Predicting Mango Sudden Decline Due to *Ceratocystis fimbriata* Under a Changing Climate

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Abstract

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Mango fruit trees are an important fruit crop due to their high value. Mango sudden decline (MSD) is a major disease that threatens mango trees in Oman and worldwide. The objective of this study was to identify those areas in northern Oman in which *Ceratocystis fimbriata* (a plant fungal pathogen causing MSD) may establish itself under various climate change scenarios. The MaxEnt model used in this study was based on data for the period 1970-2000 and then projected to future climate periods. This study modeled the future distribution of *C. fimbriata* for 2021–2040, 2041–2060, 2061–2080, and 2081–2100 climatic scenarios. Fifteen affected locations and seven bioclimatic variables were investigated in this study. The model showed values between 0.896 and 0.913 (habitat suitability) which represented a good model outcome. The jackknife test showed that the mean diurnal range in temperature, precipitation of the driest month, and elevation contributed to *C. fimbriata* distribution. From 2021 through 2040, a total area of 1,889 km^2 was found to be highly suitable for *C. fimbriata* in Northern Oman. Compared with the 2021–2040 period, the poorly suitable area would increase in both 2041–2060 and 2081–2100 periods. The moderately suitable regions for *C. fimbriata* would decrease under all scenarios investigated. However, the total area of the suitable areas, with all scenarios, would increase, except during the 2041-2060 period. This research offers a tool to better manage and prevent the possible Ceratocystis blight (*C. fimbriata)* and bark beetle (*Hypocryphalus mangiferae*) invasions under future projected climatic scenarios.

Keywords: Mango sudden decline (MSD), "*Ceratocystis fimbriata*", bioclimatic variables, climate change, Sultanate of Oman, Maxent.

Introduction

The agricultural sector is an important component of the global economy. For instance, 65% of jobs and earnings in Africa are agriculturally based (Pretty *et al.*, 2011). Therefore, the loss of agricultural production resulting from pests and diseases is a major concern for every farmer and any agriculture-based economy. According to Godfray *et al.* (2010), the sustainability of the agricultural yield relies on the continuous management of pests and diseases to ensure profitable productivity. The mango tree (*Mangifera indica*) is grown in many continents, including Asia, South America, and Africa, and has high economic value (Arauz, 2000). Mangoes are also one of the most significant perennial fruit crops in the Sultanate of Oman (hereafter: Oman). In 2004, in the Al Batinah agricultural region, orchards planted with mango reached around 2500 ha, with total fruit production estimated at 8600 t (Al-Adawi *et al.*, 2006).

However, in 1999, mango sudden decline (hereafter: MSD) appeared in Oman. Following the onset of this disease, more than 60% of mango trees were affected in northern Oman in the Al Batinah region (Al-Subhi *et al.*, 2006). MSD resulted in the loss of over 200,000 mango trees, which represented 13% of all the mango trees in the region (Al-Adawi *et al.*, 2006). MSD is a fungal disease that attacks the mango tree's vascular system and results in a quick decline or sudden death. The disease becomes a serious threat to mango trees throughout the entire region. The major symptoms of MSD are trunk secretion and wilting and the browning of leaves on single branches. In one study, most of the affected trees died six months after symptoms appeared (Pereira *et al.*, 2019). Different fungi have been reported to be associated with MSD. Pathogens such as Ceratocystis blight (*Ceratocystis fimbriata*, *C. manginecans*, *C. omanensis*, and *Lasiodiplodia theobromae*) are the fungi isolated from MSD mango trees and were most commonly found in Oman and Pakistan. The bark beetle (*Hypocryphalus mangiferae)* is the vector responsible for spreading the pathogens among mango trees (Al-Adawi *et al.*, 2003). According to Al-Adawi *et al.* (2006), *H. mangiferae* played a significant role in the dispersal of the mango sudden decline pathogen. Many countries around the world, including Iran, Australia, Egypt, India, the USA, Brazil, and Korea, have associated MSD with the fungal pathogen *Ceratocystis* sp., resulting in the wilting and death of their mango trees (Saeed *et al.*, 2017). Many other countries around the world reported similar effects of MSD. For example, Pakistan considered MSD as the most destructive disease for mango trees, and 10–28% of mango trees were reported in Punjab to be affected by the disease, resulting in heavy economic losses for mango producers (Hassan & Nazami, 2017).

