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ORIGINAL ARTICLE

Biometry, Modeling, and Statistics

Rank-based data synthesis of heterogeneous trials to identify the effects of climatic factors on the reaction of *Musa* genotypes to black leaf streak disease

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Abstract

Synthesis of crop trial data can generate insights that are not available from the analysis of individual studies, but such synthesis is often constrained by the heterogeneity of data among studies. Rank-based data synthesis provides the flexibility to combine data of heterogeneous types and from different sources. We demonstrate the application of rank-based data synthesis of heterogeneous trial data to assess the effect of climatic factors on the reaction of several *Musa* genotypes to black leaf streak disease (BLSD; caused by *Pseudocercospora fijiensis* [sexual morph: *Mycosphaerella fijiensis*]). We aggregated data from the main public repositories of *Musa* trial data. We applied model-based recursive partitioning with the Plackett–Luce model, using climatic data as covariates. The model identified the maximum length of the dry spell as the main variable influencing differences in genotypic response to BLSD, dividing the aggregated trial dataset into humid and dry environments. We found differences in the reaction of genotypes to BLSD between these environments. In humid environments, NARITA 8 was found to be the most resistant genotype, while in dry environments FHIA-01 was the best performing improved genotype. We also

Abbreviations: BLSD, black leaf streak disease; DDT, disease development time; DII, disease infection index; NFL, number of functional leaves; NSL, number of standing leaves; YLS, youngest leaf spotted.

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assessed reliability, which is the probability of outperforming the reference genotype (Calcutta 4). In humid environments, NARITA 2, NARITA 8, and FHIA-01 had the highest reliability, while in dry environments only the landrace Saba surpassed 50% reliability. The information generated by our data synthesis approach supports selecting *Musa* genotypes for further evaluations at new locations.

1 | INTRODUCTION

Crop variety trial data are essential for producing relevant information to support critical decision making in agronomy and crop science. These data are expensive to obtain, since field trials require a significant investment of time and resources. Research synthesis of heterogeneous studies can help to generalize conclusions and to better account for environmental variability, compared to the analysis of individual studies (Makowski, 2021). Furthermore, appropriate data synthesis methodologies can add value to existing crop trial data, by (1) integrating results from trials with different types of data and from different sources, (2) comparing a higher number of genotypes than would be feasible in individual field experiments, and (3) adding environmental data that were not available at the time at which each individual trial was conducted, providing new insights on the effect of environmental factors (genotype \times environment interaction).

Current data synthesis methods often encounter obstacles related to poor data standardization (Eagle et al., 2017). Combining data from multiple trials with different experimental designs, measurement scales and data quality pose problems for data management and for subsequent statistical analysis (Simko & Pechenick, 2010). Simko and Pechenick (2010) proposed the use of rank-aggregation methods to allow for the combination of heterogeneous plant breeding data from different experiments. By converting diverse numerical measurements into rankings, trial data can be aggregated in one dataset and analyzed with appropriate statistical methods. Brown et al. (2020) suggested that the rank-aggregation approach could be extended to analyze heterogeneous data from crop trial evaluations under different environmental conditions by using climatic data to account for effects of abiotic stress on genotypic performance. van Etten, de Sousa et al. (2019) analyzed farmer-participatory crop experiments in which field data were collected by farmers as rankings, following the "tricot" approach (van Etten, Beza et al., 2019), and then combined with environmental data. Brown et al. (2022) demonstrate that data synthesis of tricot trial data of common bean (*Phaseolus vulgaris* L.) genotypes in Central America provides new insights to climate adaptation by predicting the

performance of varieties beyond the locations in which they were tested.

Black leaf streak disease (BLS), also known as black Sigatoka, is a fungal disease that affects banana leaves, causing necrotic lesions which gradually reduce the plant's photosynthetic capacity (Churchill, 2011). BLS is caused by the fungus *Pseudocercospora fijiensis* (sexual morph: *Mycosphaerella fijiensis*) (Guzman et al., 2018). It is the most destructive leaf disease of bananas and is considered to be among the 10 most destructive diseases in global agriculture (Pennisi, 2010). BLS both reduces yields and fruit quality and affects the wider environment because its control currently relies heavily on frequent applications of chemical fungicides (De Lapeyre de Bellaire et al., 2010). The cultivation of BLS-resistant varieties is considered to be the most sustainable disease control method. Thus, the selection and release of such BLS-resistant varieties have become crucial for banana producers. Location-specific information on how different genotypes perform under different climatic conditions can support decision making that considers genotype by environment interactions ($G \times E$) and is useful for *Musa* breeding programs.

Here, we apply the data synthesis approach (Brown et al., 2020) to a combination of data from various evaluations of *Musa* genotype reactions to BLS and climatic data that are used as model covariates. To the best of our knowledge, this is the first application of such an approach to BLS data originally collected in a non-ranking format. Multi-environment trials of *Musa* genotypes are complex to conduct because of their intricate requirements of space and time (Tenkouano et al., 2012). Our main objective is to demonstrate application of the data synthesis approach to unveil the effect of climatic factors on the reaction of several *Musa* genotypes to BLS. Our interest is to explain rather than to predict a genotype's reaction to BLS; the models are fitted and validated accordingly. The specific objectives are to: (1) aggregate heterogeneous trial data previously deemed incompatible, (2) assess the effect of climatic variables and indices on the reaction of several genotypes to BLS, and (3) identify the best performing genotypes across different locations.

2 | MATERIAL AND METHODS

2.1 | Musa trial data

We retrieved data from the three main public data repositories currently storing field evaluation data on *Musa* genotypes: AgTrials, MusaBase, and the *Musa* Germplasm Information System (MGIS) (Bauchet et al., 2018; Hyman et al., 2017; Ruas et al., 2017). From each repository, we selected data that fulfilled the following criteria:

1. Contains evaluations of *Musa* genotype reactions to BLSD
2. Contains geographic coordinates of trial locations
3. Contains the start and end dates of the evaluation period (i.e., planting date, and either shooting or harvesting date)
4. Genotypes evaluated at least partially overlap among trials (see connectivity in Section 2.5)

Table 1 presents the studies and projects in which the selected data were originally produced, the number of evaluated genotypes, number of locations, temporal extent, and the data repository from which we retrieved the data.

Figure 1 shows the 22 unique locations of the trials. To provide a general description of the climatic conditions at the trial locations, Table 2 presents the yearly mean temperature, precipitation, and relative humidity, averaged from monthly climatologies for the reference period 1991–2020 (Hersbach et al., 2018), which roughly covers the time span of the aggregated dataset (1990–2019, Table 1).

2.2 | Converting data to rankings

To analyze the data using the Plackett–Luce model (Luce, 1959; Plackett, 1975), the data were transformed from numerical BLSD measurements to a ranking format. Five different metrics for BLSD evaluation were used in the original trial data (Table 3). The scores for these metrics were used to rank the genotypes within each trial, where the order of the ranking depended on the metric used in a trial. For instance, in evaluations where the youngest leaf spotted (YLS) was reported, genotypes with the highest values were ranked first. Conversely, for rating scales such as disease infection index (DII), representing the diseased surface per plant, genotypes with the lowest values were ranked first. If multiple measurements were made in the same evaluation, we selected the metric for which the most data were available and which resulted in a more homogeneous aggregated dataset (i.e., higher possible number of rankings are derived from the same metric). In the final aggregated dataset, 33 of the rankings were derived from the underlying variable YLS, 3 from disease development time (DDT), 41 from DII, 24 from the number of standing

Core Ideas

- Data synthesis generated new insights by bringing together heterogeneous *Musa* crop trial data.
- The novel method converts disease scores to ranks and uses environmental data.
- *Musa* genotypes react differently to black leaf streak disease with different dry spell lengths.

leaves (NSL), and 9 from the number of functional leaves (NFL).

If the trial data were reported at plant or block level, we treated each block as an individual experiment and the summarized results at the block level generated a ranking. On the contrary, where trial data were available only as summarized results, the ranking was constructed using the averaged values. Each evaluation cycle generated a separate ranking. For example, trials evaluating over two cycles (i.e., mother and first ratoon) produced two separate rankings. The evaluation also depends on decisions made when the trial was designed. For instance, YLS is usually registered at shooting, but in some cases, it may have been registered only at harvest or at both. These differences were considered in order to define the period for which climatic data were obtained for modeling (see Section 2.3). In the aggregated dataset, the evaluation period for all YLS, DDT, and NFL and for one DII was from planting to shooting. For the rest of the data, where the BLSD metric was DII and NSL, the evaluation period was from planting to harvest.

To convert the data from numerical measurements to ranks, we used the function `rank_numeric()` from the R package `gosset` (de Sousa, Brown et al., 2023). The rankings were constructed separately for each evaluation and then aggregated into a sparse matrix, where the columns are the evaluated genotypes, and the rows correspond to the evaluations. After aggregating all the evaluations, the number of rankings was 110, with 62 genotypes evaluated. Information about the evaluated genotypes is presented in Table 4. There are three types of genotype: (1) a crop wild relative, (2) landraces, and (3) improved genotypes either through breeding (hybrids) or selection of somaclonal variants.

Guzman et al. (2018) described two types of reactions and three types of interactions of *Musa* genotypes to and with BLSD:

1. Incompatible interaction characterized by high resistance (HR) or hypersensitivity (phenotype 1). This expression of high resistance is characterized by the blockage of disease development at an early stage and YLS is not observed.
2. Compatible interaction with two types of reaction:

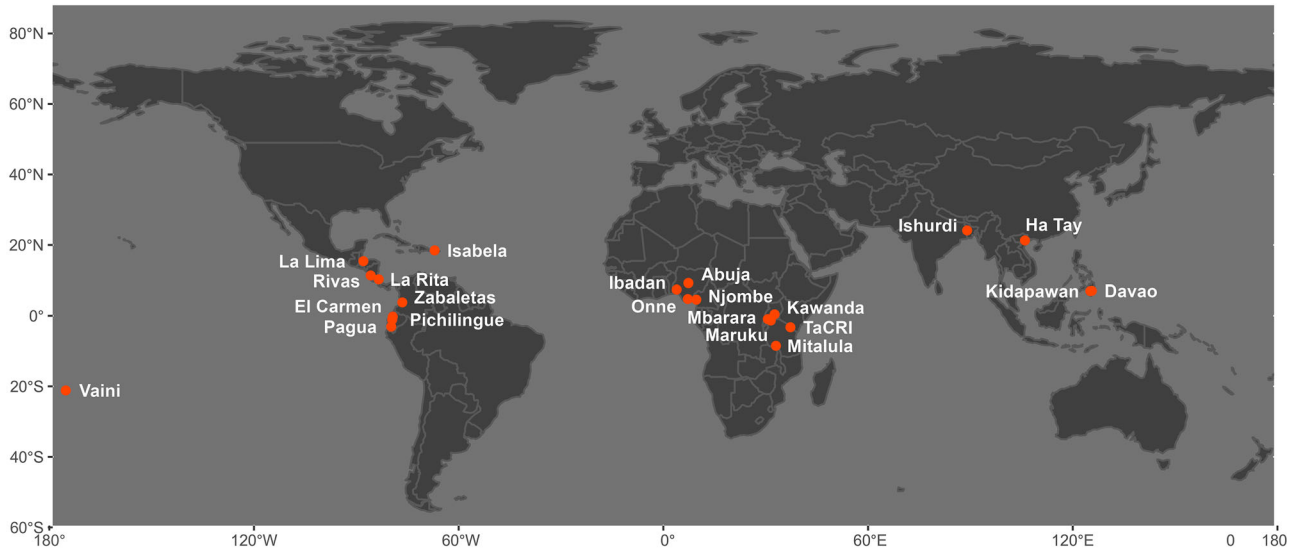


FIGURE 1 Unique locations of trials included in the aggregated data set.

