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Climate-Related Risk Modeling of Banana Xanthomonas Wilt Disease Incidence in the Cropland Area of Rwanda

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Abstract

Banana Xanthomonas wilt (BXW) is a major threat to banana production in Rwanda, causing up to 100% yield loss. There are no biological or chemical control measures, and little is known about the potential direction and magnitude of its spread; hence, cultural control efforts are reactive rather than proactive. In this study, we assessed BXW risk under current and projected climates to guide early warning and control by applying the maximum entropy (Maxent) model on 1,022 georeferenced BXW datapoints and 20 environmental variables. We evaluated the significance of variables and mapped potential risk under current and future climates to assess spatial dynamics of the disease distribution. BXW occurrence was reliably predicted (mean validation AUC values ranging from 0.79 to 0.85). Precipitation of the coldest quarter, average maximum monthly temperature, annual precipitation, and elevation were the strongest predictors, which were responsible for 22.1, 13, 12.6, and 9.4% of the observed incidence variability, respectively, while mean temperature of the coldest quarter had the highest gain in isolation. Furthermore, the most susceptible regions (western, northern, and southern Rwanda) were characterized by elevation (1,350 to 2,000 m), annual precipitation (900 to 1,700 mm), and average temperature (14 to 20°C), among other variables, suggesting that a consistent, rainy, and warm climate is more favorable for BXW spread. Under the future climate, the risk was predicted to increase and spread to other regions. We conclude that climate change will likely exacerbate BXW-related losses of banana land area and yield under the influence of temperature and moisture. Our findings support evidence-based targeting of extension service delivery to farmers and national early warning for timely action.

Keywords: banana Xanthomonas wilt, BXW, climate change, crowdsourcing, decision support, early warning, plant disease surveillance, spatial risk

The world's population is gradually growing and projected to reach 9 billion by the year 2050. Approximately 815 million people are chronically undernourished (FAO 2018), with the demand for food rising with population growth. It is important to enhance food security by increasing food production, upward of 50% of the current supply, to feed the growing population (FAO 2018). However, the global food production is threatened by pests and diseases, food losses, climate change, and changing diets, among other factors (Allen et al. 2019; Okonya et al. 2019). Monitoring and controlling the spread of crop diseases and pests, especially under changing climates, is one of the critical requirements to increase food production and improve national food security.

Banana is a major crop in the global agricultural production and trade (Arias 2003). It is a very important fruit in Central Africa (including Uganda, Rwanda, and Burundi), where studies have shown that it contributes 30 to 60% of the daily per capita caloric intake (Abele et al. 2007). Rwanda is one of the largest banana producers in Central Africa, where approximately 75% of the farmers cultivate on less than 0.7 ha of land (Tuyishime et al. 2020). Banana is a staple food and source of income for many smallholder farmers in Rwanda (Gaidashova et al. 2005). On average, the banana consumption in the country is 144 kg/capita per year (Okonya et al. 2019). Banana cultivation covers 23% of the country's agricultural land area, cultivated by approximately 90% of smallholder farmers (Gaidashova et al. 2005; Nsabimana et al. 2008; Rietveld et al. 2020), and contributes to more than 50% of the country's annual crop production by yield (Mpyisi et al. 2000), with on-farm yield reaching 6.18 t/ha (Okonya et al. 2019). However, banana production in the country is threatened by the Xanthomonas wilt disease (BXW), which has negatively impacted the region's food security (McCampbell et al. 2018; Tripathi et al. 2009).

A study by Geberewold (2019) showed that BXW disease was the greatest challenge faced by most farmers in Burundi, Rwanda, and Tanzania. BXW has been reported to cause 100% yield loss if not duly controlled (Nkuba et al. 2015). In Rwanda, a 35% reduction in banana supply and doubling of prices as a result of BXW outbreaks were reported (Nkuba et al. 2015). In another study, approximately 70% of interviewed farmers reported a significant change in their daily dietary patterns because of BXW outbreaks (Geberewold 2019). Therefore, BXW continues to pose significant implications for food security of smallholder farmers across Rwanda and East Africa.

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Data availability: The data presented in this study are available on request from the corresponding author.

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The BXW disease is caused by the bacterium *Xanthomonas campestris* pv. *musacearum* (Yirgou and Bradbury 1968). It affects all banana (*Musa* spp.) cultivars and varieties (Tripathi et al. 2009; Yirgou and Bradbury 1974). It was first reported in Ethiopia (Yirgou and Bradbury 1974), then quickly spread out to Uganda (Tushemereirwe et al. 2004), and then to other neighboring countries, including Tanzania, Kenya, Rwanda, Burundi, and the Democratic Republic of the Congo (DRC) (Carter et al. 2010). In Rwanda, the disease was first reported in 2002 and spread across the banana producing regions (Rietveld et al. 2020). The major conditions for the spread of BXW have been attributed to biological and social factors. For instance, the bacterium is insect-borne, as suggested by sudden outbreaks in old or isolated plantations (Tripathi et al. 2009), while the transport of infected banana material and contaminated tools by farmers can also lead to rapid spread to previously uninfected areas (Geberewold 2019; Rietveld et al. 2020). Infected seedlings and bacteria penetration through pest-injured roots are also known to spread the disease (Tripathi et al. 2009). The spread of BXW in Rwanda has also been attributed to these major factors.

