Exploring environmental determinants of Fusarium wilt occurrence on banana in South Central Mindanao, Philippines

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Summary This study used Maximum Entropy (MaxEnt) to explore potential environmental determinants of Fusarium wilt occurrence on banana in south-central part of the Philippines. Different variables representing topographic, bioclimatic, and edaphic features of an area were tested against data of Fusarium wilt occurrence. Based on the results, precipitation during the driest month, precipitation during the wettest month, precipitation of the warmest quarter, slope, and elevation were the most important variables for predicting the probability of Fusarium wilt occurrence on banana. Results also suggest that among the variables tested, precipitation had the major contribution to the occurrence of Fusarium wilt.

Additional keywords: Climate, MaxEnt, Panama disease, topography

Introduction

Banana (*Musa* sp.) is an important subsistence food and high value commercial crop in the world (Ghag *et al.*, 2015; Ravi and Vaganan, 2016). Banana is grown in more than 120 countries and its cultivation and related activities provide livelihood to many families in Africa, Asia, and Latin America (Roux *et al.*, 2008; Ghag *et al.*, 2015). In the Philippines, banana is the top fruit crop grown and a consistent dollar earner for the country (Solpot *et al.*, 2016). In 2015, around 0.44 million hectares were planted with banana resulting in more than 9 million metric tons of produce with an estimated value

of around USD 2.7 billion (PSA, 2017). Cavendish cultivars (50%) have the largest contribution to the country's banana production followed by Cardava (28%) and Lakatan (10%) cultivars (Solpot *et al.*, 2016). Top banana producing areas are mostly found in the southern part of the Philippines (Solpot *et al.*, 2016).

Fusarium wilt, also known as Panama disease, is an important disease of banana that has devastated thousands of hectares of plantations worldwide (Ploetz, 2006, 2015a, 2015b; Ghag *et al.*, 2015). Fusarium wilt is a soil-borne disease that causes wilt and severe die back to banana plant and can persist in the soil for at least 30 years (Stover, 1962; Cook *et al.*, 2015). The disease is caused by the fungal pathogen *Fusarium oxysporum* f. sp. *cubense* (Foc) (Ploetz, 2006; 2015a; 2015b; Ghag *et al.*, 2015). To enter the roots, Foc invades the epidermal cells on the root cap and elongation zone, and the small wounds along the lateral root base (Li *et al.*, 2011; Pattison *et al.*, 2014). Then, Foc proceeds to the vascular system causing the disease (Li *et al.*, 2011; Pattison *et al.*, 2014). Once in the vascular tissues, the pathogen disrupts the water translocation causing wilting symptoms, such as drooping foliage and leaf chlorosis that start from the lower to the upper leaves, resulting in plant necro-

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sis and death (Li *et al.*, 2011; Pattison *et al.*, 2014; Ploetz, 2015a). In Australia alone, Cook *et al.* (2015) estimated an annual loss of more than 138 million USD to the banana industry due to Fusarium wilt.

Despite numerous studies and reviews on the epidemiology and management of Fusarium wilt of banana, there is limited literature on the environmental factors that affect its incidence and severity rates (Ploetz, 2006, 2015a, 2015b; Pattison *et al.*, 2014; Ghag *et al.*, 2015). For example, Pattison *et al.* (2014) found that Fusarium wilt expression is a function of water stress (deficit and excess) and heat unit requirement of banana. Deltour *et al.* (2017) showed that the higher the clay content, pH, and electric conductivity in soil, the lesser severity of Fusarium wilt. Meanwhile, according to Perez-Vicente *et al.* (2014), severe infection is observed during the warmer and wet months of the year. Karangwa *et al.* (2016) reported that Fusarium wilt incidence and distribution is associated with elevation.

Maximum Entropy (MaxEnt) is a general-purpose machine learning method that has a simple and precise mathematical formulation well suited for modeling the geographic distribution of species using presence-only data (Phillips *et al.*, 2006). According to Phillips *et al.* (2006), MaxEnt estimates a target probability distribution based on distribution of maximum entropy (i.e. closest to uniform), subject to a set of constraints related to incomplete information regarding the target distribution. For example, the pixels of a study area constitute the MaxEnt probability distribution while the pixels with occurrence records are the sampling points, and the different environmental variables or covariates (e.g. climate, elevation, soil, vegetation) represent the features (Phillips *et al.*, 2006). MaxEnt also uses background points (points where presence or absence is unmeasured) that contrast against the occurrence points (presence locations) to estimate probability of occurrence (Merow *et al.*, 2013). According to Phillips *et al.* (2006), MaxEnt has many advantages compared with other modeling methods. MaxEnt re-

quires only presence data and environmental variables for the whole study area. Also, it can use both continuous and categorical data. In addition, it has efficient deterministic algorithms and performs better than other methods even with small sample size (Wisz *et al.*, 2008). Detailed description of MaxEnt can be found in Phillips *et al.*, (2006), Elith *et al.* (2011), Merow *et al.* (2013).