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The climatic variation appears to play a significant role in the distribution of both pests and diseases around the world. According to Rosenzweig *et al.* (2010), climate change has a huge impact on agricultural crops and insect populations in both natural ecosystems and agroecosystems. Some studies have assessed the impact of climate change on bioclimatic conditions and their role in increasing the geographical distribution of pests and diseases. For example, Biber-Freudenberger *et al.* (2016), conducted a study to model the pest distribution for tomato leafminer (*Tuta absoluta)*, mango fruit fly (*Ceratitis cosyra)*, and oriental fruit fly (*Bactrocera)* to estimate the extent and change of pest habitats across Africa under various future climate change scenarios. The authors concluded that there is slightly increasing habitat suitability for the three pests on the entire African continent. Climatic conditions also contribute to the distribution of the *H. mangiferae* (Rossetto & Ribeiro, 1990). *H. mangiferae* is the vector for MSD infection. The mango bark beetles have the capability to spread the fungal structures over long distances and may infect other parts of the plant and remain in the soil, which can result in the loss of an entire mango planted area. Once the mango trees show symptoms, then the beetle serves as a proxy for disease spread. There is no information available on the spatial distribution of mango in Oman. Therefore, this study provided a proxy of possible suitable habitat for mango and the disease as well. In other words, understanding these environmental factors is crucial for forecasting the disease distribution and its patterns in efforts to develop informed management practices. Various climate change scenarios and models are available for different anthropogenic CO_2 emission forecasts, and these help researchers generate projections for the distribution of certain diseases in anticipation of possible future outbreaks (Collins *et al.*, 2013). Several species distribution studies have been conducted to model pest and disease habitat suitability under future climate change scenarios. For instance, the potential distribution of pests and diseases in Asia, North America, and several European countries has already been modeled (De Meyer *et al.*, 2010; Solhjouy-Fard *et al.*, 2013). However, fewer modeling approaches have been constructed for disease projection with a focus on Oman (da Silva Galdino *et al.*, 2016). There is, therefore, a need to assess the impact of climate change on pest and disease distribution in order to estimate the potential losses of agricultural products. Currently, the methods to control MSD involve using grafting methods in which an exotic scion is grafted on a local plant rootstock. This is because MSD (through *H. mangiferae)* is found more on local varieties than on the exotic grafted varieties (Al-Adawi *et al.*, 2006). Because MSD issues in Oman have not yet been resolved and climate change is a fact, the impact of climate change on this mango disease needs to be assessed. This study aimed to project various climate change scenarios in the context of MSD disease and to assess the disease's future distribution and patterns to help decision-makers develop informed management practices and assist in planning the further expansion of agricultural species and potential associated risks that may arise.

This study used maximum entropy species distribution modeling (Maxent), which is based on correlative ecological niche models between species occurrences and environmental variables to generate maps of potential species distribution by fitting a probability distribution for species occurrence in a geographic area. The niche-based model is used to describe the ecological suitability of a space and to generate a geographic area of the predicted presence of the species that satisfies the fundamental niche conditions necessary for those species and their potential distribution (Phillips *et al.*, 2006). Several studies have demonstrated the use of this model in predicting pest and disease distribution. For example, given future climate conditions scenarios, the forest in the interior of the western US is predicted to see a 27% increase by 2050 of the mountain pine beetle (Evangelista *et al.*, 2011). As climate change occurs, there is a need to predict the potential MSD distribution under different climate change scenarios in order to better select appropriate growing areas for future mango cultivation and production. Therefore, the primary objective of this study is to analyze the potential suitable areas for the establishment of *C. fimbriata* in northern Oman.

Materials and Methods

Study area

Oman (Figure 1) is an arid country in the Arabian Peninsula with a population of almost 5 million as of 2019 (World Bank, 2020). The total land area is more than 309,500 km^2 (McDonnell, 2016). The country can be divided into three main land surface areas: coastal plains, deserts, and mountains (McDonnell, 2016). With 11 different administrative governorates (Figure 1), the country's main agricultural area is located in the Al-Batinah, Musandam Peninsula, interior oases, high plateaus of the eastern region, and Dhofar region (Al-Adawi *et al.*, 2003). According to Al-Adawi *et al*. (2003), the climate is generally hot and humid and hot & dry in the coastal areas and hot and dry in the interior areas. According to McDonnell (2016), the average annual precipitation for the entire country, interior and mountainous & coastal areas is around 100 mm, 20 mm, and 400 mm, for the three regions, respectively. This rain occurs during the winter months (November–April) in the north and interior regions of Oman, whereas there is a monsoon summer season (June–September) experienced in the southern (Dhofar) region of Oman (Al-Adawi *et al.*, 2003). The average temperature in the northern, interior, and Salalah plain is in the range 20–28ºC, 19–26ºC and 20–27ºC, in the three regions, respectively (MRMWR, 2008). Evaporation in the interior, Al-Batinah coast, and Salalah plain is estimated to be 3000 mm, 2100 mm, and 1700 mm, respectively (MRMWR, 2008). Due to the vast area of land dominated by mountains, the total area under agricultural production is limited. As of 2004, the cultivated land area was around 58,800 ha with annual and perennial crops around 12,700 ha and 46,000 ha, respectively (Al-Adawi *et al.*, 2003). According to the Ministry of Agriculture and Fisheries (2014), approximately 7% of the total land area in Oman has soil that can support agriculture. Oman's cropping system is mainly fruit trees including date palms, forage (i.e. alfalfa & Rhodes grass), and vegetable crops, which constitute 45%, 30%, and 17% of the cultivated area, respectively.

