Spatial Risk Mapping of West Nile Virus in Correlation to Vegetation in Montana

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Spatial Risk Mapping of West Nile Virus in Correlation to Vegetation in Montana

Submitted in partial fulfillment of the requirements for graduation with honors from the Department of Natural Sciences at Carroll College, Helena, MT

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March, 2013
This thesis for honors recognition has been approved for the Department of Natural Science by:

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Abstract

In the present study, spatial epidemiology was applied to the vegetation in Montana by combining NDVI data, landcover data, and a thermal layer to create a predictive model of *C. tarsalis* in Montana. Samples of *C. tarsalis*, which has been identified as the primary vector for West Nile Virus in Montana, were collected from June to August, 2013, at various sites across the state. ArcGIS and MaxENT software was used to create a model for June, July, and August. Overall, there was a modal correlation between vegetation density and the presence of *C. tarsalis* and a positive correlation between both the thermal and vegetation layers and the presence of *C. tarsalis*. The models and their corresponding data outputs provide insight into mosquito presence throughout Montana, an outcome which, in turn, may help isolate WNV hot spots.
Introduction

West Nile Virus (WNV), a member of the family Flaviviridae, is one of 73 species in the genus Flavivirus (Ayers et al., 2006). This genus can be divided into the mosquito-borne viruses, the tick-borne viruses, and a third for which no vectors have been identified (Ayers et al., 2006). WNV represents one of the mosquito-borne viruses and is considered to be of global importance (Yadav et al., 2012). WNV may have been present in the Middle East for centuries but was not isolated officially until 1937, in the West Nile District of Uganda (Griffith, 2005, Gosselin et al., 2005). WNV was detected in Morocco in 1996, Israel from 1998-2001, Italy in 1998, and France in 2000 and 2004 (Ward, 2009). Romania and Russia have also suffered from outbreaks of WNV recently (Ward et al., 2005). In 1999, WNV made its debut in the United States, in New York City (Ezenwa et al., 2006).

Once in the United States, the virus spread outwards in a radial pattern instead of following the flight paths of birds (Venkatesan and Rasgon, 2010). Between 2001 and 2002, WNV spanned a remarkably large geographic area (Venkatesan and Rasgon, 2010). By the end of the transmission season, the virus had crossed the Mississippi River into the Midwest and Great Plains (Venkatesan and Rasgon, 2010). At that point, 44 states had been invaded by the virus; and in 2003, the virus reached the West Coast (Venkatesan and Rasgon, 2010). An explosion of cases accompanied the expansion of the virus (Cooke et al., 2006). The United States faced the largest WNV epidemic ever documented to date in 2002, with 4156 human cases and 284 deaths (Cooke et al., 2006). In 2003, the number of human cases reached 9000 nationwide, with 220 deaths (Cooke et
Cases of the virus predominately occur in late summer or early fall in the temperate latitudes (Griffith, 2012).

WNV is a vector-borne zoonotic disease that cycles between birds and mosquitoes (Brownstein et al., 2002, Ruiz et al., 2004). Humans, horses, and a number of other vertebrates are considered incidental or dead-end hosts (Ruiz et al., 2004). Wild birds serve as the primary reservoir hosts, but the most competent avian WNV hosts tend to be passeriform birds (Ezenwa et al., 2006). Historically and currently, WNV has posed a threat to the animals mentioned above. Specifically in Montana, the American White Pelican (Pelecanus erythrorhynchos) population has been damaged (Johnson et al., 2006-2007). As of 2007, over 400 pelican chicks have died each year since the original outbreak in 2002 because of WNV (MSU News Service, 2012). Pelican deaths may indicate increased risk for WNV transmission to persons living nearby (CDC, 2010).

