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 (\textit{Musa} sp.) is an important subsistence food and high value commercial crop in the world (Ghag \textit{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 \textit{et al.}, 2008; Ghag \textit{et al.}, 2015). In the Philippines, banana is the top fruit crop grown and a consistent dollar earner for the country (Solpot \textit{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 \textit{et al.}, 2016). Top banana producing areas are mostly found in the southern part of the Philippines (Solpot \textit{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 \textit{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 \textit{et al.}, 2015). The disease is caused by the fungal pathogen \textit{Fusarium oxysporum} f. sp. \textit{cubense} (Foc) (Ploetz, 2006; 2015a; 2015b; Ghag \textit{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 \textit{et al.}, 2011; Pattison \textit{et al.}, 2014). Then, Foc proceeds to the vascular system causing the disease (Li \textit{et al.}, 2011; Pattison \textit{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-
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. Del-tour 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 requires 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; Shimwe-la 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 com
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.](image)
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 model 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).

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

<table>
<thead>
<tr>
<th>Host Cultivar</th>
<th>Province</th>
<th>North Cotabato</th>
<th>South Cotabato</th>
<th>Sarangani</th>
<th>Davao Del Sur</th>
<th>Sultan Kudarat</th>
<th>Maguindanao</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Latundan (AAB)</td>
<td></td>
<td>23</td>
<td>5</td>
<td>6</td>
<td>5</td>
<td>3</td>
<td>2</td>
<td>44</td>
</tr>
<tr>
<td>Lakatan (AAA)</td>
<td></td>
<td>12</td>
<td>0</td>
<td>3</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>17</td>
</tr>
<tr>
<td>Cavendish (AAA)</td>
<td></td>
<td>1</td>
<td>11</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>12</td>
</tr>
<tr>
<td>Cardaba (ABB)</td>
<td></td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Bungulan (AAA)</td>
<td></td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td>38</td>
<td>16</td>
<td>9</td>
<td>6</td>
<td>4</td>
<td>2</td>
<td>75</td>
</tr>
</tbody>
</table>

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

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Topographic</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Elevation</td>
<td>Elevation</td>
<td>masl</td>
</tr>
<tr>
<td>Slope</td>
<td>Slope</td>
<td>degrees</td>
</tr>
<tr>
<td>Aspect</td>
<td>Aspect or slope direction</td>
<td>-</td>
</tr>
<tr>
<td><strong>Edaphic</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Soil pH</td>
<td>Soil pH</td>
<td>pH units</td>
</tr>
<tr>
<td>CEC</td>
<td>Cation Exchange Capacity</td>
<td>cmolc/kg</td>
</tr>
<tr>
<td>Organic carbon content</td>
<td>Organic carbon content</td>
<td>g/kg</td>
</tr>
<tr>
<td>% Clay</td>
<td>Clay content (0-2 micro meter) mass fraction</td>
<td>%</td>
</tr>
<tr>
<td>% Silt</td>
<td>Silt content (2-50 micro meter) mass fraction</td>
<td>%</td>
</tr>
<tr>
<td>% Sand</td>
<td>Sand content (50-2000 micro meter) mass fraction</td>
<td>%</td>
</tr>
<tr>
<td><strong>Climatic</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Bio 1</td>
<td>Annual Mean Temperature</td>
<td>°C</td>
</tr>
<tr>
<td>Bio 5</td>
<td>Maximum Temperature of Warmest Month</td>
<td>°C</td>
</tr>
<tr>
<td>Bio 6</td>
<td>Minimum Temperature of Coldest Month</td>
<td>°C</td>
</tr>
<tr>
<td>Bio 8</td>
<td>Mean Temperature of Wettest Quarter</td>
<td>°C</td>
</tr>
<tr>
<td>Bio 9</td>
<td>Mean Temperature of Driest Quarter</td>
<td>°C</td>
</tr>
<tr>
<td>Bio 12</td>
<td>Annual Precipitation</td>
<td>mm</td>
</tr>
<tr>
<td>Bio 13</td>
<td>Precipitation of Wettest Month</td>
<td>mm</td>
</tr>
<tr>
<td>Bio 14</td>
<td>Precipitation of Driest Month</td>
<td>mm</td>
</tr>
<tr>
<td>Bio 18</td>
<td>Precipitation of Warmest Quarter</td>
<td>mm</td>
</tr>
<tr>
<td>Bio 19</td>
<td>Precipitation of Coldest Quarter</td>
<td>mm</td>
</tr>
</tbody>
</table>
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; Merow 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>
<thead>
<tr>
<th>Measure</th>
<th>Formula</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Overall accuracy</td>
<td>( \frac{a + d}{n} )</td>
<td>Rate of correctly predicted presence and absence data</td>
</tr>
<tr>
<td>Sensitivity</td>
<td>( \frac{a}{a + c} )</td>
<td>Probability that the model will correctly classify a presence data</td>
</tr>
<tr>
<td>Specificity</td>
<td>( \frac{d}{b + d} )</td>
<td>Probability that the model will correctly classify a absence data</td>
</tr>
<tr>
<td>Kappa</td>
<td>( \frac{(a + d) - (a + b)(a + c) + (c + d)(d + b)}{\left(1 - \frac{(a + b)(a + c) + (c + d)(d + b)}{n^2}\right)} )</td>
<td>Kappa and TSS normalize the overall accuracy by the accuracy due chance alone</td>
</tr>
<tr>
<td>True Skill Statistic (TSS)</td>
<td>sensitivity + specificity – 1</td>
<td></td>
</tr>
</tbody>
</table>

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 “presence” points for which was correctly predicted by the model  
- \( n \) – \( a+b+c+d \)
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 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.
Environmental determinants of Fusarium wilt occurrence on banana

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 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.
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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The authors have declared no conflict of interest.

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


Περιλήψη Η παρούσα μελέτη χρησιμοποιεί τη μέθοδο Maximum Entropy (MaxEnt) για να διερεύνησε 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 ασθένειάς στη μπανάνα, με σημαντικότερη μεταβλητή τη βροχόπτωση.

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