Analysis of ranking data of pest and disease resistance in tricot trials

MSc Thesis Plant Production Systems

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Abstract

Triadic comparison of technologies (tricot) is a recently developed on-farm evaluation method involving farmers conducting small, simple trials on their farms. Farmers are provided with a selection of three varieties from a larger set and report the best and worst varieties for traits, such as yield, resistance and overall performance. The strength of the tricot approach is that it involves a large number of farmers in diverse conditions so that researchers can obtain diverse data on the actual differences in disease resistance. On the other hand, the tricot approach has some limitations: information is lost due to ranking-based evaluation, and farmers may find it hard to evaluate hard-to-score traits like pest and disease resistance reliably. In particular, the potential of evaluating resistance using rankings is unknown, and this study focused on farmers' pest and disease resistance evaluation in the tricot trial.

Results indicated that farmers' evaluation in the tricot trial could find varietal differences in potatoes' bacterial wilt resistance rankings in Rwanda, which suggests farmers' evaluation for this was not random. Bacterial wilt resistance was a significant predictor of overall performance independently of confounding variables, yield and vigour. This indicated that farmers evaluated disease resistance independently of potential confounders. The preferred variety of bacterial wilt resistance varied depending on whether the maximum day temperature during the vegetative period was above or below 25.43°C. This result aligned with the known disease-occurring factor that bacterial wilt causes the most severe damage when the temperature ranges between 25°C and 35°C. Additionally, the susceptible variety was selected as the least preferred in warmer environments, where the disease is known to cause severe damage. These results suggest that farmers' evaluations of bacterial wilt resistance reflect the actual differences in disease resistance. On the contrary, pest and disease resistance evaluations in other crops did not show significant differences between varieties. There could be several reasons for this, including the use of pesticides, unsuitable timing of evaluations, and not focusing on a specific pest. Assessing pest resistance by farmers has been thought to be challenging due to the requirement of specialised knowledge. However, this study suggested the possibility of obtaining the actual differences in disease resistance from farmers' best and worst evaluations under the right conditions, potentially accelerating the selection of pest-resistant varieties suitable for specific on-farm environments.

Table of Contents

1. Introduction

1.1 Plant breeding for pest and disease resistance and genotype-by-environment interaction

Farmers and breeders constantly improve crops to maintain a stable and sustainable food supply. Plant breeding has contributed to improved crop productivity and increased biotic and abiotic stress tolerance (Galluzzi et al., 2020). Pest and disease resistance is essential in crop breeding, as withstanding pests and pathogens is a prerequisite for food safety and yield losses due to insects, pathogens, and weeds can be up to 20-40% of global agricultural productivity (S. Sharma et al., 2017). The emergence of new strains of plant diseases and the movement of pests and diseases render conventional resistant varieties unusable and require the introduction of varieties to cope with them.

In recent years, due to climate change, higher average temperatures and increased frequency of extreme weather events are predicted to reduce crop yields, requiring the development of new varieties in shorter cycles (Knox et al., 2012; Lesk et al., 2016). This is also the case for pest and disease resistance. Due to climate change, the emergence and movement of pests and diseases are changing as rising temperatures affect the prevalence of pests and pathogens (Dawson et al., 2015). For example, plant viruses and their insect vectors favour high temperatures until they reach their upper-temperature threshold (Trebick, 2020). Global warming is therefore expected to promote insect vectors and the viruses they transmit (FAO et al., 2021). In addition, crop-management adaptations to climate change, such as the introduction of irrigation and changes in sowing dates, may affect the ecology of pests and diseases and cause population increases (FAO et al., 2021). In this context, the resistant varieties are one of the best pest and disease management methods (FAO et al., 2021). Rapid cycle breeding is needed to ensure that farmers always have access to climate-appropriate varieties.

1.2 Evaluation of variety performance under diverse conditions

The relative performance of crop genotypes is affected by environmental interactions, a phenomenon known as genotype-by-environment interaction (GEI). GEI is the differential response of crop genotypes from one environment to another (Elias et al., 2016). In other words, if a variety expresses a superior trait value in one environment, it is not guaranteed to be superior in another environment. GEI is a challenge for plant breeders because it reduces selection efficiency. Therefore, GEI analysis is essential in variety evaluation to obtain an improved phenotype in a targeted environment (Ngailo et al., 2019). Pest and disease resistance is also affected by GEI since changes in the geographical differences within the agro-ecologies will impact disease pressure and their distribution due to changing climatic conditions (Aruna et al., 2011; Beebe et al., 2011). GEI analysis is usually done by so-called multi-environment trials (MET) in which varieties are tested across a set of environmental contrasting locations over several years (Smith et al., 2020). Since trials across a few locations and years may not adequately cover the environments in which new varieties may be grown (Bustos-Korts et al., 2019), there is a clear incentive to scale up as far as budget and resource constraints allow.

1.3 Triadic comparisons of technologies (tricot)

As mentioned above, GEI analysis benefits from scaling up, and one methodology for doing so is the recently developed on-farm evaluation method, "triadic comparison of technologies" (tricot). The tricot is a crowdsourcing approach where instead of large, complex trials conducted in research facilities, farmers host a large number of small, simple trials on their farms, with resulting data being analysed with specialised statistical methods (van Etten et al., 2020).

There are four roles within the tricot approach: researchers, implementers, field agents and farmers. Researchers choose the varieties for the project and provide seeds to implementers. Implementers, people from development agencies or NGOs, train field agents and provide trial packages to farmers. Farmers blindly receive and grow only three genotypes out of the portfolio of varieties. Farmers report feedback to field agents from various perspectives, such as yield, pest damage, marketability, taste and overall evaluation. Field agents report the feedback data to implementers through a smartphone application. Implementers compile and analyse data, and after the experiment, they provide feedback to farmers, such as the name of provided varieties, suited varieties and how to get the variety (van Etten et al., 2020). Researchers can statistically combine the rankings of the three varieties fed back from farmers (Brown et al., 2020). Tricot is an iterative process; thus, following each project cycle, researchers, implementers, field agents, and farmers jointly assess how the process might be improved in the following cycle (van Etten et al., 2020).

1.4 Strengths and weaknesses of the tricot approach

The strength of the tricot approach is that it involves a large number of farmers in diverse conditions so that researchers can obtain diverse data under actual on-farm conditions. The tricot approach can consider sociocultural and environmental diversity that varies significantly across the landscape. The tricot can help detect GEI by sampling different environments (van Etten et al., 2019). As the data includes the latitude and longitude of the study site, existing maps of temperature, rainfall, altitude, and other variables can be used to analyse varietal performance as a function of environmental factors (van Etten et al., 2020). In a recent study by van Etten (2019), a combined analysis of tricot trials on common bean (*Phaseolus vulgaris* L.) in Nicaragua, durum wheat (*Triticum durum* Desf.) in Ethiopia, and bread wheat (*Triticum aestivum* L.) in India demonstrated that the tricot approach could indicate specific effects of climate diversity on the performance of crop varieties (van Etten et al., 2019).

A vital feature of the feedback of the tricot method is that it only requires choosing the best and the worst. The ranking-based feedback allows farmers with low literacy and training needs can remain low (de Sousa et al., 2021). It also reduces the need to explain rating scales and precise yield measurements. Researchers can collect feedback through a digital platform, saving time and effort in data cleaning (van Etten et al., 2020). A significant advantage is its low cost because the farmers voluntarily participate (de Sousa et al., 2021). Besides, farmers benefit directly from discovering new varieties that fit socio-economic and environmental conditions.

Nevertheless, the tricot method has three possible limitations. The first is information loss, as tricot data only provides ranking information. The lack of actual trait values may limit obtaining information on traits. For example, there is no information on which and how many pests have occurred in terms of pest resistance. This may make it challenging to capture inter-varieties differences.

Second, evaluations rely on farmers' judgement. In the tricot approach, farmers have a no-choice option. The no-choice option provides a way of avoiding difficult choices in consumer preference studies, but while such studies are conducted anonymously through surveys, the tricot surveys are not anonymous and require reporting to local field agents. Farmers may therefore feel obligated to answer questions politely in this situation. In pest and disease resistance evaluation, farmers possibly answered as if pests occurred when pests did not occur. This may induce inappropriate or random answers. Therefore, pest and disease resistance rankings may not reflect the varieties' real pest and disease occurrence and resistance.

Third, farmers' evaluations may contain errors. In the case of pest and disease evaluation, farmers may mistakenly diagnose as having physiological disorders since farmers are not trained. Therefore, it is not sure that the pest and disease resistance score reflects the actual resistance of the variety. In a study of farmers' knowledge of plant diseases in Ethiopia, some highly damaging diseases, such as faba bean chocolate spot and chickpea ascochyta blight, were not regarded as diseases but as problems caused by excessive soil moisture (Kiros-Meles & Abang, 2008). In Honduras, a pilot test of the tricot was conducted to evaluate the disease resistance ratings of farmers. The test found that farmers' disease resistance ratings had a low internal agreement, and accuracy could be improved through training (Steinke, 2015).

1.5 Research questions

Currently, the extent to which above limitations limit the potential for pest and disease resistance evaluation in the tricot approach is not known. Three research questions were established to answer whether farmers' evaluation of pest and disease resistance ranking adequately evaluates resistance.

RQ1: Does existing tricot data reveal significant variety differences in pest and disease resistance rankings?

First, it is unknown to what extent farmer ranking data of pests and diseases is non-random. If farmers randomly ranked the pest and disease resistance, there would be no difference between varieties. Conversely, farmers' ranks are not random if a difference is observed between varieties. For this reason, whether there are differences between varieties in pest resistance scores will be tested. Hypothesised that there are statistically significant differences between varieties in some data.

RQ2: Can other variables predict pest and disease resistance rankings? Or, can pest and disease resistance rankings predict other variables?

The next step is to look at relationships with other variables. To begin with, the best method to do the analyses will be explored since an efficacy of applying ranking data to predictive models is still unknown. Then, the relationship with vigour will be analysed first. Diseases develop when the pathogen, susceptibility and environmental factors are mutually favourable for the outbreak. When plants grow unhealthily, they are more susceptible to the pathogen (Velásquez et al., 2018). There may also be a relationship with yield. Generally, pests and diseases cause yield loss; for example, a negative correlation between yield and disease damage has been reported (Bruno et al., 2017). If this generally observed trend could be observed in the ranking data, it could be said that the ranking data for pest and disease resistance is picking up the differences in disease resistance. Additionally, if pest and disease resistance rankings were significant predictors of overall evaluation independently of other variables, it would prove that farmers' evaluation can accurately reflect resistance independently of other variables. It was hypothesised that statistically significant relationships could be observed in the data where significant differences were observed in the first research question.

RQ3: Does the ranking of varieties of pest and disease resistance depend on environmental variables? If so, are these relationships consistent with the expected pest and disease pressure determinants?

Third, the relationship with environmental factors will be focused. Abiotic factors, such as temperature and rainfall, drive pest and disease numbers, growth and survival. For instance, whitefly (*Bemisia tabachi*) population build-up positively correlates with high temperature and a high humidity (Pathania et al., 2020). In contrast, black bean aphids (*Aphis fabae*) infest plants more during the dry season (Abate & Ampofo, 1996). Humidity is necessary for many plant pathogens to infect their host (Wilks & Shen, 1991). Besides, some pathogens, including late blight (*Phytophthora infestans*), prefer cool temperatures, and some pathogens, including bacterial blight (*Ralstonia solanacearum*), prefer high temperatures (Muhinyuza et al., 2007; Singh et al., 2014). If pest rankings depend on environmental variables and the relationship is consistent with the information on pest and disease ecology, this would provide evidence that the resistance rankings reflect the actual differences in disease resistance. Hypothesised that ranking differences for pest and disease scores will be most significant under conditions that favour pest and disease occurrence.

