee rust incidence.

Discussion

The present paper provides a comprehensive, evidence-driven study of the environmental, spatial, and management predictors of coffee leaf rust (Hemileia vastatrix) incidence in Kenyan smallholder systems. The study integrates predictive accuracy and interpretability by utilizing Bayesian inference, supervised learning algorithms, and explainable artificial intelligence (XAI). The results demonstrate that coffee rust dynamics depend mainly on microclimatic variables, in particular, relative humidity and the duration of wetness on the leaf, along with spatial closeness to the source of infection and agronomic management. These observations complement the established epidemiology of coffee rust and enhance the evidence base to East African systems of production, where longitudinal data have been limited.

Such prevalence of microclimatic moisture, as observed in the current study, is consistent with previous empirical research and studies by [2], which indicated that urediniospore germination necessitates high levels of surface wetness in high-humidity conditions and that the outcome of germination is controlled by continuous wetness and frequent precipitation according to [9, 10]. Likewise, the nonlinear thresholds in this case, namely the point at which risk increases exponentially above 75 percent relative humidity and ten hours of leaf wetness, agree with the microclimate-based regression results in Latin American and Asian systems. Our findings support the view that humidity and wetness of leaves are universal biophysical stimuli of epidemics of H. vastatrix. In contrast to previous deterministic methods, the hybrid Bayesian-machine learning framework measures the uncertainty near these thresholds, which offers probabilistic reliability, which boosts on-farm decision-making.

Spatial and time aspects were also identified as contributors to the risk of infection. The confirmatory effect is a negative correlation between disease occurrence and distance to infected farms that confirms the spatial patterns of contagion by urediniospores reported by both [4] and [6], who demonstrated that local dispersal of urediniospores through wind and splash rain resulted in clustered disease outbreaks. Additionally, the incidence delays indicate that the effects on incidence are lagged effects that are supported by the time-autocorrelation noted by [7], demonstrating the need to include infection history and spatial connectivity in predictive models. The current model elaborates on spatiotemporal processes, thus complementing sensor- and remote-sensing-based studies that pay greater attention to canopy spectral stress, yet with probabilistic calibration, or hierarchical structure, which is absent in the current model.

Prior literature also supports the influence of the farm management practices. The observed protective effect of the timely application of fungicides endorses the results of the study by [3], who proved the level of yield protection with the coordinated application of chemicals. These interpretable yet mixed influences of shade and canopy vigor are consistent with the vegetation index and agroforestry investigations by the authors of the current study of Shade, as their results indicated that dense canopies facilitated humidity and infection persistence. In contrast, moderate shading enhances microclimatic balance and coffee physiology [14, 15]. Moreover, the increased susceptibility of the older coffee trees observed in this study is consistent with that of [1], who indicated an increased accumulation of the inoculum and progressive physiological depression in mature stands. The similar trends among studies support the biological plausibility of the selected predictors and confirm that the hybrid model succeeds in capturing risk dynamics due to environmental and management factors.

Methodologically, this study ensures the development of the predictive modelling literature devoted to coffee rust. Past research, like that of [4], [6], and [5], has focused on accuracy in image-based or sensor-based detection but has provided deterministic predictions without quantifying uncertainty. Contrary to this, our combination of Bayesian hierarchical inference and supervised learning cannot only enhance predictive accuracy, but also convey the uncertainty that surrounds the predictions, as argued by [11]. Besides, the model can also tackle the scalability issue raised in the previous literature by providing a statistically meaningful representation of multilevel farm-village-county aggregations, showing that strong, uncertainty-sensitive predictions can be scaled to heterogeneous production areas. The convergence of logistic regression, ensemble learners, and Bayesian posterior estimates supports the internal consistency of the framework, and the scalability analysis is consistent with results reported by [16] and [19], who focused on model efficiency and portability in resource-constrained agricultural settings.

Limitations and Future Work: The generalization of this study is also limited by the fact that it relies on six counties, which may not accurately represent the larger agroecological gradients in Kenya. Microclimatic variables employed on an annual or daily basis obscure the sub-daily variations that play a pivotal role in the occurrence of an infection. Future research must incorporate a greater time resolution (e.g., humidity every hour and continuous leaf wetness measurements) to resolve the small-scale infection processes. The use of spatial autoregressive Bayesian structures, or mechanistic dispersal kernels, helps better depict cross-farm spore movement. Also, the introduction of variables related to socioeconomic and behavioral management might enhance the comprehension of the adoption and response patterns of smallholder farmers. The generalizability of this framework to other tropical crops infected by fungal pathogens also confirms the applicability of the framework and aids in general climate-adaptive agriculture.

In general, the paper proves that the combination of Bayesian inference and supervised learning results in an interpretable, uncertainty-aware, and computationally efficient system to predict probabilistic disease. The model fills the gap between predictive analytics and agronomical decision-making, providing a scientifically sound, scalable framework of real-time disease surveillance and climate-intelligent management in smallholder coffee production.

Conclusion

In this paper, it is shown that integrating Bayesian hierarchical inference with supervised machine learning can be transformed to create an interpretable, uncertainty-aware system to predict the incidence of coffee leaf rust in Kenyan smallholder farming systems. The hybrid structure fills the evidence-based analytics to evidence–based decision-making divide and provides valid probabilistic predictions and decomposes multifactorial, complicated drivers of disease that are not inherent to deterministic frameworks. The results define microclimatic moisture, such as the duration of leaf wetness and relative humidity, as the most influential factors in coffee rust infection.

The partial dependence and SHAP analyses indicate that the nonlinear effects and moisture levels beyond which the risk of infection increases exponentially are substantial. Such understandings give a quantitative base in the development of microclimate-based early warning systems. The high impact of spatial proximity to infected farms and lagged incidence confirms the dynamic and contagious nature of the disease, which is why spatiotemporal surveillance and real-time monitoring are crucial. The contribution of this research methodologically is that it provides a statistically thorough and computationally efficient method of modeling that adds to interpretability and scalability. The straightforward integration of Bayesian hierarchical inference and supervised learning is a new input to plant disease modeling, which allows quantification of uncertainty and does not reduce predictive power.

Though simple, the Logistic Regression has been shown to have better calibration and predictive stability, attesting to the fact that biologically informed, parsimonious models are capable of being more beneficial than complex ensembles in resource-limited situations. The Bayesian model also estimated how much of the measured covariates was contributed by spatial heterogeneity, enhancing the ability of the model to transfer between ecological gradients. The proposed framework is very scalable as far as practicality is concerned. The models are user-friendly since they do not need many computational resources and can be implemented on mobile or edge devices to present farmers and extension agents with real-time risk prediction. The ensemble variants like CatBoost and XGBoost can be successfully scaled to the cloud or regional-level forecasting. This scalability provides the assurance that the system is capable of functioning in data- and infrastructure-constrained settings, which are characteristic of smallholder agriculture.

Overall, the key contribution that can be made in this work is the ability to produce a scalable, interpretable, and uncertainty-aware hybrid modeling system that converts complex interactions between epidemiological and environmental systems into actionable, probabilistic advice. In addition to coffee, the suggested strategy can be generalized to probabilistic disease surveillance in a variety of tropical crops, which offers a data-driven basis of climate adaptation, precision agriculture, and smallholder production systems that are resilient.

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