For a human infection to occur, the conditions must not only promote virus amplification within avian and mosquito populations, but also lead to a spillover into the incidental host groups (Ezenwa et al., 2006). Since the first outbreak, scientists have found that the vector, Culex tarsalis, is the most common carrier of WNV in Montana. Elsewhere, Aedes vexans, Culex quinquefasciatus, Culex pipiens, Culex restuans, and Culex nigripalpus have been important vectors (Johnson et al., 2010). C. tarsalis possesses the ability to perpetuate viral amplification in bird reservoirs, bridge the virus to mammalian hosts, and travel long distances to seek blood meals or oviposition sites (Venkatesan and Rasgoon, 2010). According to multi-locus clustering analyses, three clusters of C. tarsalis populations are present in the United States: the Sonoran cluster (near Mexico), the Pacific cluster (the Western coastal, montane, and intermontane
regions), and the Midwest cluster (including Montana) (Venkatesan and Rasgoon, 2010). The virus had spanned across all three clusters by 2004 (Venkatesan and Rasgon, 2010).

The incubation period of West Nile Virus ranges from 2-14 days (Griffith, 2012). Once infected, the symptoms of the disease are similar to St. Louis encephalitis, with a fairly wide range of symptoms (Ruiz et al., 2004). Many people who are infected with the virus tend to experience only mild symptoms such as fever, headache, and skin rash (Griffith, 2012). However, less than 1% of people infected with WNV develop a more serious illness, their symptoms ranging from high fever to paralysis and coma to death (Griffith, 2012). Higher-risk people are those who are age 50 and up, those who work outdoors, and those with lower immune systems (Griffith, 2012).

Physicians and state officials are interested in new and efficient methods for monitoring the spread of disease and predicting future outbreaks (Cooke et al., 2006). One such method is spatial epidemiology, the study of spatial variation in disease incidence or risk (Ostfeld et al., 2005). This method has arisen as the principal scientific discipline committed to understanding both the causes and consequences of spatial heterogeneity in infectious diseases (Ostfeld et al., 2005). Spatial epidemiology assesses a variety of factors including socioeconomic factors, geographic factors, and environmental factors (Elliot and Wartenberg, 2004).

A specific environmental factor that is assessed using spatial epidemiology is vegetation. Vegetation is an important variable in assessing WNV risk because its abundance is specifically associated with the presence of human cases (Brownstein et al., 2002). Vegetation not only provides a resting and breeding site for mosquitoes, but also
provides avian hosts, a refuge from predators, carbohydrate resources for flight energy, and the necessary resources needed for reproduction and pathogen acquisition (Cooke et al., 2006, Brownstein et al., 2002). In New York City, spatial analysis of WNV case distribution found that vegetation abundance was significantly and positively associated with human West Nile Virus cases (Gibbs et al., 2006). A commonly used measure of vegetation density is the Normalized Differentiated Vegetation Index (NDVI; Ozdenerol et al., 2008). Previously, NDVI data have been useful in predicting the distribution of disease vectors like tsetse flies and mosquitoes (Ozdenerol et al., 2008). As the most commonly used vegetation index in health studies, NDVI data provide a comprehensive growing season profile of different ecosystems, which is useful for evaluating seasonal variations in vegetation conditions (Ward, 2009, USGS, 2011). Other studies of vegetation and occurrence of WNV have been completed in other states, such as California; however, few studies have been carried out in Montana (Ezenwa 2005, Montana State University, 2012). These studies include data layers for vegetation type and density but not a combined data layer (USGS, 2012). Combining the proposed vegetation data layer with a thermal data layer may improve models that attempt to predict the distribution of C. tarsalis.

In the present study, spatial epidemiology will be applied to the vegetation in Montana by combining NDVI data, landcover data, and a thermal layer (Murphy, 2012) to create a predictive model of C. tarsalis in Montana. My study explores two hypotheses. The first is that there will be no correlation between vegetation and the presence of C. tarsalis. A second hypothesis is that a correlation exists between the thermal layer and presence of C. tarsalis but not between both the thermal and vegetation
layers and presence of *C. tarsalis*. If a correlation indeed exists between both the thermal and vegetation layers and presence of *C. tarsalis*, then WNV should be more easily predicted using the combined model, and better prevention and control programs could be put in place.

**Materials and Methods:**

**Location:**

Montana is located in the Rocky Mountain region of the United States between 44° 26'N to 49°N (longitude) and 104° 2'W to 116° 2'W (latitude) (Netstate, 2012). The most abundant vegetation types are Grasslands (44.73%), Evergreen Forest (21.6%), Shrubland (8.69%), and Fallow (7.7%) (USGS Earth Explorer, 2012).