The tricot method has limitations, including information loss as it only provides ranking information, reliance on farmers' judgement, and potential errors in their evaluations as farmers are not specialists in pests and pathogens. However, if pest and disease resistance can be correctly assessed using the tricot method, it would be viable option for GEI analysis. This study will focused on whether the farmers' ranking evaluation in the tricot trials is adequate and if the evaluation reflects pest and disease resistance.

2. Materials and methods

2.1 The Plackett-Luce model, PLADMM and Plackett-Luce trees

The Plackett-Luce model is the key to an analysis of the tricot trial. This model is based on Luce's axiom of choice (Luce, 1977), which assumes that the probability of choosing one item over another is not influenced by the group of items from which the decision is being made. When there is a set of J items

$$S = \{i_1, i_2, \dots, i_J\}$$

Then under Luce's axiom, the probability of selecting some item j from S is given by

$$P(j|S) = \frac{\alpha_j}{\sum_{i \in S} \alpha_i}$$

where α_i represents the worth of item i. The Plackett-Luce model can estimate the probability of each element being ranked first, called the worth parameter, from a partially overlapping rankings (Brown et al., 2020). This allows ranking data to be treated as a quantitative variable. The Plackett-Luce model specifies the probability of a ranking of J items, $i_1 \succ \cdots \succ i_j$, is given by

$$\prod_{j=1}^{J} \frac{\alpha_{i_j}}{\sum_{i \in A_j} \alpha_i}$$

where α_{i_j} represents the worth of item i_j and A_j is the set of alternatives $\{i_j, i_{j+1}, \dots, i_J\}$ from which item i_j is chosen. The parameters of the Plackett-Luce model are typically inferred by the maximum likelihood estimation (Guiver & Snelson, 2009). One of the R packages supporting the Plackett-Luce model called *PlackettLuce* uses the minorization-maximization algorithm to maximise the likelihood (Hunter, 2004).

The original Plackett-Luce model does not accommodate covariates. Therefore, models that can involve covariates have been developed. The Plackett-Luce Alternating Directions Method of Multipliers (PLADMM) is one of the models that can model the log-worth as a linear function of item covariates:

$$log\alpha_i = \beta_0 + \beta_1 x_{i1} + \cdots + \beta_p x_{ip}$$

where β_0 is fixed by the constraint that $\sum_i \alpha_i = 1$. The PLADMM uses an Alternating Directions Method of Multipliers (ADMM) algorithm to estimate the parameters. The algorithm jointly estimates model parameters and the Plackett-Luce scores via a spectral method. Also, ADMM allows them to reduce ranking regression to regularised maximum likelihood estimation with precisely such a penalty (Yıldız et al., 2020). A function of the PLADMM is available in the R library *PlackettLuce* (H. L. Turner et al., 2020).

The Plackett-Luce tree allows for the analysis of the effect of location-specific covariates on variety ranks. The Plackett-Luce tree algorithm uses partitioning to identify subgroups of trials with significantly different rankings in response to specific covariates (H. L. Turner, 2022). The algorithm splits the data by the covariate if there is significant instability. The process is repeated until no significant instabilities or sub-group are produced below a certain size threshold. The generated subgroups, called nodes, show worth parameters in the node. In other words, different rankings can be obtained in different environments. The tricot trial data typically include coordinates of the survey sites so that the tricot trial data can link with environmental factors. The Plackett-Luce tree is also available in the R library "PlackettLuce" (H. L. Turner et al., 2020).

The analyses of this study were divided into two steps: the analysis of the efficacy of the Plackett-Luce Alternating Directions Method of Multipliers (PLADMM); and the analysis of the ranking data collected from farmers. All simulations and analyses were done with the software program R version 4.1.3 (R Core Team, 2022).

2.2. The efficacy of PLADMM

Before analysing the ranking data collected from farmers, a test was conducted to evaluate the efficacy of PLADMM, which has never been tested on on-farm ranking data. In research question 2, a linear model with covariates was needed to find out if pest and disease resistance rankings can predict or be predicted by other variables. PLADMM was one of the candidate models as it accepts rankings as a response variable and models the log-worth of items by a linear function of the item covariates (H. L. Turner et al., 2020). PLADMM accepts numerical values as covariates. Although the data obtained from the tricot trials are in ranking format, the Plackett-Luce model can convert these into worth parameters, allowing the values to be used as covariates in the PLADMM. However, it remained uncertain whether using worth parameters as covariates of the PLADMM would lead to accurate results. This analysis aimed to evaluate the efficacy of the PLADMM with worth parameters using simulated data.

2.2.1. Data simulation

As the data collected from farmers were only available in the ranking format, a simulation study was conducted to generate corresponding numeric values and rankings for analysis.

To generate the simulation data, ten simulated varieties and six simulated traits were established, with a population mean of 1000 for each trait. The trait means for each variety was randomly generated with the covariance matrix using the *rmvnorm* function of the R package *mvtnorm* (Genz et al., 2021), and replicates of each variety were generated by adding a random error of 50 to the trait means. Random triplets of three replicates were created to represent individual on-farm trials, including all combinations of the simulated varieties. The trait means were ranked within each triplet to obtain simulated ranking data, which were processed using the R package *PlackettLuce* to calculate the worth parameters (H. L. Turner et al., 2020). The resulting data frame contains the numeric values, ranking, and worth parameters for each simulated trait and variety combination.

2.2.2. Statistical models

Three statistical modelling methods were used:

- linear regression with the numeric values: The response variable and covariates were numeric. The *lm* function of the standard installation of the R was used;
- linear regression with the worth parameters: Both the response variable and covariates were the worth parameters obtained from the Plackett-Luce. The *lm* function of the standard installation of the R was used; and
- the PLADMM: The response variable was ranking. Covariates were the worth parameters obtained from the Plackett-Luce. The *pladmm* function of the R package *PlackettLuce* was used.

Each modelling method was tested on three simulation scenarios:

- correlated data: the response variable and all covariates were correlated;
- non-correlated data: The response variable and covariates were not correlated; and
- data with correlated and non-correlated covariates: the response variable and one of the covariates were correlated.

Therefore, there were nine combinations.

2.2.3. Comparison of the models

For all models except for the PLADMM, the analysis of variance (ANOVA) was used to test each model against an intercept-only model. The chi-squared test was used for the PLADMM with correlated and non-correlated covariates because the ANOVA function does not support the PLADMM. The residual deviances were obtained from the analysis of the deviance table. The tests were iterated 1,000 times. The obtained p values were stored in a data frame. The frequency of p values in increments of 0.05 was compared among each model of each situation.

2.3. Data collection

The data for the analysis of the tricot trial was provided by the International Institute of Tropical Agriculture (IITA) via email. Four datasets were available; common bean in Central America; common bean in East Africa; cowpea in Nigeria; and potato in Rwanda. All datasets include the latitude and longitude of the trial sites, the date of planting and harvest, and the combination of varieties distributed to farmers. Environmental covariates were obtained from the R package "climatrends" that include the maximum and minimum daily temperatures, the maximum and minimum night temperatures, and rainfall. Other variables from each dataset are listed in Table 1 and Section 2.3.

Table 1 Variables in each dataset. V: vegetative season, V1: the first survey in the vegetative season, V2: the second survey in the vegetative season. R: reproductive season, P1: the first survey in the post-harvest season, P2: the second survey in the post-harvest season and P3: the third survey in the post-harvest season.

Variables	Common bean in Central America	Common bean in East Africa	Cowpea in Nigeria	Potato in Rwanda
Pest resistance	P	V, R	V, P	-
Disease resistance	P	V, R	V, P	-
Pest/disease resistance	-	-	-	V1, V2
Bacterial wilt resistance	-	-	-	V1, V2
Drought tolerance	P	V, R	V, P	-
Flood tolerance	P	V, R	-	-
Vigour	P	P	-	V1
Yield	P	P	P	P1
Maturity	P	P	P	P1
Grain size	-	P	P	-
Tuber size	-	-	-	P1
Appearance	-	-	-	P1
Marketability	P	P	P	P1, P2
Taste	-	-	-	P1, P2
Tuber quality	-	-	-	P3
Quality	-	-	-	P3
Preference	-	-	-	P3
Overall	P	P	P	P3

2.4. Data overview

2.4.1. Common bean in Central America

The trial was conducted from 2015 to 2018 in Nicaragua, El Salvador, Honduras, Guatemala, and Costa Rica (Fig.1a). Thirty-eight varieties of common bean (*Phaseolus vulgaris*) were used. The dataset has resistance to pests and diseases, vigour, maturity, tolerance to drought, yield, marketability, and overall appreciation, all in the best and worst format (Table 1). All items were asked only once in post-harvest. The dataset has 3556 observations in total. Two thousand five hundred fifty-three observations contained pest resistance data, and 2654 observations contained disease resistance data.

2.4.2. Common bean in East Africa

The trial was conducted in 2021 and 2022 in Tanzania, Uganda and Ethiopia (Fig.1b). Forty-two varieties of common beans were used. The dataset includes resistance to pests and diseases and tolerance to drought and flood in the vegetative and reproductive seasons. Also, the dataset has disease severity, vigour, maturity, yield, grain size, marketability, and overall appreciation in post-harvest, all in the best and worst format (Table 1). The dataset has 1995 observations in total. 908 and 412 observations contained pest resistance data in the vegetative and reproductive seasons, respectively. 809 and 412 observations contained disease resistance data in the vegetative and reproductive seasons, respectively.

2.4.3. Cowpea in Nigeria

The trial was conducted in 2021 in Nigeria (Fig.1c). 18 varieties of cowpea (*Vigna unguiculata*) were used. The dataset has resistance to pests and diseases, disease severity, and tolerance to drought in vegetation season and post-harvest; also, the dataset has maturity, yield, grain size, and marketability in post-harvest, all in the best and worst format (Table 1). The dataset has 320 observations in total. 241 and 299 observations contained pest resistance data in the vegetative and post-harvest seasons, respectively. 237 and 268 observations contained disease resistance data in the vegetative and post-harvest seasons, respectively.

2.4.4. Potato in Rwanda

The trial was conducted in 2020 and 2021 in Rwanda (Fig.1d). 11 varieties of potato (*Solanum tuberosum*) were used. The dataset has resistance to bacterial wilt (*Ralstonia solanacearum*) and pest/disease obtained twice in the vegetative season; maturity, yield, tuber size, and marketability were obtained post-harvest, all in the best and worst format (Table 1). The dataset has 463 observations in total. 137 and 347 observations contained bacterial wilt resistance data in the two vegetative seasons, respectively. 83 and 228 observations contained pest/disease resistance data in the two vegetative seasons, respectively.

