MODELING THE WORLDWIDE DISTRIBUTION POTENTIAL OF *Spiroplasma kunkelii* IN ZEA MAYS

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RESUMO: A agricultura é fundamental para humanidade. As práticas agrícolas são altamente dependentes de fatores climáticos. A cultura do milho (*Zea mays* L.) é uma das principais culturas que representa o agronegócio. O clima pode afetar a agricultura de várias formas, incluindo a maior ou menor severidade de doenças e insetos praga. Dentre as doenças do milho destaca-se o enfezamento pálido, causado pela bactéria *Spiroplasma kunkelii* sp. Atualmente essa bactéria causa grande perda em países produtores de milho. Diante desse cenário, este trabalho tem como proposta elaborar um modelo de nicho ecológico usando o software MaxEnt para identificar o potencial de distribuição global de *Spiroplasma Kunkelii* sp.
PALAVRAS-CHAVE: Maxent, Modelagem de Nicho Ecológico, Enfezamento pálido do milho, Modelagem de Distribuição de Espécies,

SPATIOTEMPORAL CHANGE IN GEOGRAPHICAL DISTRIBUTION OF GLOBAL CLIMATE TO SPIROPLASMA KUNKELII IN ZEA MAYS

ABSTRACT: Agriculture is fundamental to humanity. Agricultural practices are highly dependent on climatic factors. The corn crop (Zea mays L.) is one of the main crops that represent agribusiness. The climate can affect agriculture in several ways, including the greater or lesser severity of diseases and pest insects. Among the corn diseases, corn stunt spiroplasma caused by the bacterium Spiroplasma kunkelii sp. stands out. Currently, this bacterium causes a great loss in corn-producing countries. Given this scenario, this work proposes to develop an ecological niche model using MaxEnt software to identify the global distribution potential of Spiroplasma Kunkelii sp.
KEYWORDS: Maxent, Ecological Niche Modelling, Corn Stunt Spiroplasma, Species Distribution Modelling.

INTRODUTION

Zea mays L. is an important crop representing the planet's agriculture (Abdoulaye et al., 2018). The culture is adequate on almost every continent (Zhang et al., 2020). The occurrence of pests and climate change are limiting factors in production (Ali et al., 2020a). Corn faces a series of threats and diseases throughout its phenological phase. The production suffers from 130 different pests and about 110 diseases caused by fungus, bacteria, and viruses worldwide (Pratap and Kumar 2014); consequently, the use of pesticides in the world for phytosanitary control in maize crops exceeds US$36 million annually. (FAOSTAT, 2017).

Controlling diseases is essential to maintain good production rates. In Brazil, expenditures for disease control can reach up to 22 million dollars a year (Center for Advanced Studies in Applied Economics – Cepea 2019). The pale corn stun, a disease caused by the Spiroplasma kunkelii sp., manifests itself after flowering, mainly in the grain filling stage of maize. For example, in the state of Paraná - BR, a potential loss caused by S. kunkelii sp. exceeded 16.5 million dollars in losses for corn producers (Oliveira et al., 2003).

The leafhopper Dalbulus maidis is the vector-insect of S. kunkelii, the causal agent of pale stunted maize. Corn is the only host for this leafhopper and this pathogen. Climate affects the entire life cycle of pathogen and host (Agrios, 2005). Climatic factors can favor the occurrence of epidemic outbreaks of stunting, causing large areas and causing damage (Ali et al., 2020). Climate influences the spatial distribution of plant diseases. The main factors limiting the growth and development of diseases and their vectors are temperature and rainfall (J. Bailey-Serres et al., 2019). Climate change is considered one of the main considerations for global biodiversity in the 21st century (Dawson et al., 2011). The climatic factor is the most important in determining the range of species distribution. Thus, global heat will cause not considered distribution pattern and physiological and ecological characteristics of species (Bellard et al., 2012; Guan et al., 2018).

Therefore, understanding the relationship of climate with the disease caused by Spiroplasma Kunkelii is essential for monitoring stunted pale. Weather information is easy and free to access. Species information, on the other hand, can be specific from ecological niche models. These models are key ecological research tools and include CLIMEX (Kriticos et al., 2015), GARP (Stockwell and 1999), MaxEnt (West et al., 2016), BIOCLIM (Booth et al., 2014), and DOMAIN models (Carpenter et al., 1993). These tools can be used to predict the effect of climate change on species distribution (Booth, 2018). MaxEnt has often been the most used (West et al., 2016; Yi et al., 2017) as this model generates satisfactory results (Koch et al., 2017; Phillips et al., 2017) with accurate devas to identify geographic distributions of species for a variety of applications in ecology and conservation (Graham et al. 2004).

In this scenario, the present work aimed to develop an ecological niche model to identify a potential current distribution of Spiroplasma kunkelii on a global scale.