2.1 Partial resistance (phenotype 2) expressed by slow disease evolution (from first streak symptoms to spots) and a reduction in pathogen reproduction. The YLS is high. There is a large progression of response with phenotype 2 from resistance to almost complete susceptibility.

2.2 Susceptibility (phenotype 3) expressed by rapid disease evolution; YLS is low.

The BLSD reactions indicated in Table 4 follow the types of reaction described above. The classification of any genotype into one of the three phenotypes results from evaluating the host reaction under field conditions in comparison with references of known resistance phenotypes. We used Calcutta 4 as the reference in our analysis; it is frequently used as a highly resistant reference in BLSD evaluations.

2.3 | Climatic data

To account for climatic effects on the plant host reaction to BLSD, we used climatic data retrieved from the AgERA5 database (Boogaard & van der Grijn, 2020; Copernicus Climate Change Service, 2020). We downloaded the following variables: daytime maximum temperature, nighttime minimum temperature, daily precipitation flux, and relative humidity at 6:00 a.m., 9:00 a.m., 12:00 p.m., 3:00 p.m., and 6:00 p.m. The initial set of climatic covariates (temperature, precipitation, and relative humidity) were chosen based on guidelines for *Musa* disease evaluation (Orjeda, 1998) and previous studies relating BLSD to climatic factors (Churchill, 2011; Jacome & Schuh, 1992; Yonow et al., 2019). The climatic data were extracted for the period of each evaluation that generated a ranking. This corresponds to either the time from

planting to shooting or from planting to harvest, depending on what was reported in each evaluation. If more than one cycle was reported, the start time for the ratoon cycle was computed as the end time of the previous crop cycle. For example, for a second cycle in which YLS at shooting is reported, the evaluation period of the mother is from planting to shooting, whereas for the first ratoon cycle, the evaluation time is from the shooting of the mother to the shooting of the first ratoon cycle. All relative humidity variables were averaged over the evaluation period of each trial (i.e., either planting to shooting or planting to harvest). Precipitation and temperature variables were used as inputs with R package *climatrends* (de Sousa, van Etten et al., 2023) to compute climatic indices (Table 5).

2.4 | Plackett–Luce trees

The Plackett–Luce model (Luce, 1959; Plackett, 1975) is a statistical model for ranking data. Its implementation in the R package *PlackettLuce* (Turner et al., 2020) is an extension of the original model that allows ties and partial rankings, although ties of order four or higher are difficult to analyze. Given a set S of J items $S = \{i_1, i_2, \dots, i_j\}$, the probability of selecting an item i_j from S is represented by:

$$P(i_j | S) = \frac{\alpha_{i_j}}{\sum_{i \in S} \alpha_i}$$

where $\alpha_i \geq 0$ is the worth of item i (Turner et al., 2020). An item with a higher worth value is more likely to be selected (Turner et al., 2020). To account for context-specific differences among rankings, the *PlackettLuce* package is coupled with the model-based recursive partitioning framework of the R package *partykit* (Hothorn & Zeileis, 2015; Zeileis

TABLE 1 Description of the trials included in the data synthesis.

Study/Project	Data repository	Number of locations ^a	Experimental design	Number of blocks	Number of cycles	Number of genotypes	Temporal extent	Number of generated rankings
IMTP-1	AgTrials	6	Observation plots without replication		2	17	1990–1992	4
IMTP-2	AgTrials	8	RCBD	5	1	19	1995–1997	13
IMTP-3	AgTrials	7	RCBD	3–5 ^b		40	1999–2003	26
Orlando Narváez (2004)	AgTrials	3	CRD		1	13	2003–2004	3
Irish et al. (2013)	MGIS	1	RCBD	4	2	19	2008–2009	2
Irish et al. (2019)	MGIS	1	RCBD	4	2	15	2014–2016	2
WP4-BBB-Project	MusaBase	5	RCBD	4	3	32	2016–2019	60

Abbreviations: CRD, completely randomized design; IMTP, International Musa Testing Program; MGIS, *Musa* Germplasm Information System (currently does not store trial data, but provides a curated selection of literature on phenotypic evaluations of *Musa* genotypes); RCBD, randomized complete block design; WP4-BBB, Working Package 4 Breeding Better Bananas Project.

^aSome locations are repeated across studies; unique locations are presented in Figure 1.

^bVaries among trials within the same study; information corresponds to the original design but not all data were available for data synthesis (e.g., one cycle missing).

et al., 2008). The combination of the recursive partitioning algorithm (Zeileis et al., 2008) and the Plackett–Luce model (Turner et al., 2020) produce a Plackett–Luce tree. Accordingly to Zeileis et al. (2008) and (Turner et al., 2020), the algorithm proceeds as follows:

1. The Plackett–Luce model is fitted to the entire dataset.
2. The influence of each covariate on the stability of worth parameters is assessed.
3. If instability exceeds a given minimum threshold, the dataset is split into two partitions (also referred to as "nodes"). The split is generated by selecting a split value of a certain covariate with the strongest parameter instability. Samples above and below this value are assigned to different partitions (categorical variables can also be used to create partitions). To each partition, a Plackett–Luce model is fitted separately.
4. The algorithm stops either when no significant instabilities are detected or when the resulting partitions are smaller than a pre-specified minimum size. Otherwise, steps 1–3 are repeated, analyzing stability for each of the data partitions separately, and splitting them further.

The threshold in step 3 is specified by the α parameter in the Plackett–Luce tree model function, which defines the threshold significance level at which to admit a split (Zeileis et al., 2008). We used a Bonferroni-corrected α value of 0.05. In step 4, the threshold refers to the minimum number of observations required in a node. In our case, we set the minimum node size as 35% of the aggregated dataset. In predictive mode, this threshold might be considered as too conservative. However, we are modeling in explanatory mode and very small nodes might be uninformative. Furthermore, the model requires some level of connectivity among compared items, which might not be feasible with very few observations per node. Further details about connectivity are provided in Section 2.5.

2.5 | Network connectivity

To compute finite maximum likelihood estimates (MLE) and standard errors with *PlackettLuce*, the network of items should be strongly connected, which means that a win–lose relationship should exist between each pair of items included in the rankings (Hunter, 2004; Turner et al., 2020). From the initial aggregated dataset, we removed genotypes that were weakly connected to others. To guarantee the representativeness of genotypes among trials and avoid extremely biased comparisons, we only kept genotypes that were present in at least 5% of the trials. This threshold was defined through an iterative search of the minimum amount of data that guarantees model convergence and minimizes data loss. It resulted in

TABLE 2 Location name, geographic coordinates, and yearly mean climatic data (temperature, annual precipitation, and relative humidity) for the period 1991–2020 at unique trial locations.

Country	Location	Longitude (°)	Latitude (°)	Temperature (°C)	Precipitation (mm)	Relative humidity (%)
Bangladesh	Ishurdi	89.033	24.133	25.57	1,996.97	77.04
Cameroon	Njombe	9.650	4.583	25.83	4,889.37	87.46
Colombia	Zabaletas	−76.517	3.817	19.40	2,607.82	88.99
Costa Rica	La Rita	−83.450	10.267	25.01	3,311.83	85.91
Ecuador	Pichilingue	−79.483	−1.100	23.84	1,608.95	90.27
Ecuador	El Carmen	−79.317	−0.233	23.32	3,019.01	87.61
Ecuador	Pagua	−79.769	−3.074	22.04	1,436.69	89.27
Honduras	La Lima	−87.933	15.417	24.42	1,769.74	86.89
Nicaragua	Rivas	−85.799	11.356	26.35	1,707.09	80.97
Nigeria	Abuja	7.333	9.267	26.45	1,756.53	64.04
Nigeria	Onne	7.167	4.767	26.20	1,471.82	87.43
Nigeria	Ibadan	3.900	7.433	26.09	2,874.01	80.79
Philippines	Davao	125.600	7.083	26.65	1,888.76	80.27
Philippines	Kidapawan	125.154	7.014	25.27	6,103.88	83.60
Puerto Rico	Isabela	−67.051	18.472	25.75	2,789.3	80.92
Tanzania	Mitalula	33.000	−8.500	24.57	6,581.55	55.59
Tanzania	Maruku	31.500	−1.333	20.93	1,125.93	82.07
Tanzania	TaCRI	37.246	−3.244	17.41	1,805.36	79.42
Tonga	Vaini	−175.167	−21.167	24.14	851.55	76.80
Uganda	Kawanda	32.600	0.417	21.08	614.2	86.99
Uganda	Mbarara	30.617	−0.933	20.91	1,095.14	72.74
Vietnam	Ha Tay	105.983	21.300	24.20	2,406.38	78.95

Source: Climatic data from Hersbach et al. (2018).

TABLE 3 Description of metrics commonly used for black leaf streak disease (BLSD) evaluations.

Metric	Description
Disease development time (DDT)	Number of days from infection (occurring at the appearance of the unfolded leaf) to the appearance of 10 or more necrotic mature lesions.
Disease infection index (DII)	$DII = \frac{\sum nb}{(N-1)T} 100$ $N = \text{number of grades in the scale}$ $n = \text{number of leaves in each grade}$ $b = \text{grade}$ $T = \text{total number of leaves scored}$
Number of functional leaves (NFL)	Total number of leaves per plant with more than 50% green area.
Number of standing leaves (NSL)	Total number of standing leaves per plant, starting from the highest unfolded leaf, regardless of infection status.
Youngest leaf spotted (YLS)	The first (from top to bottom) fully unfolded leaf with 10 or more necrotic lesions.

Source: Adapted from Bauchet et al. (2018), Jones & Tézenas du Montcel (1994), and Orjeda (1998).

37% of the genotypes being discarded. When a Plackett–Luce tree is fitted, a network that is initially strongly connected might become weakly connected if the dataset is divided by the recursive partitioning algorithm. The *PlackettLuce* package provides a solution for networks that are not strongly connected, through the inclusion of pseudo-rankings (Turner

et al., 2020). These are symmetric wins and losses between an artificial item and each of the real items, which make the network strongly connected. Even though our initial network was strongly connected (Figure 2) after removing the weakly connected genotypes, we used the pseudo-rankings mechanism to guarantee the connectivity of the network after partitioning

TABLE 4 Main characteristics of Musa genotypes included in the data synthesis.