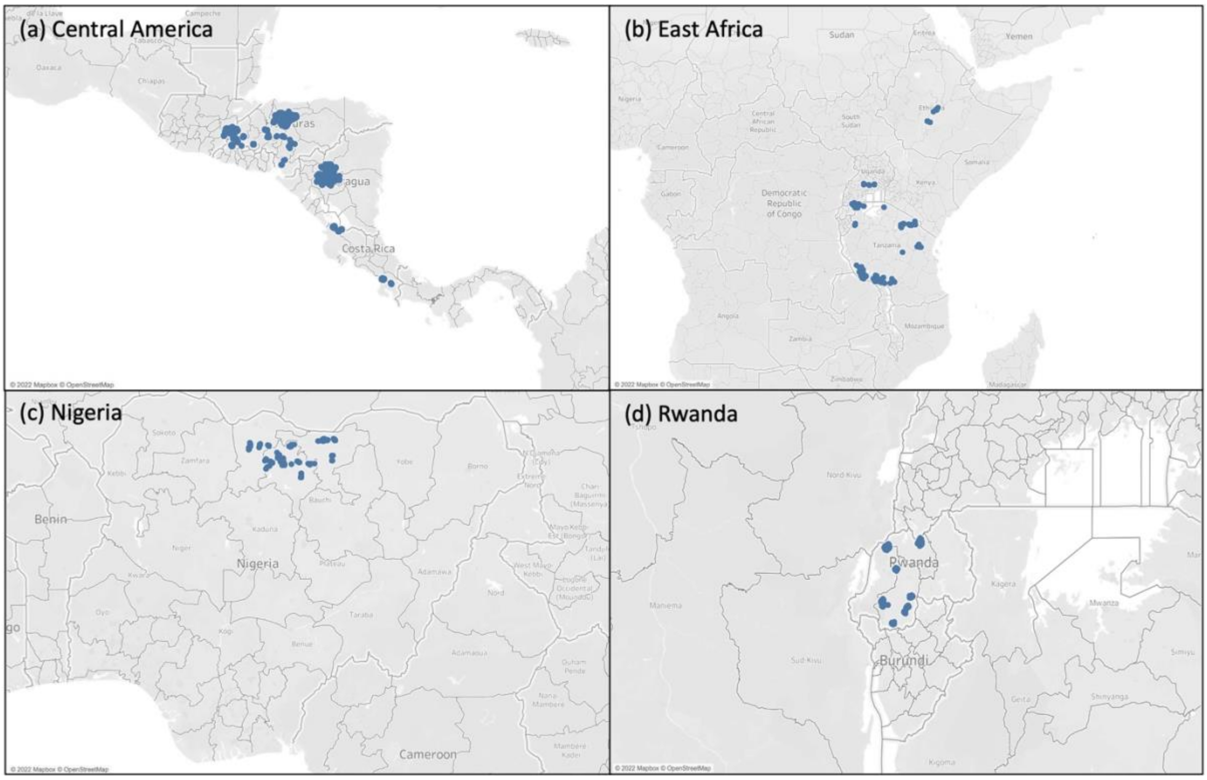

Figure 1 Places where data were taken. (a) Central America, (b) East Africa, (c) Nigeria and (d) Rwanda.

2.5. Analysis

2.5.1. Data cleaning and processing

Four datasets were analysed separately because the target crops and the regions where conducted the test were different. Rows that do not have data on pest resistance or disease resistance were removed from the datasets. The best and worst data were processed by the R package *PlackettLuce* to obtain rankings and estimate worth parameters that represent the probability of each element being ranked first.

2.5.2. Analysis of the difference between varieties in terms of pest/disease resistance (RQ1)

The likelihood ratio test tested the significant difference between varieties. The R package *PlackettLuce* was used to obtain the log-likelihood of the null model and the full model. The chi-square value was calculated and compared to the chi-square probability of $p = 0.05$.

2.5.3. Analysis of a relationship between pest/disease resistance and other variables (RQ2)

The pest and disease resistance ranking with a significant difference in RQ1 was used. The modelling method was determined by the result of the efficacy of the PLADMM (Section 2.2.3).

Whichever modelling method was chosen, the worth parameters of traits were used as a response variable and explanatory variables. The selection of explanatory variables was based on their correlation coefficients and relevance, as the number of variables was excessive. The best model was chosen by the backward stepwise method using the *step* function of the library *lmer*. The best-fit model was chosen by Akaike's Information Criterion (AIC). The multicollinearity was detected by the variance inflation factor using the *vif* function in the library *car* (Fox & Weisberg, 2019).

2.5.4. Analysis of specific patterns between pest/disease resistance and environmental factors (RQ3)

For the analysis of specific patterns between pest and disease resistance rankings and environmental factors, a Plackett-Luce tree, the R package *gosset* was used. The Plackett-Luce tree determines subgroups of rankings with significantly different sets of worth parameters based on the ranking-specific covariates (Turner et al., 2020). Also, the Plackett-Luce tree can detect an influential covariate, shown as a node in a hierarchical tree. The pest and disease resistance ranking with a significant difference in RQ1 was used as a response variable. Environmental variables, such as the maximum and minimum day and night temperature and precipitation per day, were used as covariates. When the Plackett-Luce tree detected a split, varietal difference of each node were tested. The identified influential covariates were compared with favourable/unfavourable pest and disease conditions collected from the literature.

3. Results

3.1. The efficacy of the PLADMM

Analyses were conducted to assess PLADMM's efficacy, incorporating item covariates and comparing it to the alternative models, namely linear regressions with actual values and with worth parameters. Figures 2, 3, and 4 present histograms of the probability of *p* values in 0.05 increments, resulting from ANOVA of the targeted model against a intrcept-only model. In addition, Q-Q plots were generated to assess whether *p* values were uniformly distributed as expected when the response variable and covariates are correlated or uncorrelated. When the observed and expected values correspond, the blue line representing observed values aligns with or lies close to the diagonal red line indicating expected values. In contrast, if some observed *p* values prove more significant than anticipated, the blue line will skew towards the x-axis. Four situations were considered: with an uncorrelated covariate, with a correlated covariate, with five uncorrelated variables, and with a correlated and four uncorrelated variables.

3.1.1 With an uncorrelated covariate (null model)

Figure 2 shows the histogram and Q-Q plot of the *p* values of models with an uncorrelated covariate. The linear regression with actual values was almost uniformly distributed (top in Figure 2). The proportion of $p < 0.05$ was 0.047. The linear regression with worth parameters showed a proportion of 0.052 when $p < 0.05$ and had a slightly high proportion of 0.075 in the rightmost bar in the histogram, $p > 0.95$ (middle in Figure 2). However, the Q-Q plot indicates that the *p* values were uniformly distributed. In contrast, the p-values for PLADMM were not uniformly distributed. The leftmost bar, $p < 0.05$, shows a probability of 0.133 (bottom in Figure 2). The Q-Q plot, which is right-skewed, also shows that the *p* value distribution is not uniform and has a long tail heading towards the right-hand side of the distribution. These results suggested that the PLADMM have a high proportion of $p < 0.05$ compared to linear regressions, even when there is no correlation between the response variable and covariate.

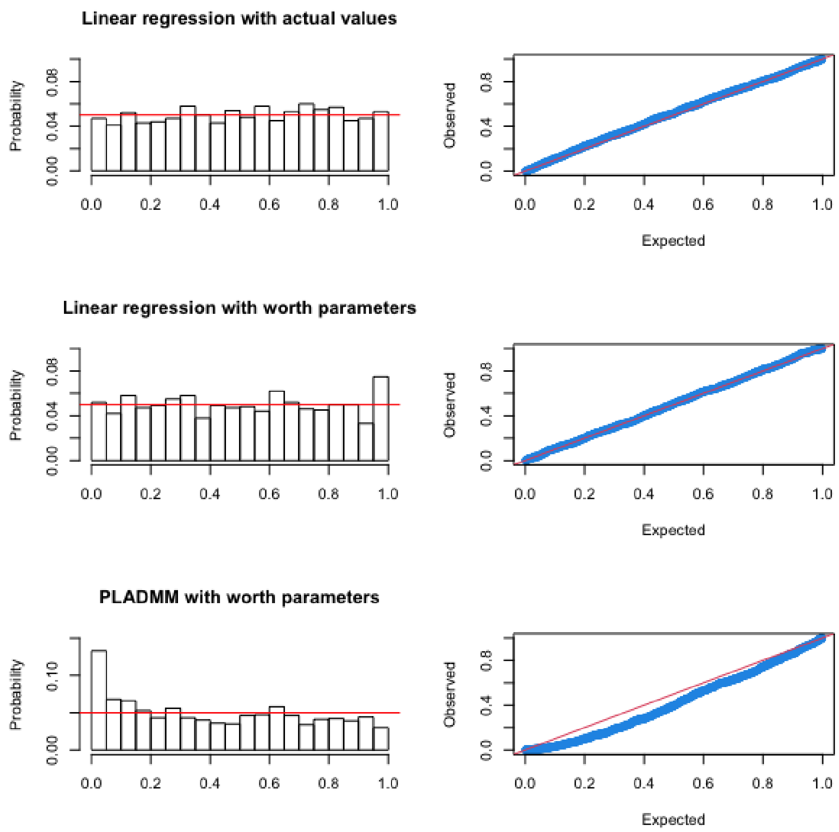

Figure 2 Histogram and Q-Q plot for the uniformly distributed random variable of p values of each model. The response variable and the covariate were uncorrelated. Top: linear regression with the actual values, middle: linear regression with the worth parameters, bottom: the PLADMM with the worth parameters. The x-axis of histograms is in 0.05 increments, and the y-axis is the probability density of p values. The red line on histograms shows y=0.05. The red line on Q-Q plots represents the expected distribution of p value, while the blue trend represents the observed distribution. The x-axis values on Q-Q plots are expected p value and the y-axis values are observed p value.

3.1.2 With a correlated covariate

Figure 3 shows the histogram and Q-Q plot of the *p* values of models with a correlated covariate. The correlation coefficient was 0.03 with correlated covariate and was less than 0.001 with uncorrelated covariate. The linear regression with actual values shows a proportion of 0.126 when $p < 0.05$ (top in Figure 3). The observed distribution, the blue trend on the Q-Q plot, is slightly skewed downward. The linear regression with worth parameters shows high proportions of 0.217 when $p < 0.05$ compared to the linear regression with actual values (middle in Figure 3). The PLADMM with worth parameters shows the highest proportion of 0.386 when $p < 0.05$ (bottom in Figure 3), and the skewness of the blue line on the Q-Q plot is the largest among the three models. These results suggested that the PLADMM have a high proportion of $p < 0.05$ compared to other models. Also, the linear regression with worth parameters showed a high proportion of $p < 0.05$ compared to the linear regression with actual values.