Pest species and presence records

The disease incidence data caused by *C. fimbriata* was obtained from the literature (da Silva Galdino *et al.,* 2016) related to a total of 15 unique affected locations in the northern part of Oman (Figure 1). The strength of Maxent is its ability to make predictions with small sample size as reported in the literature (Anderson & Gonzalez, 2011). The collected data points represent the locations of the mango trees (Figure 1) infected with MSD that showed symptoms, including branch death, wilting leaves, and bark discoloration (da Silva Galdino *et al.,* 2016). The black outlined area shown in the right panel of Figure 1, is the area used for this study.

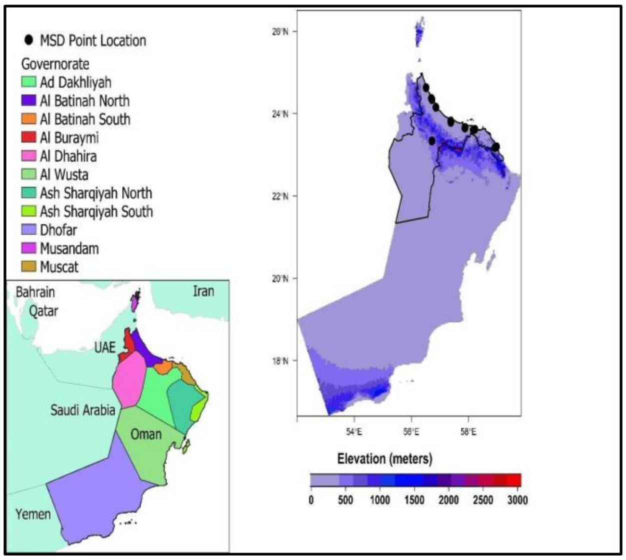

Figure 1. Sultanate of Oman map showing the mango sudden decline (MSD) locations reported by da Silva Galdino *et al*. (2016). The black outlined polygon shown to the top right represents the study area.

Environmental variables

To determine the future distribution of MSD under different climate scenarios, the study used datasets of future climate from the WorldClim data portal (https://www.worldclim.org/data/index.html). The future bioclimatic data were obtained from WorldClim v2.1, which was downscaled using CMIP6 at 2.5 minutes (4.5 km) spatial resolution. The climatic data was subject to nine Global Climate Models (GCMs) and four Shared Socio-Economic Pathways (SSP6-8.5) for the following periods: 1970-2000 (current & training period), 2021–2040, 2041–2060, 2061–2080, and 2081–2100 and were available in a Geotif raster format (Eyring *et al.,* 2016). This paper used ssp585 and the climate conditions that were represented by 19 bioclimatic variables. The 19 bioclimatic variables were extracted from the Geotif using statistical software. After the 19 bioclimatic variables for the eight models (not shown) were extracted, the average of each bioclimatic variable was calculated and used as an input for the model. The environmental variables derived from the WorldClim repository have been widely used in the prediction of the potential distribution of species as they are influenced by the changes in temperature and precipitation. As a result, these variables contribute to the ecology of species, which helps in explaining the predicted future distribution of species resulting from climate change (Zhang *et al.*, 2016).

This study considered the use of 20 environmental variables. Eleven of these variables were derived from the monthly temperature, while eight were derived from the monthly precipitation and digital elevation model. The decision to include seven bioclimatic variables in this study was based on the earlier study conducted by da Silva Galdino *et al.* (2016) to model the distribution of MSD in Oman. For the current disease distribution (training datasets), bioclimatic variables in the WorldClim database (version 1.4) included the information of 19 bioclimatic variables from 1970 until 2000. The highly correlated variables were removed at 0.8 and seven climatic variables were relevant to MSD distribution (Table 1). Accordingly, for the periods 2021–2040, 2041–2060, 2061–2080, and 2081–2100, this study incorporated these seven bioclimatic variables: mean annual temperature (bio1; °C); precipitation of the coldest quarter (bio19; mm); seasonal precipitation (CV) (bio15); precipitation of the driest month (bio14; mm); elevation (m); precipitation of the wettest month (bio13; mm); and mean diurnal range in temperature (bio2; °C). However, bio15 and bio13 appear to make a nonexistent to minimum contribution regarding the future distribution of MSD.