Name	Status	BLS D reaction	Genome	Subgroup/Type	Breeding program	Information source
Agbagba	Landrace	S	AAB	Plantain	NA	(Ferris et al., 1999)
BITA-2	Hybrid	PR	ABBB	Plantain	IITA	(Ning et al., 2007); (Noupadja & Tomekpé, 2001)
BITA-3	Hybrid	PR	AAAB	Plantain	IITA	(Bakry et al., 2009); (Ortiz & Vuylsteke, 1998)
Burro Cemsa	Landrace	PR	ABB	Bluggoe	NA	(Alvarez, 1997)
Cachaco	Landrace	PR	ABB	Bluggoe	NA	(Guzman et al., 2018)
Calcutta 4	Wild	HR	AAw	<i>M. acuminata</i> subsp. <i>burmannicoides</i>	NA	(Guzman et al., 2018)
CRBP-39	Hybrid	PR	AAAB	Plantain	CARBAP	(Cohan et al., 2003)
EMB 403	Hybrid	PR	AAAB		EMBRAPA	(Hernández Núñez, 1995)
FHIA-01	Hybrid	PR	AAAB	Pome	FHIA	(Irish et al., 2013)
FHIA-02	Hybrid	PR	AAAA		FHIA	(Karamura et al., 2012)
FHIA-03	Hybrid	PR	AABB		FHIA	(Karamura et al., 2012)
FHIA-17	Hybrid	PR	AAAA		FHIA	(Irish et al., 2013)
FHIA-18	Hybrid	PR	AAAB	Pome	FHIA	(Irish et al., 2013)
FHIA-20	Hybrid	PR	AAAB	Plantain	FHIA	(Sakyi-Dawson et al., 2008)
FHIA-21	Hybrid	PR	AAAB	Plantain	FHIA	(Irish et al., 2013)
FHIA-23	Hybrid	PR	AAAA		FHIA	(Orjeda, 2000)
FHIA-25	Hybrid	PR	AAB		FHIA	(Njukwe et al., 2010)
French Sombre	Landrace	S	AAB	Plantain	NA	(Guzman et al., 2018)
Grande Naine	Landrace	S	AAA	Cavendish	NA	(Guzman et al., 2018)
Gros Michel	Landrace	S	AAA	Gros Michel	NA	(Guzman et al., 2018)
Kisansa	Landrace	S	AAA	EAHB	NA	(Kimunye, Were et al., 2021); (Nyombi et al., 2009)
Lakatan	Landrace	U	AA		NA	IMTP-2 data
Mbwazirume	Landrace	S	AAA	EAHB	NA	(Kimunye, Were, et al., 2021)
Nakitembe	Landrace	S	AAA	EAHB	NA	(Karamura & Karamura, 1994); (Kimunye, Were et al., 2021)
NARITA 2	Hybrid	PR	AAA	EAHB	NARO-IITA	(Kimunye, Jomanga, et al., 2021)
NARITA 4	Hybrid	PR	AAA	EAHB	NARO-IITA	(Kimunye, Jomanga, et al., 2021)
NARITA 6	Hybrid	PR	AAA	EAHB	NARO-IITA	(Kimunye, Jomanga, et al., 2021)
NARITA 7	Hybrid	PR	AAA	EAHB	NARO-IITA	(Tushemereirwe et al., 2015)
NARITA 8	Hybrid	PR	AAA	EAHB	NARO-IITA	(Tushemereirwe et al., 2015)

(Continues)

TABLE 4 (Continued)

Name	Status	BLS D reaction	Genome	Subgroup/Type	Breeding program	Information source
NARITA 9	Hybrid	PR	AAA	EAHB	NARO-IITA	(Tushemereirwe et al., 2015)
NARITA 10	Hybrid	S	AAA	EAHB	NARO-IITA	(Kimunya, Jomanga et al., 2021; Tushemereirwe et al., 2015)
NARITA 11	Hybrid	PR	AAA	EAHB	NARO-IITA	(Tushemereirwe et al., 2015)
NARITA 12	Hybrid	S	AAA	EAHB	NARO-IITA	(Kimunya, Jomanga, et al., 2021; Tushemereirwe et al., 2015)
NARITA 13	Hybrid	S	AAA	EAHB	NARO-IITA	(Kimunya, Jomanga, et al., 2021; Tushemereirwe et al., 2015)
NARITA 14	Hybrid	PR	AAA	EAHB	NARO-IITA	(Kimunya, Jomanga, et al., 2021; Tushemereirwe et al., 2015)
NARITA 15	Hybrid	S	AAA	EAHB	NARO-IITA	(Kimunya, Jomanga, et al., 2021; Tushemereirwe et al., 2015)
NARITA 16	Hybrid	PR	AAA	EAHB	NARO-IITA	(Kimunya, Jomanga, et al., 2021; Tushemereirwe et al., 2015)
NARITA 18	Hybrid	S	AAA	EAHB	NARO-IITA	(Kimunya, Jomanga, et al., 2021; Tushemereirwe et al., 2015)
NARITA 19	Hybrid	S	AAA	EAHB	NARO-IITA	(Kimunya, Jomanga, et al., 2021; Tushemereirwe et al., 2015)
NARITA 20	Hybrid	PR	AAA	EAHB	NARO-IITA	(Tushemereirwe et al., 2015)
NARITA 21	Hybrid	PR	AAA	EAHB	NARO-IITA	(Tushemereirwe et al., 2015)
NARITA 22	Hybrid	PR	AAA	EAHB	NARO-IITA	(Tushemereirwe et al., 2015)
NARITA 23	Hybrid	PR	AAA	EAHB	NARO-IITA	(Tushemereirwe et al., 2015)
NARITA 24	Hybrid	S	AAA	EAHB	NARO-IITA	(Kimunya, Jomanga, et al., 2021; Tushemereirwe et al., 2015)
NARITA 25	Hybrid	PR	AAA	EAHB	NARO-IITA	(Tushemereirwe et al., 2015)
NARITA 26	Hybrid	PR	AAA	EAHB	NARO-IITA	(Tushemereirwe et al., 2015)

(Continues)

TABLE 4 (Continued)

Name	Status	BLS D reaction	Genome	Subgroup/Type	Breeding program	Information source
NARITA 27	Hybrid	PR	AAA	EAHB	NARO-IITA	(Kimunye, Jomanga, et al., 2021)
Ndizi Uganda	Landrace	S	AAA	EAHB	NA	(Karamura et al., 2012); (Kimunye, Were et al., 2021)
Niyarma Yik	Landrace	S	AA		NA	(Guzman et al., 2018)
PA 03-22	Hybrid	S	AAAB	Pome	EMBRAPA	(Irish et al., 2013)
Pisang Berlin	Landrace	S	AA	Inarnibal	NA	(Guzman et al., 2018)
Pisang Ceylan	Landrace	PR	AAB	Mysore	NA	(Guzman et al., 2018)
Pisang Jari Buaya	Landrace	S	AA	Pisang Jari Buaya	NA	(Kimunye, Were et al., 2021)
PITA-16	Hybrid	S	AAB	Plantain	IITA	(Irish et al., 2013)
PV 03-44	Hybrid	PR	AAAB	Pome	EMBRAPA	(Irish et al., 2013)
Rose	Landrace	PR	AA	<i>M. acuminata</i> subsp. <i>malaccensis</i>	NA	(Kimunye, Were et al., 2021)
Saba	Landrace	PR	ABB	Monthan	NA	(Guzman et al., 2018)
SH-3436-9	Somaclonal variant	PR	AAAA	Highgate	INIVIT	(Orjeda, 2000)
SH-3640	Hybrid	S	AAAB		FHIA	(Irish et al., 2013)
Valery	Landrace	S	AAA	Cavendish	NA	(Guzman et al., 2018)
Williams	Landrace	S	AAA	Cavendish	NA	(Guzman et al., 2018)
Yangambi Km5	Landrace	HR	AAA	Ibota Bota	NA	(Guzman et al., 2018)

Note: EAHB landraces were assumed to be susceptible. NARITAs were assumed to be partially resistant following Tushemereirwe et al. (2015), except those indicated as susceptible by Kimunye, Jomanga et al. (2021).

Abbreviations: BLS D, black leaf streak disease; CARBAP, Rural Associations' Confederation of Buenos Aires and La Pampa; EMBRAPA, Brazilian Agricultural Research Corporation; FHIA, Fundación Hondureña de Investigación Agrícola; HR, highly resistant; IITA, International Institute of Tropical Agriculture; INIVIT, Instituto de Inestigaciones de Viandas Tropicales; NA, not applicable; NARO, National Agricultural Research Organization; PR, partially resistant; S, susceptible; U, unknown.

splits. The use of pseudo-rankings also reduces the variance and bias of the worth parameter estimators (Turner et al., 2020). The number of pseudo-rankings to the artificial item is set by the *npseudo* parameter in the Plackett–Luce model; we set *npseudo* = 2. Network connectivity is also important to guarantee tree stability, as detailed in Section 2.7. Cultivars Williams and Gros Michel are commonly used as susceptible references in BLS D evaluations. Pisang Ceylan is often used as a partially resistant reference. Figure 2 shows how these reference genotypes enabled the comparison of genotypes, which were not compared to each other in the same trial. For instance, the FHIA and NARITAs were not compared directly in any of the aggregated trials.

2.6 | Handling tied ranks

In the present analysis, we found many cases in which the evaluated genotypes were tied, especially in lower rank positions. The Plackett–Luce model implemented in the R package *PlackettLuce* can handle ties up to an order of four (Turner et al., 2020). Unfortunately, the large number of ties

in our data prevented model convergence. Therefore, from the subset of tied genotypes in a single rank, we removed all except one of the tied genotypes. For instance, if six items are tied in the low part of a single ranking, we remove five genotypes and keep one from the tied subset. To avoid bias, the genotype to be retained was randomly selected. We found that changing which genotype was retained had a negligible influence on the overall results.

2.7 | Stability assessment of the Plackett–Luce tree

A well-known limitation of recursive partitioning as used in Plackett–Luce trees is model instability, which means that a small change in the input data can cause large changes in the output (Breiman, 1996; Philipp et al., 2018; Strobl et al., 2009). Stability is fundamental in the explanatory models to guarantee that similar model results (i.e., semantic similarity of the learned predictor–response relationship) are obtained using the same algorithm on a different random sample from the same data generation process (Philipp et al., 2018). We

TABLE 5 Climatic variables and indices used as model covariates. Indices were calculated for the evaluation period of each trial (e.g., planting to shooting).

Variable	Description	Unit
MLDS	Maximum length of dry spell (consecutive days with precipitation <1 mm)	day
MLWS	Maximum length of wet spell (consecutive days with precipitation ≥ 1 mm)	day
r10mm	Number of heavy precipitation days ($10 \leq \text{rain} < 20$ mm)	day
r20mm	Number of very heavy precipitation days ($\text{rain} \geq 20$ mm)	day
R95p	Total precipitation when rain >95th percentile	mm
R99p	Total precipitation when rain >99th percentile	mm
Rtotal	Total precipitation (mm) on wet days ($\text{rain} \geq 1$ mm)	mm
Rx1day	Maximum 1-day precipitation	mm
Rx5day	Maximum 5-day precipitation	mm
SDII	Simple daily intensity index (total precipitation divided by the number of wet days)	mm/day
rhum_06h	Daily relative humidity at 6:00 a.m., averaged over the evaluation period	%
rhum_09h	Daily relative humidity at 9:00 a.m., averaged over the evaluation period	%
rhum_12h	Daily relative humidity at 12:00 p.m., averaged over the evaluation period	%
rhum_15h	Daily relative humidity at 3:00 p.m., averaged over the evaluation period	%
rhum_18h	Daily relative humidity at 6:00 p.m., averaged over the evaluation period	%
CSDI	Cold spell duration index (maximum consecutive nights with temperature <10th percentile)	day
DTR	Diurnal temperature range (mean difference between daily maximum temperature and daily minimum temperature)	$^{\circ}\text{C}$
maxDT	Maximum daytime temperature	$^{\circ}\text{C}$
maxNT	Maximum nighttime temperature	$^{\circ}\text{C}$
minDT	Minimum daytime temperature	$^{\circ}\text{C}$
minNT	Minimum nighttime temperature	$^{\circ}\text{C}$
SU	Summer days (number of days with maximum temperature > 30 $^{\circ}\text{C}$)	$^{\circ}\text{C}$
T10p	10th percentile of night temperature	$^{\circ}\text{C}$
T90p	90th percentile of day temperature	$^{\circ}\text{C}$
TR ^a	Tropical nights (number of nights with maximum temperature >25 $^{\circ}\text{C}$)	$^{\circ}\text{C}$
WSDI	Warm spell duration index (maximum consecutive days with temperature >90th percentile)	day

^aRemoved from the model because it has near zero variability.

assessed stability through data sampling using the framework proposed by Philipp et al. (2018) and implemented in the R package *stablelearner* (Philipp et al., 2016). The method consists of fitting an ensemble of trees, each with a resampled instance of the original dataset, and counting the number of times each variable generates a split (Philipp et al., 2016). If the variables selected for splitting in the original tree are consistently selected across the ensemble of trees, then the original tree is considered stable (Philipp et al., 2016). We created 1000 subsamples, each using 80% of the original data (sampling without replacement). We selected this sampling method to generate sufficiently large learning samples and to ensure strong network connectivity (see Section 2.5). We fitted a Plackett–Luce tree to each of the 1000 subsamples and recorded for each variable how many times it was used to generate a split. To facilitate interpretation, we report the relative frequencies per variable using a histogram.