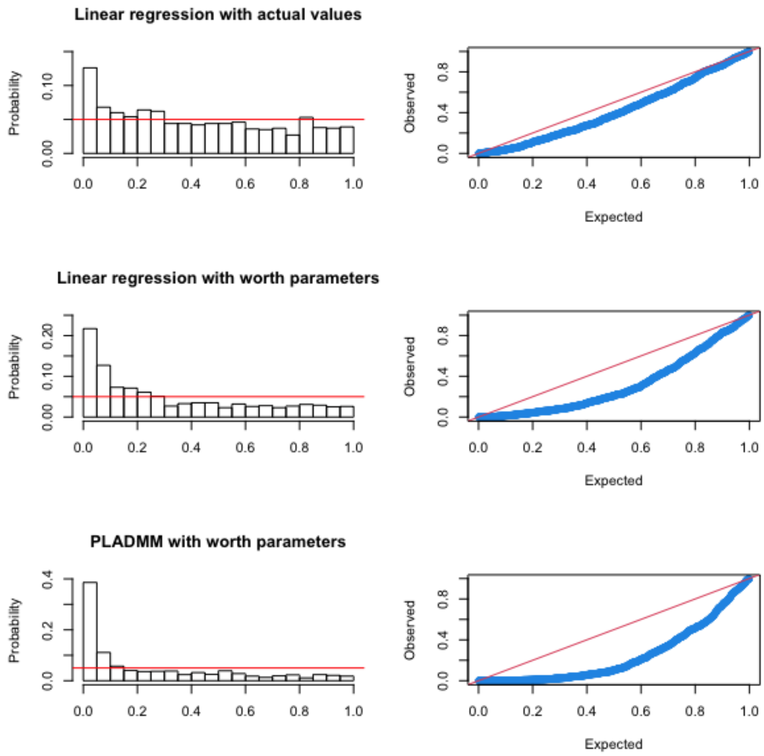

Figure 3 Histogram and Q-Q plot for the uniformly distributed random variable of p values of each model. The response variable and the covariate were correlated. Top: linear regression with the actual values, middle: linear regression with the worth parameters, bottom: the PLADMM with the worth parameters. The x-axis of histograms is in 0.05 increments, and the y-axis is the probability density of p values. The red line on histograms shows y=0.05. The red line on Q-Q plots represents the expected distribution of p value, while blue trend represents the observed distribution. The x-axis values on Q-Q plots are expected p value and the y-axis values are observed p value.

3.1.3 With five uncorrelated covariates

Figure 4 shows the histogram and Q-Q plot of the *p* values of models with five uncorrelated covariates. The linear regression with actual values was almost uniformly distributed (top in Figure 4). The proportion of $p < 0.05$ was 0.057. The linear regression with worth parameters showed a proportion of 0.042 when $p < 0.05$ (middle in Figure 4). However, the Q-Q plot indicates that the *p* values were uniformly distributed. In contrast, the PLADMM with worth parameters was not uniformly distributed. The leftmost bar, $p < 0.05$, shows a probability of 0.267 (bottom in Figure 4). The Q-Q plot, which is right-skewed, also explains that the *p* value distribution is not uniform and has a long tail heading towards the right-hand side of the distribution. These results suggested that the PLADMM have a high proportion of $p < 0.05$ compared to linear regressions, even when there is no correlation between the response variable and covariates. Compared to the result with an uncorrelated covariate (section 3.1.1), the skewness and the proportion of $p < 0.05$ of the PLADMM were larger.

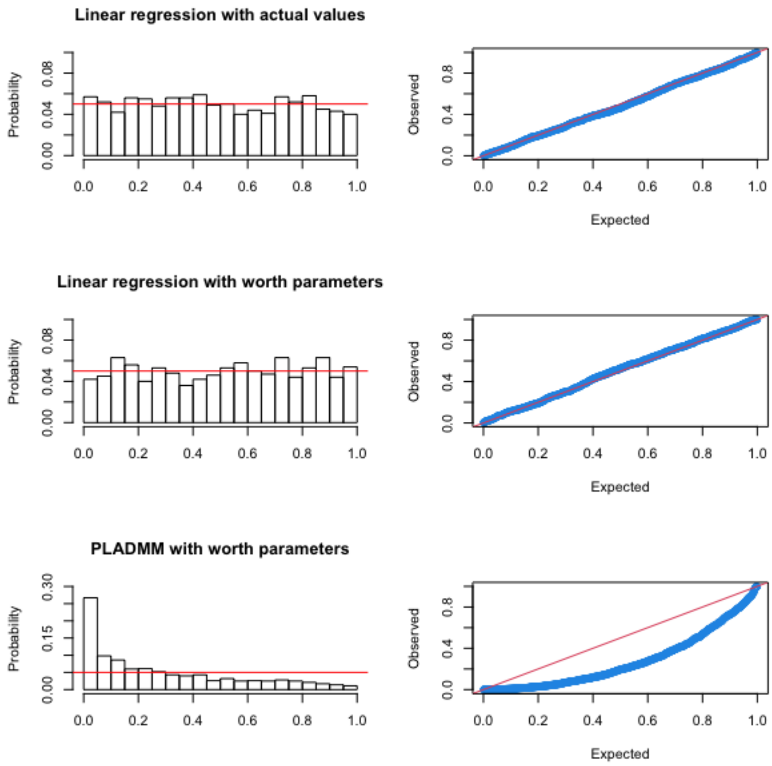

Figure 4 Histogram and Q-Q plot for the uniformly distributed random variable of p values of each model. The response variable and five covariates were uncorrelated. Top: linear regression with the actual values, middle: linear regression with the worth parameters, bottom: the PLADMM with the worth parameters. The x-axis of histograms is in 0.05 increments, and the y-axis is the probability density of p values. The red line on histograms shows y=0.05. The red line on Q-Q plots represents the expected distribution of p value, while the blue trend represents the observed distribution. The x-axis values on Q-Q plots are expected p value and the y-axis values are observed p value.

3.1.4 With a correlated covariate and four uncorrelated covariates

Figure 5 shows the histogram and Q-Q plot of the *p* values of models with a correlated covariate and four uncorrelated covariates. The correlation coefficient between the explanatory variable and the response variable before adding a random plot error was 1. The linear regression with actual values shows a proportion of 0.091 when $p < 0.05$ (top in Figure 5), which is less than the model only with one correlated covariate. The observed distribution is slightly skewed downwards. The linear regression with worth parameters shows proportions of 0.090 when $p < 0.05$ (middle in Figure 5), almost the same as the proportion of $p < 0.05$ of the linear regression with actual values. As well as the linear regression with actual values, the observed distribution is slightly skewed downwards, and the skewness is lower than the model only with one correlated covariate. The PLADMM with worth parameters shows a high proportion of 0.363 when $p < 0.05$ (bottom in Figure 5). These results suggested that the PLADMM have a high proportion of $p < 0.05$ compared to other models.

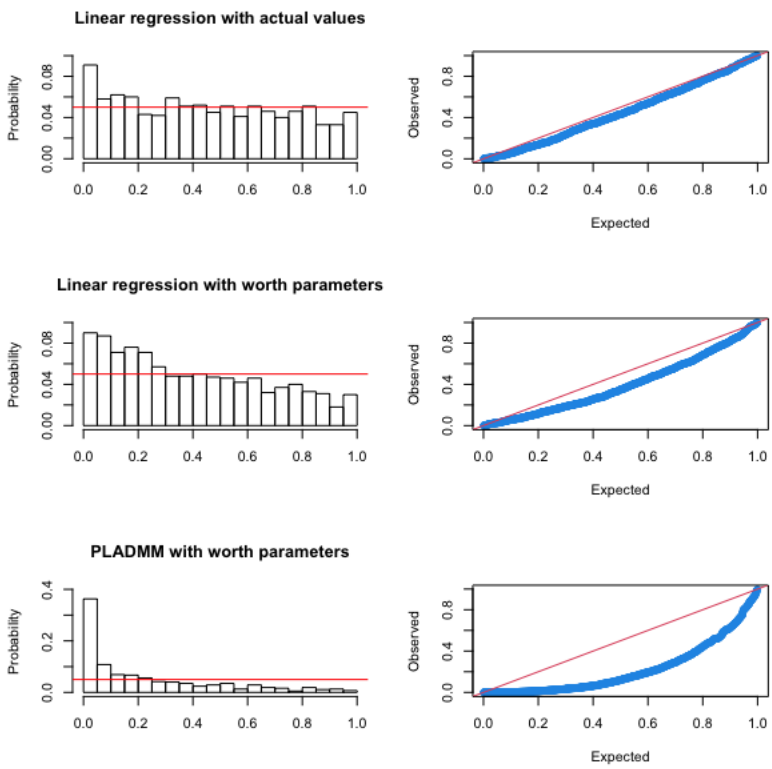

Figure 5 Histogram and Q-Q plot for the uniformly distributed random variable of p values of each model. The response variable and one of five covariates were correlated. Top: linear regression with the actual values, middle: linear regression with the worth parameters, bottom: the PLADMM with the worth parameters. The X-axis of histograms is in 0.05 increments, and the y-axis is the probability density of p values. The red line on histograms shows y=0.05. The red line on the Q-Q plots represents the expected distribution of p value, while the blue trend represents the observed distribution. The x-axis values on Q-Q plots are expected p value, and the y-axis values are observed p value.

3.1.5 Summary of the efficacy of the PLADMM

In summary, the PLADMM consistently had high proportions of $p < 0.05$ with any covariates. With uncorrelated covariate(s), the linear regressions with actual values and with the worth parameter showed almost the same proportion of $p < 0.05$. The proportion was around 0.05, the ideal value when the p values were uniformly distributed. While the PLADMM showed high proportions of $p < 0.05$, 0.133 with one covariate and 0.267 with five covariates. The high proportion of $p < 0.05$, even when the covariate(s) were uncorrelated with the response variable, indicates a high false positive rate, which is an undesirable property for a statistical model.
In the simulation with a correlated covariate and four uncorrelated covariates, the linear regression with the worth parameter showed almost the same proportion of $p < 0.05$ (0.090) compared to the linear regression with actual values (0.091). This result suggested that the power of the linear regression with the worth parameter was assumed to be sufficient.
Based on these findings, the linear regression with worth parameters was chosen to conduct analyses for research question two (Section 3.3).

3.2. Significant variety differences in pest/disease resistance rankings (RQ1)

Table 2 shows the results of the likelihood ratio test on each variable. 14 variables exhibited significant differences among the various varieties (bold in Table 2). These variables include the yield of common beans in Central America and East Africa, as well as the yield of potatoes in Rwanda. Furthermore, the maturity of cowpea in Nigeria and potato in Rwanda, as well as the overall appreciation of common beans in Central America and potatoes in Rwanda, also varied significantly across the different varieties. Additionally, there were variations in vigour, tuber size, marketability, taste, tuber quality, and preference for potatoes in Rwanda.

The only significant trait related to pest and disease resistance was found to be bacterial wilt resistance of potatoes, particularly in the vegetative season 2 evaluation ($p = 0.003$; Table 2). Figure 6 shows the varietal difference in bacterial wilt resistance worth parameters of potatoes in Rwanda in vegetative season 2. Standard error bars that do not cross indicate significant differences between Jyambere and Twihaze, as well as between Cruza and Twihaze. These findings indicate that ranking data can detect significant varietal differences in pest and disease resistance, supporting the initial hypothesis. The following analyses will focus on bacterial wilt resistance in vegetative season 2.

Table 2 Results of the likelihood ratio test on varietal difference. V: vegetative season, V1: the first survey in the vegetative season, V2: the second survey in the vegetative season. R: reproductive season, P1: the first survey in the post-harvest season, P2: the second survey in the post-harvest season and P3: the third survey in the post-harvest season. P values less than 0.05 are in bold.

