Analyzing the Correlation of Environmental Variables and Geographic Variations on the Incidence of White Pine Blister Rust among Eastern White Pine throughout St. Louis County, Minnesota USA to Develop a High Resolution Blister Rust Hazard Map

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Abstract

The populations of eastern white pine (*Pinus strobus*) throughout North America have drastically declined over the past century. Forest management practices are being implemented to preserve the species and protect against numerous damaging agents. However, white pine blister rust (*Cronartium ribicola*), a lethal fungal disease, has hampered most expectations of successful restoration. By mapping hazard levels of the disease, silvicultural decisions can be made to alleviate the destructive nature of the disease. This study used geographic information systems to analyze the environmental conditions that correlate to various disease incidence levels. Statistical electivity analyses were performed on topographies, climate summaries, water sources, and soil data. Higher blister rust incidences are linked to specific environmental factors of lower average temperatures, higher moisture conditions, steeper slopes, high elevations, northerly aspects, and well-drained soil types. A high resolution blister rust hazard map was produced from these findings covering St. Louis County, Minnesota, USA for the use of localized forest management practices.

Introduction

Eastern white pine, losing much of its known historical dominance, remains a valuable species for biotic diversity, aesthetics, wildlife habitat, and forest products (Ostry, Laflamme, and Katovich, 2010). According to Wendel and Smith (1990), eastern white pine provides food and habitat for numerous wildlife species such as songbirds, snowshoe hares, white-tailed deer, cottontails, and pocket gophers. Carey (1993) states white pine forests can support a rich community of breeding birds along with providing habitat for cavity-nesting wildlife. Young black bear cubs are raised within 600 feet of mature white pine stands for safety and protection.

Along with its significant importance to ecosystems, eastern white pine also has profound economic value. It is a valuable timber species in the eastern United States and Canada with its soft wood of medium strength that is

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easily worked, stained, and finished (Wendel and Smith, 1990). Ostry *et al*. (2010) mentions white pine also was used for Christmas trees, mast production, aesthetic attractions, and even provided some foods and medicines for Native Americans. However, the high demand for its valuable resources almost led to its demise.

The frequency of eastern white pine is drastically less in today's forests than in pre-settlement forests; eastern white pine was heavily logged in the 1800's causing poor regeneration rates due to the lack of seed sources (Carey, 1993). According to Ostry *et al*. (2010), logging almost eliminated the mature white pine resource and created conditions for the destructive fires which killed many of the remaining seedlings and saplings. This series of events significantly influenced more prevalent management and silviculture of eastern white pine present today.

As expanded reforestation efforts of eastern white pine grew, another threat to the regeneration of the species came from the arrival of the blister rust disease (*Cronartium ribicola*). For over a century, white pine blister rust, caused by the fungus *Cronartium ribicola* has linked white pines and *Ribes* into a disease pathosystem of serious economic and ecological consequences (Geils, Hummer, and Hunt, 2010).

Eastern White Pine Habitat Communities

Eastern white pine is a large evergreen conifer that may reach 55 meters tall and commonly grow as old as 200 years and sometimes may exceed 450 years (Wendel and Smith, 1990). Carey (1993) mentions in closed white pine stands, boles are free of branches for over two-thirds of their length and can reach diameters of 1 to 1.6 meters. Needles are in fascicles of five and are 5 to 13 centimeters long, and the roots are wide spreading and moderately deep without a distinct taproot (Carey, 1993).

Eastern white pine grows on nearly every type of upland soil within its distribution and in association with numerous hardwood and conifer species (Ostry *et al.*, 2010). According to Carey (1993), eastern white pine frequently dominates or codominates xeric northern pine forests. In mixed hardwood forests, it often occurs as a scattered dominant tree towering above the surrounding hardwoods (Carey, 1993).

Blister Rust Disease Pathology

White pine blister rust is caused by an Asian fungus (*Cronartium ribicola*) that is a macrocyclic pathogen that must alternate between hosts during its life cycle (Zambino, 2010). The aecial stage of *C. ribicola* occurs on white pines and the telial stage primarily on currants and gooseberries (*Ribes*) (Geils *et al*., 2010).

Childs and Kimmey (1938) state that white pine is infected through needle stomata in the late summer and early fall. Blister rust is transmitted to white pines from basidiospores produced on infected *Ribes* leaves; the basidiospores are dispersed by diffusion and mass transport in low velocity wind turbulence occurring on a local scale (Childs and Kimmey, 1938).

Geils *et al*. (2010) states blister rust largely depends on regional climate and landscape-site factors that determine the development and dispersal of blister rust at various life-cycle stages; temperature, moisture, and air flow are critical environmental conditions that

affect pathogen growth, spore dispersal, germination, and infection. The stages most influenced by the environment are the telial stage on *Ribes*, which is favored by cool summers, and the basidial stage, which requires a long, cool, wet period to form basidiospores, disperse, germinate, and infect the white pine (Ostry *et al*., 2010).

Distribution of Ribes

The currant and gooseberry genus (*Ribes)*, more specifically *Ribes glandulosum*, *R. hirtellum*, and *R. triste*, are important species contributing to the spread of blister rust in northeastern Minnesota.

Moss and Wellner (1953) state that *Ribes* grows best on well-drained soil types with surface moisture in the growing season, but it has also adapted to very moist and mixed-light conditions of riparian areas or swamps. *Ribes* primarily regenerate after prolonged survival in the seed bank or by resprouting from the crown of the plant (Moss and Wellner, 1953). According to Zambino (2010), *Ribes* establishes early and readily exploits large to small-scale openings with mineral soil exposed by fire, blow-down, and the action of root disease or insect outbreaks.