![Figure 1 Field sites with the presence of *Culex tarsalis*](image)
**Sample Collection:**

Mosquito samples were obtained using CDC light traps at sites throughout Montana (Fig. 1). Depending on the location, either a CO₂ tank or dry ice was used as an attractant. The traps were operational from dusk to dawn, placed approximately three feet off the ground. Once transported back to the lab at Carroll College, the samples were placed in a -20 °C freezer for approximately 24 hours. The samples were then sorted to isolate *C. tarsalis*. *C. tarsalis* mosquitoes were identified based on the following characteristics: median banding on the proboscis, a rounded abdomen, wide basal and apical bandings on each tarsal, and the presence of thin scales on the dorsal wing surface (Figure 2; James Gathany, 2005). The latitude and longitude coordinates for the sites that had at least one *C. tarsalis* mosquito present were recorded and transferred to a spread sheet. One-hundred fifteen sites throughout Montana had at least one *C. tarsalis* present. Locations at which no *C. tarsalis* were collected were omitted from this study.

![C. tarsalis specimen labeled with distinguishing characteristics by James Gathany, 2005](image)
Environmental Variables:

Vegetation data layers providing vegetation density and landcover type data were obtained from the USGS. These data layers were adapted to ASCII format using ArcMap10.1. ArcGIS software was used to resample the layers to 1000m x 1000 m square plots for the state of Montana. The layers were also converted to a common projected coordinate system (NAD 1983 State Plane Montana FIPS 2500) and a common datum (North American 1983). The aforementioned conversions were required for use by MaxEnt (Young et al., 2011). The landcover data set was chosen because of the number of landcover categories. Insufficient categories would not provide enough information and an excess of categories could cause over-fitting of the MaxEnt model. The landcover data set used in the current study included twenty different landcover types. The vegetation density data set, known as the Normalized Differentiated Vegetation Index, was chosen because of its use in several past studies, specifically in New York and Connecticut (Ezenwa et al., 2006; Brown et al., 2008). Also, the data set was updated every month, a necessary procedure for this project. The NDVI dataset was continuous, and the landcover data set was categorical. The thermal data was created by Murphy (2012) and resampled and converted in the same manner as the vegetation layers.

Model Development:

MaxEnt, a modeling program, uses presence-only data, environmental data, and maximum entropy theory to determine habitat suitability (Phillips et al., 2004). This program projects the probability that the species of interest will occur at any given point (Phillips et al., 2004).
To begin the MaxEnt process, a sample file including the presence localities of C. tarsalis, in .csv format, was loaded into the program. This file contained 115 northing and easting values converted from the latitude and longitude coordinates recorded at each trap site. The environmental layers were loaded next. The output was set to logistic and the boxes “create response curves,” “make pictures of predictions,” and “do jackknife to measure variable importance” were checked. The model was then run and the results were saved to output files. The output of MaxEnt produced several tables and figures that illustrate how well the model fits the data and how relevant the model is statistically.

MaxEnt was run three times with the NDVI and landcover data, once for each month of the study: June, July, and August. MaxEnt was run separately each month to increase the trials for each model type and to analyze and compare results from month to month. The same process was repeated for June, July, and August with thermal data in addition to the vegetation layers. The first three runs were considered the first cycle and then next three runs were considered the second cycle.

Results

First Cycle: Vegetation

Modeling vegetation with MaxEnt resulted in several statewide maps of C. tarsalis habitat (Figs 3, 4, and 5). A map was produced for the vegetation data for the months of June, July, and August, with AUC values of 0.854, 0.876, and 0.889, respectively. An AUC value above 0.5 indicated that the projected model predicts C. tarsalis location better than random chance. A value of 1.0 indicates perfect predictability.
Environmental variables that were incorporated into these models were vegetation type (landcover data) and vegetation density (NDVI data). For each month, landcover type had a stronger role in the model, with higher percent contributions than NDVI (Table 1).

Table 1: Relative contribution of environmental features to the model in predicting the distribution of *C. tarsalis* for June, July, and August.

