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Mapping the Potential Distribution of Oak Wilt (*Bretziella fagacearum*) in East Central and Southeast Minnesota Using Maxent

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Abstract

With the advancement of spatial analysis and remote sensing technology, potentially devastating forest pathogens can be managed through spatial modeling. This study used Maxent, a presence-only species-distribution model, to map the potential probability distribution of the invasive forest pathogen oak wilt (*Bretziella fagacearum*) in eastern and southeastern Minnesota. The model related oak wilt occurrence data to environmental variables including climate, topography, land cover, soil, and population density. Results showed that areas with the highest probability of oak wilt occur within and surrounding the Minneapolis/St. Paul metropolitan area. The jackknife test of variable importance indicated land cover and soil type as important variables contributing to the prediction of the distribution. Multiple methods of analysis showed that the model performed better than random at predicting the occurrence of oak wilt. This study shows Maxent's potential as an accurate tool in the early detection and management of forest diseases.

Keywords: oak wilt, *Bretziella fagacearum*, Minnesota, species-distribution models, SDMs, Maxent, maximum entropy, GIS, geographic information systems

Introduction

Forest Pathogens and Oak Wilt

Although most forest pathogens are innocuous and do not cause serious or long-term damage to ecosystems, others have the ability to devastate landscapes. Globalization has increased travel and trade between and within countries creating new avenues for long-distance dispersal of invasive forests pathogens. Even locally, leisure and recreation activities, such as hiking and the transportation of firewood, have been shown to carry pathogens short distances to new locations (Gibbs and French 1980, Cushman and Meentemeyer 2008). Change in land use through deforestation, expansion of agricultural fields, draining of wetlands, urban sprawl, and landscape changes because of suppression of natural events such as fire can affect the prevalence of forest pathogens (King et al. 2006, Meentemeyer et al. 2008). Human-induced climate change affects the susceptibility of forests through shifting ranges of the pathogen or host species, adaptive reproductive responses, altering habitat and ecological community of a region, and social and economic responses to climate change (Desprez-Loustau et al. 2006, Wilkinson et al. 2011, Venette 2013). All of this results in forest fragmentation and loss of forest heterogeneity that allow forest pathogens to thrive.

Management and Policy Implications

Forest diseases and pathogens can cause significant damage to an ecosystem. Understanding where they are going to occur and what variables are important in their distribution can stave off the detrimental effects they have on established and at risk ecosystems. Modeling allows researchers to determine the extent of the disease, which variables lead to the increase in infection centers, and predict the distribution of the disease. This study shows Maxent as a reliable tool forest managers and scientists can use to monitor the susceptibility of a wooded area to a specific forest pathogen. Through modeling, they can save time and money by highlighting those areas that are more likely to harbor a pathogen and focusing on-ground monitoring and detection efforts to these areas.

Oak wilt is an infectious forest disease caused by Ascomycetes fungus (*Bretziella fagacearum*), which has reached serious levels in Texas and the Upper Midwest. The pathogen targets primarily oaks but also many trees found in the family Fagaceae that have shown susceptibility (Appel 2009, Harrington 2013). Within the oak family, susceptibility varies among species. White oaks (Sect. *Quercus*) have the ability to fight off the pathogen, whereas red oaks (Sect. *Lobatae*) are easily infected, most dying from the pathogen within months. Live oaks (Sect. *Protobalanus*), the predominant group in Texas, have susceptibility between that of red and white oaks (Gibbs and French 1980, Appel 2009). Oak wilt enters a healthy tree through a fresh wound in the bark where it lodges in the xylem tissue. As the pathogen multiplies, it chokes the xylem and prevents water from reaching the crown of the tree resulting in the eponymous wilt of the tree (Gibbs and French 1980).

Transmission of oak wilt from an infected to a healthy oak occurs either overland or underground. Overland infection requires a spore mat to form on a red oak, a fresh wound to the xylem tissue to be found on a healthy oak, and an insect vector to carry spores from the infected tree to the wound in the healthy oak (Juzwik et al. 1985, Harrington 2013). Underground spread takes place via root grafting and is the most common form of spread in Minnesota occurring most commonly among red oaks (Gibbs and French 1980). Regardless of the route of transmission, oak wilt is a rapidly spreading and serious forest disease.

As of 2016, 32 counties in Minnesota have had a confirmed case of oak wilt (USDA 2017). This forest pathogen has the potential to rapidly alter the makeup of forests. With the advancement in technology, remote sensing imagery, and the open availability of data comes the ability to accurately predict the occurrence and potential distribution of forest pathogens using species-distribution models (SDMs). The use of these technologies can assist in the detection, management, and eradication of destructive forest disease and minimize their impacts.

SDMs

SDMs are important tools in the fields of ecology, biogeography, conservation biology, and, more recently, climate-change studies in understanding how the distribution of a species is dictated by local environmental factors (Guisan et al. 2005). SDMs create a distribution of a species by relating known species occurrence locations with environmental variables (Guisan and Zimmermann 2000).

Scientists use SDMs to understand the distribution of a species or predict where the species may occur. Most often, SDMs are used to understand or describe the distribution of one species (Ahmed et al. 2015). By using SDMs in such a way, scientists can better understand which variables are associated with the presence or absence of a species, information that can prove particularly beneficial in studies on rare or endangered species (Wilson et al. 2011, Maria Teresa et al. 2014, Morinha et al. 2017). In addition, with the continued acceleration of climate change, SDMs are becoming popular tools in studying the effects that shifting temperature and precipitation will have on a species distribution (Venette 2013, Ikegami and Jenkins 2018).