MaxEnt (Phillips *et al.*, 2006) is the most popular software package used for modeling species geographic distribution using presence-only data (Elith *et al.*, 2011; Merow *et al.*, 2013). According to Elith *et al.* (2011), since MaxEnt became available in 2004, it has been extensively utilized for species distribution modeling that aims at finding correlates of species occurrence, mapping current and future species distribution across many ecological, evolutionary, conservation, and biosecurity applications. In fact, since 2006, there are thousands of publications about the application of MaxEnt (Merow *et al.*, 2013). In plant pathology, several studies have used MaxEnt to identify environmental determinants and map potential distribution of plant diseases and their vectors (e.g. Wyckhuys *et al.*, 2012; Bosso *et al.*, 2016; Galdino *et al.*, 2016; Narouei-Khandan *et al.*, 2016; Shimwela *et al.*, 2016; Vallejo Pérez *et al.*, 2017). This study aims to identify environmental factors (i.e. topographic, edaphic, and bioclimatic) favoring Fusarium wilt infection of banana in South Central Mindanao, Philippines *via* the MaxEnt-modeling approach in order to develop a model for predicting disease occurrence and assessing the risk.

Materials and Methods

Presence-Only Data

Presence-only data were adapted from the earlier study by Solpot *et al.* (2016) in which Foc-infected plant samples (75 points) were collected from different provinces in the south-central part of the country (Fig. 1). Plants that showed typical external and internal symptoms of Foc, such as wilting, yellowing of leaves, and pseudostem and corm

discoloration were collected. Geographic coordinates of sampled plants were tagged using a global positioning system (GPS) receiver. Foc was isolated using the tissue plating technique. Full details of sampling and analysis of Foc sampled plants can be found in Solpot *et al.* (2016). Table 1 summarizes the number of Foc isolates by location and banana cultivar collected from the study area (Solpot *et al.*, 2016).

Environmental Data

Environmental data used in the study included topographic, edaphic, and climatic variables (Table 2). Topographic data included elevation, slope, and aspect. Elevation data of the study area at 1 km x 1 km

spatial resolution was extracted from shuttle radar topography mission (SRTM) (Farr *et al.*, 2007). Slope and aspect were derived from elevation data using terrain function of R software (Ihaka and Gentleman, 1996; R Core Team, 2014) raster package (Hijmans, 2014). Meanwhile, 1km x 1km spatial resolution soil data (i.e. pH, CEC, organic carbon content, % clay, % silt, and % sand) of the study area were downloaded from the Soil-Grids database at 250 m resolution (Hengl *et al.*, 2017). Bioclimatic data were derived from downscaled (1 km x 1 km) Climate Research Unit Time Series (CRU TS) data (Harris *et al.*, 2014) for the Philippines (Salvacion *et al.*, 2018). Ten bioclimatic variables (Booth *et al.*, 2014) were used in this study.

Figure 1. Location map of *Fusarium oxysporum* f. sp. *cubense* (Foc) and banana cultivars sampling points in south-central Mindanao, Philippines.

MaxEnt Modeling

Presence-only data were split (80:20) into training (60 points) and test/validation data (15 points) sets. Also, background data (1000 points) were generated randomly across the study area. A step-wise mod-

el building was also adapted by removing variables with permutation importance less than 5% (Heumann *et al.*, 2011; Kalle *et al.*, 2013; Zeng *et al.*, 2016). Permutation importance measures how the model depends on the variable (Galdino *et al.*, 2016). In this

Table 1. Number of *Fusarium oxysporum* f. sp. *cubense* (Foc) isolates per host cultivar collected in different provinces in south-central Philippines.

Host Cultivar	Province						Total
	North Cotabato	South Cotabato	Saranggani	Davao Del Sur	Sultan Kudarat	Maguindanao	
Latundan (AAB)	23	5	6	5	3	2	44
Lakatan (AAA)	12	0	3	1	1	0	17
Cavendish (AAA)	1	11	0	0	0	0	12
Cardaba (ABB)	1	0	0	0	0	0	1
Bungulan (AAA)	1	0	0	0	0	0	1
Total	38	16	9	6	4	2	75

Table 2. Environmental data for modeling Fusarium wilt in banana.