Variables	Common bean in Central America	Common bean in East Africa	Cowpea in Nigeria	Potato in Rwanda
Pest resistance	p = 0.238 (P)	p = 0.350 (V) p = 0.515 (R)	p = 0.460 (V) p = 0.572 (P)	-
Disease resistance	p = 0.093 (P)	p = 0.061 (V) p = 0.837 (R)	p = 0.445 (V) p = 0.468 (P)	-
Pest/disease resistance	-	-	-	p = 0.654 (V1) p = 0.580 (V2)
Bacterial wilt resistance	-	-	-	p = 0.056 (V1) **p = 0.003 (V2)**
Drought tolerance	p = 0.504 (P)	p = 0.227 (V) p = 0.882 (R)	p = 0.915 (V) p = 0.900 (P)	-
Flood tolerance	-	p = 0.947 (V) p = 0.999 (R)	-	-
Vigour	p = 0.075 (P)	p = 0.221 (R)	-	**p < 0.001 (V1)**
Yield	**p = 0.017 (P)**	**p = 0.013 (P)**	p = 0.750 (P)	**p < 0.001 (P1)**
Maturity	p = 0.626 (P)	p = 0.077 (P)	**p = 0.012 (P)**	**p < 0.001 (P1)**
Grain size	-	p = 0.497 (P)	p = 0.318 (P)	-
Tuber size	-	-	-	**p < 0.001 (P1)**
Marketability	p = 0.161 (P)	p = 0.999 (P)	p = 0.220 (P)	p = 0.700 (P1) **p < 0.001 (P2)**
Taste	p = 0.205 (P)	p = 0.999 (P)	-	p = 0.568 (P1) **p = 0.024 (P2)**
Quality	-	-	-	**p < 0.001 (P3)**
Preference	-	-	-	**p < 0.001 (P3)**
Overall	**p = 0.011 (P)**	p = 0.695 (P)	p = 0.833 (P)	**p < 0.001 (P3)**

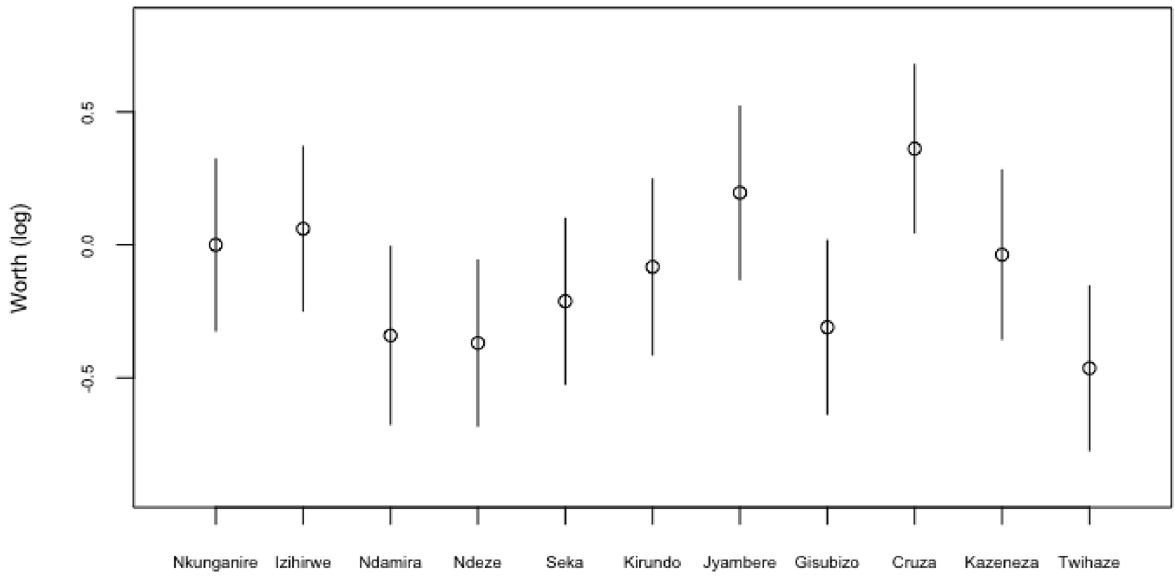

Figure 6 Worth parameters of bacterial wilt resistance (vegetative season 2) of potato varieties in Rwanda. Nkunganire is the reference. Intervals are based on quasi-standard errors. The x-axis is varieties and the y-axis is worth parameters.

3.3. Relationship between pest and disease resistance rankings and other rankings (RQ2)

3.3.1 Correlation between variables of potatoes in Rwanda

Figure 7 displays a correlation chart indicating the relationship between variables of potatoes in Rwanda. A statistically significant correlation was observed between bacterial wilt resistance in vegetative season 1 and vegetative season 2, with a correlation coefficient of 0.75 ($p < 0.01$). Additionally, a significant correlation was found between bacterial wilt resistance in vegetative season 2 and taste, with a correlation coefficient of 0.63 ($p < 0.05$). No other correlation with bacterial wilt resistance in vegetative season 2 was found.

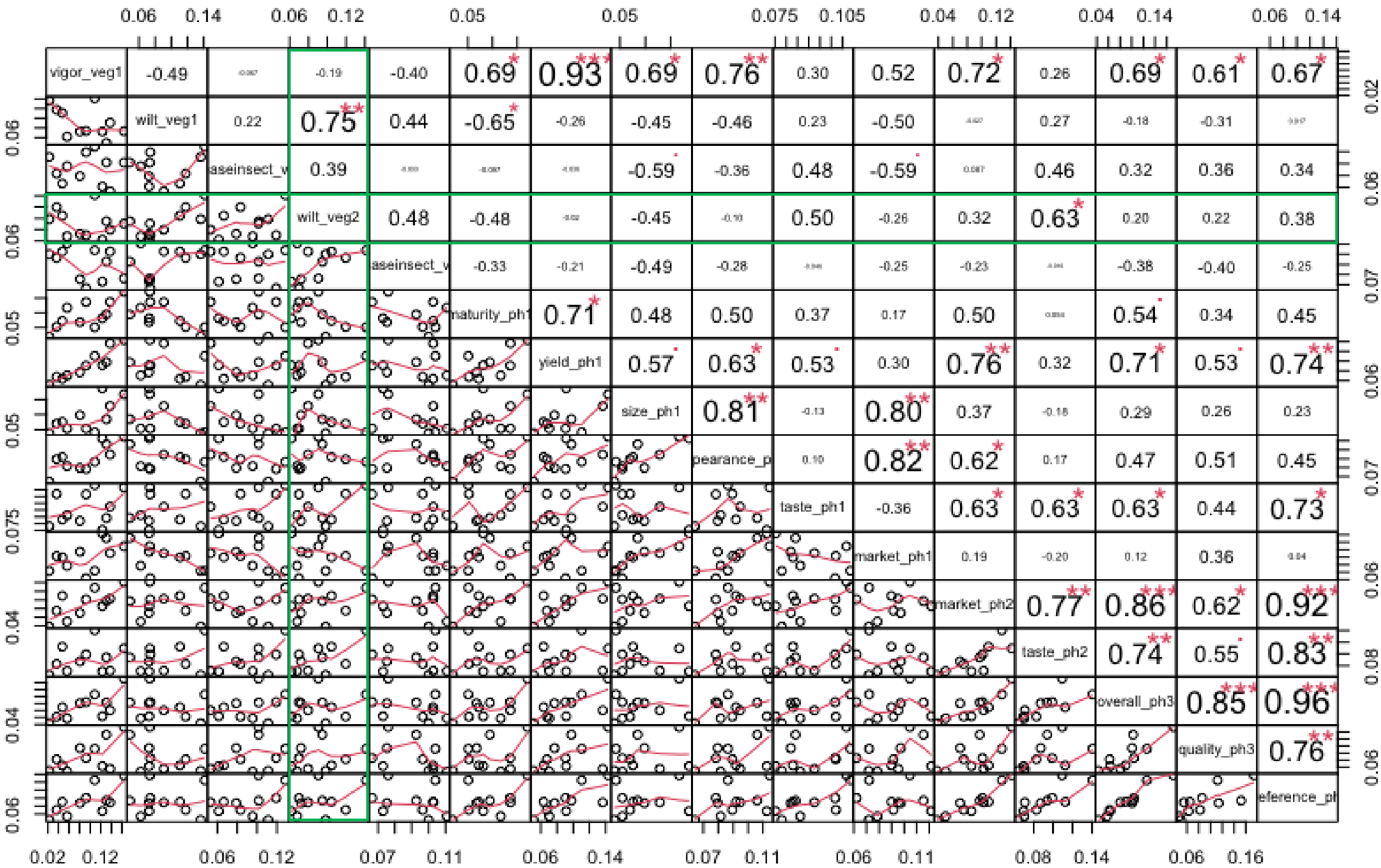

*Figure 7 Correlation chart of variables of potatoes in Rwanda. The distribution of each variable is shown on the diagonal. on the bottom of the diagonal, the scatter plots with a fitted line are displayed. On the top of the diagonal, the values of the correlation and the significance levels are displayed. Each significance level is associated with symbols; p values (0.001, 0.01, 0.05, 0.1): symbols ("***", "**", "*", "."). The fourth column and row are bacterial wilt resistance in vegetative season 2, highlighted with green boxes.*

3.3.2 As a response variable

The worth parameters of the bacterial wilt resistance of potatoes in Rwanda surveyed in vegetative season 2 were focused on as a response variable because significant differences between varieties were found in Section 3.2. The worth parameters of pest and disease resistance and vigour in vegetative season 1 and pest and disease resistance in vegetative season 2 were used as explanatory variables as these variables were assumed to be related to bacterial wilt resistance in the dataset. The linear regression was used based on Section 3.1.

The stepwise method selected a model that included two explanatory variables, disease/insect resistance in vegetative seasons 1 and 2, based on the AIC (Table 3). The regression coefficients indicated that both explanatory variables had positive effects on the response variable, with a value of 0.408 for vegetative season 1 and 0.785 for vegetative season 2. The standardised regression coefficients showed that the vegetative season 2 was more important than the vegetative season 1. However, the *t* values for the vegetative season 1 and the vegetative season 2 were not significant, with *p* values larger than 0.05, indicating that neither variable was a significant predictor of bacterial wilt resistance. The model itself was not statistically significant, with an F value of 2.677 and a p value of 0.129, and an R^2 value of 0.251 (Table 3). The AIC of the model was -49.27, while the AIC of the intercept-only model was -47.63. This suggests that the model was not a significant improvement over the intercept-only model. Furthermore, there was no multicollinearity between the variables. Contrary to the initial hypothesis, other variables were unable to predict pest and disease resistance rankings.

Table 3 Summary of regression analysis for the bacterial wilt resistance (vegetative season 2) of potatoes in Rwanda. The adjusted R^2 value in the intercept row is the value of the full model. Otherwise, it shows the adjusted R^2 values when the variable in the same row is removed.

Response variable	Explanatory variable	Estimate	Std. error	t-value	*p* value	*F* value	Adj.R^2	AIC
Bacterial wilt resistance (vegetative season 2)	Intercept	-0.018	0.048	-0.368	0.722	F (2, 8) = 2.677, p = 0.129	0.251	-49.27
	Disease/insect resistance (vegetative season 1)	0.408	0.272	1.499	0.172		0.148	
	Disease/insect resistance (vegetative season 2)	0.785	0.433	1.811	0.108		0.062	

3.3.3 As an explanatory variable

The worth parameters of the bacterial wilt resistance of potatoes in Rwanda surveyed in vegetative season 2 were focused on as an explanatory variable. The worth parameter of yield and overall performance were selected as response variables as these variables are assumed to be more important for variety selection.