Knowledge of where and when a disease occurs is crucial for improving the efficiency of surveillance and identifying necessary control strategies (Madden et al. 2007). Epidemiological studies on BXW have been conducted (Adikini et al. 2013), and studies on the spatial and temporal distribution of BXW in relation to environmental factors have been conducted in the surrounding countries (Haile 2020; Ocimati et al. 2019; Shimwela et al. 2017). Despite these efforts, there is a general lack of knowledge about the spatial and temporal distribution of BXW, the risk of its spread in banana-growing areas of Rwanda, and the main factors affecting the spread. Species distribution modeling and geographical information systems provide promising approaches to assessing the distribution of BXW by unraveling the patterns of occurrence and risk levels at field, regional, and national spatial scales. Several species distribution models (SDMs), such as maximum entropy (Maxent), have been proven effective for disease risk modeling (Pearson et al. 2007; Shimwela et al. 2017). Environmental and climatic factors significantly influence the biological and chemical activities of living organisms; therefore, they are often regarded as determinants of the geographical distribution of diseases and pests. For instance, in a comparative study by Maina et al. (2006), higher spread rates have been reported at mid altitudes (800 to 1,500 m) as compared with higher altitudes (Maina et al. 2006) as the effect of insect vectors is less in cold, higher areas (Tripathi et al. 2009). In general, SDMs can help to evaluate climatic requirements for disease establishment and how environmental covariates relate to the spatial occurrence of a disease. Maxent (Phillips et al. 2006) is a presence-only prediction tool that applies the maximum entropy approach for modelling species distributions. It has been shown to work better with smaller sample sizes, in combination with continuous and categorical variables (Phillips et al. 2006), and driven by machine learning algorithms. Considering that the Maxent model has been used to determine the potential regions that are at high risk of BXW pathogen establishment in Tanzania (Shimwela et al. 2017), the model can also be used to determine potential BXW spread under future climates. According to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC), global climate change is occurring at an extraordinary rate, with average temperatures expected to rise by a minimum of 0.3 to 1.7°C and a maximum of 2.6 to 4.8°C by the year 2100 (Stocker 2014). With the evolving knowledge of climate change and its impact on farming systems, an understanding of BXW distribution under future climatic scenarios can aid in policy making for timely and relevant actions.

To effectively advance the control and prevention of BXW spread across the cropland in Rwanda, it is imperative to assess and delineate potential areas that are at high risk of BXW spread in both the present and future climatic conditions. Knowledge of vulnerable regions and potential hotspots is necessary for timely action toward minimizing the negative impact on banana production and overall national food security. Potential occurrence maps are crucial for risk assessment, surveillance, and allocation of the necessary resources by the government to combat the incidence and spread of BXW. Therefore, the aim of this study is to spatially assess the vulnerability of banana-cultivated lands in Rwanda to BXW disease under both the current climate and the projected climate for the 2050s. This study contributes to the regional interest in evolving and supporting relevant policies for BXW mitigation by addressing the following research questions: (i) What are the climatic and environmental risk factors that have the most influence on the spread of BXW in Rwanda? (ii) Are the identified environmental risk factors different under climate change scenarios? (iii) Which are the most vulnerable areas to the risk of BXW occurrence under current and future climate scenarios?

Materials and Methods

Study region

The study was conducted in Rwanda (Fig. 1), one of the most densely populated countries in Africa with a population of 12.5 million as of 2018, of which 80% live in the rural areas where food crops are the main source of food and income (Tuyishime et al. 2020). Agriculture is the major economic activity in the country and contributes to approximately 33% of the national GDP (FAO 2018). Rwanda is a land-locked country, with elevation ranging from 950 to 4,519 m above sea level and annual rainfall ranging from 700 to 1,600 mm. The mean annual temperature is 19.1°C and varies seasonally, ranging from 10°C in the colder season to 22°C in the hotter season.

Maxent model overview

Maxent (version 3.4.1) is an open-source modeling tool that is designed for assessment and prediction of species distributions based on the attainment of maximum entropy under various ecological conditions (Phillips et al. 2006). Maxent predicts the potential distribution of a species by analyzing location-based data as a function of environmental variables (Elith et al. 2006). It requires only the data about occurrence of a species to predict its suitable habitat, based on underlying ecological variables. Maxent algorithms are based on computation of occurrence probability that is derived from randomly generated background points and occurrence data to subsequently determine the maximum entropy of the distribution. The model uses a set of features (e.g., linear, quadratic, product, threshold, and hinge) that are functions of environmental variables to constrain the geographic distribution of the target species and applies regularization parameters to control or avoid overfitting. Maxent can be used when distribution data are sparse because it leverages machine learning algorithms based on information about the presence of the species and consequently generates a spatial prediction of incidence risk of ecological suitability for the species occurrence. The Maxent model assumes that the region of interest is systematically or randomly sampled (Phillips et al. 2009; Royle et al. 2012), and its prediction accuracy is evaluated using area under curve (AUC) values (Phillips et al. 2019). The AUC value ranges from 0 to 1 (Fielding and Bell 1997), which represents the proportion of area under the receiver operating characteristic curve plot, indicating the performance of the binary classifier (i.e., present or not present). An AUC value of 0.5 would indicate that the model did not perform better than the random model, whereas an AUC value of 1.0 indicates perfect discrimination (Swets 1988). AUC values above or equal to 0.7 are recommended to validate the performance of the Maxent model (Hosmer et al. 1989), with AUC greater than 0.9 indicating high performance.

Data

BXW occurrence data. We collected data on the presence of BXW disease in farmers' fields through enumerator-led field surveys and farmer-implemented data reporting with a diagnostic tool, the BXW app (www.ict4bxw.com). The BXW app is an android-based smartphone application, which was codeveloped for BXW surveillance, diagnosis, and control. It was developed through a participatory inclusive technology development process, under the auspices of a project that leveraged citizen science and digital tools to advance the prevention and control of BXW in Rwanda. Through the app, farmers and extension providers contribute to data collection on BXW occurrence across various regions of the country. Other than location and disease presence data, farmers provide the demographic information, time of data submission, and the information on farm sizes and administrative regions. The collected dataset was subsequently used for near-real time surveillance of the disease. The disease incidence (or presence) data consist of georeferenced point locations of observed BXW occurrence in banana farms from Oct 2018 to Feb 2022. The field survey was conducted in four major banana-production districts using a stratified random sampling design. We accessed the database of land parcel owners to gather information about banana farmers (and plots) within the spatial strata (districts) and conducted a random selection of target plots for BXW diagnosis, using the spatial sampling tool in ArcGIS 10.8.1. The crowdsourced incidence data were curated through village-level farmer promoters who visited peer farmers within their respective villages to diagnose BXW disease within respective farms using the android-based BXW app. The app allows users to access information about BXW, conduct a stepwise diagnosis based on the in-built decision-tree algorithm, and implement relevant control or prevention measures based on the guided procedure within the application, as shown in Supplementary Figures S2 and S3. Internally, the app automatically logs the results of the stepwise diagnosis (either positive or negative) and records the geographic coordinates of the location, with subsequent transmission of the data to a back-end cloud-based database where the data (plus metadata) are stored. In total, 4,486 diagnoses were completed and downloaded from the database, with 1,022 records of positive BXW diagnosis. Based on the input requirement of the Maxent model, BXW incidence data were extracted and formatted into comma delimited (.csv) format and were checked for missing values, duplicates, and inconsistent coordinates. The point locations of the dataset were used in combination with environmental variables to spatially predict the potential risk of BXW occurrence within the country.