Variable	Description	Unit
<i>Topographic</i>		
Elevation	Elevation	masl
Slope	Slope	degrees
Aspect	Aspect or slope direction	-
<i>Edaphic</i>		
Soil pH	Soil pH	pH units
CEC	Cation Exchange Capacity	cmolc/kg
Organic carbon content	Organic carbon content	g/kg
% Clay	Clay content (0-2 micro meter) mass fraction	%
% Silt	Silt content (2-50 micro meter) mass fraction	%
% Sand	Sand content (50-2000 micro meter) mass fraction	%
<i>Climatic</i>		
Bio 1	Annual Mean Temperature	°C
Bio 5	Maximum Temperature of Warmest Month	°C
Bio 6	Minimum Temperature of Coldest Month	°C
Bio 8	Mean Temperature of Wettest Quarter	°C
Bio 9	Mean Temperature of Driest Quarter	°C
Bio 12	Annual Precipitation	mm
Bio 13	Precipitation of Wettest Month	mm
Bio 14	Precipitation of Driest Month	mm
Bio 18	Precipitation of Warmest Quarter	mm
Bio 19	Precipitation of Coldest Quarter	mm

study, MaxEnt package (Phillips *et al.*, 2006; 2018) was run via R *dismo* package (Hijmans *et al.*, 2016) using default settings.

Model Validation

Area under the curve (AUC) was calculated for both training and test data sets to determine the model's predictive power and potential over-fitting (Elith *et al.*, 2011; Mellow *et al.*, 2013; Bosso *et al.*, 2016). According to Rödder *et al.* (2009), AUC ranges from 0.5 (no predictive ability) to 1.0 (perfect prediction). An AUC value of 0.7-0.8 means that the model is useable, a value of 0.8-0.9 indicates good performance, and a value of 0.9-1.0 signifies very good predictive power (Rödder *et al.*, 2009). Meanwhile, other measures (Table 3) of model's predictive accuracy were calculated using the test data points for model validation (Allouche *et al.*, 2006). According to Allouche *et al.* (2006), true skill statistic (TSS) values range from -1 to +1, where values of zero or less indicate poor performance and +1 indicates perfect agreement.

Results

Step-wise model selection and validation

Only five out of the 19 variables in the initial model were left in the final model (Table 4). These variables included slope, elevation, precipitation on the driest month, precipitation on the wettest month, and precipitation on the warmest quarter. Precipitation during the wettest month had the highest permutation importance (26.1%) followed by slope (24.9), while precipitation during the warmest quarter had the lowest (12%). The AUC for the training and test data was 0.89 and 0.88, respectively. This suggests that the final model performed very well with respect to the training and test data (Elith, 2000; Rödder *et al.*, 2009; Abdullah *et al.*, 2017). These results were further confirmed by the different measures of model accuracy (Allouche *et al.*, 2006) in Table 5 using validation data points. Figure 2 shows the predicted presence of *Fusarium* wilt along with training (Fig. 2a) and validation data points (Fig. 2b).

Table 3. Measure of predictive accuracy of the model (Source: Allouche *et al.*, 2006).

Measure	Formula	Description
Overall accuracy	$\frac{a + d}{n}$	Rate of correctly predicted presence and absence data
Sensitivity	$\frac{a}{a + c}$	Probability that the model will correctly classify a presence data
Specificity	$\frac{d}{b + d}$	Probability that the model will correctly classify a absence data
Kappa	$\frac{\left(\frac{a + d}{n}\right) - \frac{(a + b)(a + c) + (c + d)(d + b)}{n^2}}{1 - \frac{(a + b)(a + c) + (c + d)(d + b)}{n^2}}$	Kappa and TSS normalize the overall accuracy by the accuracy due chance alone
True Skill Statistic (TSS)	sensitivity + specificity – 1	

where: *a* - number of "presence" points for which was correctly predicted by the model

b - number of "absence" points which the model predicted as "presence"

c - number of "presence" points which the model predicted as "absent"

d - number of "absence" points for which was correctly predicted by the model

n – *a*+*b*+*c*+*d*

Table 4. Permutation importance of environmental variables included in the final model.