For the model with yield as a response variable, the candidate variables were disease/insect resistance, bacterial wilt resistance and vigour (vegetative season 1), disease/insect resistance and bacterial wilt resistance (vegetative season 2), and tuber size, appearance and maturity (post-harvest 1). A model with vigour (vegetative season 1), disease/insect resistance and bacterial wilt resistance (vegetative season 2), tuber size, appearance and maturity (post-harvest 1) as explanatory variables was selected. The model was statistically significant with an *F* value of 87.73 and a *p* value less than 0.001, and a high R^2 value of 0.981, indicating that the model explained a large portion of the variance in the yield. There was no multicollinearity among them. The AIC value was -85.09, while the AIC value of the intercept-only model was -43.33. The analysis revealed that five variables, including bacterial wilt resistance (vegetative season 2), were significant predictors of yield. The adjusted R2 values in Table 4 showed the values when the explanatory variable in the same row was removed from the full model. When bacterial wilt resistance (vegetative season 2) was removed from the selected model, the adjusted R^2 value was decreased to 0.832. This reduction was next to vigour (vegetative season 1). These results were consistent with the hypothesis that statistically significant relationships could be observed between bacterial wilt resistance and yield.

Table 4 Summary of regression analysis for the yield of potatoes in Rwanda. The adjusted R^2 value in the intercept row is the value of the full model. Otherwise, it shows the adjusted R^2 values when the variable in the same row is removed.

Response variable	Explanatory variable	Estimate	Std. error	t-value	*p* value	*F* value	Adj.R^2	AIC
Yield (post-harvest 1)	Intercept	0.012	0.013	0.927	0.406	F (6, 4) = 87.73, $p < 0.001$	0.981	-85.09
	Vigour (vegetative season 1)	0.546	0.055	9.915	< 0.001		0.614	
	Disease/insect resistance (vegetative season 2)	0.263	0.105	2.496	0.067		0.961	
	Bacterial wilt resistance (vegetative season 2)	0.551	0.087	6.369	0.003		0.832	
	Tuber size (post-harvest 1)	0.297	0.062	4.768	0.009		0.899	
	Appearance (post-harvest 1)	-1.074	0.195	-5.505	0.005		0.871	
	Maturity (post-harvest 1)	0.281	0.048	5.871	0.004		0.855	

For the overall performance, firstly, the candidate variables were vigour and bacterial wilt resistance (vegetative season 1), bacterial wilt resistance (vegetative season 2), yield, appearance and maturity (post-harvest 1), marketability and taste (post-harvest 2) and quality (post-harvest 3). A model with vigour and bacterial wilt resistance (vegetative season 1), bacterial wilt resistance (vegetative season 2), yield and appearance (post-harvest 1), taste (post-harvest 2) and quality (post-harvest 3) as explanatory variables was chosen (F (7, 3) = 111.3, p < 0.001) with an R^2 value of 0.987. The AIC value was -85.97, while the AIC value of the intercept-only model was -38.77. The adjusted R2 values in Table 5 showed when the explanatory variable in the same row was removed from the full model. Bacterial wilt resistance (vegetative season 2) was a significant predictor. When bacterial wilt resistance (vegetative season 2) was removed from the selected model, the adjusted R^2 value was decreased to 0.842.

Table 5 Summary of regression analysis for the overall performance of potatoes in Rwanda. The initial model contains vigour as an explanatory variable. The adjusted R^2 value in the intercept row is the value of the full model. Otherwise, it shows the adjusted R^2 values when the variable in the same row is removed.

Response variable	Explanatory variable	Estimate	Std. error	t value	p value	F value	Adj.R^2	AIC
Overall (post-harvest 3)	Intercept	-0.054	0.014	-3.913	0.030	F (7, 3) = 111.3, p < 0.001	0.987	-85.97
	Vigour (vegetative season 1)	-0.563	0.131	-4.315	0.023		0.931	
	Bacterial wilt resistance (vegetative season 1)	0.331	0.104	3.175	0.050		0.958	
	Bacterial wilt resistance (vegetative season 2)	-0.986	0.145	-6.805	0.006		0.842	
	Yield (post-harvest 1)	0.975	0.152	6.399	0.008		0.860	
	Appearance (post-harvest 1)	0.275	0.153	1.802	0.169		0.980	
	Taste (post-harvest 2)	0.957	0.091	10.566	0.002		0.634	
	Quality (post-harvest 3)	0.601	0.058	10.344	0.002		0.649	

However, the above model had multicollinearity, with the variance inflation factor (VIF) of vigour being 21.46, so vigour was removed. Then, bacterial wilt resistance (vegetative season 1), bacterial wilt resistance (vegetative season 2), yield, appearance and maturity (post-harvest 1), marketability and taste (post-harvest 2) and quality (post-harvest 3) were used as candidate variables. A model with bacterial wilt resistance (vegetative seasons 1 and 2), yield (post-harvest 1), taste (post-harvest 2) and quality (post-harvest 3) as explanatory variables was selected. The model was statistically significant, with an F statistic of 34.28 and an R^2 value of 0.943 (Table 6). The bacterial wilt resistance (vegetative season 2), yield (post-harvest 1), taste (post-harvest 2) and quality (post-harvest 3) were significant predictors. There was no multicollinearity between the variables in the second model based on the VIF. The AIC value was -67.97, while the AIC value of the intercept-only model was -38.77. The adjusted R2 values in Table 6 showed when the explanatory variable in the same row was removed from the full model. When bacterial wilt resistance (vegetative season 2) was removed from the selected model, the adjusted R^2 value was decreased to 0.875. These results supported the hypothesis that statistically significant relationships between bacterial wilt resistance and overall performance could be observed.

Table 6 Summary of regression analysis for the overall performance of potatoes in Rwanda. Vigour was removed from the initial model in consideration of multicollinearity. The adjusted R^2 value in the intercept row is the value of the full model. Otherwise, it shows the adjusted R^2 values when the variable in the same row is removed.

Response variable	Explanatory variable	Estimate	Std. error	t value	p value	F value	Adj.R^2	AIC
Overall (post-harvest 3)	Intercept	-0.031	0.105	-2.151	0.084	F (5, 5) = 34.28, $p < 0.001$	0.943	-67.97
	Bacterial wilt resistance (vegetative season 1)	0.378	0.201	1.883	0.118		0.919	
	Bacterial wilt resistance (vegetative season 2)	-0.773	0.269	-2.869	0.035		0.875	
	Yield (post-harvest)	0.352	0.113	3.117	0.026		0.861	
	Taste (post-harvest)	0.871	0.184	4.723	0.005		0.742	
	Quality (post-harvest)	0.518	0.115	4.491	0.006		0.762	

3.4. Relationship between pest and disease resistance rankings and environmental variables (RQ3)

The rankings of bacterial wilt resistance of potatoes in Rwanda surveyed in vegetative season 2 were analysed with the Plackett-Luce tree. The x-axis indicates the logarithmic scale of the worth parameter estimates, which are the probabilities of each variety to be ranked first. The maximum daytime temperature during the growing season split the rankings into two nodes (Figure 8). Preference for varieties differed over the maximum daytime temperature. In regions with maximum daytime temperatures of 25.43 °C or below, Cruza was most preferred, and Ndamira was least preferred. In regions with maximum daytime temperatures higher than 25.43 °C, Izihirwe was most preferred, closely followed by Nkunganire. Twihaze, in contrast, was the least preferred. The likelihood ratio test tested varietal differences in each node, and both nodes showed significant differences between varieties ($p = 0.007$ in node 2 and $p < 0.001$ in node 3).

When faced with a high risk of disease, a difference in estimates between resistant varieties and susceptible varieties assumes to be large compared to a low risk of disease. If the difference in the estimate is larger for one node, the variance is also expected to be larger and not equal to the variance of the other node. For this reason, the standard deviation and the equality of variance were checked. The standard deviation of estimates of nodes 2 and 3 were 0.32 and 0.42, respectively. Levene’s test showed that nodes 2 and 3’s variances did not significantly differ ($F(1, 20) = 0.68$, $p = 0.421$).

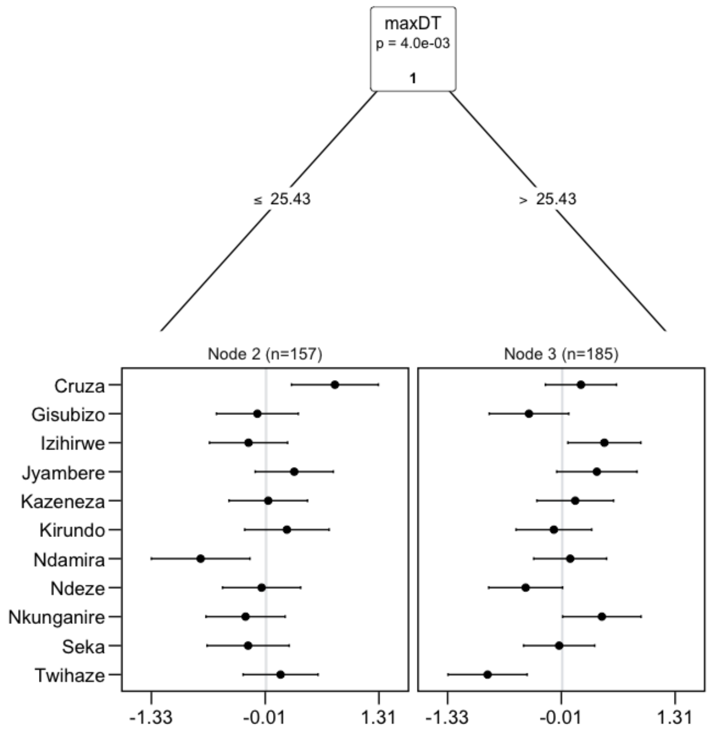

Figure 8 Effect of the maximum daytime temperature (maxDT) on bacterial wilt resistance in on-farm trials. The y-axis presents potato varieties. The x-axis presents worth, the log-probability of outperforming the other varieties in the set.

Table 7 shows that there were two susceptible varieties in the tested varieties. Twihaze, one of the susceptible varieties, was the least preferred when the maximum temperature was higher than 25.43 °C, shown in node 3 of Figure 8. In contrast, Kirundo, another susceptible variety, was not chosen as the least preferred in both nodes.

In summary, the maximum daytime temperature during the growing season split the bacterial wilt resistance rankings into two nodes. One of the susceptible varieties, Twihaze, was the least preferred in regions where the maximum daytime temperatures were higher than 25.43 °C. Each node showed significant varietal differences between varieties. A difference in the variance of estimates between nodes was expected, but there was none.