Use of GIS in Disease Epidemiology

Utilizing GIS, white pine blister rust hazard can be mapped at a large scale for distinguishing among broad geographic zones that vary in the environmental risk of supporting an infestation (Carey, 1993). For a given point on the landscape, natural vegetation is influenced by a suite of variables including soil, landform, climate, and disturbance that function at different scales (White, Brown, and Host, 2002). It is assumed that the same is true for plant disease hazard modeling, in that blister rust hazard for a given location on the landscape is a function of climate, elevation, topography, and *Ribes* presence (White *et al*., 2002). Therefore, the collection of specific, localized data is required for hazard mapping rather than relying exclusively on regional averages.

When used with site-specific knowledge of local climate, physiography, and vegetation, a hazard map helps maximize success by identifying landscapes where disease control practices such as site selection, pruning, and other blister rust management could be effective (Carey, 1993). White pine silviculture and management pertaining to blister rust is a risky investment, calling for further research of specific environmental trends and geographic variances that will aid in the mitigation of the disease (Ostry *et al*., 2010). Using GIS modelling and other techniques in the study of white pine blister rust enables a broader scope of landscape dynamics, allows the input of many environmental factors into a model, and can incorporate a larger study area too extensive to reach by foot (Smith, 2009).

Purpose

Given appropriate management, white pines can thrive as a valuable commercial and ecologically important keystone species (Hunt, Geils, and Hummer, 2010). By utilizing geographic information systems and knowledge about the environmental conditions, efficient silvicultural management practices pertaining to white pine regeneration can be found.

The purpose of this study was to determine the degree of correlation between various environmental variables and the susceptibility of white pine blister rust on eastern white pine stands throughout St. Louis County, Minnesota. The results are displayed as a high resolution disease hazard map. The hazard map can be used by various government organizations for localized blister rust management and determining future planting site locations.

Methods

The project study area encompasses the entire region of St. Louis County, Minnesota. According to the United States Census Bureau (2014), the county covers approximately 17,800 km^2, of which 16,180 km^2 is land and 1,590 km^2 water. Land formations are shaped by morainal deposits and hills formed from glacial drift along with sandy outwash plains and channels (Albert, 1995). The climate is characterized by long, cool winters and short, mild summers with average annual precipitation of approximately 27 inches (McNab and Avers, 1994).

Creating White Pine Sample Plots

Testing environmental correlates impact on blister rust incidence requires data collections on tree stands dominated by white pine. The stands must also be at least 1 hectare in size for accurate sampling in landscape scale studies; plots smaller than 1 hectare may not represent overall spatial patterns occurring at a broader scale or for predicting populations (Kelly and Meentemeyer, 2002).

Datasets used for deriving sample stands included forest cover inventories from Minnesota Department of Natural Resources, Superior National Forest, and St. Louis County. These datasets included polygons of primary and regeneration species with estimates on total cords or sticks of wood. Queries were performed on the three datasets depicting eastern white pine as the primary species and were combined using ArcMap software.

For quality assurance purposes, stands were analyzed using a derived canopy height layer. Canopy heights were determined from Lidar data analysis using Fusion software provided by United States Forest Service. The Canopy Model tool was used within Fusion which created a canopy height model. The canopy height model uses the return with the highest elevation to compute canopy surface subtracted by the ground elevation interpolated from the bare-earth surface points (McGaughey, 2014). Since white pines are significantly taller in mature stands, sample plots were verified for white pine trees (Figure 1). 2013 Pictometry provided by St. Louis County was also used as a secondary verification process for identifying white pines within stands (Figure 2).

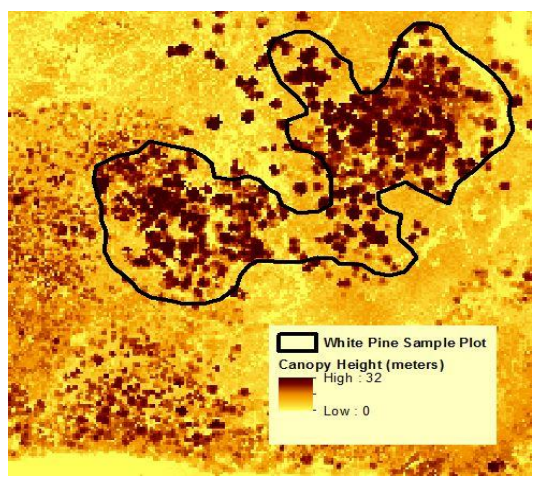

Figure 1. Sample white pine stand showing canopy heights for distinguishing species.

Sample plots less than 1 hectare were omitted from the dataset. Sample plots without distinguished white pine species were also removed to reduce sources of error. The final dataset included 840 white pine plots containing a mean size of 7.47 hectares and standard deviation of 8.21 hectares.

Figure 2. 2013 Pictometry identifies eastern white pine indicated by red circle.

Finding Blister Rust Occurrence

There is minimal information about white pine blister rust incidence levels throughout St. Louis County; therefore, rust occurrence was derived from information about *Ribes* suitability and white pine crown condition. Since blister rust requires the presence of both host species to disperse spores, white pine blister rust occurrence is associated with distances between suitable sites for *Ribes* and the white pine stands. The two variables tested were soil classifications and distance of basidiospore dispersal.

The forest cover layers contained information about crown health conditions based on a scale of 0-5. Low condition values were associated with poor crown health and conditions of heavy stress. High values were associated with vigorous growth and low environmental stress. Stands were converted to a raster layer based on crown conditions and analyzed in relation to suitable *Ribes* sites.

Ribes are restricted to well-drained soil types. Fungal spores can travel distances up to 27 kilometers based on wind and other climatic factors (White *et al*., 2002). There is a negative correlation between blister rust occurrence and the distance between sample stands and *Ribes*; therefore, greater distances are associated with lower incidence levels.