Model and analyses

This study used Maxent v.3.3., which was obtained from the web portal of Princeton University at http://www.cs.princeton.edu/. The software can forecast the extent and map the possible species distribution based on maximum entropy or environmental variables. The model uses climatologic variables in combination with species' locations to predict the species' capability of establishing itself in new areas. Maxent has the capability in producing various suitability indices ranging between 0 for unsuitable areas and 1 for highly suitable areas. Maxent yields in two assessment models: the area under the receiving operating characteristic (ROC) curve (AUC) and jackknife testing 17]. This study utilized Maxent to forecast the future distribution of MSD because of Maxent's ability to work with records of few locations at the same time (Pearson *et al.,* 2007).

Maxent uses AUC in assessing the model's performance, which is considered an excellent index indicator for the model's performance. At the same time, the ROC is used to assess the AUC model's performance through thresholding (Prabhulinga, 2017). The assessment of the AUC model's performance employs five categories: not suitable (0.5–0.6), low suitability (0.6–0.7), moderate suitability (0.7–0.8), suitabile (0.8-0.9), highly suitable (0.9–1) (Swets, 1988). The AUC values closer to 1, represent the good performance of the model. Therefore, low values of AUC are considered unreliable and vice versa.

Table 1. Environmental variables considered for the *C. fimbriata* Niche model and the average percent contribution of environmental variables in the mango sudden decline best Maxent model.

Period Scenarios Variables	1970-2000 % Cont.*	 PI*	2021–2040 % Cont.	 PI	2041–2060 % Cont.	 PI	2061–2080 % Cont.	 PI	2081–2100 % Cont.	 PI
Mean annual temperature (biol; °C)	0.5	7.4	0.7	14.7	2	26.7	2.2	37.8	4.3	51.7
Precipitation of coldest quarter (bio19; mm)	5.2	27.7	0.7	1.3	13.1	1.1	0.1	0.2	0.2	0.1
Precipitation seasonality (CV) (bio15)	0.1	-	-	-	-	-	-	-	-	-
Precipitation of driest month (bio14; mm)	36.7	13.6	31.4	15.6	32	35.6	37.5	38.8	37.5	32.5
Elevation (m)	4.2	6.9	15.1	8.4	4.6	7.1	7.1	9.4	9.3	12.5
Precipitation of wettest month (bio13; mm)	0.1	0.1	-	-	0.3	15	0.1	-	0.3	-
Mean diurnal range in temperature (bio2; °C)	53.3	44.3	52	59.9	48	14.4	53	13.7	48.5	3.1

* % Cont.= % Contribution; PI= Permutation importance

The jackknife test is used to assess the leading bioclimatic variables and map the possible distribution of *C. fimbriata*. The jackknife test is built-in to the software used to calculate the habitat suitability curves of each variable; it is also used to assess each climatic variable's contributions to the habitat model (Li *et al.*, 2016). More information on this model's modeling approach can be found in Philips and Dudik (2008).

Evaluation of the model performance

Because the data was limited, this study used cross-validation for 15 replications with a threshold at 10 percentile training presence (Shcheglovitova & Anderson, 2013). The following parameters such as auto-features and regularization multiplier used the default settings. The default parameter settings were used because they are effective and are suitable for a wide-range of species occurring data sets. 15 replicated runs were used to get the output of the average logistic. The output of the replication is used to estimate the likelihood of the presences indices per category between 0 (not likely to occur) and 1 (most likely to occur) (Phillips *et al.*, 2006; Phillips & Dudík, 2008).

AUC was used to estimate the goodness of fit under the ROC curve, where the highest value indicated the best performer. The jackknife, the percentage contribution, and the permutation importance were used to estimate the most important environmental variables governing MSD distribution. Response curves were generated in Maxent and were used to indicate the relationships between predicted probabilities of the presence of the disease with respect to the variations within each environmental variable.

Results

Bioclimatic variables contribution and Maxent performance

C. fimbriata forecasting during the 2021–2040 climatic scenario was found to be AUC mean = 0.913. The outcomes of the model presented that some of the designated seven bioclimatic variables of *C. fimbriata* showed the distribution of MSD for the period 2021–2040 very well. Among the seven bioclimatic variables, three contributed significantly to the disease occurrence such as bio2 with 52% contribution, bio14 with 31.4% contribution, and elevation with 15.1% contribution. In contrast, the distribution of the bioclimatic variable of *C. fimbriata* for the period 2041–2060 was for bio2 with 48% contribution, bio14 with 32% contribution, and elevation with 4.6% contribution. The bioclimatic variables' distribution of *C. fimbriata* for the period 2061–2080 were for bio2 with 53% contribution, bio14 with 37.5% contribution, and elevation with 7.1% contribution. For the period 2081–2100, the bioclimatic variables' contribution to MSD distribution were for bio2 with 48.5% contribution, bio14 with 37.5% contribution, in addition to elevation with 9.3% contribution (Table 1).