Environmental variables. We selected and sourced environmental covariates that have been documented to have potential influence on BXW spread. Many climatic variables have been used by researchers to predict potential distributions of species, mainly under the influence of temperature and precipitation changes. The selected climatic variables (and elevation) in this study have been previously reported to influence the likelihood of transmission by the disease pathogen and infection of the host plant (Biruma et al. 2007; McCampbell et al. 2018; Ocimati et al. 2019; Shimwela et al. 2017; Tripathi et al. 2009). In addition, proximity to roads was included in the model setup based on the reports suggesting that BXW may have spread to Rwanda from the DRC's Kivu region because of continuous exchange of people and goods across the Rubavu–Goma border (McCampbell et al. 2018; Reeder et al. 2007). Most of our environmental variables were sourced as raster data files from open-source databases (Table 1). For instance, current and historical climatic data were obtained from the WorldClim database (Fick and Hijmans 2017) at 30 arc seconds resolution and future climate data (2050s) from the CCAFS database (Ramírez-Villegas and Jarvis 2010), which includes 18 global climate models (GCMs) for two representative concentration pathways (RCPs; 6.0 and 8.5). The RCPs, as described by IPCC, show the potential future emission scenarios, where RCP 6.0 represents the intermediate emission scenario and RCP 8.5 represents the highest baseline scenario for rising emissions throughout the 21st century. In essence, the projections under RCP 8.5 indicate a more severe climate than the climate projections under RCP 6.0. For the current and historical climate data (which were precipitation and temperature), we computed averages for 1970 to 2000 and also 10-year averages from 2008 to 2018. The elevation data layer was sourced from the CGIAR database (Ramírez-Villegas and Jarvis 2010) at a resolution of 90 m. The land cover data were modeled using the available ground truth data to include banana land cover while the proximity of the roads layer was obtained locally using Rwandan major roads. A croplands raster, as defined by NASA (Xiong

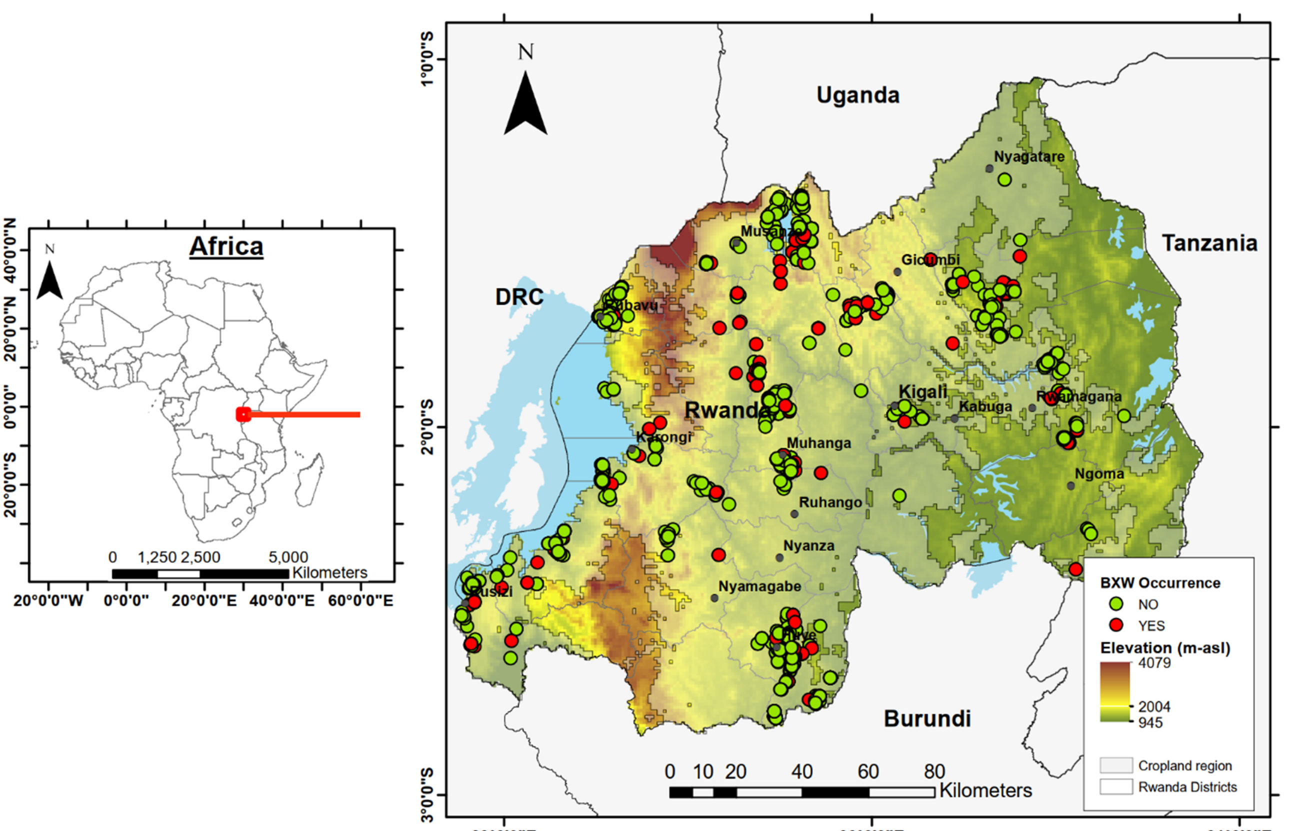

Fig. 1. Banana Xanthomonas wilt (BXW) occurrence data collected across Rwanda. The red-filled circles indicate the presence of BXW and the green-filled circles indicate the absence of the disease. DRC, Democratic Republic of the Congo.

et al. 2017), was used to mask occurrence predictions to cropland regions only. These raster layers were processed by clipping to the same extent as the region of study (Rwandan boundary), applying the same resolution (30 arc seconds) and the same geographic projection (WGS 84).