Soil data were used from the Soil Survey Geographic database (SSURGO) for assessing drainage and soil types. Sites identified as well-drained or partially well-drained were extracted as suitable *Ribes* sites. Euclidean distance analysis was performed on the extracted sites and masked to the sample stands. The distance values were reclassified as a probability layer with higher probabilities of blister rust occurrence associated with smaller distance values on a proportion scale. A Zonal Mean was performed on the probability layer for each white pine sample stand for even distribution throughout the stands.

The Raster Calculator was used to combine the probability layer with crown conditions to determine blister rust incidence throughout the sample sites. Sites were labelled with blister rust presence if they met a conditional statement of a crown health value less than 2 and probability of *Ribes* presence at least 0.2, or a crown health value less than 4 with probability of *Ribes* at least 0.8.

Testing Variables' Correlation to Blister Rust

As stated, blister rust occurrence largely depends on regional climate and landscape variations. Significant factors

that determine the development and dispersal of blister rust at various life-cycle stages are temperature, moisture, and air flow. Therefore, analyses were performed on various topographic data, climate summaries, and distances to waterbodies for testing correlations to blister rust incidence throughout the county.

Analyzing the different environmental variables' correspondence with blister rust required the use of an electivity index. Electivity indices were formulated to measure the utilization of food types in relation to their abundance or availability in the environment (Lechowicz, 1982). Jacobs (1974) modified the electivity index as a ratio of log Q which could be used to test whether blister rust selectively occurred on any environmental class within each sample site with the formula:

$$[1] \qquad E_{ij} = \ln \frac{(r_{ij})(1-p_j)}{(p_j)(1-r_{ij})}$$

where E_{ij} is the electivity for blister rust incidence *i* on environmental variable class *j*. r_{ij} is the proportion of blister rust incidence *i* throughout all similar plots of variable class *j*, and p_j is the proportion of the environmental variable throughout all similar plots that occurs in class *j*. Greater electivity scores indicated a likely association of blister rust incidence with the environmental variable interval, while lower scores indicate a selection against that variable for blister rust incidence.

Topographic Data

St. Louis County provided a 30-meter resolution digital elevation model that was used to derive information about elevation, slope, and aspect environmental classes. Zonal statistics were performed on these environmental variables to determine central tendencies for all sample sites. Each sample site contained one value for every environmental variable class for calculating the proportion used in the electivity analysis.

The zonal mean was performed on the continuous topographic datasets for elevation and slope. The mean values were classified by equal interval breaks of 50 meters for elevation values and breaks of 2 degrees for slope values. The zonal majority was performed on categorical data for the 9 different aspect classes (Figure 3).

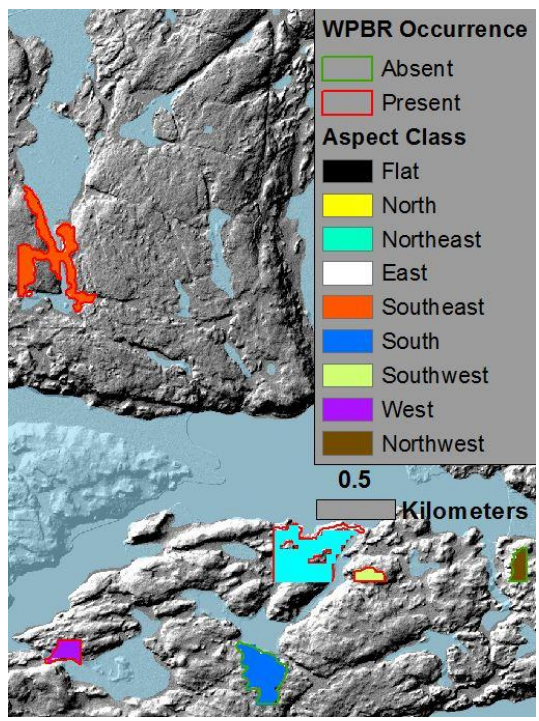

Figure 3. The zonal majority layer for the aspect environmental variable within each sample stand as represented by white pine blister rust (WPBR) occurrence.

Climate Data

Climate data were derived from 30-year (1983-2013) climatological summaries published by the National Climatic Data Center. Various weather stations

throughout St. Louis County collected data pertaining to monthly mean temperatures, precipitation, and other climatic variables. Primary spore dispersal occurs from July through September so only these values were used for this analysis.

The nine climatic variables were divided into three separate monthly periods (July, August, and September) by mean maximum temperature, mean minimum temperature, and total precipitation. The data were interpolated using the inverse distance weight method (IDW) at a 30-meter grid cell resolution based on latitude, longitude, and elevation information of each station (Figure 4). The zonal mean was performed to create nine layers representing the central tendencies of the different climatic variables within each sample site.

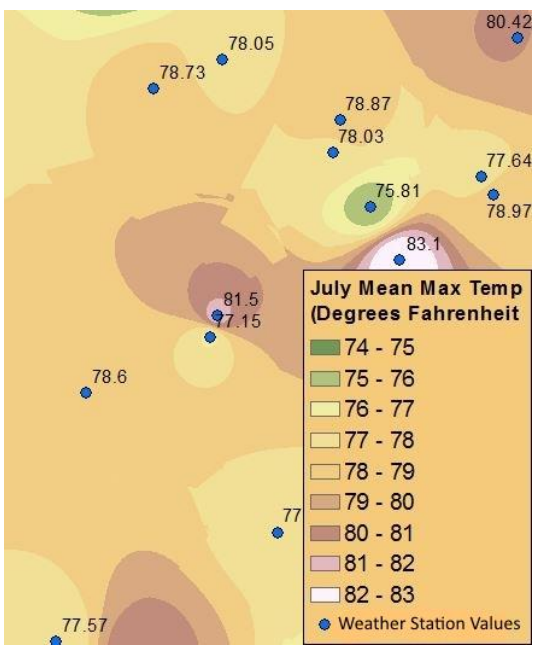

Figure 4. An example of an IDW interpolation performed on the mean maximum temperatures for the month of July.