MATERIAL AND METHODS

The occurrence data of Spiroplasma kunkelii present in the corn crop were collected in different searches in the literature, blogs, news, and videos. Thus, a total of 196 points were found.

Initially, we used 19 bioclimatic variables for the WorldClim version 2.1 dataset released in January 2020 (https://www.worldclim.org). All variables have a spatial resolution equal to 2.5 arc-min (~5km) (Fick and Hijmans, 2017). We used the SDM tool toolbox 2.4 (Brown, et al., 2017) in ArcGIS software to remove variables with high correlation ($r \geq |0.70|$), and only one variable per group with strong correlation was specified based on the coefficient Pearson correlation (Rank et al., 2020; Kumar et al., 2014). Thus, the predictor variables used in the final model were: BIO1 = Mean Annual Temperature; BIO2 = Mean diurnal range (monthly average (Max. temp. - Min. temp.); BIO4 = Temperature seasonality (standard deviation × 100); BO5 = Maximum temperature of the warmest month; BIO10 = Mean temperature of the warmest quarter; BIO12 = Annual precipitation.

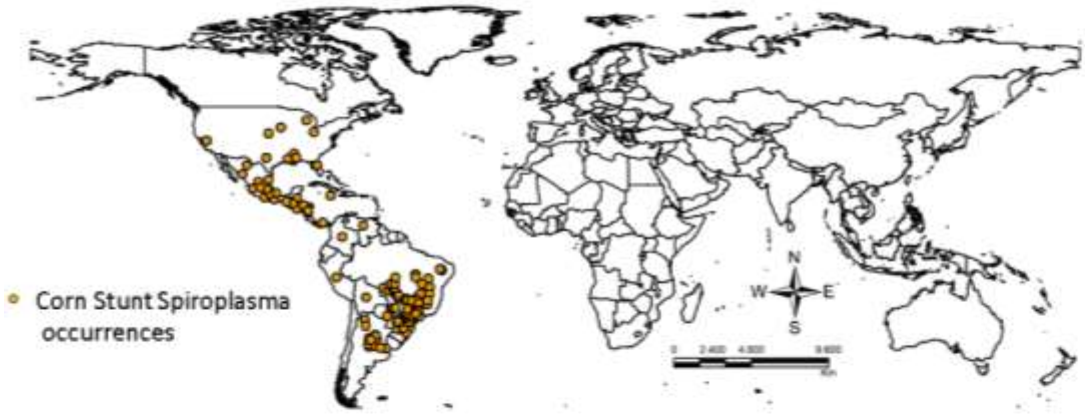
The Maximum Test Sensitivity Plus Specificity (MTSPS) threshold, considered simple and effective and at least as good as other more complicated approaches (Liu et al., 2005), was chosen to extract from the predictive model four suitability class for S. kunkelii (highly unsuitable: 0-MTSPS; low: MTSPS-0.5; medium: 0.5–0.7 and high: 0.7–1.0).

To start the model, a file containing the corn stunting distribution data (“sample”) and the set of 6 bioclimatic (predictors) variables were manually provided as input to MaxEnt (Phillips et al. 2006).

RESULTS AND DISCUSSION

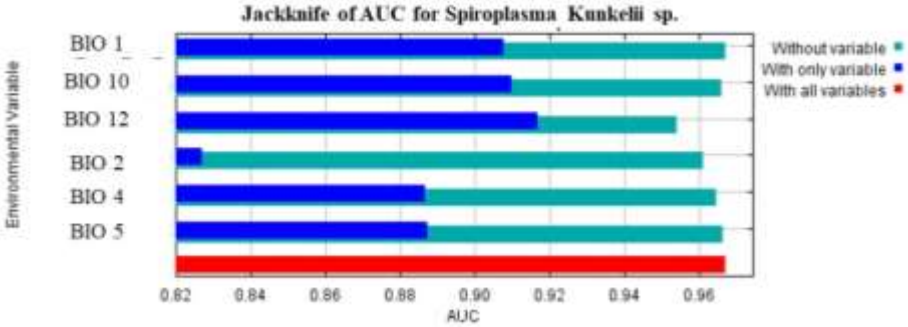
A total of 196 known occurrence points of the S. Kunkelii bacterium were found worldwide, as shown in Figure1.

Figure 1. Current occurrence of Spiroplasma Kunkelii on a global scale.