Predictive modeling

To predict potential spatial risk of BXW in Rwanda, the disease presence location data were combined with the environmental covariates within the modeling framework. The model validation and assessment of performance were conducted by running a fivefold cross-validation with inbuilt tools in Maxent based on specified split of the dataset into 70 and 30% test and validation datasets, respectively. Based on the model's rigorous routine, it randomly generates background points as it fits the "presence data" to the underlying variability of the environmental factors. As a required input, we specified the maximum number of background points ($n = 5{,}000$) with five replicate runs, and the results from the model runs were averaged for each scenario. The complementary log–log (cloglog) was used to transform the output into a probabilistic representation of BXW occurrence (ranging from 0 to 1). Maxent's relative suitability probability >0.5 is a fixed default threshold corresponding to a temporal and spatial scale of sampling that results in a 50% chance of the species being present in suitable areas (Elith et al. 2011). To visualize the ecological suitability for the disease occurrence, the model outputs were rendered as maps using R (version 4.2.0; R Core Team 2010). The model runs were implemented for both current and future climates to assess the potential outlook for BXW risk under changing climatic conditions. For the future climate, 18 GCM outputs were averaged to generate final spatial layers for each climate change scenario (RCP 6.0 and 8.5). On the basis of the incidence risk probability score, the classified pixels of the raster files were also categorized into low risk (0 to 0.2), medium risk (0.2 to 0.5), and high risk (0.5 to 1.0) to visualize the risk distribution.

Model performance and reliability of the prediction outputs were assessed using the area under curve (AUC) of the receiver operating curve, as described by Phillips et al. (2019). The relative contribution of each environmental variable to the prediction of BXW distribution (so-called gain) was assessed using the jackknife test. The environmental covariate with high gain has more influence on the model's predictive power than those with lower gain. Default settings were retained for the other model parameters, and corresponding response curves were generated to show the relationship between BXW occurrence and the environmental covariates. We reviewed the response curves for each variable to ensure that there was no autocorrelation between the variables. The response curves indicate covariation of predicted probability of BXW occurrence with each environmental variable, while keeping all other environmental variables at their average values based on resampled locations within the model.

Results

Influence of environmental variables on BXW incidence

The most influential variables include elevation, annual precipitation, and quarterly metrics of temperature and precipitation (Fig. 2). For elevation, cropland areas 1,350 to 1,600 m above sea level (a.s.l.) have a higher probability of BXW infection risk than other areas, as evidenced by high incidence count. However, cropland areas at elevations >1,600 m a.s.l. have lower probabilities and incidence counts, especially at higher altitudes. During the rainy quarter (the wettest 3 months) annually, higher infections or BXW activity are more likely to occur starting at 350 mm/month and peak at 400 to 450 mm/month. When considering precipitation of the coldest quarter, the risk of BXW continues to increase starting at 140 mm. For average monthly maximum temperature (2009 to 2018), probability of BXW occurrence is high at 20 to 28°C. For annual precipitation, the probability of BXW occurrence increases from 900 to 1,700 mm/year and is highest at around 1,000 mm/year, while for monthly average precipitation for 10 years (2008 to 2018), probability of BXW occurrence relative to average monthly precipitation increases from 80 to 140 mm/month and peaks at around 85 mm/month. The results also show that regions closer to roads are at higher risk compared with areas farther from roads (<10 km), most probably as a result of human activity (Fig. 3). Some of the response curves of the environmental covariates are shown in Figure 3, while the rest are included in the supplementary materials.

Table 1. Environmental variables included in the modeling framework for the prediction of banana Xanthomonas wilt occurrence

Environmental variable	Unit	Spatial resolution	Mean ± SD	Reference
Elevation	m (a.s.l.)	90 m	1,693.64 ± 346.25	Biruma et al. (2007); Ocimati et al. (2019); Tripathi et al. (2009)
Average maximum temperature (long term)[a]	°C	30 arc seconds	24.52 ± 2.36	Inferred: effect of temperature
Average minimum temperature (long term)[a]	°C	30 arc seconds	12.92 ± 1.69	Inferred: effect of temperature
Annual precipitation	mm	30 arc seconds	1,160.76 ± 235.36	Ocimati et al. (2019); Shimwela et al. (2017)
Average monthly minimum temperature 2009–2018	°C	30 arc seconds	12.64 ± 1.78	Inferred: effect of temperature
Average monthly maximum temperature 2009–2018	°C	30 arc seconds	23.05 ± 2.60	Inferred: effect of temperature
Average monthly minimum temperature 2018	°C	30 arc seconds	13.80 ± 2.10	Inferred: effect of temperature
Average monthly maximum temperature 2018	°C	30 arc seconds	26.27 ± 2.29	Inferred: effect of temperature
Precipitation, coldest quarter	mm	30 arc seconds	250.85 ± 113.00	Shimwela et al. (2017)
Precipitation, wettest quarter	mm	30 arc seconds	445.03 ± 76.17	Shimwela et al. (2017)
Precipitation, warmest quarter	mm	30 arc seconds	241.33 ± 95.17	Shimwela et al. (2017)
Precipitation, driest quarter	mm	30 arc seconds	72.32 ± 29.77	Shimwela et al. (2017)
Temperature, driest quarter	°C	30 arc seconds	18.76 ± 2.04	Shimwela et al. (2017)
Temperature, wettest quarter	°C	30 arc seconds	18.76 ± 2.01	Shimwela et al. (2017)
Temperature, coldest quarter	°C	30 arc seconds	18.51 ± 2.02	Shimwela et al. (2017)
Temperature, warmest quarter	°C	30 arc seconds	19.22 ± 2.05	Shimwela et al. (2017)
Wind average	m/s	30 arc seconds	1.94 ± 0.18	Shimwela et al. (2017)
Proximity to roads/trade routes	m	10 m	4,522.18 ± 4,170.01	McCampbell et al. (2018); Ocimati et al. (2019)
Land cover	Categorical	10 m	N/A	Ocimati et al. (2019)

[a] Long-term average climatic data from 1970 to 2000.