Distance to Waterbodies

Open water data was extracted from the National Wetlands Inventory for the creation of three environmental variables based on water body size: < 5 ha, 5 ha – 100 ha, and > 100 ha. Only distinct open water sources were used for the analysis. Wetland classifications of bogs, seasonal floods, shrub swamps, upland, wet meadows, and wooded swamps were removed from the Euclidean distance measurement.

Euclidean distances were performed on the three distance environmental classifications throughout all sample sites (Figure 5). The zonal mean captured the central tendencies at each site for the electivity analysis.

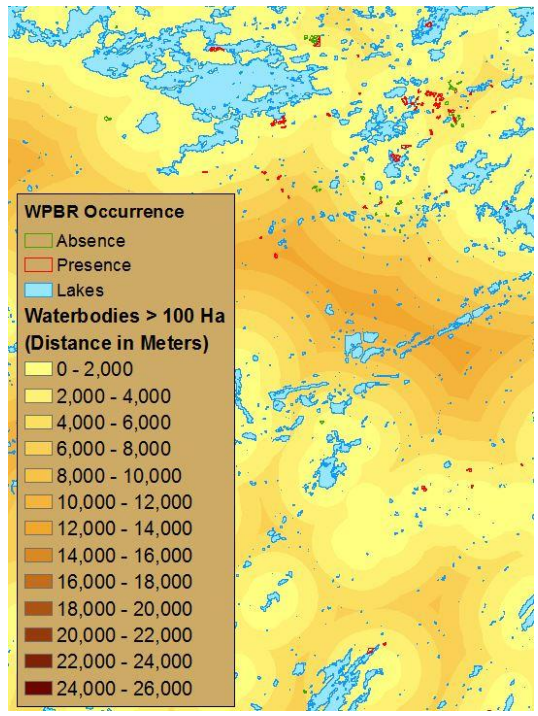

Figure 5. Example of Euclidean distance performed on all waterbodies greater than 100 hectares.

Electivity Analysis

With the central tendencies of each environmental variable captured at each sample site, proportions of each environmental classification (p_j) were calculated based on its occurrence at all

sample site areas. The zonal mean and majority layers were reclassified to equal interval classifications that contained attribute information of cell counts for determining proportional areas for calculation.

The reclassified layers were converted to polygons for determining blister rust occurrence for each environmental classification. Blister rust proportions (r_{ij}) were calculated based on the ratio of disease presence to disease absence. The final electivity score (E_{ij}) was calculated using the environmental and blister rust proportion values in the electivity formula (Appendix A).

Constructing Blister Rust Hazard Map

The electivity values calculated for the fifteen environmental variables were used to create the blister rust hazard map. The environmental layers expanding the entire county were reclassified to represent the same classification as the layers used for determining electivity. The reclassified layers were given the attribute of their respected electivity value. An overlay analysis of the layers was performed to sum all electivity scores using the raster calculator. A layer was then created that represented the spread of electivity scores throughout the study region.

By knowing the range of electivity values, blister rust hazard levels were determined for classifying the electivity scores. Eastman (1999) explains the use of the distribution of the sum of electivity scores and values of user-defined constants (k) for decision risk assessment for developing hazard levels. This protocol was used for calculating three levels of hazard: low, moderate, and high. The following formulas were used to find the threshold values for determining hazard classification:

[2] $$T_L = \mu^p - k_1 \times s^p$$

[3] $$T_U = \mu^p - k_2 \times s^p$$

T_L and T_U are the threshold values representing the lower and upper hazard breaks respectively. μ^p is the mean of sums for electivity scores within sample sites with blister rust presence and s^p is the standard deviation of these sums. k_1 and k_2 are the user defined constants for separating low hazard sites from high hazard sites. This method of determining hazard levels limits the amount of bias when determining the classifications by relying mostly on distributions. The constants give the user some flexibility to create the optimal classification breaks by identifying hazard by multiples of the standard deviation.

The levels of hazard were calculated by creating a zonal statistics table on the electivity sum layer with a defined extent of blister rust present in sample sites. The mean of sums (μ^p) was determined by averaging all electivity sums for each record. The statistical distribution calculated the standard deviation (s^p) of the sums. The values set for the constants were $k_1 = 1$ and $k_2 = -1$. The thresholds were then calculated based on their distributions (Appendix B).

The classification of white pine blister rust hazard determined by the decision risk assessment was defined as follows: low hazard states blister rust may occur sporadically but little management intervention is required; moderate hazard states no strong weight of evidence for or against low or high hazard, so blister rust can occur

requiring some management intervention; high hazard states greatest probability of blister rust infection rates, so significant management intervention is required to grow and maintain white pine stands.

Results

Electivity Analysis

The results of the electivity analysis were used to measure the strength of correlation between blister rust incidence and the environmental variables. Stronger correlations are associated with higher electivity values and lower values reflect weaker correlations. Line graphs were used to represent the results of the electivity analysis. Trend lines display overall tendencies of electivity for depicting any patterns within each variable.

Elevation showed strong positive and negative relationships with blister rust occurrence within the topographic variables. Elevations below 350 meters were strongly negative, while elevations above 350 meters had strongly positive electivity (Figure 6a). Slope also indicated a positive inclination with steeper slopes pertaining to higher electivity and flatter terrain possessing lower electivity values (Figure 6b). The flat aspect classification supported the results found by slope which also had a significantly lower electivity value compared to other aspect classifications. It is also noted that northerly aspects showed greater electivity values overall as compared to southerly aspect classifications (Figure 6c).