Table 7 Resistance of varieties. A: (Rwanda Agriculture Board, 2020)*, B:* (Uwamahoro et al., 2020)*, C:* (K. Sharma et al., 2021)

	Name of varieties	Introduced year	Bacterial wilt resistance	Reference
1	Nkunganire	2019	Yes	A
2	Izihirwe	2019	Yes	A
3	Ndamira	2020	Yes	A
4	Ndeze	2019	Yes	A
5	Seka	2020	Yes	A
6	Kirundo	30 years ago	Susceptible	B
7	Jyambere	2020	Yes	A
8	Gisubizo	2020	Yes	A
9	Cruza	30 years ago	Yes	B
10	Kazeneza	2019	Yes	A
11	Twihaze	2019	Susceptible	C

4. Discussion

This study aimed to analyse the rankings of pest and disease resistance in tricot trials, which were conducted in two steps. First, the efficacy of the Plackett-Luce Alternating Directions Method of Multipliers (PLADMM) was analysed since the effectiveness of using the worth parameter from the Plackett-Luce model as a covariate in the PLADMM was unknown. The efficacy analysis showed that the PLADMM with worth parameters was highly likely to reject the null hypothesis, even when the covariate was uncorrelated with the response variable. This suggested that the PLADMM has a high false positive rate. Therefore, the linear model with worth parameters was selected to investigate the relationship between pest and disease resistance and other variables. Next, pest and disease resistance ranking data collected from tricot trials were analysed with three research questions. The first research question aimed to confirm significant variety differences in pest and disease resistance rankings to see if farmers can discriminate varieties. It was found that the bacterial wilt resistance rankings of Rwandan potatoes had significant variety differences. This result suggested that farmers' evaluation of bacterial wilt resistance was not random. The second research question sought to investigate whether pest and disease resistance could be predicted by other variables or vice versa to see if the trends generally observed in non-ranking are also available in the ranking. Hypothesised that vigour and other pest and disease resistance rankings would be significant predictors of bacterial wilt resistance. However, none of these variables were found to be significant. It was also hypothesised that the bacterial wilt resistance would be a significant explanatory variable of yield and overall performance. This hypothesis was confirmed, as bacterial wilt resistance proved to be one of the significant predictors of yield and overall performance. Notably, bacterial wilt resistance predicted overall performance independently of other variables, such as vigour and yield. It was proof that farmers evaluated based on disease resistance independently of yield and vigour, which are potential confounders. The third research question was formulated to determine whether environmental variables influence the ranking of pest and disease resistance of varieties and, if so, whether these relationships are consistent with the expected determinants of pest and disease pressure. The assumption was that the resistance rankings would provide evidence of the actual differences in disease resistance by showing the expected determinants' relationship. The results revealed that the maximum temperature during the vegetative season significantly affected potatoes' bacterial wilt resistance in Rwanda. This relationship's consistency with the expected disease-pressure determinants is discussed in detail below.

4.1 The efficacy of the PLADMM

The efficacy analyses indicated that the PLADMM with worth parameters had a higher probability of rejecting the null hypothesis than the linear regression with actual values and parameters. This trend was observed even when the response and explanatory variables were uncorrelated, although linear regression showed a uniform distribution. This suggested that the PLADMM with worth parameters had a high false positive rate. This was expected to be due to the sensitivity of the PLADMM to even small correlations based on the PLADMM with five uncorrelated covariates (Section 3.1.3).

This study selected the linear regression with worth parameters for the following analyses because the simulations without correlation revealed a low false positive rate. Additionally, in the model with one correlated and four uncorrelated covariates, the probability of rejecting the null hypothesis was almost the same as in the linear regression with actual values. However, in the model with a correlated covariate, the linear regression with the worth parameter showed a higher rejection rate than the linear regression with actual values. A possible reason is that the Plackett-Luce model already summarised the worth parameters, representing only partial information. In particular, the effect of outliers may have been reduced when parameterising, which may affect the model's predictions. This factor should be considered to improve selecting models with worth parameters as covariates.

4.2 The randomness of farmers' evaluation

A significant variety difference was found in the bacterial wilt resistance of potatoes in Rwanda. This result indicated that farmers' ranks were not random in this evaluation. Evaluating pest and disease resistance was assumed to pose a challenge to farmers since they possibly answer as if pests occurred when pests did not occur, as they may feel obligated to answer questions politely and are not trained to diagnose plant pests and diseases. Nevertheless, a possible reason for the statistically significant difference could be that the evaluation focused on a single disease, a primary constraint for potato production in Rwanda (Shimira et al., 2020). A study reported bacterial wilt disease in 86% of potato farms (Uwamahoro et al., 2018). Untrained farmers may find identifying the wilting symptom caused by bacterial wilt straightforward. According to Uwamahoro et al. (2018), 98.3% of Rwandan potato farmers recognise that wilting of the leaves is one of the symptoms of bacterial wilt. Focusing on one critical disease and the high proportion of farmers familiar with the disease may have contributed to the accurate evaluation by farmers.

Pest and disease resistance rankings of potatoes in Rwanda, other than bacterial wilt, showed no statistical differences between varieties. Some pests and diseases other than bacterial wilt cause potato yield loss in Rwanda, namely white grubs (*Phyllophaga spp*. and other Scarabaeidae), potato tuber moths (*Phthorimaea operculella*) and late blight disease (*Phytophthora infestans*) (Shimira et al., 2020). Assuming that farmers can diagnose these pests and diseases, three possible explanations exist for the lack of differences in pest and disease resistance rankings. First, insecticides are commonly used against late blight and white grubs (Muhinyuza et al., 2007; Shimira et al., 2020), whereas bactericides are unavailable for bacterial wilt during the growing season. The pesticides might give protection other than the varieties' resistance, and resistance could not be correctly evaluated. Second, white grubs and potato tuber moths can cause damage to potatoes in the soil. However, pest and disease resistance was evaluated during the growing season. It is, therefore, possible that damage in the soil caused by these pests was not taken into account in the evaluation. Symptoms of bacterial wilt are visible on the ground. Third, a grouping of several pests and diseases made evaluations difficult. This is also true for common beans in Central America and East Africa and cowpea in Nigeria, which did not exhibit significant variety differences in pest and disease resistance. Except for the bacterial wilt resistance evaluation of potatoes in Rwanda, other evaluation items lumped pests and diseases together in one or two categories, such as pest resistance and disease resistance or pest and disease resistance. Grouping pests and diseases may cause inaccurate evaluations as different pests and diseases might attack different varieties. Therefore, considering the specific pest or disease of interest in genotype-by-environment interaction tests for pest and disease resistance is assumed to be necessary. Previous studies have also focused on specific pests, such as charcoal rot in common beans and thrips in cowpea, which support this assumption (García-Olivares et al., 2012; Toyinbo et al., 2021).

4.3 Relationship between pest and disease resistance and other variables

The relationship between pest and disease resistance and other variables was tested to see if the trends commonly observed in non-ranking are also available in the ranking. If this commonly observed trend could be observed in the ranking data, it could be said that the ranking data for pest and disease resistance is picking up actual differences in disease resistance.

In the analysis with bacterial wilt as the response variable, vigour and pest/disease resistance other than bacterial wilt were used as explanatory variables. The variables were selected since the plant's resistance can decrease due to the damage caused by other pests and diseases or its inherent vigour, making it more susceptible to bacterial wilt infection. However, the model did not show a relationship between the resistance and selected variables. This could be due to other conditions affecting bacterial wilt resistance. Plant diseases occur when the pathogen, plant susceptibility and environmental factors are three favourable conditions for disease development (Velásquez et al., 2018). The model explained only part of this plant susceptibility. Bacterial wilt is a soil-borne disease affected by soil disinfection, crop rotation, and wider spacing planting (Ahmed et al., 2013; Katafiire et al., 2005; Uwamahoro et al., 2018). If these variables were available, it could be checked whether the bacterial wilt resistance ranking reflects actual differences.

The ranking of bacterial wilt resistance was a significant predictor of yield, essential factor for selecting varieties. A study reported a negative correlation between yield and disease damage (Bruno et al., 2017). Bacterial wilt causes severe damage as it induces chlorosis, stunting and wilting, eventually killing leaves and stems (Ahmed et al., 2013). Previous studies have reported that pests and diseases can cause yield reductions ranging from 50% to 100% in Kenya (Muthoni et al., 2014a) and up to 75% in Australia (Stansbury et al., 2001). Thus, bacterial wilt resistance can be inferred to have been a significant explanatory variable for yield.

Bacterial wilt resistance was a significant predictor of overall performance, even when potential confounder vigour was removed. Furthermore, there was no multicollinearity between bacterial wilt resistance and yield, which is also a potential confounder. These results showed that bacterial wilt resistance predicted overall performance independently of other confounding variables, such as vigour and yield. It was one of the proofs that farmers evaluated disease resistance independently of potential confounders.

4.4 Relationship between bacterial wilt and environmental factors

The varietal differences in bacterial wilt resistance of potato plants in Rwanda were shown to be related to the maximum day temperature during the vegetative period. The variety performance changed as the maximum day temperature crossed the threshold of 25.43°C. The bacterium causing wilt disease, *Ralstonia solanacearum*, is known to cause the most severe damage to plants when the temperature ranges between 25°C and 35°C (Singh et al., 2014). Therefore, it was assumed that the node above 25.43°C showed a high disease pressure. Twihaze, one of the susceptible varieties, was selected as the least preferred under high disease pressure. It suggested that bacterial wilt was present, reflected in differences in resistance, and farmers correctly discriminated. Kirundo was also a susceptible variety, although it performed well above and below 25.43°C. This result indicated that farmers' resistance evaluation might identify susceptible varieties but not always.

In high disease pressure, differences in resistance performance between susceptible and resistant varieties are assumed to be larger. Therefore, it was expected to see a significant difference in the variance above or below 25.43°C in high disease pressure. However, low disease pressure, where the maximum day temperatures were below 25.43°C, showed an equal variance as high disease pressure. This could be due to a significant difference between Cruza, the most preferred, and Ndamira, the least preferred. Research has shown bacterial wilt becomes less aggressive when temperatures are below 18°C (Singh et al., 2014); however, the minimum daytime temperature remained above 18°C at all sites in the trials of potatoes in Rwanda. So it is quite possible that the disease could have occurred. Even with low disease pressure, plants can be made vulnerable or more resistant to disease because the interaction between plants and pathogens can be affected by abiotic stress (Sinha et al., 2016). This possibly caused differences among varieties, even when at lower temperatures.

Bacterial wilt is also known to cause more damage when rainfall is heavy. For example, *R. solanacearum* is famous as a waterborne pathogen that spreads to non-infested plants after rainfall (Manda et al., 2020). Also, it develops when there are high soil moisture accumulations due to heavy rainfall (Hayward, 1991). However, this trend was not shown in the Plackett-Luce tree. This was probably because there were only 342 observations in the dataset used for the Plackett-Luce tree. Increasing the sample size may increase the statistical power and detect more relationships with environmental factors. Collecting more data may reveal other relationships with environmental variables not captured in this study.

4.5 Recommendations

In order to improve the accuracy of evaluating pest and disease resistance by tricot trials, it may be more beneficial to collect rankings for one target pest or disease rather than a broad target of pests and diseases. Farmers are more likely to be familiar with the symptoms of a critical pest or disease, so this would make rankings more accurate. It is also recommended to include other factors related to pests and diseases in the survey, such as the use of pesticides and crop rotation history. Furthermore, it is essential to identify the relevant environmental factors that affect the developmental conditions of targeted pests and diseases, such as temperature, rainfall, humidity, light intensity, and wind speed. These factors can significantly impact pest and disease outbreaks and dispersion and, thus, should be taken into account during the evaluation process. It is necessary to conduct a literature review and consult with plant pathologists. By doing so, the evaluation process can be more reliable and effective in determining target crops' pest and disease resistance, which can lead to improved crop management practices and increased crop yields.