Model reliability and variable importance for prediction of BXW incidence risk

The maximum entropy modeling of BXW incidence provided more reliable prediction of the potential incidence than random assessment, with the mean AUC values ranging from 0.79 to 0.85 for current and future climate scenarios, respectively. The current distribution of BXW is mainly affected by precipitation variables, with their contribution ranging from 0.3 to 22.1%. The estimates of

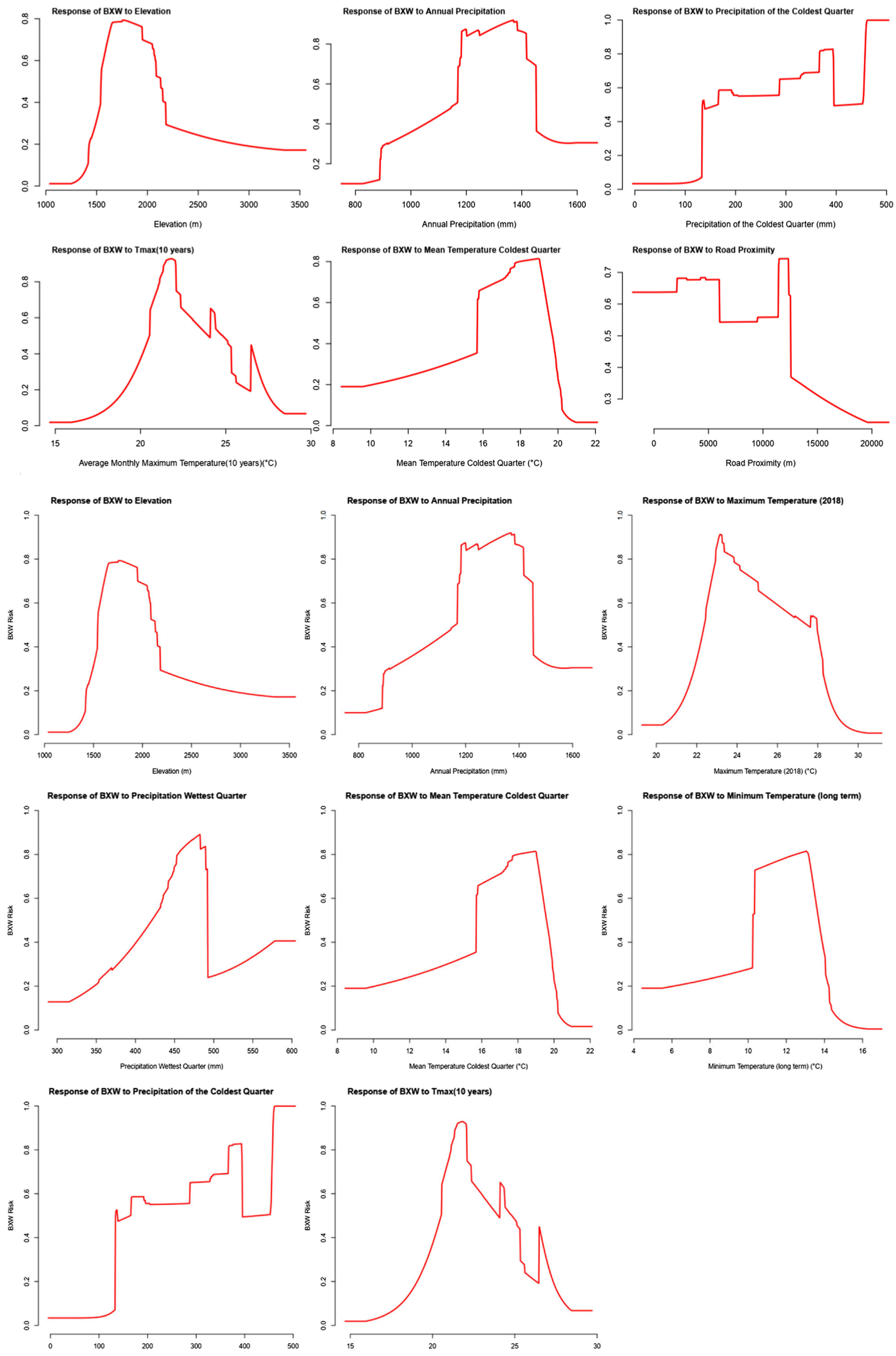

Fig. 2. Response curves of key environmental variables showing their relationships with the probability of banana Xanthomonas wilt (BXW) occurrence. The values are an average of the cross-validated model replicates.

percent contribution and relative importance of the selected environmental variables (Table 2) show that temperature, precipitation, and elevation were the main influential variables for predicting the potential occurrence of BXW. Precipitation of coldest quarter had the highest percent contribution of 22.1%, followed by average maximum temperature over 10 years (2010 to 2018), annual precipitation, and elevation with 13, 12.6, and 9.4%, respectively, while the remaining variables contributing less than 7%.

Based on the jackknife test of variable importance (Fig. 3), mean temperature of the coldest quarter is the environmental variable with highest gain when considered as an isolated variable, providing the most useful explanation about the spatial distribution of BXW incidence. This indicates that during the rainy season, higher BXW transmission, infections, and symptomatic expression of the disease occur. Relative to other variables, the exclusion of the "average maximum temperature over 10 years (2010 to 2018)" caused the highest reduction in the prediction accuracy gain, suggesting that this variable provides the most relevant information that is not conveyed by the other variables. Land cover was the variable that had the least gain when considered in isolation, and its exclusion had the least reduction in prediction accuracy gain. These results are also shown in Figure 3. In the future climate of the 2050s, annual precipitation, precipitation of warmest quarter, and elevation were consistent as the most important variables for both RCP 6.0 and 8.5 scenarios.