Variable	Permutation Importance (%)
<i>Climatic</i>	
Precipitation of Wettest Month	26.1
Precipitation of Driest Month	21.2
Precipitation of Warmest Quarter	12.0
<i>Topographic</i>	
Slope	24.9
Elevation	15.8

Environmental Responses

In terms of bioclimatic variables, similar behavior was observed for the effect of precipitation during the driest (Fig. 3a) and wettest (Fig. 3b) months of the year. Higher probability was estimated for lower values of precipitation for these months (Fig. 4). For the wettest month of the year, the highest probability of occurrence (0.95) was calculated for monthly precipitation of 100 mm and eventually decreased to zero starting at monthly precipitation of 332 mm (Fig. 4a). For the driest month of the year, the highest probability of occurrence (0.46) was calculated at 43 mm of precipitation and decreased to zero starting at 120 mm monthly precipitation (Fig. 4b). On the other hand, the probability of Fusarium wilt occurrence showed a different response to precipitation during the warmest quarter (Fig. 4c). Higher probability of occurrence was observed on higher precipitation amount. More specifically, the highest probability (0.99) was estimated for quarterly precipitation of more than 839 mm and the lowest (0.01) for quarterly precipitation of less than 207 mm (Fig. 4c). Figure 5 shows the warmest quarter corresponding the sampling locations of Fusarium wilt occurrence.

Regarding topographic variables, higher probabilities of Fusarium wilt occurrence were estimated at lower slope and elevation values (Fig. 6). This means that higher chance of Fusarium wilt infection is expected in flat and lowland areas compared to

Table 5. Calculated measure of predictive accuracy of the final model.

Measure	Value
Overall accuracy	0.70
Sensitivity	1
Specificity	0.68
Kappa	0.21
True Skill Statistic (TSS)	0.68

sloping and upland ones. The highest probability of Fusarium wilt (0.47) was estimated at 0.10° slope and decreased exponentially to zero starting at slope equal to 8.51° (Fig. 6a). With respect to elevation, the highest probability of Fusarium wilt occurrence (0.23) was observed at 40 meters above sea level (masl) and exponentially decreased to zero starting at 1108 masl (Fig. 6b).

Discussion

Results suggest that bioclimate (i.e. precipitation) is the major contributory factor on Fusarium wilt occurrence. Low (less than 120 mm) monthly precipitation during the driest and wettest month of the year also results to higher probability of occurrence. Conversely, higher probability of occurrence is expected for higher precipitation (greater than 800 mm) during the warmest quarters. Topography (slope and elevation) of the area also influences occurrence of the disease. The probability of Fusarium wilt occurrence is higher on flat areas (less than 8° of slope) and areas with low elevation (less than 40 masl).

The effect of precipitation and slope on the occurrence of Fusarium wilt of banana can be attributed to the response of Foc and banana plant to water availability or soil moisture. Low rainfall during the driest and wettest quarter can subject the banana plant to low moisture or water deficit stress condition making it highly susceptible to severe infection by the pathogen (Lee *et al.*, 2004; Ghaemi *et al.*, 2011; Pattison *et al.*, 2014). Also, such conditions promote increased root colonization of tomato plants

Figure 2. Predicted occurrence of *Fusarium oxysporum* f. sp. *cubense* (Foc) in south central Mindanao, Philippines, with (a) training, and (b) validation data points.

Figure 3. Driest (a) and wettest (b) months of each province in south-central Mindanao, Philippines, corresponding to *Fusarium oxysporum* f. sp. *cubense* (Foc) sampling points.

Figure 4. Response curve of *Fusarium wilt* (*Fusarium oxysporum* f. sp. *cubense*) occurrence with respect to precipitation on: (a) the wettest month; (b) the driest month, and (c) the warmest quarter in south-central Mindanao, Philippines.

by *Fusarium oxysporum* f. sp. *lycopersici* (Ghaemi *et al.*, 2011). Meanwhile, higher precipitation during the warmest quarter can result in higher probability of Fusarium wilt occurrence because such conditions (warm and wet) are conducive to severe infection of banana by the pathogen (Perez-Vicente *et al.*, 2014). Also, higher rainfall can saturate soil producing anoxic conditions, which can enhance Foc root infection (Aguilar, 1998; Aguilar *et al.*, 2000; Pattison *et al.*, 2014).

Areas with flat to near flat topography tend to have relatively higher moisture

Figure 5. Warmest quarter of each province in south-central Mindanao, Philippines corresponding to *Fusarium oxysporum* f. sp. *cubense* (Foc) sampling points.

availability compared to the sloping ones, thus providing optimum conditions for fungal growth (Stover, 1953; Salvacion, 2016). In addition, slope can affect different soil properties (Su *et al.*, 2010), which may also affect Foc presence or abundance (Fu *et al.*, 2016; Deltour *et al.*, 2017). This could probably be the reason why soil variables in this study showed no significant effect on Fusarium wilt occurrence.