This research used the Maxent SDM to map the probability distribution of oak wilt in east central and southeastern Minnesota (Figure 1). Maxent is machine-learning software that requires only presence data to create a robust model of distribution and has quickly become a favorite tool among SDM users (Ahmed et al. 2015). It is easy to download, simple to use, and efficient, allows the user to alter parameters, and calculates statistical tests. Maxent creates a probability distribution of a species occurrence based on the principle of maximum entropy because it agrees with what is known and does not assume anything that is not known. The algorithm uses attempts to create a statistical model that recreates the distribution of the training data by assuming a uniform distribution throughout the study area, then altering that distribution only as much as constraints, statistical values found using values of

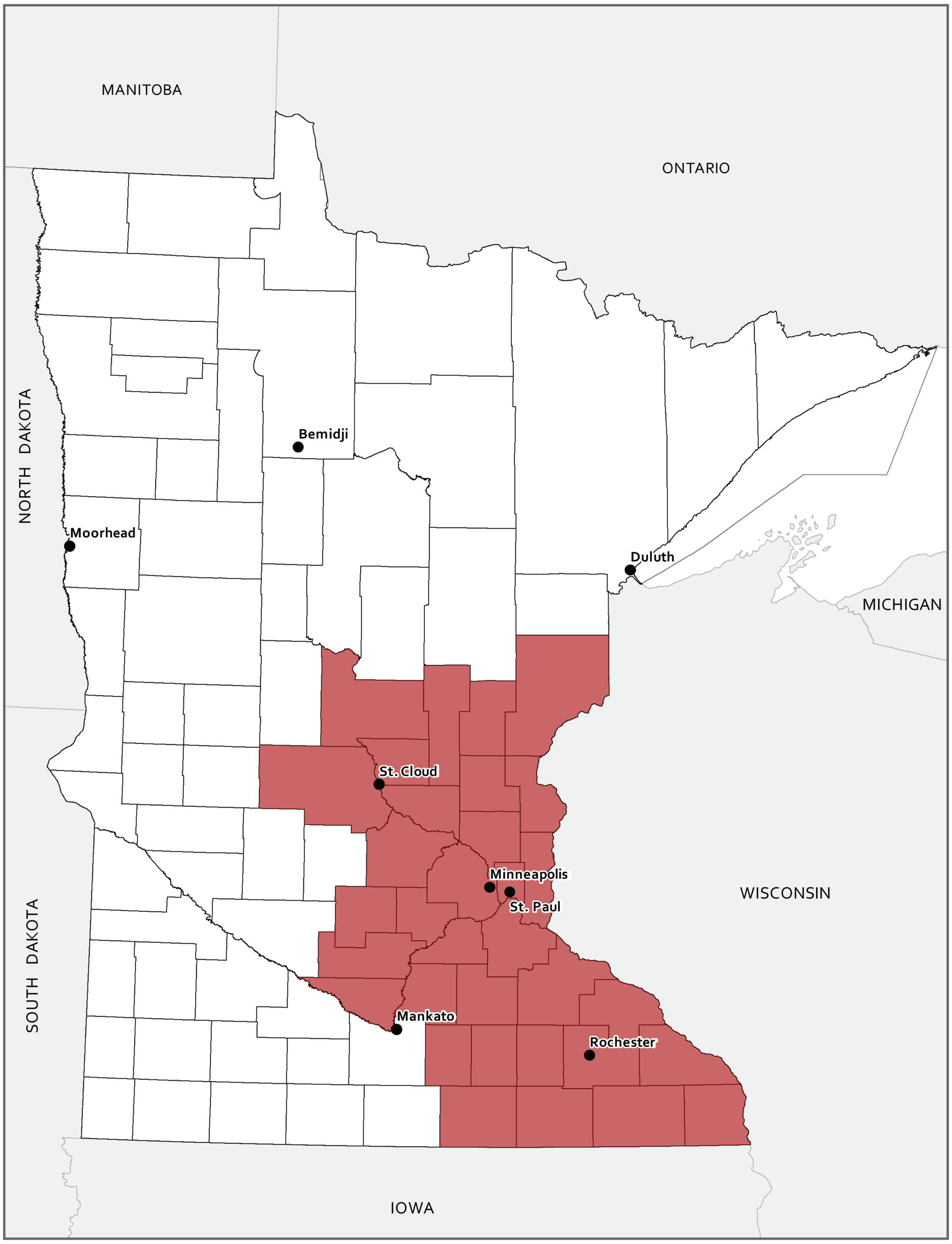

Figure 1. Study area consisting of 33 counties in east central and southeastern Minnesota.

environmental variables at the known occurrence locations, allow (Phillips et al. 2006).

This research demonstrates how the potential distribution of oak wilt in east central and southeastern Minnesota can be mapped using Maxent and determines which variables were important in the creation of that distribution to assist forest managers in the state to better predict the future spread of oak wilt.

Methods

Creation of a probability distribution of oak wilt in Minnesota using Maxent first required the creation of an oak wilt occurrence database and selection of the appropriate environmental variables. The model was then set up and run with the appropriate parameters followed by model evaluation using the area under the receiver operating characteristic curve (AUC) and the true skill statistic (TSS) (Allouche et al. 2006, Phillips et al. 2006).

Occurrence and Environmental Data

Occurrence Data

To create a database of oak wilt occurrences, confirmed oak wilt locations between 2007 and 2016 were obtained from the Minnesota Department of

Natural Resources (DNR) and Three Rivers Park District (TRPD) and combined into one master dataset (n = 460) (Figure 2). Each organization gathered oak wilt data by different means. The MN DNR data came from on-the-ground observations in communities that applied and received funding from the DNR for oak wilt management. TRPD data came from aerial surveys that were ground truthed for positive oak wilt presence.

Climate Data

Previous studies have shown that climate variables, specifically temperature and precipitation, affect the presence of certain forest pathogens including oak wilt (Meentemeyer et al. 2004, Juzwik 2009). The climate data used came from 30-year (1981–2010) normal climate datasets from the PRISM Climate Group (http://prism.oregonstate.edu/) including average annual precipitation, average temperature for the two coldest months (December and February to January were not used because of data-integrity issues), and average temperatures of the three hottest months (June, July, and August). Each climate variable came in a nationwide raster dataset with a resolution of 800 m and clipped to the study area.

Topography Data

This research used a digital elevation model (DEM) of Minnesota: statewide, 1:24,000, Level 2, raster that was created from a United States Geological Survey (USGS) DEM as the elevation layer (https://gisdata.mn.gov/dataset/elev-30m-digital-elevation-model). With a standardized grid size of 30 m and a vertical resolution of 10 m, the resolution was a perfect fit for use in this research. Using the corresponding tools in ArcMap, slope and aspect layers were both derived from the DEM raster layer.