Trend lines for all the climate variables showed similar patterns throughout July, August, and September (Figure 7). Mean maximum and mean minimum temperatures had overall negative inclinations whereas lower temperatures were strongly associated with blister rust occurrence and higher temperature averages were not. Higher temperatures in August had the lowest electivity values, while lower temperature values in September had the largest electivity values. This is related with the highest and lowest overall mean temperatures throughout the three month period. Electivity scores for mean total precipitation were strongly positive for higher precipitation and significantly lower for low monthly precipitation.

Distances to different water body size variables indicated mostly random associations and patterns pertaining to electivity values between classifications. However, there was significantly weak correlation at the farthest distance classification pertaining to all water body sizes (Figure 8).

White Pine Blister Rust Hazard Map

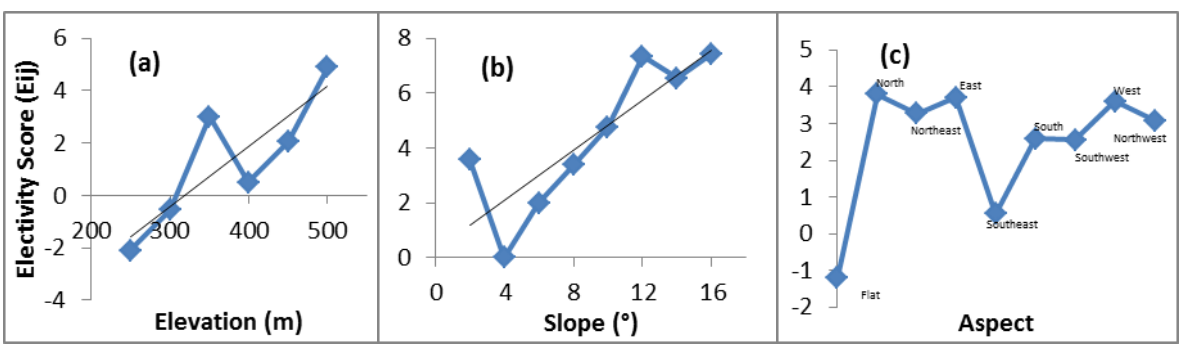

Figure 6. Graphs portraying the topographic electivity results of elevation, slope, and aspect.

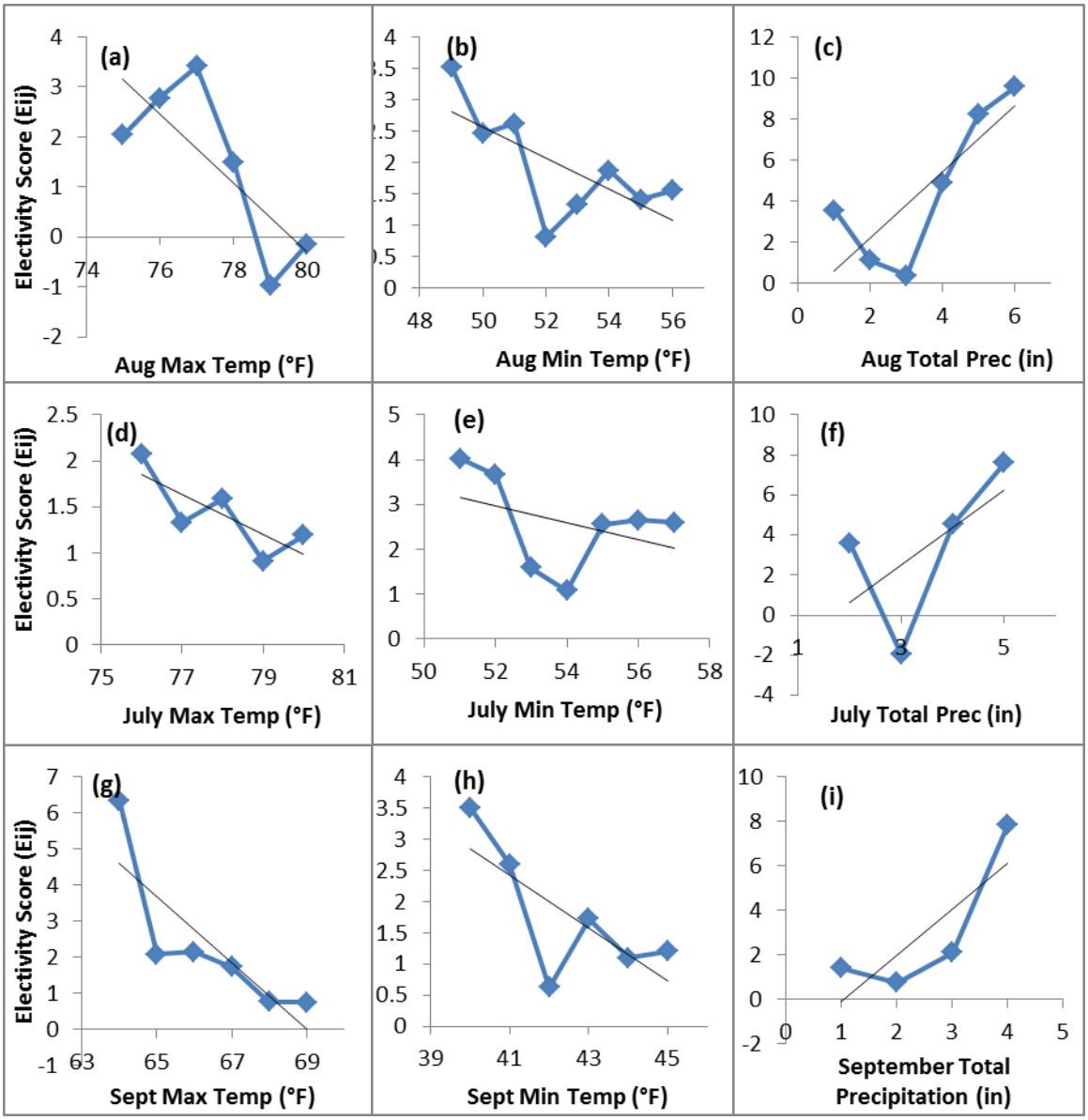

Figure 7. Graphs portraying climatic electivity results for temperature and precipitation variables from July through September.