2.8 | Supporting software

We used the following R (R Core Team, 2022) packages for data management and preparation: *readr*, *readxl*, *janitor*, *dplyr*, *gosset*, and *caret* (de Sousa, Brown et al., 2023; Firke, 2021; Kuhn, 2022; Wickham & Bryan, 2022; Wickham, François et al., 2022, 2022). Climatic variables were obtained using the packages *ag5Tools* and *climatrends* (Brown et al., 2023; de Sousa, van Etten et al., 2023). The statistical modeling was performed with the packages *PlackettLuce*, *stablelearner*, *gosset*, and *qvcalc* (de Sousa, Brown et al., 2023; Firth, 2020; Philipp et al., 2016; Turner et al., 2020). The figures were made with packages *ggplot2*, *ggparty*, *patchwork*, *GGally*, and *tmap* (Borkovec & Madin, 2019; Pedersen, 2020; Schloerke et al., 2021; Tennekens, 2018; Wickham, 2016). The geospatial data were handled with packages *sf* and *terra* (Hijmans, 2021; Pebesma, 2018).

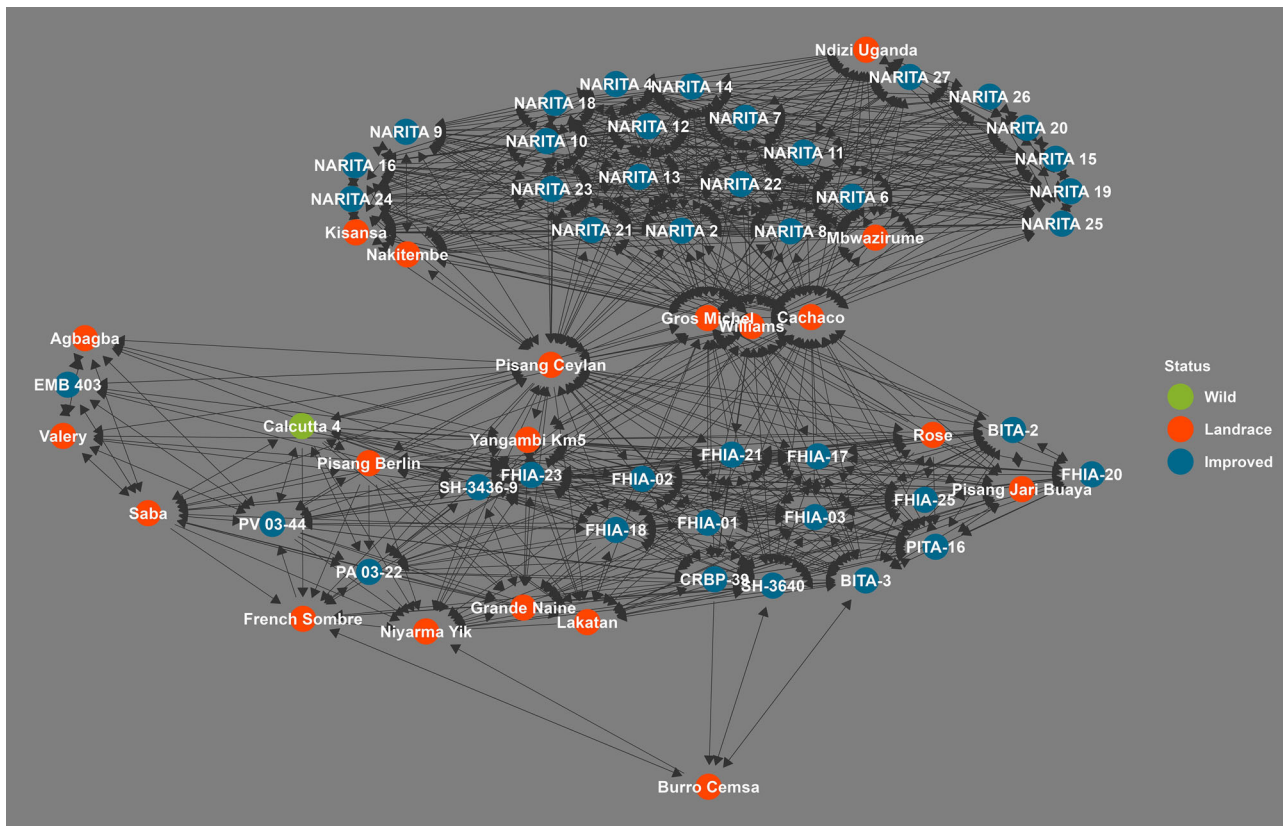


FIGURE 2 Network of win (outgoing arrows) and lose (incoming arrows) relationships between each pair of evaluated *Musa* genotypes. Incoming and outgoing arrows between the same pair indicate different outcomes at independent evaluations.

3 | RESULTS

3.1 | Plackett–Luce tree

The model selected the variable (maximum length of dry spell [MLDS], consecutive days with precipitation < 1 mm) as the best splitting variable, partitioning the dataset in two. While MLDS is a rainfall-derived index, it is only very weakly correlated with rainfall indices such as R_{total} ($r = -0.06$) and r_{10mm} ($r = -0.03$). However, MLDS has a strong negative correlation with r_{hum_09} ($r = -0.75$). Figure 3 shows how the environments of the two nodes selected by the model differ in terms of length of dry spell and relative humidity, expressed by the variables MLDS and r_{hum_09} . There are no major differences between the environments in terms of rainfall variables such as r_{10mm} and R_{total} . Therefore, the Plackett–Luce model discriminated two main environmental conditions, humid environments (node 2) and dry environments (node 3).

The Plackett–Luce tree model that resulted from fitting the aggregated data is presented in Figure 4.

Figure 5 presents a visualization of the Plackett–Luce tree model that is complementary to Figure 4. While some genotypes seem to outperform the reference (Calcutta 4), only

NARITA 8 does so in humid environments with statistical significance (Tables 6 and 7). However, there are statistically significant differences among genotypes.

The horizontal black bars in Figure 4 represent quasi-standard errors (Firth & De Menezes, 2004) and reflect the unbalanced distribution of genotype evaluations across the environments identified by the Plackett–Luce tree model (humid and dry) (Figure 6).

The (log) worth estimates for the Plackett–Luce tree model are presented in Table 6 for node 2 (humid environments) and in Table 7 for node 3 (dry environments). In addition to the difference in estimated worth values, we calculated reliability, which is the probability of each genotype outperforming the check or reference genotype (Eskridge & Mumm, 1992). The reliability estimates are conservative because of the shrinkage effect of using pseudo-rankings (Section 2.5).

3.2 | Stability assessment

The results of fitting 1000 Plackett–Luce trees by subsampling 80% of the data are presented in Figure 7. In 855 of the 1000 Plackett–Luce trees, the splitting variable was MLDS, as shown in the case of the single tree presented in Figure 4. Therefore, the original tree can be considered stable.

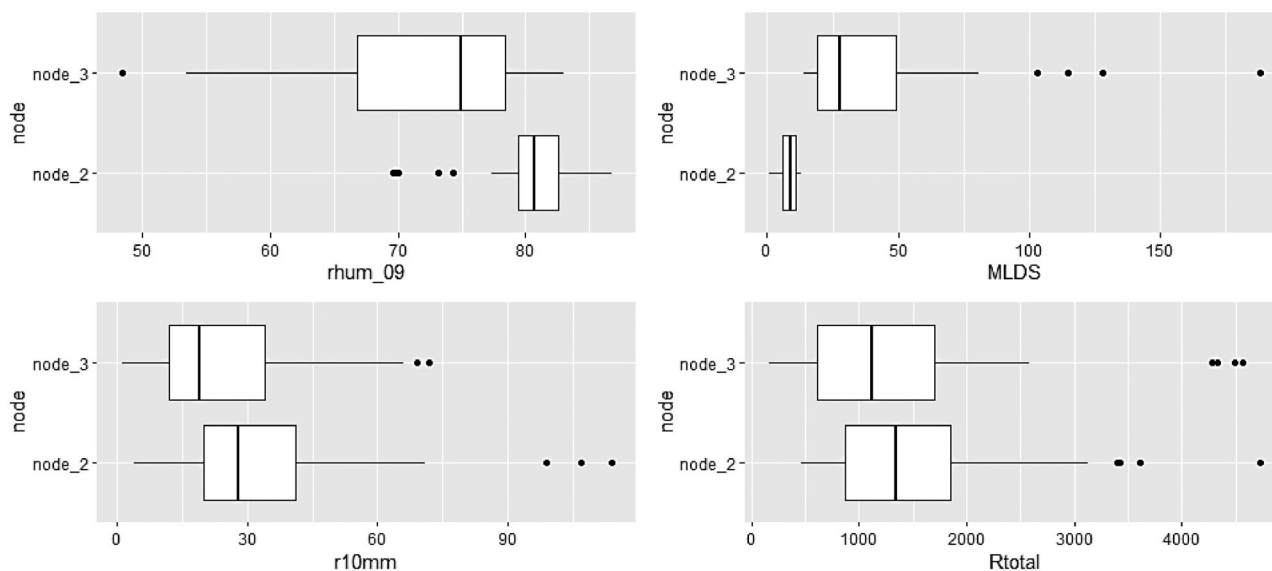


FIGURE 3 Differences between the two nodes resulting from the Plackett–Luce tree model, in terms of relative daily humidity at 09:00 (rh_{um}09), maximum length of dry spell (MLDS), number of days with heavy precipitation (r10mm), and total precipitation on wet days (Rtotal).

TABLE 6 Worth estimates and reliability for the top 10 ranked genotypes in humid environments (node 2). The worth estimates are presented in the logarithmic scale. The worth of genotype Calcutta 4 is zero as it serves as the reference.

Genotype	Estimate	Std. error	z value	Pr(> z)	quasiSE	quasiVar	Reliability	relSE
NARITA 8	1.496	0.810	1.848	0.065	0.415	0.172	0.817	0.070
FHIA-01	1.193	0.800	1.492	0.136	0.511	0.262	0.767	0.103
NARITA 2	0.956	0.851	1.123	0.261	0.489	0.240	0.722	0.108
EMB 403	0.314	1.140	0.275	0.783	0.959	0.920	0.578	0.234
NARITA 14	0.309	0.785	0.394	0.693	0.365	0.133	0.577	0.091
NARITA 23	0.201	0.786	0.256	0.798	0.364	0.133	0.550	0.091
Calcutta 4	0.000	0.000	NA	NA	0.657	0.432	NA	0.159
FHIA-25	-0.148	0.738	-0.200	0.841	0.377	0.142	0.463	0.091
NARITA 9	-0.216	0.865	-0.249	0.803	0.514	0.265	0.446	0.121
Pisang Ceylan	-0.225	0.679	-0.332	0.740	0.222	0.049	0.444	0.054

Significance levels ***, 0.001; **, 0.01; *, 0.05; relSE, standard error of reliability.

TABLE 7 Worth estimates and reliability for the top ten ranked genotypes in dry environments (node 3). The worth estimates are presented in the logarithmic scale. The worth of genotype Calcutta 4 is zero as it serves as the reference.