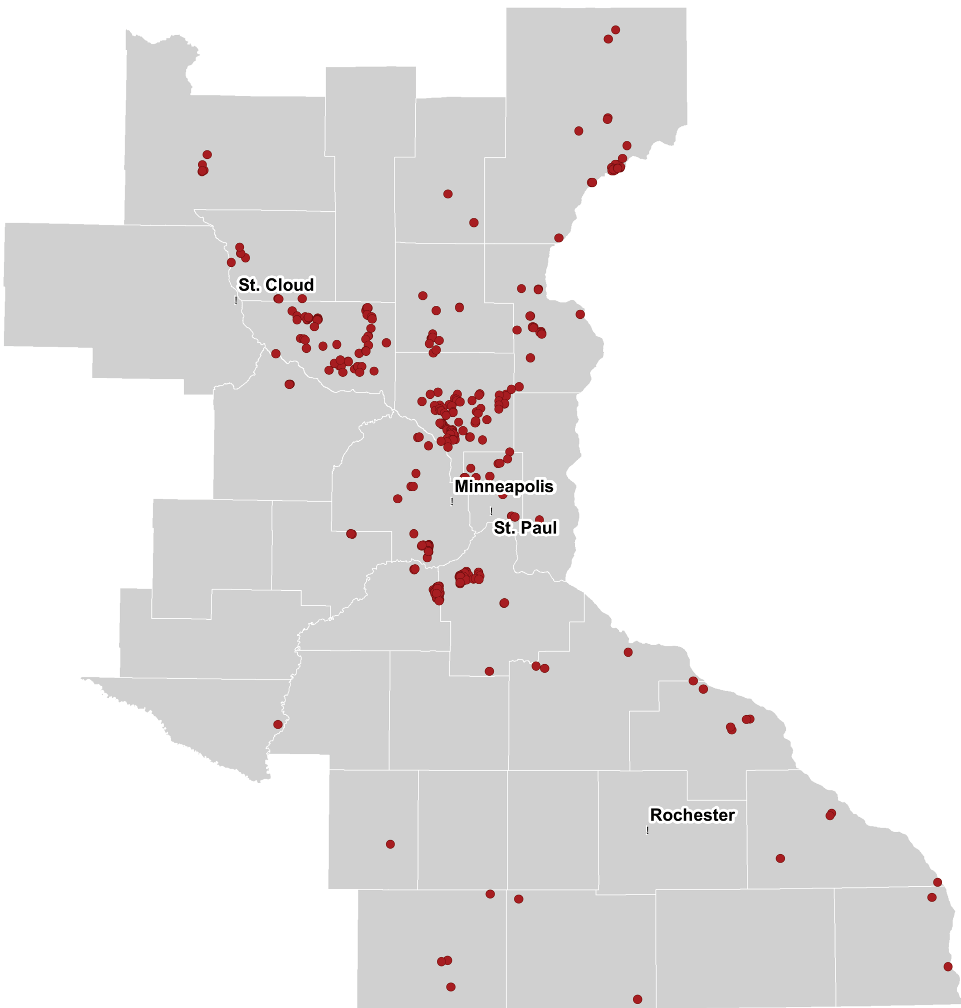

Figure 2. Oak wilt occurrence locations between 2007 and 2016 obtained from the Minnesota Department of Natural Resources and Three Rivers Park District.

Land-cover Data

The Minnesota Land Cover 1991–92 map, a product of the USGS Gap Analysis program (https://gisdata.mn.gov/dataset/biota-landcover-gap), which used satellite imagery to produce detailed vegetation maps with a resolution of 30 m, was used for this research. The data used divide the land cover in Minnesota into 49 classes, 40 of which are found in the study area. The last accuracy assessment of this data took place between 1995 and 2000. Although 20 years have passed since the last accuracy assessment, and much development in the metropolitan areas has occurred, the level of detail found in this layer made it the ideal choice for this research.

Soil Types

Soil suborder data were acquired through the Natural Resources Conservation Service's Soil Survey Geographic (SSURGO) database (https://websoilsurvey.nrcs.usda.gov/). Included in the download were dozens of tables of soil data that link to the spatial element via a map unit key. Using this key, the component table was joined to the shapefile to create a map with an attribute table that included soil-order information.

Population Density

Population density was acquired from the Gridded Population of the World (GWP), Population Density version 4.10 for the year 2015 from the Socioeconomic Data and Applications Center (SEDAC) (http://sedac.ciesin.columbia.edu/). This layer showed the estimated number of people per square kilometer using national census numbers. Although the resolution for these data is coarse, SEDAC provides the only gridded (raster) datasets on population counts and density that is not constrained to political boundaries.

Maxent Setup

This research used Maxent software version 3.4.0 (https://biodiversityinformatics.amnh.org/open_source/Maxent/). The oak wilt occurrence data file was uploaded into the Samples pane of Maxent and the ASCII variable files into the Environmental variables pane. Data type was selected from the drop-down menu for each environmental variable: aspect, Gap Analysis Program (GAP), and soil types were designated as categorical, and the remaining variables as continuous.

Overfitting is a common issue with Maxent but one that can be controlled by altering specific parameters within the model. As stated before, Maxent uses a set of constraints to create a distribution, and overfitting occurs when the model adheres too closely to these values. Preventing this issue requires altering one of two parameters. First, increasing the regularization parameter will relax the constraints allowing for a greater range of values around the constraint. Second, and the method chosen for this research, the type of restriction can be chosen manually between linear, product, quadratic, threshold, and hinge features. The feature class chosen determines how constraints are calculated (Phillips et al. 2006). Hinge feature only was selected because research on the accuracy of models using specific feature classes showed hinge feature created the most accurate models without becoming overly complex and overfitting the occurrence locations (Phillips and Dudik 2008).

Within the settings of Maxent, various parameters can be changed to customize the model to fit the species and data being modeled. This research used random seed to set aside a random 25 percent of the occurrence data for testing.

Model Evaluation

The best method for evaluating a Maxent distribution from presence-only data is still being debated (Gusian et al. 2005, Elith and Leathwick 2009). This research used multiple methods to evaluate the performance of the model. Maxent produced a receiver operating characteristics (ROC) AUC and an analysis of omission/commission to evaluate the model. In addition, the TSS was used as an independent measure of validity. The TSS is calculated from the model's proportion of accurately predicted presences and the proportion of accurately predicted absences with a value ranging between −1, indicating the results are no better than a random model, and +1, indicating a perfect model (Allouche et al. 2006).