The influence of elevation on Fusarium wilt incidence observed in the present study was similar to that of previous studies elsewhere (Kangire *et al.*, 2001; Karangwa *et al.*, 2016). According to Karangwa *et al.* (2016), the effect of elevation on Fusarium wilt development may be due to the temperature variation as influenced by elevation. Fusarium wilt development is encouraged by higher temperatures at lower altitudes (Karangwa *et al.*, 2016).

The results of this study corroborate to previous studies conducted elsewhere. Lee *et al.* (2004) observed higher severity of Fusarium wilt in sweet potato at precipitation lower than 80 mm during planting

Figure 6. Response curve of *Fusarium wilt* (*Fusarium oxysporum* f. sp. *cubense*) occurrence with respect to: (a) slope, and (b) elevation (meters above sea level, masl) in south-central Mindanao, Philippines.

season. *Fusarium wilt* of sweet potato was higher in flat areas compared to that in areas situated in sloping sites (Lee *et al.*, 2004). In Australia, Pattison *et al.* (2014) observed higher incidence of *Fusarium wilt* of banana during months with rainfall less than 100 mm and greater than 500 mm. Karagwa *et al.* (2016) observed higher incidence of *Fusarium wilt* infection on banana farms located at elevations less than 1600 masl in east and central Africa.

Models like MaxEnt also have uncertainties resulting from sampling bias, quality of occurrence data, spatial resolution of environmental data, spatial autocorrelation and species characteristics (Dormann *et al.*, 2008; Jarnevich *et al.*, 2015; Galdino *et al.*, 2016). In the case of the present study, sampling was done based only on the reported cases of *Fusarium wilt* occurrence. In addition, spatial autocorrelation among sampling points and environmental variables was not considered in the model building. Furthermore, the environmental data used in the study has also uncertainties (Hijmans *et al.*, 2005; Hengl *et al.*, 2017; Salvacion, Macandog *et al.*, 2018). Lastly, the resolution of the environmental data might also have impact on the final model (Gillingham *et al.*, 2012; West

et al., 2015, 2016). At present, there is no or limited high resolution and updated environmental data (e.g. topography, climate, soil) in the country. Therefore, caution is recommended in interpreting the results of this study. Also, other approaches to analyze spatially referenced disease data might have different results (Turechek and McRoberts, 2013; Galdino *et al.*, 2016).

The information, such as the range of environmental conditions favoring occurrence of Foc on banana and the model derived in this study can be used as a preliminary tool to assess potential risk of disease occurrence in other parts of the country. In addition, since climate has a major role in *Fusarium wilt* occurrence, the model derived from this study can also be used to determine potential impact of climate change on disease presence in the country. Such information can help farmers, managers, and policy makers to have an informed decision on how to avoid or minimize losses due to *Fusarium wilt* of banana.

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Διερεύνηση των περιβαλλοντικών παραμέτρων που καθορίζουν την εμφάνιση της αδροφουζαρίωσης στη μπανάνα στο Νότιο Κεντρικό Μιντανάο, Φιλιππίνες

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Περίληψη Η παρούσα μελέτη χρησιμοποίησε τη μέθοδο Maximum Entropy (MaxEnt) για να διερευνήσει τις πιθανές περιβαλλοντικές παραμέτρους που καθορίζουν την εμφάνιση της αδροφουζαρίωσης στη μπανάνα (*Fusarium oxysporum* f. sp. *cubense*), στο νότιο-κεντρικό τμήμα των Φιλιππίνων. Ελέγχθηκαν διάφορες μεταβλητές που αντιστοιχούν σε τοπογραφικά, βιοκλιματικά και εδαφικά χαρακτηριστικά μιας περιοχής σε σχέση με τα δεδομένα εμφάνισης της αδροφουζαρίωσης. Με βάση τα αποτελέσματα, η βροχόπτωση κατά τη διάρκεια του ξηρότερου και υγρότερου μήνα, η βροχόπτωση κατά τη διάρκεια του θερμότερου τριμήνου του έτους, η κλίση του εδάφους και το υψόμετρο της περιοχής ήταν οι πιο σημαντικές μεταβλητές για την πρόβλεψη της πιθανότητας εμφάνισης της ασθένειας στη μπανάνα, με σημαντικότερη μεταβλητή τη βροχόπτωση.

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