Genotype	Estimate	Std. error	z value	Pr(> z)	quasiSE	quasiVar	Reliability	relSE
Saba	0.036	1.394	0.026	0.979	0.677	0.458	0.509	0.164
Calcutta 4	0.000	0.000	NA	NA	1.285	1.651	NA	0.283
FHIA-03	-0.060	1.586	-0.038	0.970	0.964	0.929	0.485	0.221
NARITA 24	-0.117	1.350	-0.087	0.931	0.341	0.116	0.471	0.083
FHIA-01	-0.294	1.455	-0.202	0.840	0.729	0.531	0.427	0.163
FHIA-02	-0.322	1.705	-0.189	0.850	1.146	1.313	0.420	0.233
FHIA-21	-0.325	1.413	-0.230	0.818	0.705	0.497	0.419	0.156
FHIA-18	-0.411	1.496	-0.275	0.783	0.813	0.661	0.399	0.171
Rose	-0.680	1.589	-0.428	0.669	0.962	0.925	0.336	0.174
Pisang Ceylan	-0.685	1.299	-0.527	0.598	0.258	0.066	0.335	0.055

Significance levels ***, 0.001; **, 0.01; *, 0.05; relSE, standard error of reliability.

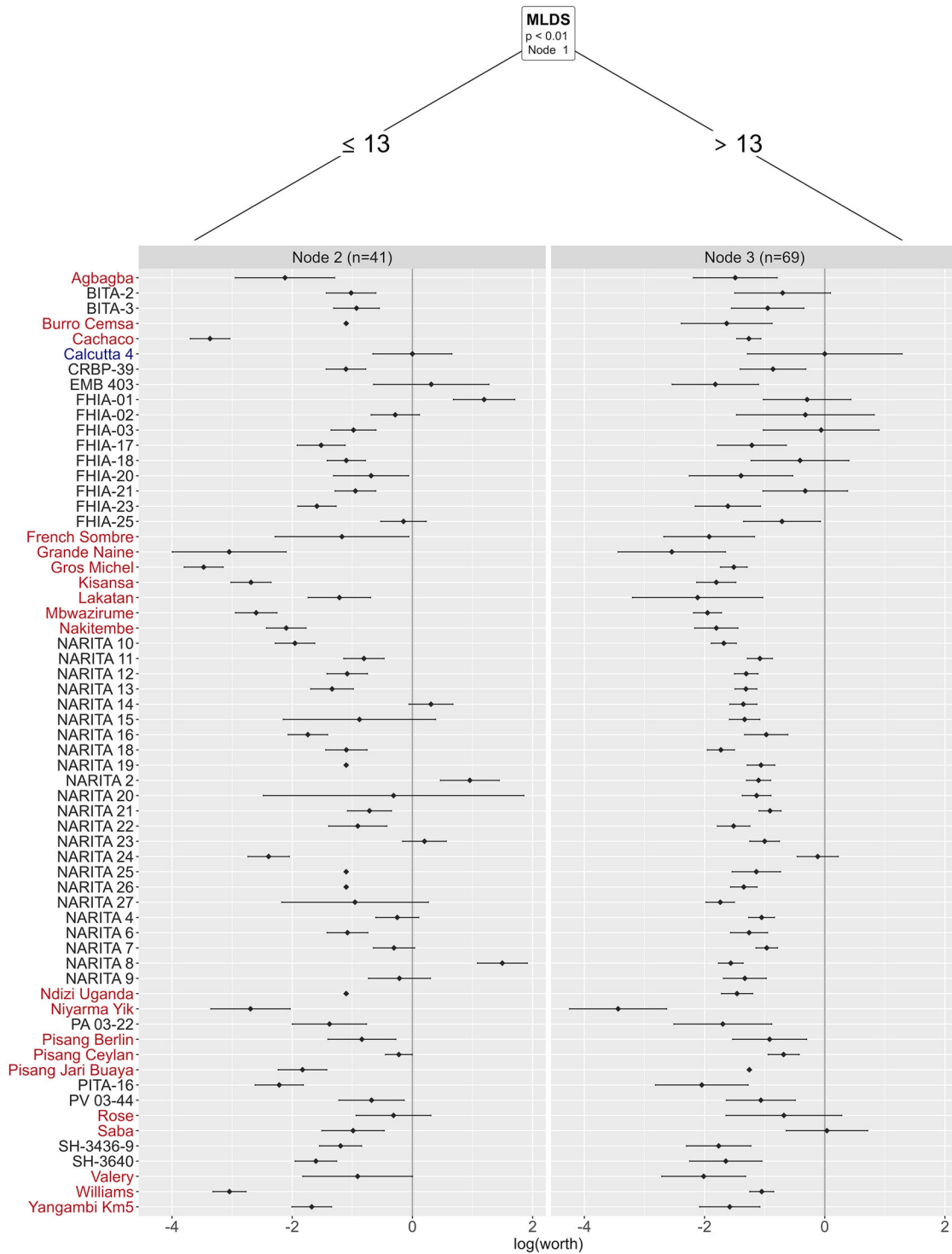


FIGURE 4 Plackett–Luce tree of *Musa* genotypes split into two nodes by variable maximum length of dry spell (MLDS) during the Black leaf streak disease (BLSD) evaluation period. The worth estimates of each genotype are presented on the x-axis on a logarithmic scale. The worth estimate for Calcutta 4 is set to zero as it served as the BLSD-resistant reference. The vertical gray lines show the zero intercept. Horizontal black bars represent quasi-standard errors of each estimated worth. The y-axis shows genotype names, with color indicating genotype status (blue, wild; red, landrace; gray, improved genotype). Node 2 = humid environments; node 3 = dry environments.

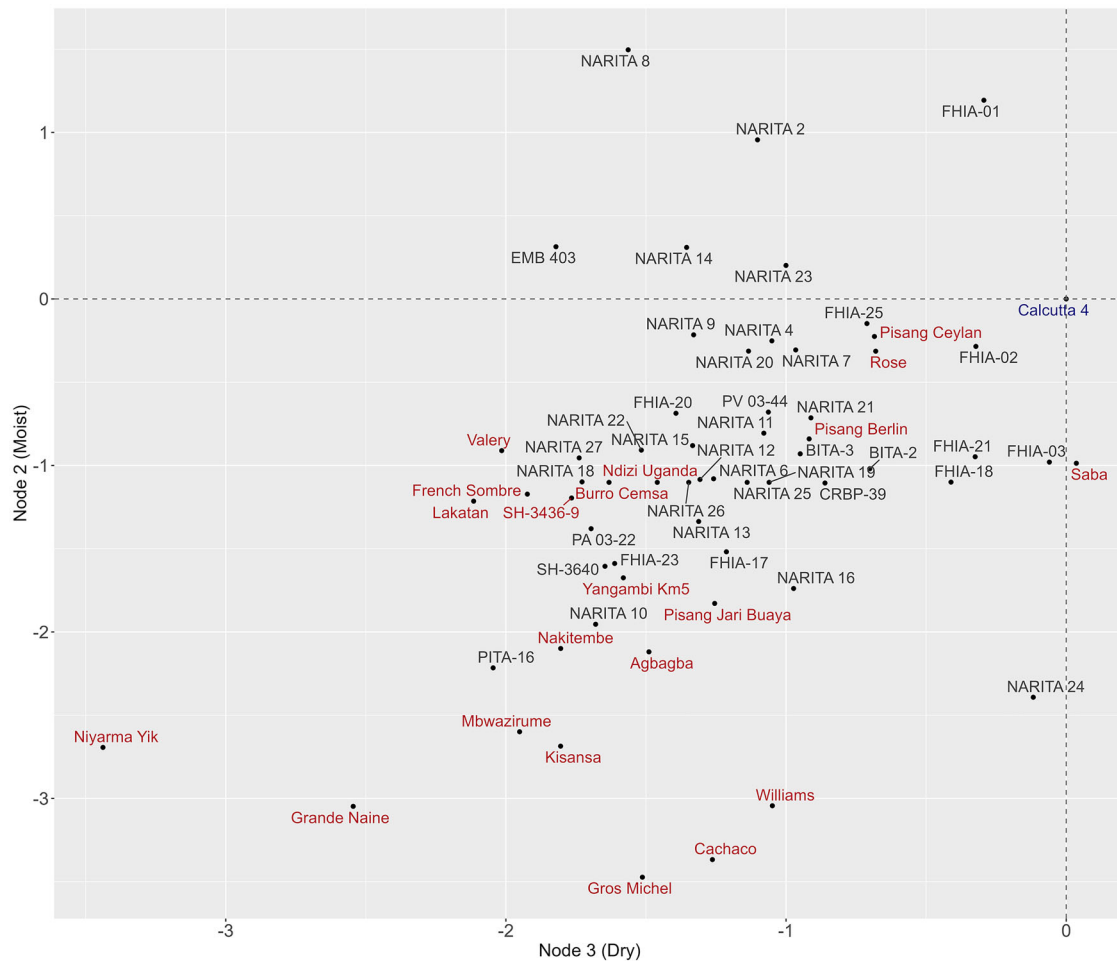


FIGURE 5 Worth estimates (on logarithmic scale) of each genotype in each of the nodes from the Plackett–Luce tree model. Color indicates genotype status (blue, wild; red, landrace; gray, improved genotype).

4 | DISCUSSION

The Plackett–Luce tree model (Figure 4) identified the MLDS as the most important climatic variable determining *Musa* genotypes' reactions to BLSD. MLDS is a rainfall-derived climatic index, expressed as the number of days with precipitation less than 1 mm. While it is derived from rainfall, it is strongly negatively correlated with relative humidity ($r = -0.75$). The Plackett–Luce model partitioned the aggregated dataset into two contrasting environments: humid environments (node 2) in which the dry spell is less than or equal to 13 days, and dry environments (node 3) with a dry spell of more than 13 days. Humid environments (node 2) are assumed to be more favorable than dry environments (node 3) to BLSD development (Churchill, 2011; Guzman et al., 2018). Humidity is indeed required during various steps in the BLSD infection cycle, such as for infection efficacy (spore penetration in stomates), lesion growth on leaves, and fungus sporulation (Guzman et al., 2018). Therefore, humid environments (node 2) are considered appropriate climatic conditions in which to evaluate differences in BLSD (Perez-Vicente et al.,

2021). However, dry environments cannot be considered to be disease-free, as differences were found among genotypes. Environmental conditions act on both the host (banana plant) and the pathogen (*P. fijiensis*). From our results, it is not possible to discriminate between the two but only to formulate plausible hypotheses to be further investigated or considered in future research.