<table>
<thead>
<tr>
<th>Month</th>
<th>Environmental Variable</th>
<th>Percent Contribution to the Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>June</td>
<td>Landcover</td>
<td>83.6</td>
</tr>
<tr>
<td></td>
<td>NDVI</td>
<td>16.4</td>
</tr>
<tr>
<td>July</td>
<td>Landcover</td>
<td>76.1</td>
</tr>
<tr>
<td></td>
<td>NDVI</td>
<td>23.9</td>
</tr>
<tr>
<td>August</td>
<td>Landcover</td>
<td>70.4</td>
</tr>
<tr>
<td></td>
<td>NDVI</td>
<td>29.6</td>
</tr>
</tbody>
</table>

The jackknife plots were all similar (Figs. 6-8). The environmental variable that contributed most to resolution is the landcover data. This result indicates that landcover is the most useful variable when analyzing that data set independently of the other variables. The environmental variable that decreases the gain the most when omitted from the model is landcover. This indicates that landcover data had the most information content.

MaxEnt also produced a set of response curves, for the variables landcover and NDVI, where each variable was used independently in producing the model. For each month, the top four types of landcover that had the biggest effect on the model were: Low
Intensity Residential, Commercial/Industrial/Transportation, Urban/Recreational Grasses, and Woody Wetlands (Figs. 9-11). Evergreen Forest was the landcover type that produced the lowest effect on the model. Another set of response curves indicated that the presence of *C. tarsalis* is negatively correlated with vegetation density (NDVI) for the months of June and August and positively correlated with the month of July (Figs. 12-14).

### Second Cycle: Vegetation and Thermal

The second cycle of MaxEnt resulted in adjusted statewide maps of *C. tarsalis* habitat (Figs. 15-17). A map was produced for the vegetation and thermal data for the months of June, July and August, with AUC values of 0.910, 0.921, and 0.941, respectively. These values are higher than in the previous set of models, indicating that adding the thermal area increased its predictability.

Environmental variables incorporated into the second cycle of models were vegetation type (landcover data), vegetation density (NDVI data), and the thermal layer created by Murphy (2012). For each month, landcover type had a stronger role in the model, with higher percent contributions (Table 2). The variables that differed were the NDVI and thermal data. For the months June and August, the thermal layer contributed more to the model than the NDVI layer. For the month of June, the NDVI layer contributed more to the model than did the thermal layer.

The jackknife plots for the second cycle are similar for the months of June, July, and August (Figs. 18-20). For all three plots, landcover had the highest gain, followed by the thermal data, and then the NDVI data. This finding indicated that landcover contributed the most to the model and NDVI contributed the least.
Table 2: Relative contribution of environmental features to the model in predicting the distribution of *C. tarsalis* June, July, and August.

<table>
<thead>
<tr>
<th>Month</th>
<th>Environmental Variable</th>
<th>Percent Contribution to the Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>June</td>
<td>Landcover</td>
<td>59.4</td>
</tr>
<tr>
<td></td>
<td>NDVI</td>
<td>16.9</td>
</tr>
<tr>
<td></td>
<td>Thermal</td>
<td>23.7</td>
</tr>
<tr>
<td>July</td>
<td>Landcover</td>
<td>54.8</td>
</tr>
<tr>
<td></td>
<td>NDVI</td>
<td>23.6</td>
</tr>
<tr>
<td></td>
<td>Thermal</td>
<td>21.6</td>
</tr>
<tr>
<td>August</td>
<td>Landcover</td>
<td>43.6</td>
</tr>
<tr>
<td></td>
<td>NDVI</td>
<td>24.8</td>
</tr>
<tr>
<td></td>
<td>Thermal</td>
<td>31.5</td>
</tr>
</tbody>
</table>

The response curves for landcover produced from the second cycle were similar to the response curves for the first cycle. For each month, these four landcover categories had the biggest effect on the model: Low Intensity Residential, Commercial/Industrial/Transportation, Urban/Recreational Grasses, and Woody Wetlands (Figs. 21-23). As before, the landcover type Evergreen Forest had the lowest effect on the model. The response curves for vegetation density (NDVI) indicated that the presence of *C. tarsalis* is negatively correlated with vegetation density for the months of June and August and positively correlated for the month of July (Figs. 24-26). The third set of response curves indicated that the presence of *C. tarsalis* positively correlates with the thermal data (Figs. 27-29).
Discussion