The jackknife test for the period 2021–2040 showed that bio2, bio13, bio14, and elevation were the main variables (Figure 2), and in terms of permutation the main variables were bio2 with 59.9%, bio14 at 15.6%, and elevation at 8.4% contribution. These figures demonstrate that temperature and precipitation play a significant role in forecasting the possible dispersal of *C. fimbriata*. Based on the species response curves acquired, *C. fimbriata* prefers a mean diurnal range in temperature, limited precipitation, and moderate elevation.

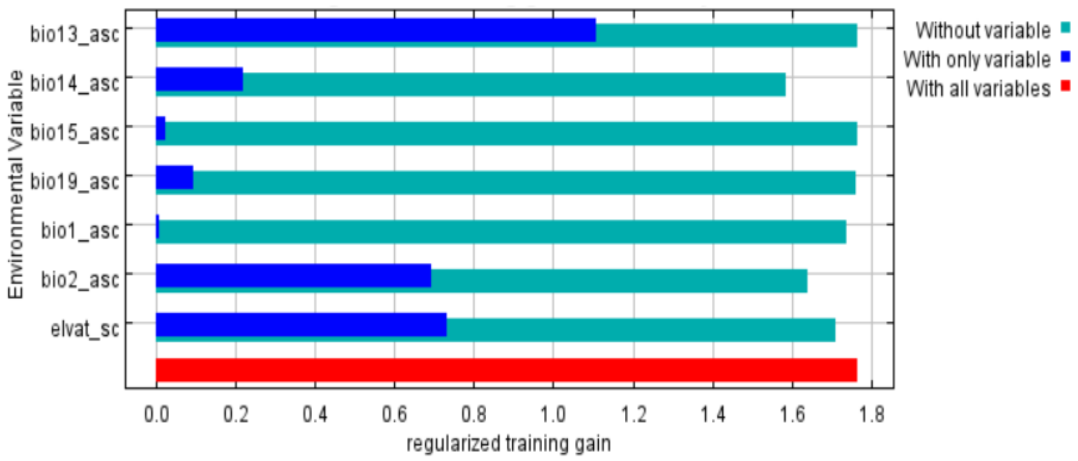

Figure 2. Jackknife test of environmental variable importance for *C. fimbriata*. Y-axis represent the seven environmental variables in ASCII raster format (bio1 = Annual Mean Temperature; bio2 = Mean Diurnal Range (Mean of monthly (max temp - min temp)); bio13 = Precipitation of Wettest Month; bio14 = Precipitation of Driest Month; bio15 = Precipitation Seasonality (Coefficient of Variation); bio19 = Precipitation of Coldest Quarter).

The mean AUC values showed in Table 2 for *C. fimbriata* in the future periods (2041–2060, 2061–2018, and 2081–2100) performed well, indicating trustworthy predictability, and the AUC values of 0.913, 0.896, and 0.907, respectively, were considered high. The model outcome shows that the simulations can be used to analyze the impact of climate change on the distribution of *C. fimbriata* in Oman.

Table 2. AUC values when modeling *C. fimbriata* distribution of various climate change scenarios for three future periods (2041–2060, 2061–2080, and 2081–2100; 15 replicated runs).

Period	AUC mean	AUC SD mean
2041–2060	0.913	0.023
2061–2080	0.896	0.002
2081–2100	0.907	0.021

Predicted current potential distribution

Using ArcGIS 10.8, the map in Figure 3 shows the potential MSD spreading projection for *C. fimbriata* based on observed occurrences and the environmental variables projected by the Maxent model for 2021–2040.

The coastal area in northern Oman showed high suitability for *C. fimbriata* disease distribution. The total area of suitable locations (including less suitable habitat, moderately suitable area, and highly suitable area) was 64,393 km^2. The highly suitable areas for *C. fimbriata* were primarily located along the coast in northern Oman with a presence probability > 0.6, which was only 5% of the total area for the training & histrorical period 1970–2000 (Figure 3).