Results

Potential Distribution

The areas with the highest probability of oak wilt are found in the center of the study area near the Minneapolis–Saint Paul metropolitan area and to the north and west near the Mississippi River. The model placed the highest probability areas mainly surrounding known occurrence locations (Figure 3). Very high probabilities can be found in nearly half of the counties within the study area. Hennepin, Ramsey, and Anoka counties have significant areas classified as very

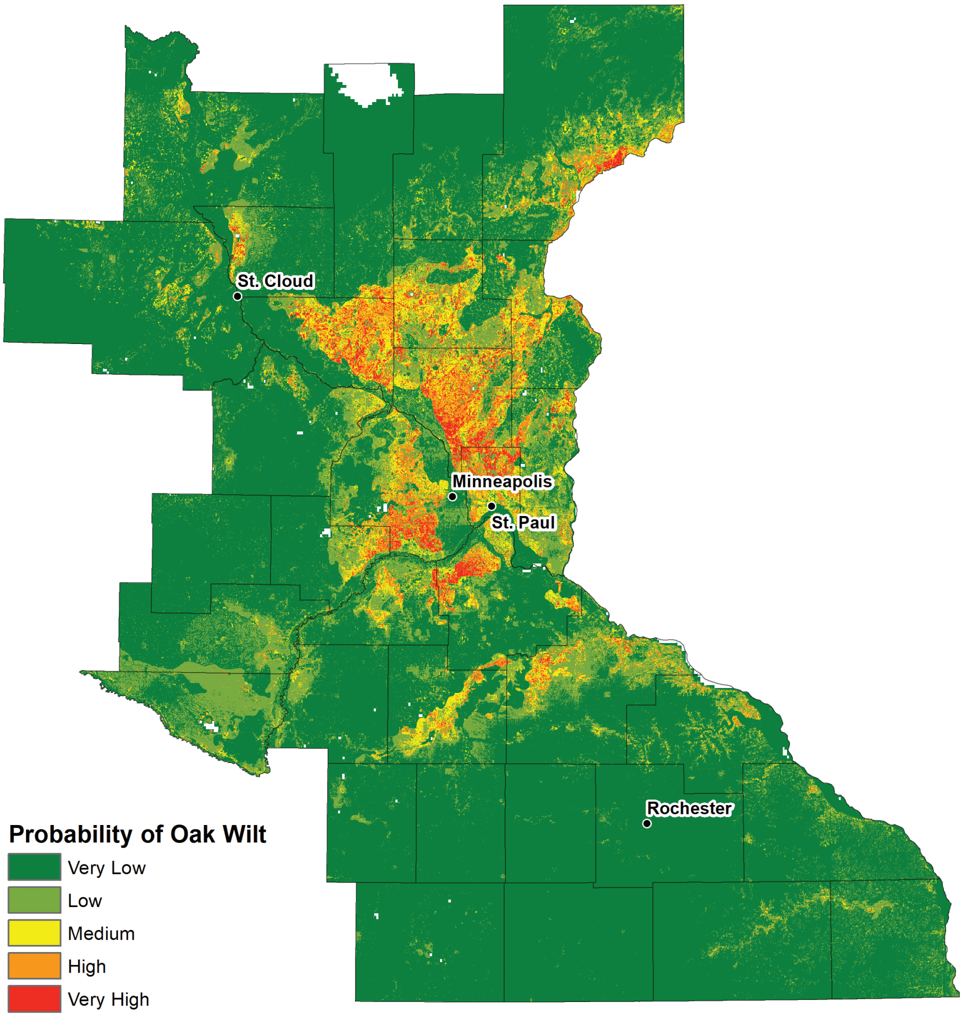

Figure 3. Reclassified Maxent output into five categories representing the probability of oak wilt occurrence using Jenks Natural Breaks Classification.

high or high followed closely by Sherburne, Isanti, and Washington counties. Counties in the far north or far south of the study area show very low probabilities of oak wilt distribution with the exception of Pine County along its border with Wisconsin. The Maxent model also predicted high probability for regions in southern Dakota county, northern Rice county, and western Goodhue county, although they have few occurrence locations.

Variable Importance

Variable contribution shows how much the model relied on each variable to create the final output (Table 1). The GAP-derived vegetation cover variable contributed the most (37.1 percent) to the model with soil type (23.0 percent) and population density (22.2 percent) rounding out the top three environmental variables. Of the 12 variables used in the study, nine contributed

Table 1. Percentage contribution of each variable to the creation of the final Maxent model.

Variable	Percentage contribution
GAP	37.1
Soil type	23.0
Population density	22.2
Elevation	5.3
Annual precipitation	4.3
Dec min temp	2.3
Jun max temp	2.2
Aspect	1.4
Feb min temp	0.9
Slope	0.5
Jul max temp	0.4
Aug max temp	0.3

Note: Higher percentages mean that the model placed greater weight on those variables when creating the distribution model.

only 17.6 percent. It is important to note that the table of variable importance represents only the model created and that alternate models using the same data will generate a table with different percentages.

The jackknife test of variable importance shows the amount of useful and unique information within each variable. To create the plot, Maxent runs three models: one with all variables, one with only a single variable, and one with all but one variable. The red bars indicate the usefulness of the information within each variable toward the creation of the model, and the blue bar indicates the uniqueness of the information within the variable. In the plot created by this model (Figure 4), the vegetation cover variable has both the longest red bar and the shortest blue bar, indicating this variable has the most useful and unique information of all the variables. Soil type had the second greatest uniqueness of information. Other highly useful variables include soil types, elevation, and July maximum temperature.

Response curves are yet another option to study the effects of each environmental variable on the model. The curves, for continuous data, and bar graphs, for categorical data, created for this thesis are based on the model using only that variable and represent how the probability of oak wilt differs when that variable changes. The plot for GAP (Figure 5) shows that areas with land cover primarily made up of northern pin oak and bur/white oak almost guarantee the presence of oak wilt. Low-intensity urban and red oak land cover resulted in about an 80 percent chance of oak wilt occurrence. Interestingly, areas in the study area covered in jack pine and red/white pine–deciduous mix also had an almost 100 percent probability of oak wilt presence. Two soil suborders stand out above the rest in terms of probability of oak wilt occurrence (Figure 6). The presence of Psamments and Hemists soils will result in an approximately 88 percent and 81 percent chance of oak wilt occurrence respectively.