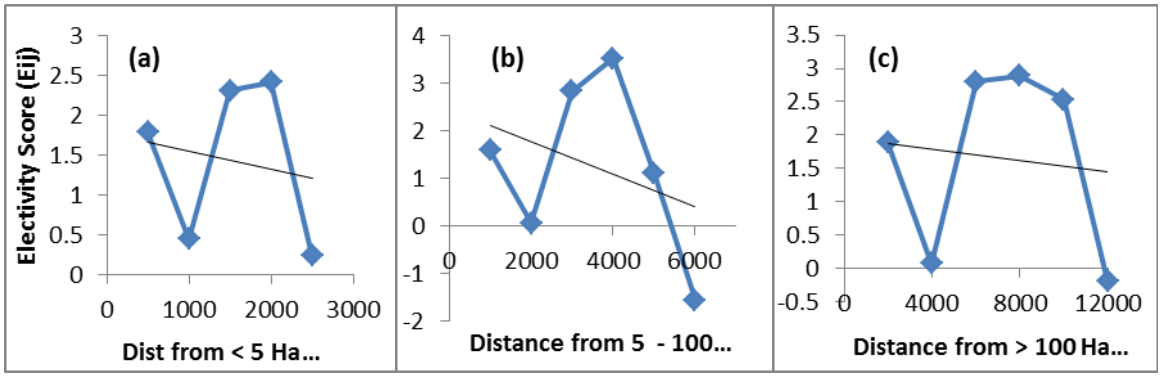

Figure 8. Graphs portraying distance from waterbody electivity results for varying open water source sizes.

The values of correlation from the electivity analysis were summed for each 30-meter pixel of St. Louis County to produce a continuous surface of the sum of electivity scores (Figure 9a). This layer indicated the strength of the correlation between blister rust incidence and all environmental variables tested.

While the sum of electivity map shows relative differences in blister rust hazard, it is not useful for silvicultural purposes unless it has a specified hazard classification. Hazard class distributions as determined by the risk assessment formulas [2] and [3] were given intervals based on the user defined constants of 1 and -1 respectively. Figure 9b shows this distribution of white pine blister rust hazard in St. Louis County. Areas of high hazard are concentrated around the central regions of the county. Moderate hazard levels are found most prevalent in southwestern and northwestern regions. Low hazard areas are found mostly in the area close to Lake Superior and the northeastern region of the county.

Discussion

Risk Factors

A risk assessment for any given location throughout St. Louis County was based on the cumulative electivity scores for 15 environmental variables. However, individual variables carry varying levels of influence on the overall hazard classifications. Since each variable is weighted by the strength of its relationship with blister rust occurrence, greater ranges in electivity values within the classification scale of each variable has a greater proportional influence. For instance, elevation and slope have greater ranges in electivity (-2.1 to 4.9 and 0 to 7.4 respectively) as compared to aspect (majority of values from 2 to 3); therefore, elevation and slope will impact the level of hazard at a greater scale.

The topographic factors that carry the greatest weight in relation to blister rust occurrence are high-elevation stands and steeper slopes. Hunt (1983) found similar results on a hazard assessment performed in British Columbia. Hunt stated that flat sites have less exposure to night breezes, a period when there is the greatest spore dispersal. The electivity values for aspect variables also support this by showing significant differences between a flat aspect compared to all other classifications. Within these classifications, northerly aspects tended to have overall greater values which relate to the amount of sunlight exposure across the landscape. Sites in areas with longer periods of shade throughout the day will have increased moisture levels.

As mentioned, elevation has a strong influence on blister rust distribution. Higher elevations throughout the study region contributed to increased hazard levels. White *et al*. (2002) performed similar research on the Laurentian mixed forest province and concluded, with increasing elevation, wind exposure increases and evaporation levels decrease, creating more favorable conditions for blister rust infection.

Climate factors that influence greater blister rust incidence are lower average temperatures and higher precipitation. In the Lake States region white pine blister rust infection rates tend to decrease on a southward latitudinal gradient due to the increasing growing season temperatures that create unfavorable conditions for the completion of the pathogen life cycle (Van Arsdel, Riker, Suomi, and Bryson,