Future climatic distribution scenarios

The estimated future climate change distributions for *C. fimbriata* with various climate change projections for the periods of 2021-2040, 2041–2060, 2061–2080, and 2081–2100 are presented in Figure 4. The results showed that there was an increase of 5% between the total number of suitable habitats in 2021–2040 and those predicted for 2081–2100 (Figure 4). Compared with the 2021–2040 distribution, the total area of the moderately suitable regions for *C. fimbriata* under the three climatic scenarios for the periods 2021-2040, 2041–2060, 2061–2080, and 2081–2100 would increase by 1.44%, 0.52%, and 0.33% respectively. In contrast, the total area of the highly suitable habitats would increase by 1.7%, 4.5%, 4.41%, and 5% respectively (Table 3). Under the scenarios for 2021-2040, 2041–2060, 2061–2080, and 2081–2100, the areas of the less suitable regions would decrease by -1.97%, -5.95%, -4.93, and -3.09%, respectively, and the areas of the unsuitable regions would decrease by 16% (Table 3).

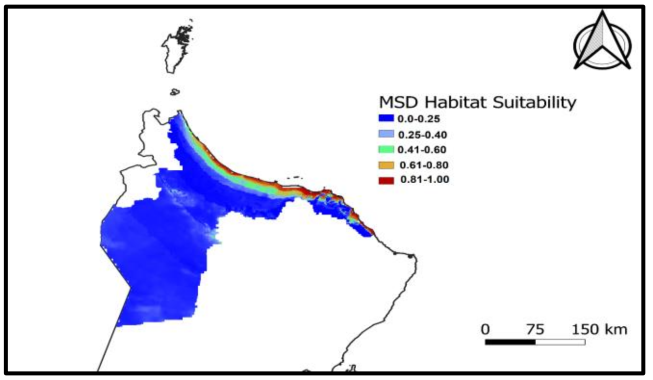

Figure 3. Suitable climatic distribution of *C. fimbriata* in north Oman for the historical period 1970-2000. The MaxEnt model was trained with this historical period. The blue color (0.0–0.2) and red color (0.8–1.0) show the least and most suitable locations for *C. fimbriata*, respectively.

Table 3. Predicted suitable areas for *C. fimbriata* in future Climatic Conditions

Scenarios	Predicted area (km^2)					Rate increase/decrease (%) compared to 2020-2040				
Period	**UH***	**PSH**	**MSH**	**SH**	**HSH**	**UH**	**PSH**	**MSH**	**SH**	**HSH**
1970-2000 (Historical & Training)	57822	1507	1850	1081	2133					
2021-2040	7916	287	172	175	167	-1%	-0.95%	0.89%	-0.33%	1.40%
2041–2060	2422	49	36	12	0	-6.35%	0.40%	1.44%	1.20%	3.3
2061–2080	2458	57	61	15	0	-5.07%	0.14%	0.52%	1.10%	3.31%
2081–2100	2426	80	66	19	0	-3.84%	-0.75%	0.33	0.95%	3.31%

* UH= Unsuitable habitat (0-0.25), PSH= Poorly suitable habitat (0.25-0.40), MSH= Moderately suitable habitat (0.41-0.60), SH= Suitable habitat (0.61-0.80), HSH= Highly suitable habitat (0.81-1.0).

Figure 5 shows the standard deviation (SD) associated with the climatic projections. The SD values quantify the uncertainty of the predictions from the models. It is clear from these figures that predictions of climate projections (farther into the future 2061-2080 and 2081-2100) have more slightly variability (high SD) in habitat suitability when compared with the immediate climatic projection periods (2021-2040 & 2041-2060).

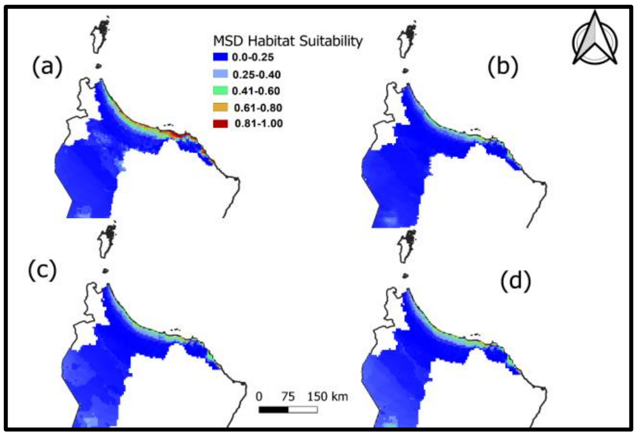

Figure 4. Potentially suitable climatic distribution of *C. fimbriata* under different climate change scenarios in north Oman for the future periods (a) 2021-2040 (b) 2041–2060, (c) 2061–2080, and (d) 2081–2100. The blue color (0.0–0.2) and red color (0.8–1.0) show the least and most suitable locations for *C. fimbriata*, respectively.