Model Evaluation

The AUC value for this mode (0.926) indicates that the model fit the training data much better than average. A perfect model would have an AUC value of 1 represented by a right angle on the graph, indicating all known occurrence locations were labeled as such in the model, and no areas absent of oak wilt were labeled as present by the model. The high AUC of this model shows that Maxent did far better than random in creating a model to represent oak wilt occurrence locations (Figure 7). The TSS value for this model was 0.748, indicating a model statistically better than random.

Discussion

The results indicate that the Maxent approach is capable of creating a potential distribution model of oak wilt in Minnesota. However, the results are simply based on the data the model was given, which does not ensure that the results are ecologically meaningful. To

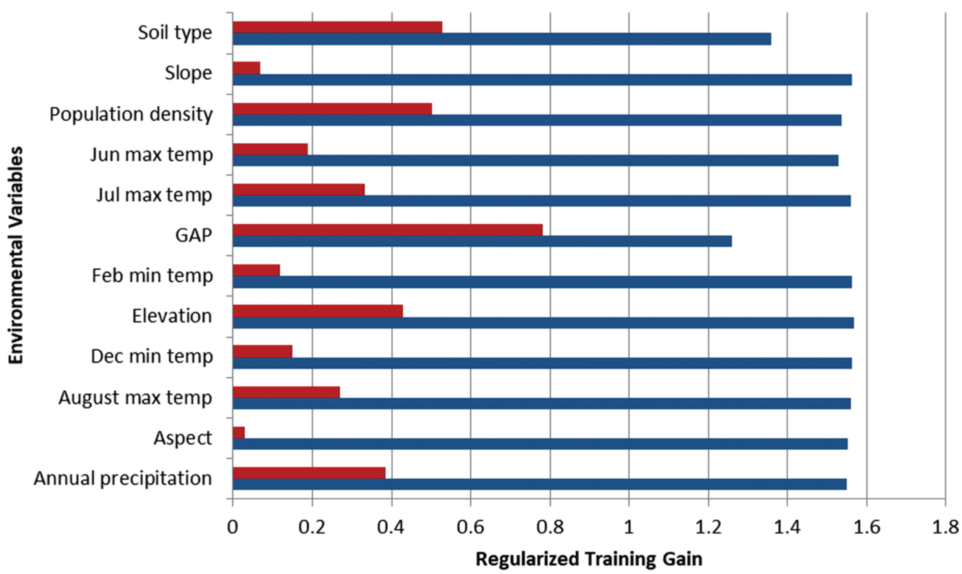

Figure 4. Jackknife test of variable importance. The top bar for each variable indicates the model run with only that variable, while the bottom bar indicates the model run excluding that variable. High red bars and low blue bars indicate unique or important variables to the model.

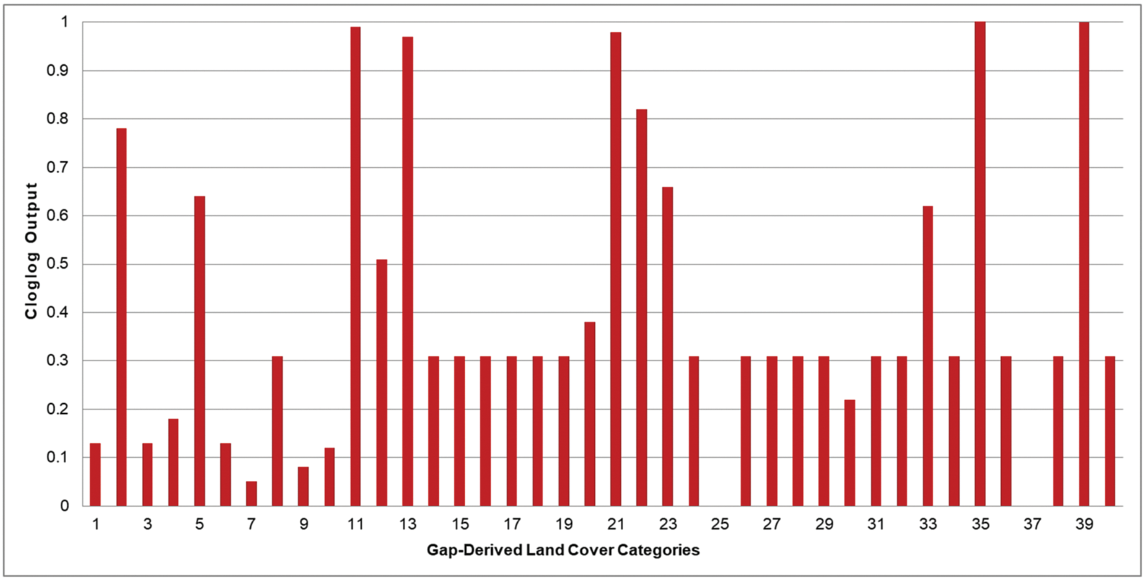

Figure 5. Response curve for GAP-derived land cover. The presence of northern pin oak (35), bur/white oak (21), red oak (22), low-intensity urban (2), and jack pine (11) results in a greater probability of oak wilt occurrence.

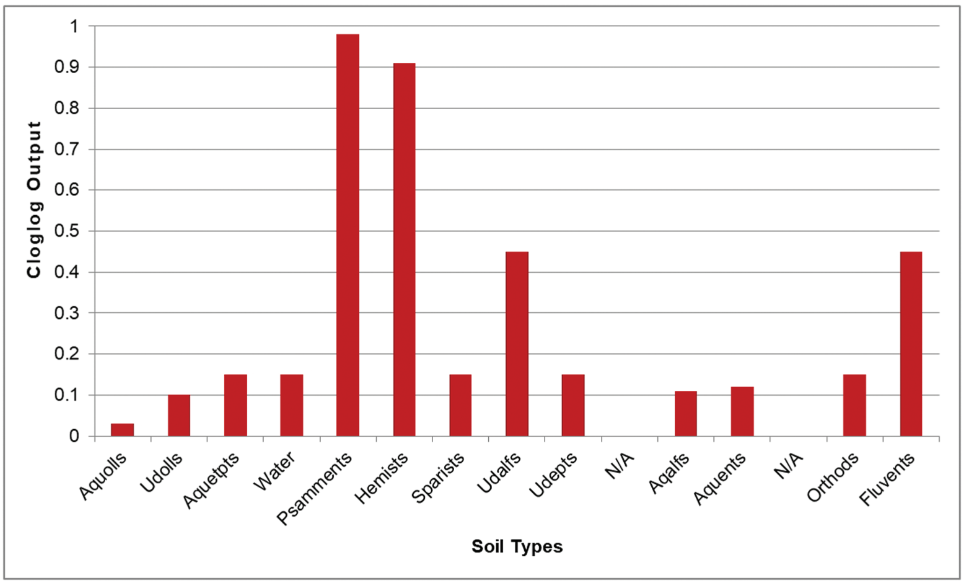

Figure 6. Response curve for soil subtypes. The presence of Psamments (5) and Hemists (6) result in a greater probability of oak wilt occurrence.

understand how well the model predicted distribution based on ecological terms, we compared the variables deemed most important by the model (GAP-derived land cover, soil type, and population density) with research that has been completed on the subject.