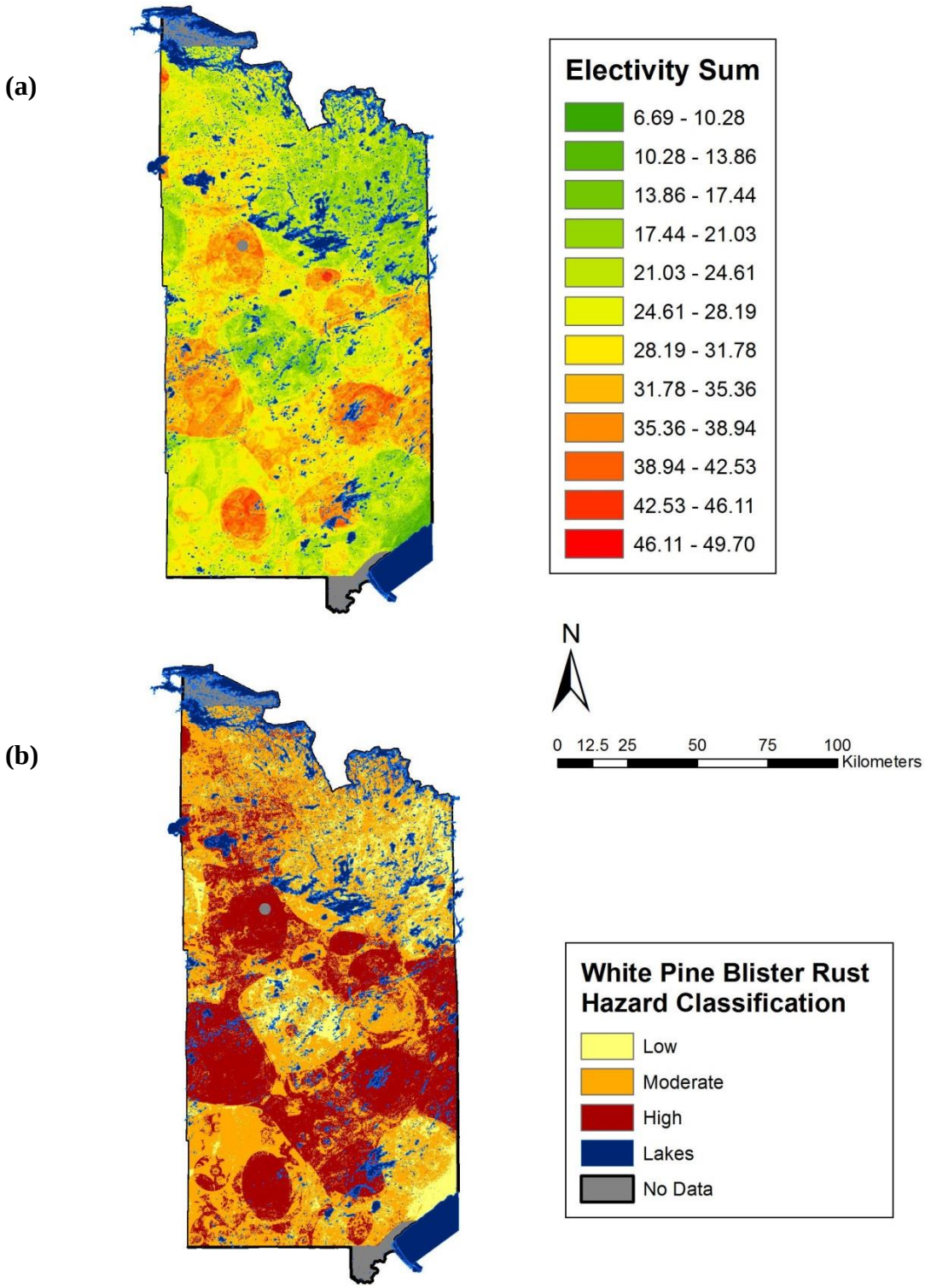

Figure 9. (a) The sum of electivity scores for blister rust presence or absence for 15 environmental variables. Color gradation indicates relative blister rust hazard. (b) White pine blister rust hazard classification based on the threshold values calculated from the statistical distribution of the sum of electivity scores.

1961). The electivity ranges for all average temperature variables (mean maximum and mean minimum) are smaller than other variables so they carry less weight towards hazard classification. St. Louis County may not encompass a large enough geographic area to detect significant changes in temperature, therefore it will not greatly influence overall trends in risk assessment.

Total precipitation variables throughout the three month period showed very distinct trends associated with high blister rust occurrences among higher precipitation values. It is stated that moisture is a key component for the life cycle of blister rust and required for optimal dispersal.

Other moisture analyses pertaining to waterbody sizes did not show significant trends to make any assumptions based on electivity alone. Trend lines show that there may be a small decrease in hazard correlation as the distances increase. However, this test may be erroneous due to the large number of waterbodies less than 5 hectares in size throughout the study region. Van Arsdel *et al*. (1961) described a pattern around smaller lakes and Lake Superior in which the distance to heavily infected areas was usually associated with the first high ridge away from the waterbodies. This may be influenced by increased wind exposure and humidity around similar landscapes. Lake Superior was not included in the classification of waterbodies tested in this project. This may lead to inaccuracies in the hazard map in areas within basidiospore dispersal range from the shoreline.

Limitations and Error

The methods used for the electivity analysis were applied for determining correlation among environmental variables with blister rust occurrence. Blister rust occurrence for the model is based on the estimation of *Ribes* presence in accordance with stand level white pine crown health. Although this type of sampling was necessary for analysis, without site level inventory collected pertaining to precise blister rust incidence, there will be error present. In addition to the error based on estimation, there was a limitation on the total number of sample sites used for testing electivity, which is partly due to the declining populations of white pine stands throughout St. Louis County.

Environmental variables used for this project were chosen based on previous research and studies of similar intent. Unavailable datasets led to limitations on all variables that were tested. Ideally evaporation values would be valuable along with an accurate *Ribes* cover layer. Any variable left out of the analysis degrades the overall accuracies of the sum of electivity layer throughout the project.

Processing constraints and input environmental data also provided restrictions to the overall accuracies by the use of the 30 meter spatial resolution. This limited the capability of detecting site-level conditions that influence white pine blister rust infection risk.

Future Work

It is apparent that achieving greater accuracies with risk assessment analyses lead to ongoing research and projects for improving decision-support systems. Studies such as this can be used as a foundation for future work to build upon

for reducing limitations and errors that exist in this work.

Areas to improve this project include eliminating the use of estimation of blister rust occurrence. This can be achieved by extensive field data collection of sample sites throughout the project area. Blister rust incidence should be surveyed for accurate site-level hazard assessment.

A balanced ratio of blister rust presence to absence should also be used for determining proportions throughout sites. This will eliminate most electivity outliers that exist for more accurate assumption of blister rust hazard influence. To capture better trends among environmental variables throughout the landscape, there should be more classifications to represent the overall distribution of electivity values. More specificity among variables and higher resolution data will lead to better management and mitigation techniques.

Conclusion

The outputs created from this project can be used as a decision-support tool for local or regional planning as a first step in determining areas where white pine regeneration is more likely to be successful in St. Louis County. The methodologies used can also be implemented by other organizations for determining hazard risks of diseases in other regions. With the use of disease hazard mapping in conjunction with current management practices, maintaining and restoring eastern white pine populations to healthy distributions is possible in St. Louis County, Minnesota.