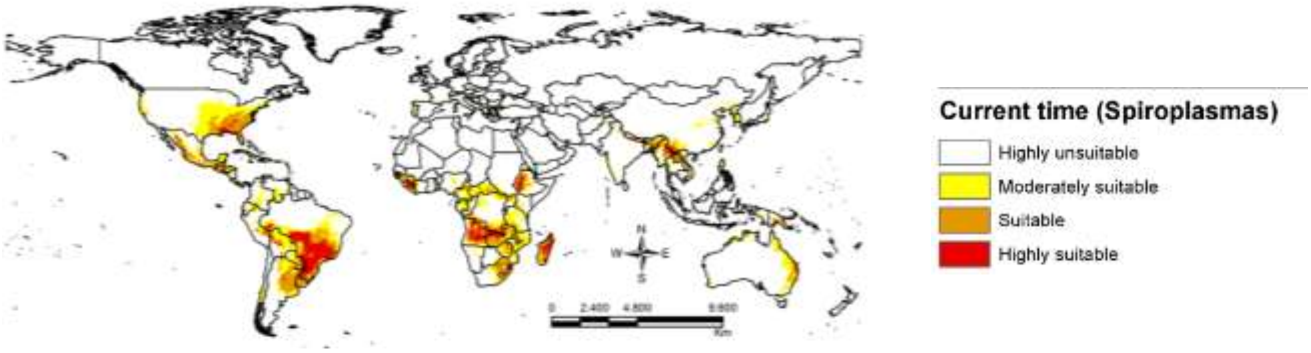
Based on the tenfold cross-validation, this model exceeded a random distribution, had an AUC value of 0.967 (Figure 2). The annual precipitation (56,5%), Mean Diurnal Range (12%), and Annual Mean Temperature (9.7%) contributed more than 78% to the results of the projections for pale stunting (percentages in parentheses).The Jackknife test identified the environmental variables that most influenced the distribution of the pest. The environmental variable with the greatest gain in the model, when used alone, was BIO1 = Mean Annual Temperature, which therefore seems to have the most useful information on its own. The environmental variable that makes the most gain when omitted for a BIO2 = Mean Diurnal Range. Values are averages over replicated runs (Figure 2).

Figure 2. Jackknife test result for the variables used.



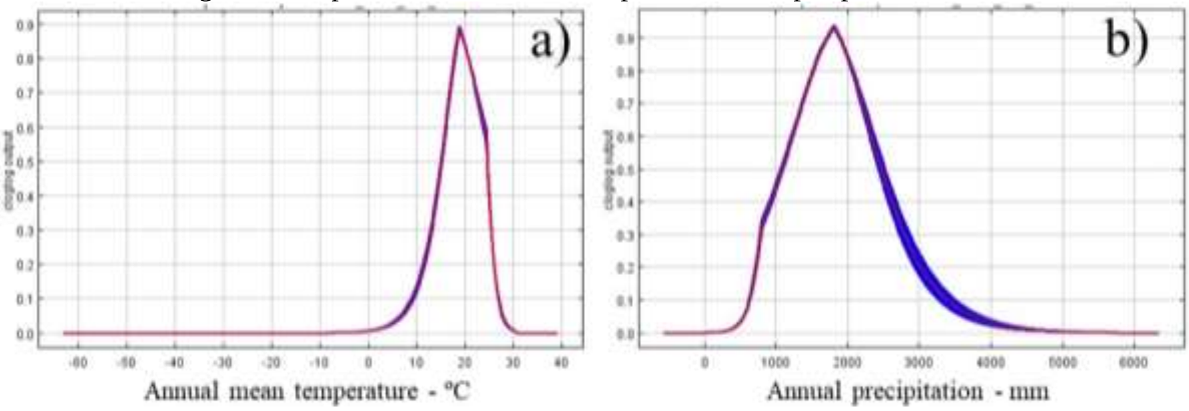
In Figure 3, it is observed that, in general, the Midwest, South, and Southeast of Brazil have high suitability for the pest. Furthermore, some regions in southern Africa and few points in Asia are also beyond this suitability. States such as Acre, Mato Grosso, Goiás, Minas Gerais, Rio de Janeiro, São Paulo, Mato Grosso do Sul, Santa Catarina, Paraná, and Rio Grande do Sul; and as countries Argentina, Uruguay, Guatemala, El Salvador, Mexico, USA, Guinea, Sierra Leone, Liberia, Nigeria, Cameroon, Angola, Ethiopia, Zambia, Zimbabwe, Malawi, Tanzania and Mozambique young suitable for the Spiroplasma bacteria (Figure 3).

Figure 3. Class of suitability to Spiroplasma kunkelii under current climatic conditions using the MaxEnt model.



The probability of the presence of Spiroplasma Kunkelii was higher in areas with an annual mean temperature of 19ºC (Figure 4a) and annual precipitation of around 1850 mm (Figure 4b). The more distances of 19ºC and 1850mm, the smaller the probabilities of S. Kunkelii in these areas.

Figure 4. Response curves of the best predictors of Spiroplasma kunkelii.



CONCLUSION

The corn-producing regions in the world that present a mean annual temperature of around 19 ° C and complete near 1850 mm have, in general, greater potential for the occurrence of Spiroplasma kunkelii.

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