Environmental variables must be chosen carefully because Maxent models create the best output possible regardless of the quality of the variables. Careful consideration of which variables to use is necessary, as irrelevant or unnecessary variables may change the accuracy of the variables or display variables as important when, in reality, they are not (Elith and Leathwick 2009). Even when caution is taken, understanding the important variables in the Maxent output leads to a greater understanding of the model and its performance.

Spread of Oak Wilt

Oak wilt can spread in one of two ways: above ground via insect vector or underground through root grafting. Overland spread requires a spore mat to form on an infected oak, a sap beetle to visit the spore mat and pick

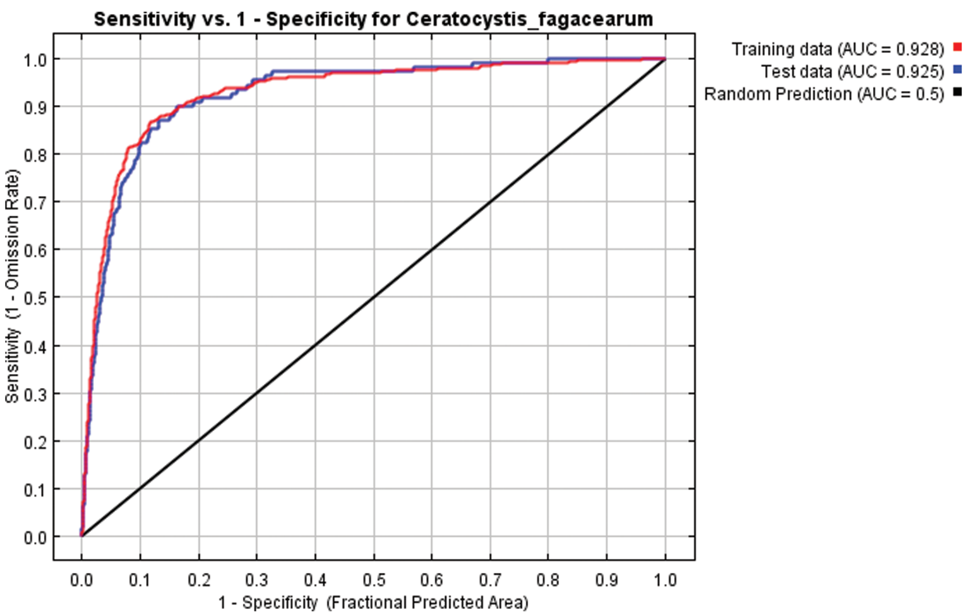

Figure 7. Receiver operating characteristic curve created for the Maxent model. The curves represent the training and test data. AUC, area under the receiver operating characteristic curve.

up spores, and the insect to visit a fresh wound on a healthy oak tree (Juzwik et al. 2011). Root grafting is the creation of a shared root system. The oak wilt pathogen can spread rapidly through the shared xylem tissue found within these shared roots with the possibility of infecting a large number of trees in a single year (Appel 2009, Juzwik et al. 2011). Land cover, soil type, and population density may all contribute to the establishment and spread of oak wilt, as explained below.

Land Cover and Oak Wilt

Forest composition is thought to determine whether oak wilt is capable of maintaining a presence in an area. Forests with high diversity of plant species may have lower incidences of oak wilt simply because the distance separating oak trees inhibits the spread of the pathogen regardless of mode of transmission (Gibbs and French 1980, MacDonald et al. 2009). Conversely, a more homogenous forest with many oaks growing close together is more likely to sustain an oak wilt infection (Juzwik 2009).

While an oak-only input layer would have been best to use, the best available option at the time of our research was to use the GAP-derived land-cover layer selecting several categories where oak was known to be present: bur/white oak, northern pin oak, red oak, and white/red oak, as well as upland conifer–deciduous and upland deciduous with oak species (Figure 8). The model thus uses information about where there is a high probability of the presence of oak trees, and this was the layer that had the largest contribution to the model, but was not the exclusive factor for oak wilt to be present. The presence of northern pin oak had the greatest increase in probability of oak wilt occurrence, whereas the presence of bur or white oak and red oak categories ranked lower. Certain soil types and proximity to humans were also important. Future studies would benefit from an accurate oak presence layer, which could be used to determine whether any other factors apart from those found in this study affect the distribution of oak wilt within oak stands.

In the model output, some areas, most notably in the counties of far southeastern Minnesota including Houston, Winona, and Wabasha Counties, have a high presence of oak (Figure 8) but low probability of oak wilt as shown in Figure 3. Conversely, there are some areas where oaks were not common, but oak wilt is predicted to occur based on other variables including areas of Pine County along its border with Wisconsin and near Faribault and along the Cannon River in Rice County.