The objective of this study was to analyze a model containing vegetation density, landcover, and thermal data to locate mosquito hot spots. The model that resulted from this experiment predicted habitat suitability for *C. tarsalis* with an AUC value of 0.924. This value indicates that the models from the second cycle have a high predictability for habitat suitability, as a value of 1.00 indicates perfect prediction. Since the second cycle phase contained the highest AUC value, the data of the first cycle will not be further discussed. Overall, a modal correlation existed between vegetation density and the presence of *C. tarsalis*. The modal distribution showed that low- and high-density vegetation contained the lowest predicted presence of *C. tarsalis*, and medium-density vegetation showed a strong correlation between density and the predicted presence of *C. tarsalis*. Thus, we reject the first hypothesis that no correlation exits between vegetation and the presence of *C. tarsalis*. According to the response curves located in the Appendix (Figures 24-29), there is a positive correlation between both the thermal and vegetation layers and the presence of *C. tarsalis*. Originally, it was hypothesized that no correlation would exist between the combination of the thermal and vegetation layers and the presence of *C. tarsalis*, so the second hypothesis was rejected as well.

Previous studies, in states other than Montana, have investigated the effects that landcover has on mosquito populations. In a study performed in Arizona, it was found that landcover was correlated to mosquito abundance (Landau and van Leeuwen, 2012). Although this study was performed in a different state, with abundance rather than presence data, it shows that there is a connection between the type of landcover and
mosquito locations. In the current study, landcover was the highest contributing variable for the risk model, which verifies the importance of landcover type in disease risk maps.

The current study found that specific landcover types are more associated with probability of tarsalis presence than others. Low Intensity Residential, Commercial/Industrial/Transportation, Urban/Recreational Grasses, and Woody Wetlands had the four highest probabilities of presence. This factor indicates that, in areas containing one of these four landcover types, a higher likelihood exists that *C. tarsalis* will be present. Chuang *et al.* (2011) found that *C. tarsalis* was most abundant in landscapes dominated by grasslands, pasture, and hay in South Dakota. This finding was interesting because, in the present study, developed land had the highest predicted probability of *C. tarsalis*; whereas the Chuang *et al.* study found that agricultural land played the biggest role. Previous studies have found that *C. tarsalis* primarily breed in agricultural habitats but seek blood meals in developed areas (Chuang *et al.*, 2011). Thus, both studies could be correct. The high probability of presence in the developed areas of the current study does not indicate that a higher abundance exists in those areas, but instead suggests a higher likelihood that there will be *C. tarsalis* present in urban areas searching for blood meals. The high abundance in the predominately rural areas likely exist because *C. tarsalis* breed and develop in those areas. One large disadvantage of comparing the current study with that of Chuang *et al.* (2011) is that the South Dakota study used only five landcover categories; whereas, the current study used 21 different landcover categories. Future studies performed in Montana should investigate the relationship between vegetation type and abundance of *C. tarsalis*, instead of solely using presence data.
Zhou *et al* (2007) and Vezzani *et al* (2005) both found that mosquito presence positively correlates with higher vegetation coverage. The current study contained contradictory results, with a modal relationship between vegetation density and mosquito presence. The model relationship is likely due to a variety of factors. Vegetation provides a breeding site for mosquitoes, refuge from predators, carbohydrate resources for flight energy, and avian host blood resources needed for reproduction and pathogen acquisition (Cooke *et al*., 2006, Brownstein *et al*., 2002). Thus, a mosquito would be less likely to be in areas where there is low vegetation density. High density vegetation would impede a mosquito’s ability to obtain resources and also restrict access by other animals, which could serve as blood meals. Medium density areas would provide for the needs of *C. tarsalis*, with fewer physical barriers without providing too many physical barriers. The contradiction between the current study, Zhou *et al.* (2007) and Vezzani *et al.* (2005) is likely due to other factors, such as regional climate and vegetation type, as well as the specific vector being studied.