Discussion

This paper is considered as one of the pioneers in investigating *C. fimbriata* distribution in relation to climate change consequences in northern Oman using Maxent modeling. Maxent is widely used in research, primarily because of its ability to provide speedily and thorough outcomes on past, current, and future presence of a specified species (da Silva Galdino *et al.*, 2016). At least two studies have used Maxent to estimate the probable dispersal of many species (De Meyer *et al.*, 2010; Solhjouy-Fard *et al.*, 2013). The potential MSD distributions were predicted to change as a direct result of future climate change scenarios (da Silva Galdino *et al.*, 2016). This study projected the probable dissemination of *C. fimbriata* and explored the potential geographic distribution of MSD with various future climatic scenarios. In this paper, the probable spread of *C. fimbriata* is centered on bioclimate variables, with seven leading variables (bio1, bio2, bio13, bio14, bio15, bio19, and elevation) instead of focusing on the other abiotic factors, such as soil and water-type influences and the type of mango tree cultivar (Al-Adawi *et al.*, 2003). Climatic factors are the most crucial elements that contribute to the regeneration and spread of MSD (da Silva Galdino *et al.*, 2016).

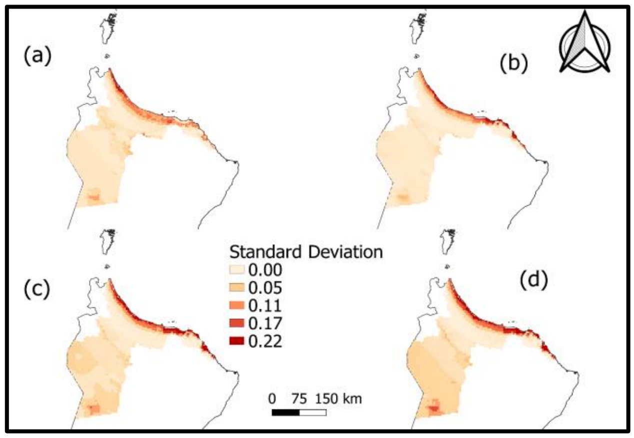

Figure 5. The Standard deviation maps of the species distribution in Maxent for climatic projections (a) 2021-2040 (b) 2041-2060 (c) 2061-2080 (d) 2081-2100.

The model outcomes showed that the highly suitable areas for *C. fimbriata* potentially increased by 3.31% in 2081–2100, covering an area of about 2234 km^2. da Silva Galdino *et al*. (2016) explained the potential effects of global warming on MSD distributions through expansions and shifts in the species' range. This paper showed that under the projected future climatic scenarios, the distribution for *C. fimbriata* would expand under all projections in 2041–2060, 2061–2080, and 2081–2100 periods, proving that more areas would exist for MSD invasion. The change was more obvious for the period 2081–2100 than for 2061–2080, and the outcomes predicted by this study were consistent with those of other studies showing the consequences of habitat change under the effects of future climate change (Biber-Freudenberger *et al.*, 2016). Even so, under different climatic scenarios, the results did not show the same trend, which might be due to the variation in humidity and temperature that influence *C. fimbriata* spread. In addition, averaging the bioclimatic variables might also have contributed to the uncertainty by creating overlapping results.

As this study provided a spatial mapping for the possible disease distribution in northern Oman, techniques such as integrated approaches or strategies such as the development of hybrid species could abate the spread and also provide an increased resistance to *C fimbriata*. Other approaches could be, for instance, incorporating pest management policies could help in managing the disease invasion *(*Al-Adawi *et al.,* 2003). The important maps produced in this study are indicators of the possible establishment of MSD disease and potential areas that are at risk of its invasion. Therefore, the result of this study can be used by decision-makers in preventing the establishment of this disease in the agricultural corridor of Oman. The best defense mechanism is improvement in agricultural policy and governance in crop production and soil management. Moreover, the agricultural land in Oman is composed of mixtures of various crops; as a result, the current spatial distribution of Mango as a specific crop is not mapped or known. However, with Oman being an arid country, the suitable areas for crop production are known which is usually along the lowland of the coastal area. This study will help the farmers to identify the suitable area for mango production and the vulnerable area for disease distribution in current and future climate change scenarios. Since most of Oman's land is not suitable for agricultural practices this type of study is important as it help the farmers and the decision-makers to conserve the suitable agricultural land and to protect their agricultural crops from diseases and from other possible reasons of converting this land to urban land use. Furthermore, one of the challenges in this study was the lack of spatial data on the MSD distribution. However, this study will help in identifying possible sites that could help the decision-makers in mapping and quantifying the potential vulnerable sites and farms.

In conclusion, even though this study indicated possible changes in environmental and climatic conditions, it did not provide definitive predictions. It was important to evaluate the effects of the global climate change scenario on the potential distribution of MSD diseases, because by doing so it provided a helpful understanding of the relationship between the prevalence of MSD and the corresponding environmental variables. This study, therefore, helps to identify areas of potential MSD distribution and to establish operational strategies for managing and inhibiting the future distribution of the disease.