From the Plackett–Luce tree, we identified a contrasting reaction of genotypes across environments. For example, NARITAs 8 and 24 have relatively extreme and opposite responses to BLSD in humid (node 2) and dry (node 3) environments. In these cases, it might be that the genetic component of resistance in these genotypes has a different expression in different environments (Craenen & Ortiz, 1997) or at a particular stage (e.g., sporulation) of the disease cycle (Abadie et al., 2003). In the case of NARITA 8, it seems that its resistance component is expressed in humid (node 2) but not in dry (node 3) environments. On the other hand, NARITA 24 appeared susceptible in humid environments (node 2), while in dry environments (node 3), its performance did not differ from that of the reference,

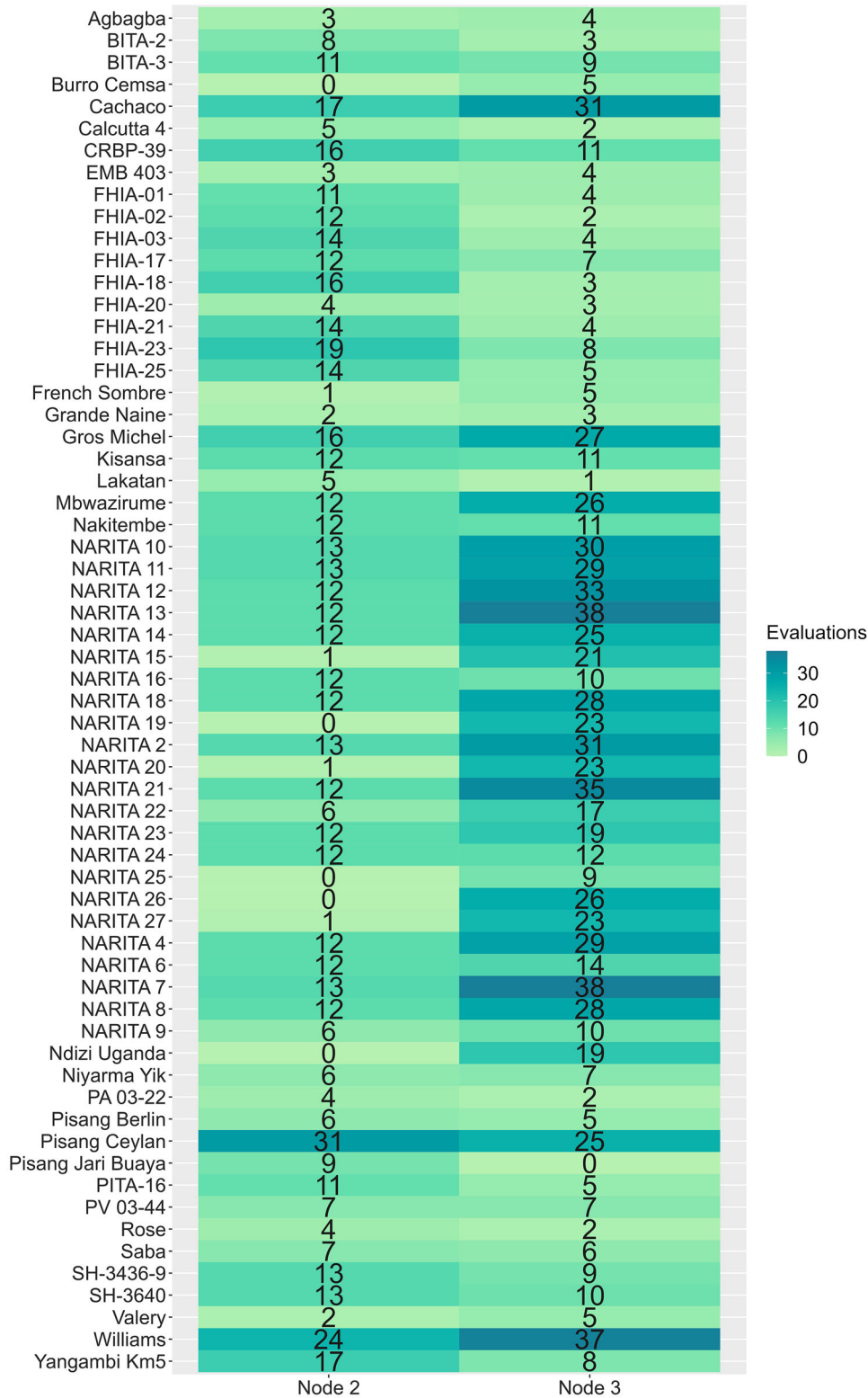


FIGURE 6 Number of times that each genotype has been evaluated in each environment (node 2 = humid; node 3 = dry).

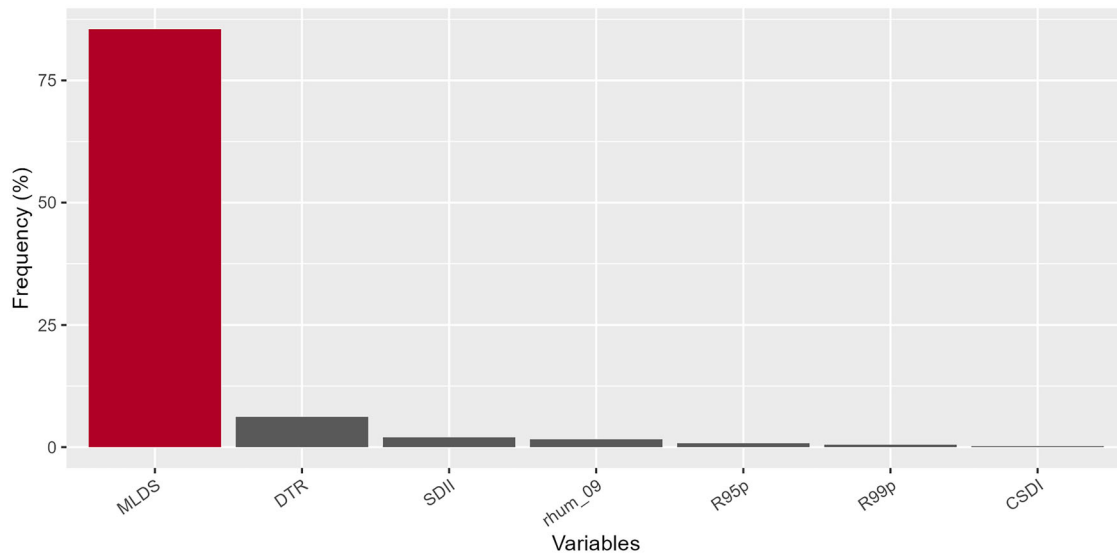


FIGURE 7 Relative frequencies with which a variable is selected for a split in each of the 1,000 runs of the ensemble of trees. The red bar indicates the variable selected in the original tree. Only variables that were selected at least once are shown. See Table 5 for variables' descriptions. CDSI, cold spell duration index; DTR, diurnal temperature range; MLDS, maximum length of dry spell; R95p, R99p, total precipitation when rain >95th and >99th percentiles, respectively; rhum_09h, daily relative humidity at 9:00 a.m.; SDII, simple daily intensity index.

Calcutta 4. Our results might help to explain the contradictory results among previous studies in which NARITA 24 was evaluated. For instance, in evaluations of NARITAs by Tushemereirwe et al. (2015), NARITA 24 was among the best performing genotypes with respect to BLSD reaction. In contrast, it performed poorly in two locations in Uganda in evaluations conducted by Kimunye, Jomanga et al. (2021). Another contrasting result between environments is FHIA-03, which performed better in dry environments than in humid environments. We concur with Kimunye, Were et al. (2021) that the effect of environmental factors on the reaction of genotypes to BLSD should be further investigated at different locations.

While Calcutta 4 was used as the highly resistant reference, failure of a genotype to outperform Calcutta 4 cannot be considered poor performance. Calcutta 4 has qualitative resistance, which blocks disease development at an early stage (Guzman et al., 2018). In contrast, quantitative resistance allows disease development but seems to be more durable than qualitative resistance (Guzman et al., 2018). Therefore, we advise against interpreting our results through dichotomization of whether or not a genotype outperforms the resistant reference. In dry environments (node 3), differences between the reference, Calcutta 4, and each of the genotypes included in the top 10 are not statistically significant (Table 7). Hence, we cannot say that the top 10 genotypes performed differently from the reference, but they did perform better than the rest of the genotypes.

Water is a major limiting abiotic factor for banana growth (Turner, 1995). We hypothesize that plant growth could be negatively affected in dry conditions (node 3), as banana

plants react very early to water deficit (Eyland et al., 2022) and require constant rainfall for normal development (Turner et al., 2007). The genotype FHIA-01 performed well in both humid and dry environments, which is in agreement with both its partial resistance to BLSD and its tolerance of extended periods of deficient rainfall (Rowe & Rosales, 1993). Furthermore, of the top 10 best performing genotypes in dry environments, 6 contain the *Musa balbisiana* (B) genome, which has been identified to contribute to drought tolerance (Thomas et al., 1998; van Wesemael et al., 2019; Vanhove et al., 2012). Abiotic stresses can affect plant reaction to diseases (Bostock et al., 2014). In the case of *Musa*, there is evidence that nutritional deficiencies and poor soil conditions predispose BLSD infection (Guzman et al., 2018). Our results suggest that predisposition to BLSD caused by drought should be further explored.

Evaluation metrics based on leaf number (e.g., YLS) strongly depend on plant growth (Guzman et al., 2018). Slower plant growth in dry environments could induce some bias in rankings in which the disease variable is linked to leaf number, such as YLS, NFL, and NSL. In spite of this potential bias, the Plackett–Luce tree model seems to adequately detect the different reactions of genotypes with partial resistance among environments ($G \times E$), while it is also consistent with the expected performance of susceptible genotypes, such as Grand Naine, Gros Michel, and Niyarma Yik.

Our results could help to select genotypes of interest to breeders for further testing. For example, NARITA 8, FHIA-01, and NARITA 2 were not only the best performing genotypes in humid environments, but also the most reliable in outperforming the reference Calcutta 4 (Table 6). This

can provide impetus for breeding programs to include certain genotypes in new evaluations, based on their overall reliability in addition to their worth (ranking probability). In humid environments, only genotypes EMB 403, FHIA-01, and NAR-ITAs 2, 8, 14, 20, and 23 have more than 50% reliability, while in dry environments, only the landrace Saba marginally surpassed 50% reliability. Reliability is especially relevant given the lengthy process of developing and releasing a *Musa* genotype. For instance, FHIA-21 took 30 years from crossing to release (Tenkouano et al., 2019). Our results support the use of both ranking-probabilities and reliability as criteria for selecting genotypes for further testing in new locations, minimizing the risk of investment.

5 | CONCLUSIONS

Our work presents the first application of the data synthesis approach in combining heterogeneous trial data and using climatic data as model covariates to discover *Musa* genotypes' reactions to BLS. We aggregated data from 110 evaluations in 31 heterogeneous trials evaluating *Musa* genotypes for reaction to BLS. The rank-based data synthesis methodology enabled the comparison of 62 genotypes, aggregated from trials established at 22 unique locations, with a temporal range from 1990 to 2019. The large number of banana genotypes analyzed in our study would typically be challenging to compare in a single advanced multi-location testing trial. We have demonstrated how field trial environmental conditions can be reconstructed using publicly available climate datasets even where locally sensed weather data are lacking. In our work, the large temporal range for which the AgERA5 data is available (1979 to present) allowed the addition of climatic data as model covariates for all the data selected for the study. The MLDS, a precipitation-derived climatic index, was found to be the best splitting variable in the Plackett–Luce tree model. We found that humidity is the main climatic factor driving differential reactions of genotypes to BLS. Our results support previous evidence that genetic components of resistance to BLS are triggered under different environmental conditions, leading to different genotypic response patterns. We have provided insights to support the use of reliability in selecting genotypes for further evaluation.

One limitation of our study is the inherent information loss from the transformation of metric data to rankings. In the present case, information loss is reduced by the documented knowledge about different reactions of genotypes to BLS. This supports the importance of considering expert knowledge in the implementation of the data synthesis approach (Brown et al., 2020).

Another limitation of our study is that despite the aggregation of several trials, the sample size of the aggregated dataset is still relatively small, due to the relative scarcity of *Musa*

evaluation data in public repositories. Increased availability of trial data in public repositories is therefore required for further applications of the data synthesis approach to efficiently (re)use crop trial data. We expect our findings to motivate plant breeding programs to share their data in public repositories, to enable future reanalysis with extended versions of the dataset used in our study.