Aboveground spread of oak wilt depends on the variety of trees found in a forest, but it also can depend on the different groups of oaks found in a forest. Oaks found in the white oak and red oak sections have varying susceptibility to oak wilt. White oaks, including bur oaks, are less vulnerable to oak wilt than other species with highly resistant white oaks such as *Quercus alba* showing dieback of a few branches a year, taking

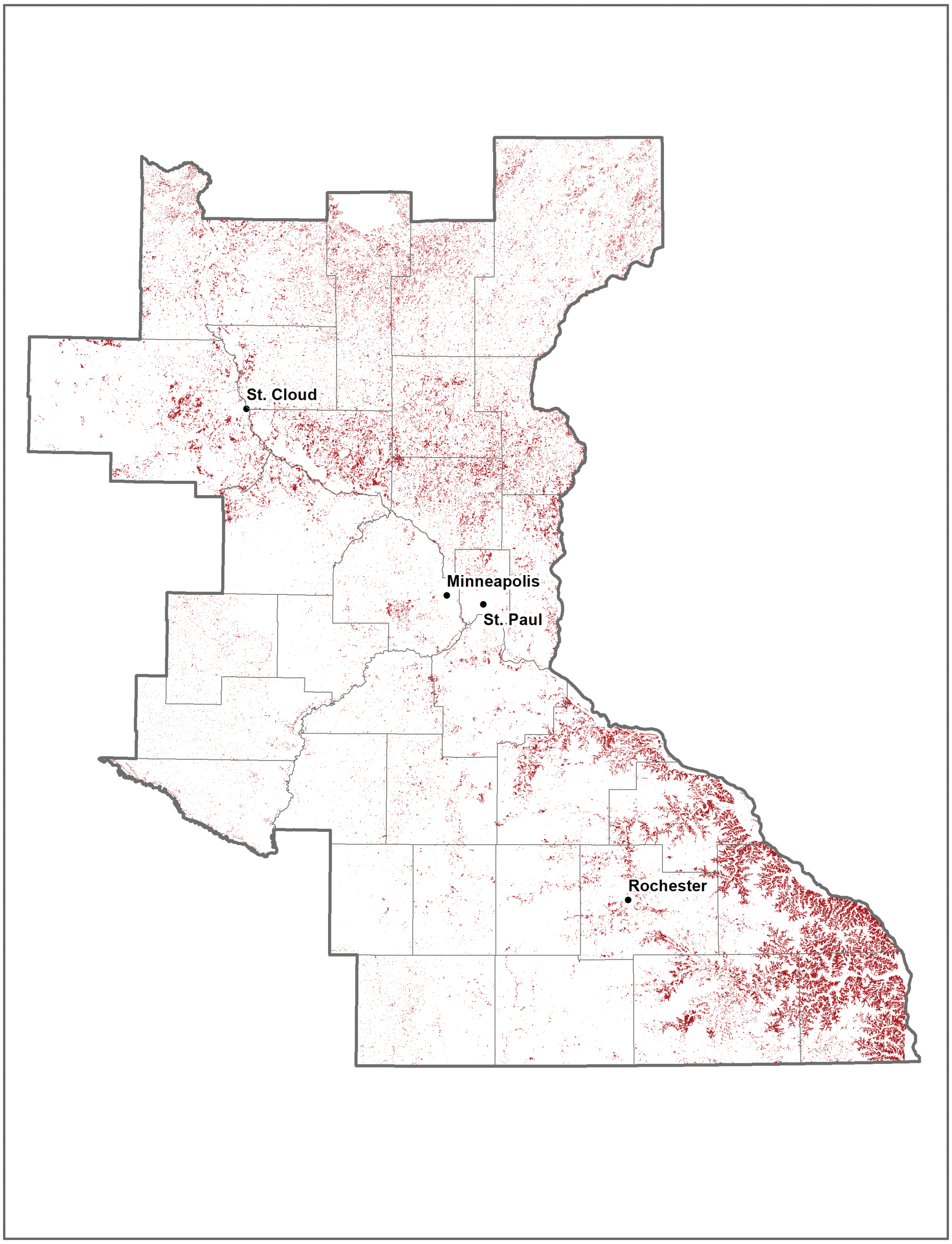

Figure 8. Location of land-cover containing oaks derived from GAP land-cover data. Adapted from data from the MN DNR—Division of Forestry.

a decade to die, if at all (Juzwik et al. 2011). On the other hand, northern pin and red oaks are significantly more susceptible and will die within the same year they are infected (Harrington 2013). Differences in susceptibility are thought to be due to anatomical and physiological differences between the species. Within infected white oaks, the pathogen, once it enters the xylem, is unable to move laterally and is often soon surrounded by a new layer of xylem tissue (Jacobi and MacDonald 1980). These two events essentially isolate the pathogen and prevent it from spreading. Northern pin and red oaks do not have such advantages, and the pathogen is free to spread rapidly both laterally and vertically throughout the tree's vascular system.

Underground, root grafting most commonly occurs among trees of similar species. Among oaks, roots can graft among and between species. Oaks of similar species or in the same section of the genus tend to graft more commonly than oaks of different species or sections (Juzwik 2009). In areas where oak wilt is present but at low levels, root grafting plays a role in its spread; however, the diversity of the forest and the relative isolation of oak trees to small groupings prevent the pathogen from spreading widely (MacDonald et al. 2009). The frequency of root grafting also differs among oak species in Minnesota. Grafting is not common in bur oaks but is far more common in red oaks, with one study showing all northern pin oaks within 15 meters having grafted together (Parmeter et al. 1956).

The GAP-derived land-cover variable also showed low-intensity urban and jack pine land covers as also having high levels of oak wilt probability. In Minnesota, large numbers of oak trees can be found in the regions labeled as low-intensity urban, and the reason for the large oak wilt probability will be discussed in the Population Density and Oak Wilt section. Jack pine, on the other hand, is an interesting anomaly. The GAP-derived land-cover layer used in this study shows that jack pine is located in only a few counties in the northern range of the study area. Thirty-seven of the 460 oak wilt occurrence points used in this study were found in approximately a 2-square-mile area of jack pine in northern Pine County on the Wisconsin border. The high density of oak wilt occurrence so far from other major oak wilt infection centers may be because of a local introduction into a small oak stand, spread from infected trees across the border in Wisconsin, or simply because of a sampling bias.

Although land-cover was the largest contributor and considered the most important variable in the Maxent mode, it is by no means the only indicator of oak wilt presence. Other variables such as soil type and population density contributed significantly to the formation of the model.

Soil Type and Oak Wilt

The response curves for soils show two suborders whose presence significantly increase the chances of oak wilt occurring. The existence of Psamments results in an approximately 88 percent probability of oak wilt, whereas the occurrence of Hemists results in an approximately 82 percent likelihood of oak wilt. In the study area, Psamments can be found along few rivers and in a large area north of the Minneapolis–St. Paul metropolitan area known as the Anoka Sand Plain subsection of the Minnesota and Northeast Iowa Morainal section of the Ecological Classification System used by the Minnesota DNR, whereas Hemists can be found throughout Hennepin County and in pockets of northern Pine County. (Figure 9). These locations also correspond to areas of higher probability of oak wilt occurrence.