This study was one of the first in providing future projections of *C. fimbriata* in northern Oman. The MaxEnt model was trained with a previous period (1970-2000) and then projected to future climate periods (2021-2040, 2041–2060, 2061–2080, 2081–2100). The results showed Maxent provided a good representation of MSD pattern and distribution by using data from 15 affected locations and 7 bioclimatic variables in predicting the consequence of climate change on the mango trees. The following conclusions are drawn:

i. Between the period 2081 and 2100, the extent of extremely suitable category for *C. fimbriata* would increase by 5% under the projection of climate change for that period.
ii. Climate change consequences on the probable spread of MSD must therefore be considered, primarily to estimate the loss of mango production and to prevent the potential establishment of MSD, as the area of suitable habitat will increase 5% by 2100.
iii. This study found that the following bioclimatic variables such as biol (Mean Annual Temperature), and bio2 (Mean Diurnal Range (Mean of monthly (max temp - min temp) and bio14 (Precipitation of Driest Month) contribute significantly to the possible distribution of MSD in northern Oman. The change in future climatic scenarios will foster an outbreak in mango tree diseases. Therefore, strategic planning such as defining vulnerable areas for the protection of mango and conservation initiatives (which can help in minimizing the impacts) should be considered for mango planting farms.

The results of this study would be of immense benefit to decision-makers from the local to national levels, where informed best management practices would be made for sustainable mango production in Oman under a changing climate.

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الملخص

الرحيلي، آمنة، ألابا بولوواده وعلي الصبحي. 2021. تخمين حدوث الموت المفاجيء للمانجو المتسبب عن الفطر *Ceratocystis fimbriata* تحت ظروف التغير المناخي. مجلة وقاية النبات العربية، 39(3): 215–223. https://doi.org/10.22268/AJPP-039.3.215223

تعتبر أشجار المانجو من المحاصيل المهمة لقيمتها الغذائية والاقتصادية العالية. يعد مرض الموت المفاجئ (MSD) من الأمراض الرئيسية التي تهدد أشجار المانجو في عمان وجميع أنحاء العالم. هدفت هذه الدراسة إلى تحديد المناطق في شمال عمان التي ينتشر فيها فطر *Ceratocystis fimbriata* المسبب لمرض – MSD الذي يتكيف وينتشر في ظل التغير المناخي. استخدم في هذه الدراسة نموذج MaxEnt واعتمد على بيانات الفترة 1970–2000 وبناءً عليها تم توقع التغيرات في فترات المناخ في المستقبل. صممت هذه الدراسة التوزيع المستقبلي لفطر *C. fimbriata* للسيناريوهات المناخية في الفترات التالية: 2021–2040، 2041–2060، 2061–2080، و2081–2100. تم في هذه الدراسة تضمين خمسة عشر موقعاً متأثراً بالمرض واستخدام سبعة متغيرات مناخية حيوية. أظهر استخدام

اختبارات النمذجة قيماً تتراوح بين 0.896 و 0.913 (ملاءمة الموائل) مما يمثل نموذجاً جيداً للنتائج. أظهر اختبار jackknife أن متوسط المدى النهاري لدرجة الحرارة وهطل الأمطار سيسهم في أكثر الشهور جفافاً في زيادة إنتشار العامل الممرض *C. fimbriata*. من العام 2021 حتى عام 2040، تم العثور على مساحة إجمالية قدرها 1889 كم مربع ملائمة جداً لنمو واننتشار فطر *C. fimbriata* في شمال سلطنة عمان، وستزيد مساحات المناطق غير الملائمة في الفترات 2041−2060 و2081−2100 مقارنة بفترة 2021−2040. كما ستنخفض المناطق الملائمة بشكل معتدل لانتشار فطر *C. fimbriata* في ظل جميع السيناريوهات التي تمت دراستها، إلا أن المساحة الإجمالية للمناطق الملائمة مع جميع السيناريوهات ستزداد ما عدا الفترة 2041−2060. ستساعد نتائج هذه البحث في إدارة ومنع مرض الموت المفاجئ لأشجار المانجو (MSD) بشكل أفضل من خلال السيناريوهات المناخية المتوقعة في المستقبل مما سيساعد في السيطرة على فطر *C. fimbriata* وخنفساء اللحاء (*Hypocryphalus mangiferae*) باعتبار أن لهما الدور الرئيس في انتشار هذا المرض.

كلمات مفتاحية: الموت المفاجئ للمانجو، *Ceratocystis fimbriata*، المتغيرات المناخية الحيوية، التغيرات المناخية، سلطنة عمان، نموذج MaxEnt.

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