Current and future potential occurrence under different climatic scenarios

The output prediction raster grids for current and future climate scenarios were masked to cropland regions (Xiong et al. 2017). Based on current climatic conditions, potential areas of BXW

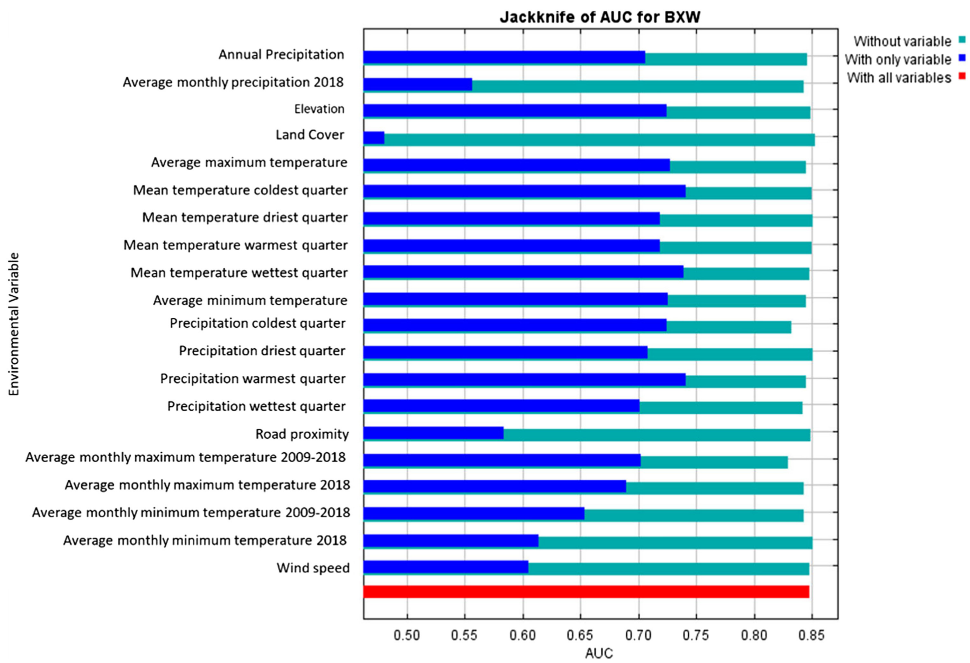

Fig. 3. The jackknife test results showing the relative importance of selected environmental variables for assessing the risk of BXW in banana-cultivated lands of Rwanda. AUC, area under curve; BXW, banana Xanthomonas wilt.

Table 2. Estimates of relative contributions of the environment variables obtained using the Maxent model

Environmental variable	Percentage contribution	Permutation importance
Precipitation, coldest quarter	22.1	12.4
Average monthly maximum temperature 2009–2018	13	19.2
Annual precipitation	12.6	17.6
Elevation	9.4	4
Average minimum temperature (long term)	6.4	12.8
Average monthly maximum temperature 2018	5.8	6.5
Precipitation, wettest quarter	5.4	8.9
Mean temperature, coldest quarter	5.1	0.6
Average monthly precipitation 2018	4.2	1.8
Precipitation, warmest quarter	3.7	2.4
Average monthly minimum temperature 2009–2018	2.7	1.8
Mean temperature, warmest quarter	2.6	5
Average monthly minimum temperature 2018	1.4	1.1
Land cover	1.3	0.5
Precipitation, driest quarter	1.3	2.3
Mean temperature, driest quarter	1.2	0.1
Wind speed	1	0.7
Proximity to roads	0.8	1.4
Average maximum temperature (long term)	0.6	0.8
Mean temperature, wettest quarter	0.3	0.1

incidence risk are associated with the western, northern, and southern parts of Rwanda. The average risk probability, as predicted for future (2050s) climate scenarios (RCP 6.0 and 8.5), showed an increase in BXW risk in areas that are already mapped for high probability of BXW incidence under the current climate as described above, with further spread to new regions in the eastern parts of Rwanda (Figs. 4 and 5).

The distribution of the classified pixels (Fig. 6) shows that there is a general shift in the risk probability as climate transitions from current conditions to future scenarios. For the current climate, 60.4% of the cropland area is associated with low BXW risk, but this reduced to 32.8 and 33.5% under both future scenarios, respectively. Conversely, 18% of the cropland area has high BXW risk under the current climate, but this increases to 33.4 and 31.2% under both future scenarios, respectively.

Discussion

From our results, the hotspot areas for BXW risk were concentrated around the central (mid north–south) and southwestern regions of Rwanda. These areas are more prone to BXW incidence and spread because of the inherently favorable ecological conditions for transmission, combined with extensive banana cultivation. Beyond the existing knowledge, this maximum entropy modeling shows that the climatic and environmental factors that have the most influence on BXW spread are the precipitation of the coldest quarter, average maximum monthly temperature, annual precipitation, and elevation, with the highest percentage contribution. Furthermore, the mean temperature of the coldest quarter showed the highest influence when considered as an isolated variable, but its influence was presumably doused as other factors posed complementary or opposing effects on the transmissibility of the disease or susceptibility of the host plant. In general, the influence of various climatic variables on the dynamics of disease spread can be nuances; therefore, our findings provide new insights into BXW incidence risk by revealing that major climatic variables (such as precipitation) do not merely influence disease burden, but the periodicity of the climatic variable is also a major underlying factor.

Implication of disease incidence rate

The impact of BXW disease is evident in the East African region, based on reports from ground-level extension activities. A study on the impact of BXW on farmers' livelihood showed that a total economic loss of US$ 14.05 million in banana production was caused by the disease in 2012 in Tanzania, Rwanda, and Uganda (Nkuba et al. 2015). Assessment of future risk of BXW disease requires an understanding of current incidence severity and its relationship with environmental factors. The georeferenced datapoints on BXW incidence, crowdsourced through the digital smartphone application, provided an indispensable input for scenario-based modeling. This automated crowdsourcing of georeferenced data on BXW incidence in Rwanda is unprecedented and offers a unique opportunity to understand the major factors that may influence the disease burden in space and time. Although the crowdsourced data do

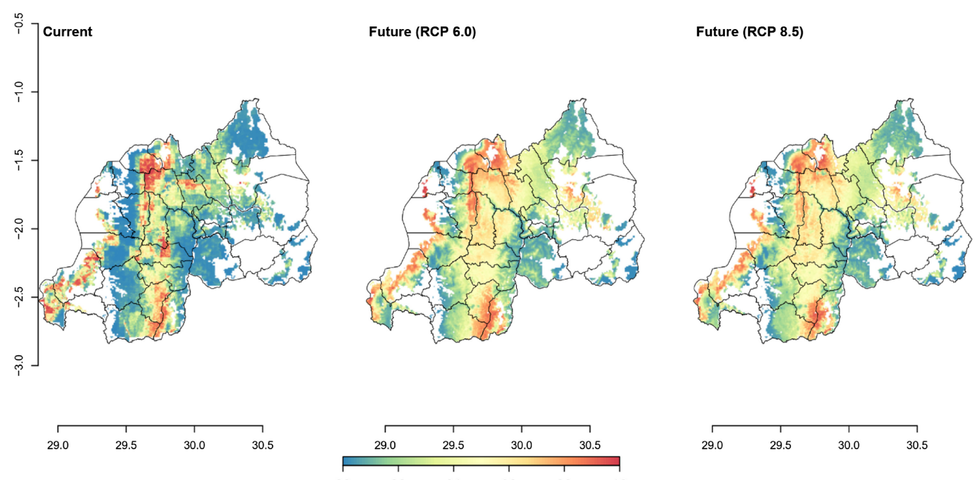

Fig. 4. Overall potential spatial distribution of banana Xanthomonas wilt (BXW) risk in Rwanda for the current climate and the future climate (2050s) for RCP 6.0 and 8.5 scenarios, on a scale of 0 to 1, where the red area shows the high probability and the blue area shows the low probability of BXW occurrence, respectively.