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Appendix A. Electivity analysis for all 15 environmental variables by varying classification.

			Classification	r_{ij}	p_j	E_{ij}
Environmental Variables	Climate	July Maximum Temperature (°F)	76-77	0.60625	0.162765	2.06938
			77-78	0.827189	0.557797	1.33361
			78-79	0.336842	0.094053	1.58773
			79-80	0.263158	0.125351	0.91309
			80-81	0.172414	0.059358	1.19435
		July Minimum Temperature (°F)	51-52	0.872549	0.108802	4.02672
			52-53	0.795181	0.090239	3.66716
			53-54	0.816794	0.474091	1.59850
			54-55	0.489209	0.245953	1.07714
			55-56	0.333333	0.03727	2.55844
			56-57	0.384615	0.042062	2.65564
			57-58	0.021	0.001583	2.60491
		July Total Precip (in)	2-3	0.053	0.001583	3.56391
			3-4	0.663842	0.931677	-1.93227
			4-5	0.864407	0.064251	4.53093
			5-6	0.833333	0.002489	7.60264
		August Maximum Temperature (°F)	75-76	0.929368	0.630869	2.04107
			76-77	0.782313	0.182565	2.77826
			77-78	0.84375	0.150058	3.42054
			78-79	0.130435	0.032694	1.49021
			79-80	0.001	0.002662	-0.98079
			80-81	0.001	0.001151	-0.14095
		August Minimum Temperature (°F)	48-49	0.514286	0.03042	3.51891
			49-50	0.603604	0.11558	2.45547
			50-51	0.57377	0.089462	2.61747
			51-52	0.65847	0.460377	0.81531
			52-53	0.511278	0.21808	1.32201
			53-54	0.225	0.042709	1.87293
			54-55	0.125	0.033773	1.40782
			55-56	0.044	0.009598	1.55798
		August Total Precip (in)	1-2	0.053	0.001583	3.56391
			2-3	0.703125	0.437785	1.11238
			3-4	0.625	0.530053	0.39047
			4-5	0.8	0.029096	4.89391
			5-6	0.76	0.000806	8.27550
			6-7	0.909091	0.000676	9.60074
		September Maximum Temperature (°F)	64-65	0.666667	0.003497	6.34556
			65-66	0.917927	0.582073	2.08321
			66-67	0.621622	0.160707	2.14942
			67-68	0.344262	0.085519	1.72526
			68-69	0.295775	0.162995	0.76861
			69-70	0.011	0.005209	0.75332
		September Minimum Temperature (°F)	40-41	0.5	0.029298	3.50050
			41-42	0.597701	0.099032	2.60393
			42-43	0.614583	0.460334	0.62562
			43-44	0.504132	0.153843	1.72130
			44-45	0.449541	0.214741	1.09406
			45-46	0.128205	0.042062	1.20872
		September Total Precip (in)	1-2	0.053	0.013512	1.40755
			2-3	0.62536	0.438332	0.76030
			3-4	0.908654	0.546256	2.11175
			4-5	0.833333	0.001899	7.87372

			Classification	r_{ij}	p_j	E_{ij}
Topography	Elevation (m)		250-300	0.0001	0.00082	-2.10428
			300-350	0.001	0.001768	-0.57088
			350-400	0.722689	0.114763	3.00083
			400-450	0.754717	0.6496	0.50665
			450-500	0.690265	0.225515	2.03517
			500-550	0.5	0.007534	4.88078
	Slope (°)		0-2	0.716981	0.065045	3.59496
			2-4	0.630901	0.625877	0.02152
			4-6	0.595238	0.166739	1.99458
			6-8	0.73913	0.088064	3.37896
			8-10	0.825	0.038834	4.75944
			10-12	0.909091	0.006513	7.32999
			12-14	0.833333	0.007146	6.54351
			14-16	0.75	0.001783	7.42638
	Aspect		Flat	0.0001	0.000331	-1.19624
			North	0.645833	0.039294	3.79736
			Northeast	0.62069	0.058733	3.26670
			East	0.775862	0.078847	3.69982
			Southeast	0.637795	0.504529	0.54769
			South	0.61	0.104756	2.59277
			Southwest	0.454545	0.060631	2.55808
			West	0.74359	0.073441	3.59970
			Northwest	0.653061	0.079437	3.08254
Distance to Waterbodies	Distance from Less than 5 Ha Waterbodies		0-500	0.723301	0.304276	1.78791
			500-1000	0.691176	0.588351	0.44847
			1000-1500	0.46875	0.080213	2.31429
			1500-2000	0.233	0.026369	2.41740
			2000-2500	0.001	0.000791	0.23495
	Distance from 5 Ha to 100 Ha Waterbodies		0-1000	0.713147	0.334064	1.60058
			1000-2000	0.620985	0.602763	0.07674
			2000-3000	0.477273	0.050916	2.83434
			3000-4000	0.2	0.007268	3.53074
			4000-5000	0.001	0.000332	1.10433
			6000-7000	0.001	0.004658	-1.54217
	Distance from Greater than 100 Ha Waterbodies		0-2000	0.691892	0.254166	1.88549
			2000-4000	0.62931	0.612882	0.06982
			4000-6000	0.555556	0.070602	2.80062
			6000-8000	0.486486	0.049848	2.89358
			8000-10000	0.125	0.011277	2.52770
			10000-12000	0.001	0.001224	-0.20254

Appendix B. Chart representing the values used in the decision risk assessment formula for calculating the hazard levels.

Decision Risk Assessment Thresholds				
Thesholds	μ^p	s^p	Constants	Classification Values
T_L	25.006388	4.484376	1	20.522012
T_U	25.006388	4.484376	-1	29.490764