4.6 Conclusion

This study indicates that farmers' evaluation in the tricot trial can find varietal differences in potatoes' bacterial wilt resistance rankings in Rwanda, which suggests that farmers' evaluation was not random. Bacterial wilt resistance was a significant predictor of overall performance independently of yield and vigour, potential confounding variables. It was one of the proofs that farmers evaluated disease resistance independently of potential confounders. The preferred variety of bacterial wilt resistance varied depending on whether the maximum day temperature during the vegetative period was above or below 25.43°C. This result was aligned with the known disease-occurring factor that bacterial wilt causes the most severe damage when the temperature ranges between 25°C and 35°C. Additionally, the susceptible variety was selected as the least preferred in warmer environments, where the disease is known to cause severe damage. These results indicated that farmers' evaluations of bacterial wilt resistance seemed to reflect the actual differences in disease resistance. On the contrary, pest and disease resistance evaluations in other crops did not show significant differences between varieties. There could be several reasons for this, including the use of pesticides, unsuitable timing of evaluations, and not focusing on a specific pest. Assessing pest resistance by farmers has been thought to be challenging due to the requirement of specialised knowledge. However, this study suggested the possibility of obtaining the actual differences in disease resistance from farmers' best and worst evaluations under the right conditions. The tricot trial will accelerate the selection of pest-resistant varieties suitable for their environment.

5. References

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Appendix. Relationship between rankings (related to RQ2)

The analyses below were conducted on the variables selected on the basis of research question 2. The stepwise regression was used to select the model, and the best model was selected based on AIC. The candidate variables were selected that seemed relevant. Abbreviations used in this appendix are V for vegetative seasons, R for reproductive seasons, and PH for post-harvest.

1. Common bean in Central America

For the yield, disease resistance, pest resistance and vigour were selected as the candidate variables. A model with vigour as an explanatory variable was chosen ($F(1, 36) = 8.434$, $p = 0.006$) with an R^2 of 0.167 (Table 1). For the overall appreciation, disease resistance, pest resistance vigour and yield were selected as the candidate variables. A model with pest and yield as explanatory variables was chosen ($F(2, 35) = 22.12$, $p < 0.001$) with an R^2 of 0.533 (Table 1). The yield was a significant predictor of the overall appreciation. There was no multicollinearity between the variables.

Table 1 Relationship between variables of common bean in Central America

Response variable	Explanatory variable	Coefficient	t-value	*p* value	F-value	R-squared	AIC
Yield	Intercept	0.016	4.212	< 0.001	F (1, 36) = 8.434, *p* < 0.006	0.167	-399.67
	Vigour	0.402	2.904	0.006			
Overall	Intercept	0.006	1.978	0.056	F (2, 35) = 22.12, *p* < 0.001	0.533	-429.37
	Pest resistance	0.180	1.608	0.117			
	Yield	0.577	5.270	< 0.001			

2. Common bean in East Africa

The candidate variables were disease resistance (V), pest resistance (V), drought tolerance (V), vigour (R), disease resistance (R), pest resistance (R), plant survival (R), plant survival (PH) and grain size (PH). A model with disease resistance (vegetative and reproductive), pest resistance (reproductive) and plant survival (PH) as explanatory variables was chosen ($F (4, 25) = 9.357$, $p < 0.001$) with an R^2 of 0.536 (Table 2). The disease (vegetative and reproductive) and plant survival (PH) were significant predictors of the yield. There was no multicollinearity between the variables.

Table 2 Relationship between variables of common bean in East Africa

Response variable	Explanatory variable	Coefficient	t-value	*p* value	F-value	R-squared	AIC
Yield	Intercept	0.061	7.002	< 0.001	F (4, 25) = 9.357, *p* < 0.001	0.536	-260.74
	Disease resistance (vegetative season)	-0.520	-2.737	0.011			
	Disease resistance (reproductive season)	1.130	2.757	0.011			
	Pest resistance (reproductive season)	-0.818	-1.756	0.091			
	Plant survival (post-harvest)	-0.743	-4.130	< 0.001			

3. Cowpea in Nigeria

The candidate variables were disease resistance (V), pest resistance (V), drought tolerance (V), disease resistance (PH), pest resistance (PH), drought tolerance (PH) and striga resistance (PH). A model with drought tolerance (V) and disease resistance (PH) as explanatory variables was chosen ($F (2, 15) = 3.08$, $p = 0.076$) with an R^2 of 0.197 (Table 3). Both predictors did not have a significance on the maturity. There was no multicollinearity between the variables.

Table 3 Relationship between variables of cowpea in Nigeria

Response variable	Explanatory variable	Coefficient	t-value	*p* value	F-value	R-squared	AIC
Maturity	Intercept	0.059	2.601	0.020	F (2, 15) = 3.08, *p* = 0.076	0.197	-148.74
	Drought tolerance (vegetative season)	-0.523	-1.947	0.071			
	Disease resistance (post-harvest)	0.464	1.546	0.143			

4. Potato in Rwanda

For the vigour (V1), disease/insect resistance and bacterial wilt resistance (both in V1) were candidate explanatory variables. A model with bacterial wilt resistance as an explanatory variable was chosen (F (1, 9) = 2.78, p = 0.130) with an R^2 of 0.151 (Table 4). The bacterial wilt resistance was not a significant predictor of vigour.

For the maturity (PH1), the candidate variables were disease/insect resistance, bacterial wilt resistance and vigour (V1), disease/insect resistance and bacterial wilt resistance (V2), and tuber size and appearance (PH1). A model with vigour as explanatory variables was chosen (F (1, 9) = 2.78, p = 0.130) with an R^2 of 0.151 (Table 4). The vigour was not a significant predictor of bacterial wilt resistance.

For the tuber size (PH1), the candidate variables of the tuber size were disease/insect resistance, bacterial wilt resistance and vigour (V1) and disease/insect resistance and bacterial wilt resistance (V2). A model with vigour in V1 and bacterial wilt resistance in V2 as explanatory variables was chosen (F (2, 8) = 5.935, p = 0.026) with an R^2 of 0.497 (Table 4). The vigour was a significant predictor of maturity. There was no multicollinearity between the variables.

For the marketability (PH2), the candidate variables were vigour and bacterial wilt resistance (V1), bacterial wilt resistance (V2), yield, tuber size, appearance, maturity and taste (PH1) and taste (PH 2). A model with vigour and bacterial wilt resistance in V1, appearance and maturity in PH1 and taste in PH 2 as explanatory variables was chosen (F (5, 5) = 30.69, p < 0.0001) with an R^2 of 0.937. The bacterial wilt resistance, maturity and taste were significant predictors of the marketability. There was no multicollinearity between the variables.

For the taste (PH2), the candidate variables were vigour, bacterial wilt resistance and disease/insect resistance (V1), bacterial wilt resistance and disease/insect resistance (V2) and taste (PH2). A model with vigour in V1 and bacterial wilt resistance in V2 as explanatory variables was chosen (F (2, 8) = 4.957, p = 0.040) with an R^2 of 0.442 (Table 4). The bacterial wilt resistance was a significant predictor of the taste (PH2). There was no multicollinearity between the variables.

For the quality (PH 3), firstly, the candidate variables were vigour and bacterial wilt resistance (V1), bacterial wilt resistance (V2), yield, tuber size and appearance (PH1) and marketability and taste (PH2). A model with vigour and bacterial wilt resistance (V1), bacterial wilt resistance (V2), yield, appearance and tuber size (PH1) and marketability (PH2) as explanatory variables was chosen (F (7, 3) = 3.154, p = 0.187) with an R^2 of 0.601. However, there was multicollinearity between the variables, so vigour and appearance were removed. Secondly, bacterial wilt resistance (V1), bacterial wilt resistance (V2), yield and tuber size (PH1) and marketability and taste (PH2) were selected as candidate variables. A model with bacterial wilt resistance (V1), appearance, marketability and taste (PH1), and taste (PH2) as explanatory variables was chosen (F (5, 5) = 3.57, p = 0.094) with an R^2 of 0.562 (Table 4). There was no significant predictor. There was no multicollinearity between the variables in the second model.

For the overall, firstly, the candidate variables were vigour and bacterial wilt resistance (V1), bacterial wilt resistance (V2), yield, appearance and maturity (PH1), marketability and taste (PH2) and quality (PH3). A model with vigour and bacterial wilt resistance (V1), bacterial wilt resistance (V2), yield and appearance (PH1), taste (PH2) and quality (PH3) as explanatory variables was chosen ($F(7, 3) = 111.3$, $p < 0.001$) with an R^2 of 0.987. However, there was multicollinearity between the variables, so vigour was removed. Secondly, bacterial wilt resistance (V1), bacterial wilt resistance (V2), yield, appearance and maturity (PH1), marketability and taste (PH2) and quality (PH3) were used as candidate variables. A model with bacterial wilt resistance (V1 and 2), yield (PH1), taste (PH2) and quality (PH3) as explanatory variables was chosen ($F(5, 5) = 34.28$, $p < 0.001$) with an R^2 of 0.943 (Table 4). The bacterial wilt resistance (V2), yield (PH1), taste (PH2) and quality (PH3) were significant predictors. There was no multicollinearity between the variables in the second model.

Table 4 Relationship between variables of potato in Rwanda

Response variable	Explanatory variable	Coefficient	t-value	*p* value	F-value	R-squared	AIC
Vigour (vegetative season 1)	Intercept	0.157	3.778	0.004	F (1, 9) = 2.78, *p* = 0.130	0.151	-67.71
	Bacterial wilt resistance (vegetative season 1)	-0.724	-1.667	0.130			
Maturity (post-harvest 1)	Intercept	0.097	2.022	0.078	F (2, 8) = 5.935, *p* = 0.026	0.497	-73.2
	Vigour (vegetative season 1)	0.604	2.698	0.027			
	Bacterial wilt resistance (vegetative season 2)	-0.673	-1.582	0.152			
Tuber size (post-harvest 1)	Intercept	0.232	3.522	0.010	F (3, 7) = 12.45, *p* = 0.003	0.775	-79.3
	Vigour (vegetative season 1)	0.575	3.230	0.014			
	Disease/insect resistance (vegetative season 1)	-1.147	-3.719	0.007			
	Disease/insect resistance (vegetative season 2)	-0.978	-1.834	0.109			
Marketability (post-harvest 2)	Intercept	-0.104	-4.007	0.010	F (5, 5) = 30.69, *p* < 0.001	0.937	-103.3
	Vigour (vegetative season 1)	0.157	1.521	0.189			
	Bacterial wilt resistance (vegetative season 1)	0.333	2.734	0.041			
	Appearance (post-harvest 1)	0.652	2.549	0.051			
	Maturity (post-harvest 1)	0.257	2.891	0.034			
	Taste (post-harvest 2)	0.740	5.867	0.002			
Taste (post-harvest 2)	Intercept	0.011	0.418	0.687	F (2, 8) = 4.957, *p* = 0.040	0.442	-86.69
	Vigour (vegetative season 1)	0.202	1.668	0.134			
	Bacterial wilt resistance (vegetative season 2)	0.678	2.943	0.019			

Quality (post-harvest 3)	Intercept	-0.217	-1.790	0.134	F (5, 5) = 3.57, *p* = 0.094	0.562	-74
	Bacterial wilt resistance (vegetative season 1)	-0.585	-1.640	0.162			
	Appearance (post-harvest 1)	-2.480	-1.481	0.199			
	Marketability (post-harvest 1)	2.850	2.045	0.096			
	Taste (post-harvest 1)	2.436	1.896	0.117			
	Taste (post-harvest 2)	1.169	2.193	0.080			