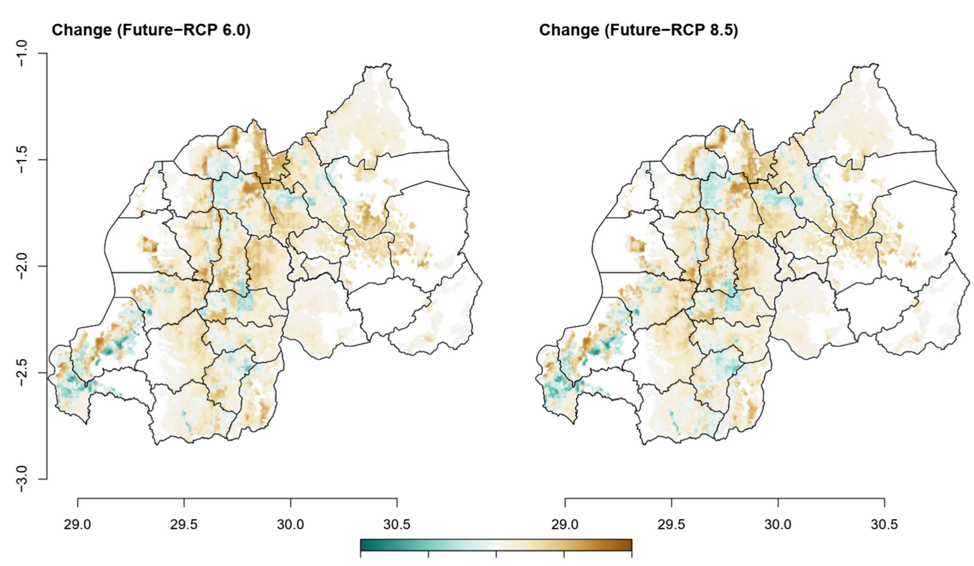

Fig. 5. Change in banana Xanthomonas wilt occurrence risk in the future climate for RCP 6.0 and RCP 8.5, relative to the current climate and the change between RCP 6.0 and 8.5. The brown area shows the increasing risk (positive values), the green area shows reduced risk (negative values), and the white area shows that the risk remained the same.

not exhaustively cover the overall extent of the country, they are spatially distributed across the major banana producing areas, covering major districts and sectors, to provide useful data on BXW incidence rates and clusters at the subnational level. Considering that 4,486 georeferenced data points were initially collected, out of which 23% (positive diagnosis recorded) were utilized in this study, it is likely that BXW disease is more widespread and undetected in areas that are yet to be covered by the surveillance efforts. Yet, this is considered inconsequential for the Maxent model because it is intrinsically designed to predict presence or occurrence of a disease based on the suitability of the underlying environmental covariates.

Our findings are eye opening regarding the potential outlook for BXW disease impact on banana production in Rwanda, based on the current threat of the disease and the evolving threat of climate change. In addition to the value of banana as a food security crop, it is also a major source of income for smallholder farmers in Rwanda, especially in the western and eastern regions where banana cultivation is more prominent (Nsabimana et al. 2008). The topography and climatic conditions in these regions are suitable for most varieties of banana that are grown by smallholder farmers, but anticipated climate change is expected to cause a shift in the agroecological suitability of these areas for banana production (Manners et al. 2021). Similarly, these ecological factors can influence the incidence and spread of BXW and its potential vectors, with potential impacts on the health and productivity of banana stands. Specifically, projected changes in climatic conditions are expected to impact ecological suitability of major crops in the East African region (Manners et al. 2021), and this may be complicated by the dynamics of pests and diseases. For instance, combination of higher temperatures and increased rainfall may favor the cultivation of banana at higher altitudes, but projected gains in banana productivity can be severely eroded if the spread of BXW disease and disease vectors increases significantly, without effective mitigation of the risk.

Drivers of BXW risk under current climatic conditions

Based on the modeling results, approximately 18% of the cropland area is prone to high BXW occurrence risk under the current climate. The strong positive association of BXW occurrence with precipitation, especially in the coldest quarter, is informative about the inherent and barely understood influence of moisture on the dynamics of BXW disease. Other studies have previously reported a positive correlation between BXW and precipitation (Ocimati et al. 2019; Shimwela et al. 2017; Tripathi et al. 2009). There are different potential pathways for moisture to influence the spread of BXW. For instance, Gottwald et al. (2002) explained that rain splash and wind-driven rain are responsible for short- and long-distance dispersal of BXW (Gottwald et al. 2002). As expected, the effect of temperature is constrained to a limited range, based on the net effect on biological activities of the disease and its vectors (Běhrádek 1930). However, the sharp decline above ~20°C (Fig. 2) suggests that BXW disease is suppressed at higher temperature ranges, thereby supporting the notion that farm implements should be disinfected after each use by fire treatment to avoid or minimize transfer of the disease pathogen within or between farms.

It is noteworthy that the areas within the altitude of approximately 1,300 to 2,000 m asl. are prone to BXW occurrence, indicating that the banana cultivated at midrange elevation is more susceptible to BXW. This is consistent with a previous study in Uganda, where high spread rates were observed in altitudes <1,500 (Tushemereirwe et al. 2004). In a study to compare BXW spread in mid (800 to 1,500) and high (>1,800) altitudes, Maina et al. (2006) observed higher insect-transmitted infections in the mid altitudes than in the high altitudes (Maina et al. 2006). The microclimate at higher altitudes may explain the effects on BXW occurrence. Temperature at higher altitudes is usually cooler (Montgomery 2006), with a likelihood of slowing down the rate of biochemical activities of the disease vector and pathogen. Although a high altitude is relatively unfavorable for BXW disease, warm temperatures at the otherwise cooler altitudes can conversely accelerate biochemical activities and enhance the spread of the disease under future climatic scenarios.