Consistent with the current study, Murphy (2012) found that, overall, temperature is positively correlated with the presence of *C. tarsalis*. Also, the CDC says that late summer or early fall, which usually has the highest temperatures, is the most common time to become infected with WNV. Chuang *et al.* (2011) found that, in mid-June, a large increase arose in the *C. tarsalis* population and continued to rise rapidly, until peaking in July. A likely cause of this trend would be that warm temperatures accelerate larval development, leading to an explosion in the population of *C. tarsalis*. Reisen *et al.* (2006) found that during years with above-normal temperatures, WNV always dispersed into new areas. Decreased or delayed virus activity was associated with cooler summers,
especially at Northern latitudes. Not only do warmer temperatures lead to a higher predicted presence of *C. tarsalis*, a higher likelihood of WNV transmission also exists, making temperature a crucial variable to watch (Reisen *et al.*, 2006).

Future studies should investigate the effects of vegetation using higher-resolution data. Also, it would strengthen future studies to ground truth the vegetation data, to confirm that the data sets used in the study are accurate and a good representative of Montana’s vegetation. This project served as a useful starting point in making prediction maps for WNV. Although the risk maps created in this study only investigated three variables, they provide insight into mosquito presence throughout Montana, findings which in turn may help isolate WNV hot spots. Eventually this knowledge can lead to greater awareness and the institution of better prevention measures.
Appendix

First Cycle:

Figure 3. MaxEnt model for *C. tarsalis* for the month of June. Warmer colors indicate areas with better predicted conditions. Field sites with the presence of *C. tarsalis* are noted in white.

Figure 4. MaxEnt model for *C. tarsalis* for the month of July. Warmer colors indicate areas with better predicted conditions. Field sites with the presence of *C. tarsalis* are noted in white.
Figure 5. MaxEnt model for *C. tarsalis* for the month of August. Warmer colors indicate areas with better predicted conditions. Field sites with the presence of *C. tarsalis* are noted in white.

Figure 6. Jackknife test of variable importance for the month of June.

Figure 7. Jackknife test of variable importance for the month of July.
Figure 8. Jackknife test of variable importance for the month of August

Figure 9. Contribution of relative landcover categories to the model for June.

Figure 10 Contribution of relative landcover categories to the model for July.

Figure 11. Contribution of relative landcover categories to the model for August.

Figure 12. Correlation between NDVI and the probability of finding C. tarsalis for the month of June.

Figure 13 Correlation between NDVI and the probability of finding C. tarsalis for the month of July.

Figure 14. Correlation between NDVI and the probability of finding C. tarsalis for the month of August.
Second Cycle:

Figure 15. Updated MaxEnt model for *C. tarsalis* using landcover, NDVI, and thermal data for the month of June. Warmer colors indicate areas with better predicted conditions. Field sites with the presence of *C. tarsalis* are noted in white.

Figure 16. Updated MaxEnt model for *C. tarsalis* using landcover, NDVI, and thermal data for the month of July. Warmer colors indicate areas with better predicted conditions. Field sites with the presence of *C. tarsalis* are noted in white.
Figure 17. Updated MaxEnt model for *C. tarsalis* using landcover, NDVI, and thermal data for the month of August. Warmer colors indicate areas with better predicted conditions. Field sites with the presence of *C. tarsalis* are noted in white.

Figure 18. Jackknife test of variable importance for landcover, NDVI, and thermal data for the month of June.

Figure 19. Jackknife test of variable importance for landcover, NDVI, and thermal data for the month of July.
Figure 20. Jackknife test of variable importance for landcover, NDVI, and thermal data for the month of August.

Figure 21. Contribution of relative landcover categories to the model for June.

Figure 22. Contribution of relative landcover categories to the model for July.

Figure 23. Contribution of relative landcover categories to the model for August.

Figure 24. Correlation between thermal data and the probability of finding *C. tarsalis* for the month of June.

Figure 25. Correlation between thermal data and the probability of finding *C. tarsalis* for the month of July.

Figure 26. Correlation between thermal data and the probability of finding *C. tarsalis* for the month of August.

Figure 27. Correlation between NDVI and the probability of finding *C. tarsalis* for the month of June.

Figure 28. Correlation between NDVI and the probability of finding *C. tarsalis* for the month of July.

Figure 29. Correlation between NDVI and the probability of finding *C. tarsalis* for the month of August.
Literature Cited