Psamments have a sandy texture, consist of less than 35 percent rock fragments, and have a low water-holding potential (USDA 1999). Hemists are wet soils with an intermediate level of decomposing material with a bulk density below 0.3 g/cm^3, making it a very light and porous substrate (USDA 1999). The sandy characteristics of Psamments and the lightness of Hemists make them ideal substrates for roots to reach out and graft with the roots of other trees. The distance and frequency at which roots graft depend heavily on soil composition and texture. Studies have shown that the distance roots are able to reach out, and the amount of grafting occurring increases from heavy and dense to light and sandy soils (Anderson and Anderson 1963, Bruhn et al. 1991). The expansion of oak wilt because of grafted roots varies between regions. In Michigan's Upper Peninsula oak wilt, expansion through root grafting has been shown to be as much as 12 meters per year, in Minnesota it can range from 1.9 to 7.6 meters per year, whereas in Texas oak wilt can spread up to 50 meters per year (Bruhn et al. 1991, Appel 2009, Juzwik 2009). Overall presence of very sandy or organically rich porous soils may facilitate the spread of oak wilt.

Population Density and Oak Wilt

Human population density may not, at first glance, seem as important a variable when determining the distribution of most forest pathogens. However, as stated before, humans can promote the spread of forest pathogens through trade, travel, recreation, and land-use change.

This research showed, through the population density response curve, that the probability of oak wilt was high and steady at moderate population densities with a rapid and continuous decline of probability when population density reached around 1,700 people per square kilometer. This corresponds to the response curve for land cover that shows that low-intensity urban land cover had a high probability of oak wilt presence (about 79 percent), whereas high-intensity urban areas had a very low probability of oak wilt presence (about 14 percent).

Population density plays a role in the overland spread of oak wilt. In order for a healthy tree to become infected, a fresh wound has to be present. In populated areas, that damage is often caused by human activity. Juzwik et al. (1985) gathered observations of tree pruning and wounding between 1953 and 1979. They demonstrated how the pruning or wounding of trees between May and June would result in greater

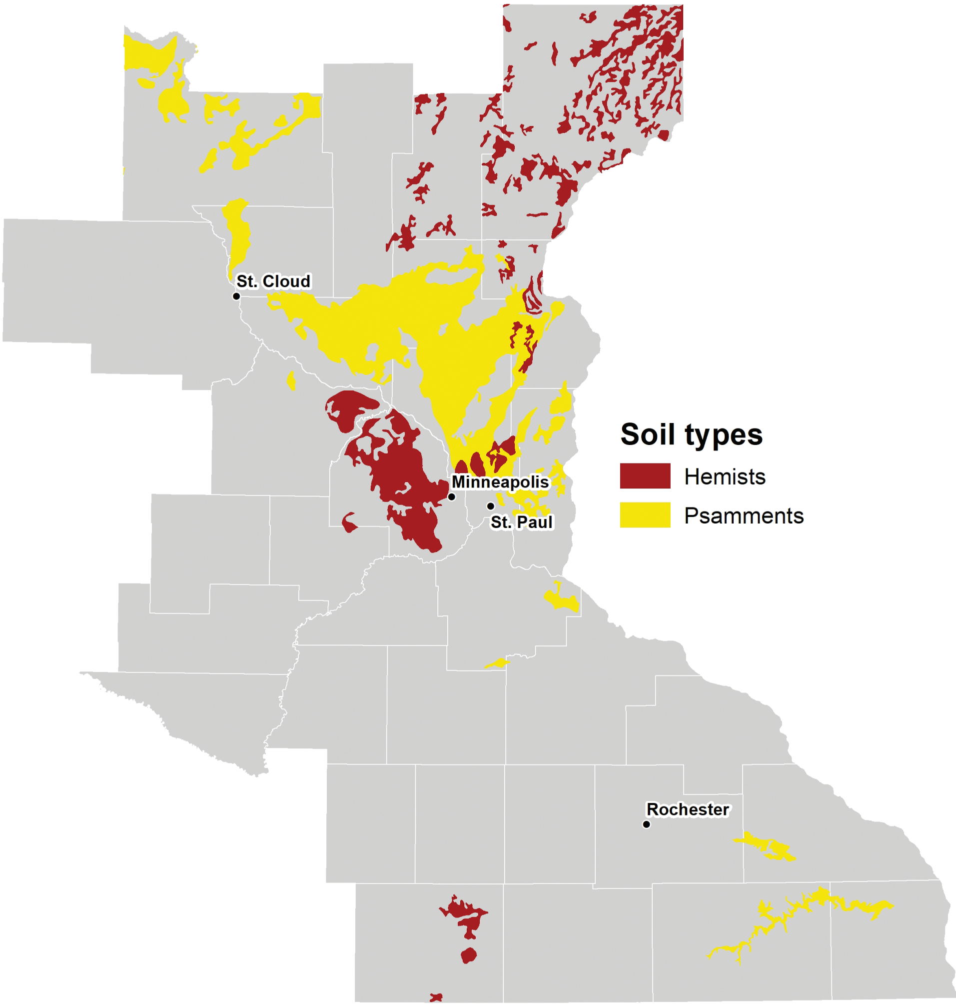

Figure 9. Location of Psamment and Hemist soil types in the study area.

occurrences of oak wilt, whereas the swift application of wound dressings prevented infection. Downing et al. (2009) used classification tree analysis to predict the distribution of oak wilt and discovered population and population change as important factors, although the authors did not discuss reasoning for its importance.

Conclusion

Some forest pathogens have the ability to alter a landscape quickly. SDMs have the potential to limit the effects of forest pathogens if they are used in the detection and monitoring of these pathogens. The purpose of this research was to test a popular SDM, Maxent, in its ability to predict the potential distribution of an invasive forest pathogen. Using oak wilt presence locations and a set of 11 environmental variables, the potential distribution of oak wilt was successfully modeled in east central and southeastern Minnesota with Maxent.

In addition to creating a potential distribution, the model was also able to highlight areas of concern, including locations that currently have very little oak wilt but have a highly suitable habitat. One such area is south of the Minneapolis–St. Paul metropolitan area in southern Dakota and northern Rice counties where a line of high-probability habitat can be seen running along the Cannon River, but only one oak wilt occurrence location was in the area. Highlighting areas of concern is where Maxent can do the most good in bringing attention to these locations to assist in monitoring and managing forest pathogens.

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