AUTHOR CONTRIBUTIONS

David Brown: Conceptualization; data curation; formal analysis; investigation; methodology; software; visualization; writing—original draft; writing—review and editing. **Sytze de Bruin:** Conceptualization; formal analysis; methodology; supervision; writing—review and editing. **Kauê de Sousa:** Data curation; formal analysis; methodology; software; writing—review and editing. **Catherine Abadie:** Formal analysis; investigation; writing—review and editing. **Sebastien Carpentier:** Formal analysis; investigation; writing—review and editing. **Lewis Machida:** Data curation; formal analysis; investigation; writing—review and editing. **Jacob van Etten:** Conceptualization; data curation; formal analysis; funding acquisition; investigation; methodology; software; supervision; visualization; writing—review and editing.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

All the R code and data required to reproduce the analysis are publicly available in the public repository https://github.com/AgrDataSci/Data_Synthesis_Musa_Trials_BLS


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REFERENCES

- Abadie, C., Elhadrami, A., Fouré, E., & Carlier, J. (2003). Efficiency and durability of partial resistance against black leaf streak disease. In L. Jacome, P. Lepoivre, D. Marin, R. Ortiz, R. Romero, & J. V. Escalant

- (Eds.), *Mycosphaerella leaf spot diseases of bananas: Present status and outlook*. (pp. 161). INIBAP.
- Alvarez, J. (1997). Introduction, evaluation, multiplication and dissemination of FHIA hybrids in Cuba. In *Infomusa*, 6, 10–14.
- Bakry, F., Carreel, F., Jenny, C., & Horry, J.-P. (2009). Genetic improvement of banana. In S. M. Jain, & P. M. Priyadarshan (Eds.), *Breeding plantation tree crops: Tropical species* (pp. 3–50). Springer New York. https://doi.org/10.1007/978-0-387-71201-7_1
- Bauchet, G. J., Morales, N., Karanja, M., Ogbonna, A. C., Ellerbrock, B., Crichton, R., Tumuhimbise, R., Uwimana, B., Brown, A., & Shah, T. (2018). Musabase: A phenotyping and breeding database for banana. Plant and Animal Genome XXVI Conference (January 13–17, 2018)..
- Boogaard, H., & van der Grijn, G. (2020). *Agrometeorological indicators from 1979 to present derived from reanalysis*. Copernicus Climate Change Service. <https://doi.org/10.24381/cds.6c68c9bb>
- Borkovec, M., & Madin, N. (2019). *ggparty: “ggplot” Visualizations for the “partykit” Package* (Version 1.0.0). <https://CRAN.R-project.org/package=ggparty>
- Bostock, R. M., Pye, M. F., & Roubtsova, T. V. (2014). Predisposition in plant disease: Exploiting the nexus in abiotic and biotic stress perception and response. *Annual Review of Phytopathology*, 52(1), 517–549. <https://doi.org/10.1146/annurev-phyto-081211-172902>
- Breiman, L. (1996). Heuristics of instability and stabilization in model selection. *The Annals of Statistics*, 24(6), 2350–2383. 2334. <https://doi.org/10.1214/aos/1032181158>
- Brown, D., de Bruin, S., de Sousa, K., Aguilar, A., Barrios, M., Gómez, M., Hernandez, J. C., Chaves, N., Madriz, B., Machida, L., Mejía, P., Mercado, L., Pavón, M., Rosas, J. C., Steinke, J., Suchini, J. G., Zelaya, V., & van Etten, J. (2022). Rank-based data synthesis of common bean on-farm trials across four Central American countries. *Crop Science*, 62(6), 2246–2266. <https://doi.org/10.1002/csc2.20817>
- Brown, D., de Sousa, K., & van Etten, J. (2023). ag5Tools: An R package for downloading and extracting agrometeorological data from the AgERA5 database. *SoftwareX*, 21, 101267. <https://doi.org/10.1016/j.softx.2022.101267>
- Brown, D., Van den Bergh, I., de Bruin, S., Machida, L., & van Etten, J. (2020). Data synthesis for crop variety evaluation. A review. *Agronomy for Sustainable Development*, 40(4), 25. <https://doi.org/10.1007/s13593-020-00630-7>
- Churchill, A. C. L. (2011). *Mycosphaerella fijiensis*, the black leaf streak pathogen of banana: Progress towards understanding pathogen biology and detection, disease development, and the challenges of control. *Molecular Plant Pathology*, 12(4), 307–328. <https://doi.org/10.1111/j.1364-3703.2010.00672.x>
- Cohan, J.-P., Abadie, C., Tomekpé, K., & Tchango Tchango, J. (2003). Agronomic performance and resistance to black leaf streak of the hybrid ‘CRBP-39’. *InfoMusa*, 12(1), 29–32.
- Copernicus Climate Change Service. (2020). *Agrometeorological indicators from 1979 to present derived from reanalysis*. AgERA5. <https://doi.org/10.24381/cds.6c68c9bb>
- Craenen, K., & Ortiz, R. (1997). Effect of the bs1 gene in plantain-banana hybrids on response to black sigatoka. *Theoretical and Applied Genetics*, 95(3), 497–505. <https://doi.org/10.1007/s001220050589>
- De Lapeyre de Bellaire, L., Fouré, E., Abadie, C., & Carlier, J. (2010). Black leaf streak disease is challenging the banana industry. *Fruits*, 65(6), 327–342. <https://doi.org/10.1051/fruits/2010034>
- de Sousa, K., Brown, D., Steinke, J., & van Etten, J. (2023). *gosset*: An R package for analysis and synthesis of ranking data in agricultural experimentation. *SoftwareX*, 22, 101402. <https://doi.org/10.1016/j.softx.2023.101402>
- de Sousa, K., van Etten, J., Neby, M., & Solberg, S. Ø. (2023). Climate variability indices for ecological and crop models in R: The climatrends package. *Journal of Open Source Software*, 8(85), 4405. <https://doi.org/10.21105/joss.04405>
- Eagle, A. J., Christianson, L. E., Cook, R. L., Harmel, R. D., Miguez, F. E., Qian, S. S., & Ruiz Diaz, D. A. (2017). Meta-analysis constrained by data: Recommendations to improve relevance of nutrient management research. *Agronomy Journal*, 109(6), 2441–2449. <https://doi.org/10.2134/agronj2017.04.0215>
- Eskridge, K. M., & Mumm, R. F. (1992). Choosing plant cultivars based on the probability of outperforming a check. *Theoretical and Applied Genetics*, 84(3), 494–500. <https://doi.org/10.1007/BF00229512>
- Eyland, D., Luchaire, N., Cabrera-Bosquet, L., Parent, B., Janssens, S. B., Swennen, R., Welcker, C., Tardieu, F., & Carpentier, S. C. (2022). High-throughput phenotyping reveals differential transpiration behaviour within the banana wild relatives highlighting diversity in drought tolerance. *Plant, Cell & Environment*, 45(6), 1647–1663. <https://doi.org/10.1111/pce.14310>
- Ferris, R. S. B., Ortiz, R., & Vuylsteke, D. (1999). Fruit quality evaluation of plantains, plantain hybrids, and cooking bananas. *Postharvest Biology and Technology*, 15(1), 73–81. [https://doi.org/10.1016/S0925-5214\(98\)00067-2](https://doi.org/10.1016/S0925-5214(98)00067-2)
- Firke, S. (2021). *janitor: Simple tools for examining and cleaning dirty data*. <https://CRAN.R-project.org/package=janitor>
- Firth, D. (2020). *qvcalc: Quasi variances for factor effects in statistical models* (Version 1.0.2). <https://CRAN.R-project.org/package=qvcalc>
- Firth, D., & De Menezes, R. X. (2004). Quasi-variances. *Biometrika*, 91(1), 65–80. <https://doi.org/10.1093/biomet/91.1.65>
- Guzman, M., Pérez Vicente, L., Carlier, J., Abadie, C., de Lapeyre de Bellaire, L., Carreel, F., Marin, D., Romero, R., Gauhl, F., & Pasberg-Gauhl, C. (2018). Black leaf streak. In D. R. Jones (Ed.), *Handbook of diseases of banana, Abacá and Enset*. CABI.
- Hernández Núñez, R. (1995). *Selección in vitro e invernadero de clones de Musa sp. para la evaluación de su resistencia a la Sigatoka negra (Mycosphaerella fijiensis, Morelet)*. CATIE. <https://repositorio.catie.ac.cr/handle/11554/3945>
- Hersbach, H., Muñoz Sabater, J., Nicolas, J., Rozum, I., Simmons, A., Vamborg, F., Bell, B., Berrisford, P., Biavati, G., Buontempo, C., Horányi, A., Peubey, C., Radu, R., Schepers, D., Soci, C., Dee, D., & Thépaut, J.-N. (2018). *Essential climate variables for assessment of climate variability from 1979 to present*. Copernicus Climate Change Service (C3S).
- Hijmans, R. J. (2021). *terra: Spatial data analysis. R package version* (Version 1.4-9). <https://rspatial.org/terra/>
- Hothorn, T., & Zeileis, A. (2015). partykit: A modular toolkit for recursive partitioning in R. *The Journal of Machine Learning Research*, 16(1), 3905–3909. <https://www.jmlr.org/papers/v16/hothorn15a.html>
- Hunter, D. R. (2004). MM algorithms for generalized Bradley-Terry models. *Annals of Statistics*, 32(1), 384–406. <https://doi.org/10.1214/aos/1079120141>
- Hyman, G., Espinosa, H., Camargo, P., Abreu, D., Devare, M., Arnaud, E., Porter, C., Mwanza, L., Sonder, K., & Traore, S. (2017). Improving agricultural knowledge management: The AgTrials experience [version 2; peer review: 2 approved]. *F1000Research*, 6, 317. <https://doi.org/10.12688/f1000research.11179.2>
- Irish, B. M., Goenaga, R., Montalvo-Katz, S., Chaves-Cordoba, B., & Van den Bergh, I. (2019). Host response to black leaf streak and agro-