BXW risk under future climate scenarios

In contrast to the current climatic condition, banana-cultivated areas at risk of BXW incidence are predicted to increase under future climatic conditions. These predicted high-risk regions under the current climate are consistent with previous studies, especially in the western region of Rwanda (Reeder et al. 2007). BXW is known to infect banana plants, causing fatality and total loss of the banana plant (Nkuba et al. 2015). The increased risk of spread with the future climate projection suggests potential further loss of banana-cultivated land area in Rwanda. In 2005, Kayobyo et al. (2005) predicted that BXW will cause 8% loss of banana land area per annum, causing a production loss of 53% within 10 years (Di Cori et al. 2018; Kayobyo et al. 2005). Our results suggest that as climatic conditions continue to change, it is likely that banana production will face more severe threat from BXW disease if appropriate measures and tools are not deployed to empower farmers at the farm level for timely and efficient control.

Despite ongoing efforts to control BXW through direct (elimination of infected host banana plants) and indirect (dissemination of awareness information among farmers) means, the threat posed by the disease to Rwandan smallholder farmers remains a significant concern. The approaches for managing or controlling the disease must be efficient and timely deployable at minimal cost and offering potential for gains in banana production. The mapping of high-risk areas can support this aspiration by empowering the extension delivery system to prioritize interventions for different areas, based on their modeled risk level and considering other emerging risk factors. Furthermore, control measures can include recommendations for improved agronomic practices to achieve optimal returns on investment

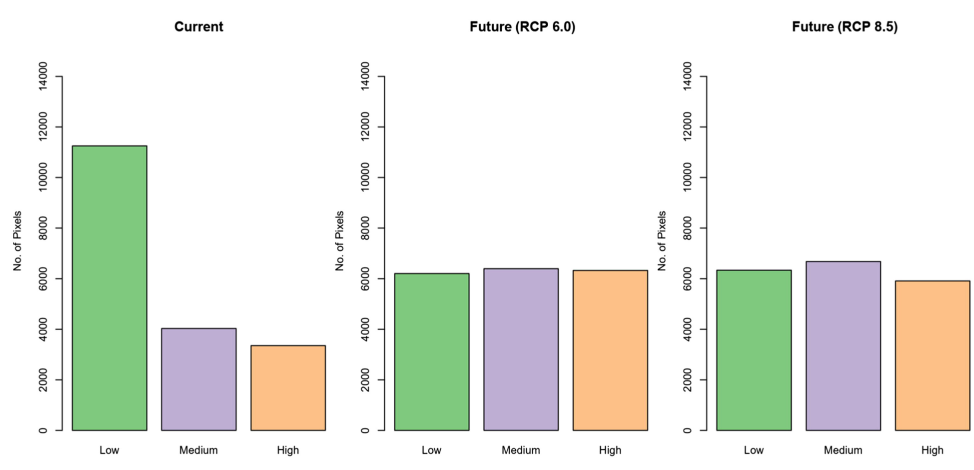

Fig. 6. Distribution of pixels representing low, medium, and high banana Xanthomonas wilt (BXW) risks. The classified pixels of the risk probability score are categorized into low risk (0 to 0.2), medium risk (0.2 to 0.5), and high risk (0.5 to 1.0).

(Tripathi et al. 2009). To mitigate current and future risks of BXW spread, it is important to proactively empower smallholder farmers, government agencies, and other banana crop stakeholders to access, adopt, and implement relevant control measures. Rietveld et al. (2020) presented evidence supporting the cost effectiveness of a relatively new approach, the single diseased stem removal, which contrasts with alternative approaches (Rietveld et al. 2020). Furthermore, previous studies showed that appropriate ICT and citizen science innovations can enhance BXW control and prevention (McCampbell et al. 2018), and integration of technological and nontechnological approaches may be appropriate to address a complex problem like BXW (Schut et al. 2015).

Digital tools for BXW control

In the past 4 years, scalable digital tools have emerged for the control of BXW, including smartphone-based mobile applications, such as BXW app (available on Android Playstore). Through the BXW app and other digital tools (IVR and chatbot), farmers can independently access information that includes on-farm diagnosis of BXW, a stepwise process for mitigating the spread, and basic preventative measures for control. While digital tools are democratizing access to timely and accurate information for farmers, continued risk mapping can support additional layers of intervention focused on location-specific surveillance and intensified support for farmers in high-risk regions, such as those along the central north–south axis of the country. Furthermore, our findings provide the first data-driven evidence regarding the future risks of BXW, which can aid policymakers and nonprofit organizations to upgrade contextually relevant regulations, policies, and control measures for BXW, to sustain banana production in Rwanda.

As an emerging approach for data-driven measures, this study leverages a major opportunity of access to a nationally crowdsourced (and surveyed), spatially explicit, point location dataset for BXW incidence. However, the dataset is evidently nonexhaustive in terms of diagnosed banana farms and may be unrepresentative of all ecological conditions across the country because the locations are likely biased toward areas where banana is produced. Yet, this is inconsequential for Maxent-based risk modeling of BXW disease incidence because the model is intrinsically designed with optimization algorithms that mine background data to isolate conditions that are suitable for a species' presence or a specific ecological process. Considering that this research provides a major foundation for assessing the spatial dynamics of BXW risk in Rwanda, it will be useful to direct efforts toward fusion of near-real-time data points from the crowdsourcing tool (BXW app) with high-resolution remotely sensed spatial environmental data for continuous surveillance and more accurate alert systems for BXW. The ground-level crowdsourced incidence data, combined with submeter resolution imageries may reveal the impact of small-scale land-use dynamics on BXW risk and possibly inform better control practices. As more users adopt and use the digital BXW app tool, robust and more spatially representative datapoints can unlock new understanding, especially with shifts in cropping systems, to proactively control BXW disease and other economically important crop diseases in Rwanda.

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