- onomic performance of banana genotypes in Puerto Rico. *HortScience horts*, 54(10), 1808. <https://doi.org/10.21273/HORTSCI113876-19>
- Irish, B. M., Goenaga, R., Rios, C., Chavarria-Carvajal, J., & Ploetz, R. (2013). Evaluation of banana hybrids for tolerance to black leaf streak (*Mycosphaerella fijiensis* Morelet) in Puerto Rico. *Crop Protection*, 54, 229–238. <https://doi.org/10.1016/j.cropro.2013.09.003>
- Jacome, L. H., & Schuh, W. (1992). Effects of leaf wetness duration and temperature on development of Black Sigatoka disease on banana infected by *Mycosphaerella fijiensis* var. *difformis*. *Phytopathology*, 82(5), 515–520. <https://doi.org/10.1094/Phyto-82-515>
- Jones, D., & Tézenas du Montcel, H. (1994). *Final Report for UNDP/World Bank on the Results of the International Musa Testing Programme (Phase I)*. INIBAP.
- Karamura, D., & Karamura, E. (1994). *A provisional checklist of banana cultivars in Uganda*. INIBAP.
- Karamura, D., Karamura, E., & Tinzaara, W. (2012). *Banana cultivar names, synonyms and their usage in East Africa*. Bioversity International, Uganda.
- Kimunye, J., Jomanga, K., Tazuba, A. F., Were, E., Viljoen, A., Swennen, R., & Mahuku, G. (2021). Genotype X environment response of ‘Matooke’ hybrids (Naritas) to *Pseudocercospora fijiensis*, the cause of Black Sigatoka in banana. *Agronomy*, 11(6), 1145. <https://doi.org/10.3390/agronomy11061145>
- Kimunye, J., Were, E., Swennen, R., Viljoen, A., & Mahuku, G. (2021). Sources of resistance to *Pseudocercospora fijiensis*, the cause of black Sigatoka in banana. *Plant Pathology*, 70(7), 1651–1664. <https://doi.org/10.1111/ppa.13408>
- Kuhn, M. (2022). *caret: Classification and regression training* (Version 6.0-91) CRAN. <https://CRAN.R-project.org/package=caret>
- Luce, R. D. (1959). *Individual choice behavior: A theoretical analysis*. Dover Publications. <https://doi.org/10.1037/14396-000>
- Makowski, D. (2021). Editorial of the special issue “Evidence synthesis in agronomy”. *European Journal of Agronomy*, 122, 126183. <https://doi.org/10.1016/j.eja.2020.126183>
- Ning, S.-P., Xu, L.-B., Lu, Y., Huang, B.-Z., & Ge, X.-J. (2007). Genome composition and genetic diversity of *Musa* germplasm from China revealed by PCR-RFLP and SSR markers. *Scientia Horticulturae*, 114(4), 281–288. <https://doi.org/10.1016/j.scienta.2007.07.002>
- Njukwe, E., Amah, D., Ndango, R., & Tenkouano, A. (2010). Fast-track release of black leaf streak resistant banana and plantain (*Musa* spp.) hybrids and related technologies to farmers in cameroon: A strategy to enhance food security. *Acta Horticulturae*, 879, 577–584. <https://doi.org/10.17660/ActaHortic.2010.879.64>
- Noupadja, P., & Tomekpé, K. (2001). Agronomic performance of HTAs improved *Musa* germplasm at CRBP, Njombé, Cameroon. *The African Crop Science Journal*, 9(3), 481–486. <http://www.bioline.org.br/request?cs01067> <https://doi.org/10.4314/acsj.v9i3.27594>
- Nyombi, K., Van Asten, P. J. A., Leffelaar, P. A., Corbeels, M., Kaizzi, C. K., & Giller, K. E. (2009). Allometric growth relationships of East Africa highland bananas (*Musa* AAA-EAHB) cv. Kisansa and Mbawzirume. *Annals of Applied Biology*, 155(3), 403–418. <https://doi.org/10.1111/j.1744-7348.2009.00353.x>
- Orjeda, G. (1998). *Evaluation of Musa germplasm resistance to Sigatoka diseases and Fusarium wilt*. INIBAP technical guidelines.
- Orjeda, G. (2000). *Evaluating bananas: A global partnership: Results of IMTP Phase II*. Bioversity International.
- Orlando Narváez, A. A. (2004). *Evaluación agronómica y de la resistencia a fitonemátodos y sigatoka negra de cultivares mejorados de banano y plátano en Ecuador CATIE*. Turrialba (Costa Rica).
- Ortiz, R., & Vuylsteke, D. (1998). ‘BITA-3’: A starchy banana with partial resistance to Black Sigatoka and tolerance to Streak Virus. *HortScience*, 33(2), 358–359. <https://doi.org/10.21273/HORTSCI.33.2.358>
- Pebesma, E. (2018). Simple features for R: Standardized support for spatial vector data. *The R journal*, 10(1), 439–446. <https://doi.org/10.32614/RJ-2018-009>
- Pedersen, T. L. (2020). *patchwork: The composer of plots* (Version 1.1.1). <https://CRAN.R-project.org/package=patchwork>
- Pennisi, E. (2010). Armed and dangerous. *Science*, 327(5967), 804–805. <https://doi.org/10.1126/science.327.5967.804>
- Perez-Vicente, L., Carreel, F., Roussel, V., Carlier, J., & Abadie, C. (2021). Guidelines for the evaluation of *Pseudocercospora* resistance to leaf spots of banana. In M. Dita, (Ed.), *Practical guidelines for early screening and field evaluation of banana against Fusarium wilt, Pseudocercospora leaf spots and drought*. Bioversity International.
- Philipp, M., Rusch, T., Hornik, K., & Strobl, C. (2018). Measuring the stability of results from supervised statistical learning. *Journal of Computational and Graphical Statistics*, 27(4), 685–700. <https://doi.org/10.1080/10618600.2018.1473779>
- Philipp, M., Zeileis, A., & Strobl, C. (2016). *A toolkit for stability assessment of tree-based learners*. <http://hdl.handle.net/10419/146128>
- Plackett, R. L. (1975). The analysis of permutations. *Journal of the Royal Statistical Society. Series C (Applied Statistics)*, 24(2), 193–202. <https://doi.org/10.2307/2346567>
- R Core Team (2022). *R: A language and environment for statistical computing*. R Foundation for Statistical Computing. <https://www.R-project.org/>
- Rowe, P., & Rosales, F. (1993). Diploid breeding at FHIA and the development of Goldfinger (FHIA-01). *InfoMusa*, 2(2), 9–11.
- Ruas, M., Guignon, V., Sempere, G., Sardos, J., Hueber, Y., Duvergey, H., Andrieu, A., Chase, R., Jenny, C., Hazekamp, T., Irish, B., Jelali, K., Adeka, J., Ayala-Silva, T., Chao, C. P., Daniells, J., Dowiya, B., Effa effa, B., Guecco, L., ... Rouard, M. (2017). MGIS: Managing banana (*Musa* spp.) genetic resources information and high-throughput genotyping data. *Database*, 2017, bax046. <https://doi.org/10.1093/database/bax046>
- Sakyi-Dawson, E., Asamoah-Bonti, P., & Amponsah Annor, G. (2008). Biochemical changes in new plantain and cooking banana hybrids at various stages of ripening. *Journal of the Science of Food and Agriculture*, 88(15), 2724–2729. <https://doi.org/10.1002/jsfa.3399>
- Schloerke, B., Cook, D., Larmarange, J., Briatte, F., Marbach, M., Thoen, E., Elberg, A., & Crowley, J. (2021). *GGally: Extension to ‘ggplot2’*. <https://CRAN.R-project.org/package=GGally>
- Simko, I., & Pechenick, D. A. (2010). Combining partially ranked data in plant breeding and biology: I. Rank aggregating methods. *Communications in Biometry and Crop Science*, 5(1), 41–55. http://agrobiol.sggw.waw.pl/~cbcs/articles/CBCS_5_1_7.pdf
- Strobl, C., Malley, J., & Tutz, G. (2009). An introduction to recursive partitioning: Rationale, application and characteristics of classification and regression trees, bagging and random forests. *Psychological Methods*, 14(4), 323–348. <https://doi.org/10.1037/a0016973>
- Tenkouano, A., Lamien, N., Agogbua, J., Amah, D., Swennen, R., Traoré, S., Thiemele, D., Aby, N., Kobenan, K., Gnonhouiri, G., Yao, N., Astin, G., Sawadogo-Kabore, S., Tarpaga, V., Issa, W., Lokossou, B., Adjanohoun, A., Amadji, G. L., Adangnitode, S., ... Ortiz, R. (2019). Promising high-yielding tetraploid plantain-bred hybrids in

- West Africa. *International Journal of Agronomy*, 2019, 3873198. <https://doi.org/10.1155/2019/3873198>
- Tenkouano, A., Ortiz, R., & Nokoe, S. (2012). Repeatability and optimum trial configuration for field-testing of banana and plantain. *Scientia Horticulturae*, 140, 39–44. <https://doi.org/10.1016/j.scienta.2012.03.023>
- Tennekes, M. (2018). tmap: Thematic maps in R. *Journal of Statistical Software*, 84(6), 1–39. <https://doi.org/10.18637/jss.v084.i06>
- Thomas, D. S., Turner, D. W., & Eamus, D. (1998). Independent effects of the environment on the leaf gas exchange of three banana (*Musa* sp.) cultivars of different genomic constitution. *Scientia Horticulturae*, 75(1), 41–57. [https://doi.org/10.1016/S0304-4238\(98\)00114-9](https://doi.org/10.1016/S0304-4238(98)00114-9)
- Turner, D. W. (1995). The response of the plant to the environment. In S. Gowen (Ed.), *Bananas and plantains* (pp. 206–229). Springer. https://doi.org/10.1007/978-94-011-0737-2_9
- Turner, D. W., Fortescue, J. A., & Thomas, D. S. (2007). Environmental physiology of the bananas (*Musa* spp.). *Brazilian Journal of Plant Physiology*, 19, 463–484. http://www.scielo.br/scielo.php?script=sci_arttext&pid=S1677-04202007000400013&nrm=iso <https://doi.org/10.1590/S1677-04202007000400013>
- Turner, H. L., van Etten, J., Firth, D., & Kosmidis, I. (2020). Modelling rankings in R: The PlackettLuce package. *Computational Statistics*, 35, 1027–1057. <https://doi.org/10.1007/s00180-020-00959-3>
- Tushemereirwe, W., Batte, M., Nyine, M., Tumuhimbise, R., Barekye, A., Tendo, S., Talengera, D., Kubiriba, J., Lorenzen, J., Swennen, R., & Uwimana, B. (2015). *Performance of NARITA banana hybrids in the preliminary yield trial for three cycles in Uganda*. I. NARO. http://www.iita.org/c/document_library/get_file?uuid=1500c39e-7c05-4219-b649-85cdb1bd73f6&groupId=25357
- van Etten, J., Beza, E., Calderer, L., van Duijvendijk, K., Fadda, C., Fantahun, B., Kidane, Y. G., van de Gevel, J., Gupta, A., Mengistu, D. K., Kiambi, D. A. N., Mathur, P. N., Mercado, L., Mitra, S., Mollel, M. J., Rosas, J. C., Steinke, J., Suchini, J. G., & Zimmerer, K. S. (2019). First experiences with a novel farmer citizen science approach: Crowdsourcing participatory variety selection through on-farm triadic comparisons of technologies (tricot). *Experimental Agriculture*, 55(S1), 275–296. <https://doi.org/10.1017/S0014479716000739>
- van Etten, J., de Sousa, K., Aguilar, A., Barrios, M., Coto, A., Dell'Acqua, M., Fadda, C., Gebrehawaryat, Y., van de Gevel, J., Gupta, A., Kiros, A. Y., Madriz, B., Mathur, P., Mengistu, D. K., Mercado, L., Nurhisen Mohammed, J., Paliwal, A., Pè, M. E., Quirós, C. F., ... Steinke, J. (2019). Crop variety management for climate adaptation supported by citizen science. *Proceedings of the National Academy of Sciences*, 116(10), 4194–4199. <https://doi.org/10.1073/pnas.1813720116>
- Vanhove, A.-C., Vermaelen, W., Panis, B., Swennen, R., & Carpentier, S. (2012). Screening the banana biodiversity for drought tolerance: Can an in vitro growth model and proteomics be used as a tool to discover tolerant varieties and understand homeostasis [Original Research]. *Frontiers in Plant Science*, 3, 176. <https://doi.org/10.3389/fpls.2012.00176>
- van Wesemael, J., Kissel, E., Eyland, D., Lawson, T., Swennen, R., & Carpentier, S. (2019). Using growth and transpiration phenotyping under controlled conditions to select water efficient banana genotypes [Original Research]. *Frontiers in Plant Science*, 10, 325. <https://doi.org/10.3389/fpls.2019.00352>
- Wickham, H. (2016). *ggplot2: Elegant graphics for data analysis*. Springer-Verlag. <https://ggplot2.tidyverse.org>
- Wickham, H., & Bryan, J. (2022). *readxl: Read excel files* (Version 1.4.0). <https://CRAN.R-project.org/package=readxl>
- Wickham, H., François, R., Henry, L., & Müller, K. (2022). *dplyr: A grammar of data manipulation* (Version 1.0.8). <https://CRAN.R-project.org/package=dplyr>
- Wickham, H., Hester, J., & Bryan, J. (2022). *readr: Read rectangular text data* (Version 2.1.2). <https://CRAN.R-project.org/package=readr>
- Yonow, T., Ramirez-Villegas, J., Abadie, C., Darnell, R. E., Ota, N., & Kriticos, D. J. (2019). Black Sigatoka in bananas: Ecoclimatic suitability and disease pressure assessments. *PLoS ONE*, 14(8), e0220601. <https://doi.org/10.1371/journal.pone.0220601>
- Zeileis, A., Hothorn, T., & Hornik, K. (2008). Model-based recursive partitioning. *Journal of Computational and Graphical Statistics*, 17(2), 492–514. <https://doi.org/10.1198/106186008X319331>

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