Dean's Scholars Honors Undergraduate Thesis

Optimized Mosquito Surveillance in St. Tammany's Parish, LA

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ABSTRACT

Since its emergence in the United States in 1999, West Nile Virus has caused hundreds of deaths and has been spreading geographically. In order to efficiently control West Nile Virus outbreaks, it is necessary to monitor the spread of its primary mosquito vectors. This report contains a new computational method to optimize the surveillance methods of West Nile Virus vectors at St. Tammany Parish, Louisiana. Based on multiple years of data, the distribution of mosquito density was thoroughly anazlyed. The results include the identification of multi-year patterns and high-risk zones for West Nile Virus in the parish and correlations in mosquito prevalence across these zones. A spatial statistical model was developed for the surveillance network regarding the West Nile Virus vector *Culex Quinquefasciatus*. An approximation algorithm was applied to determine the optimal location of surveillance sites that provide the most informative locations for *Culex Quinquefasciatus* surveillance in the parish. The results of this paper indicate that a greedy algorithm, thus far, is the best possible solution to determine the optimal surveillance sites. In its current state, the algorithm is simplified as the most informative locations as those that decrease the variance the most. An improved algorithm involving more variables such as rainfall will enhance the ability to determine an optimal mosquito surveillance network. Optimizing mosquito surveillance methods can improve the ability to monitor mosquito vectors and significantly reduce costs.

INTRODUCTION

West Nile Virus is a mosquito-borne zoonotic arbovirus. The disease is carried by hundreds of species of mosquitos across the world. The most common species found in the United States include *Culex pipiens*, *Culex tarsalis*, and *Culex quinquefasciatus*. The most commonly infected animals are birds, which serve as the prime reservoir host[1]. Over time the disease has quickly spread to humans and other mammals. Up to eighty percent of people infected with West Nile Virus will have no symptoms and will recover on their own; however, some cases can cause serious illness or death[11]. Currently, no vaccine exists to fight against West Nile Virus. Mosquito control through insecticides and eliminating standing water are the two primary methods to diminish the number of outbreaks[3].

West Nile Virus first appeared in the United States in New York City in 1999[4]. As it first emerged, the disease was a zoonotic pathogen that entered infected birds and mosquitos. Since then West Nile Virus has caused widespread human epidemics across North America. As reported by the Centers for Disease Control and Prevention, over the last decade a total of 1,100 deaths have occurred with human cases reported in 47 of the 50 states. In 2012 alone there were 5,476 reported cases and 286 deaths due to the disease[5]. The current trends for West Nile Virus have created a major cause for concern and more and more steps are being taken to reduce the risk of potential outbreaks.

Environmental sampling is the primary method to monitor West Nile Virus outbreaks. Some of the ways the disease is monitored include pooling of trapped mosquitoes via ovitraps, carbon dioxide-baited light traps, and testing blood samples drawn from wild birds, dogs and sentinel monkeys, as well as testing brains of dead birds found by various animal control agencies and the public[6]. The recent tendencies in outbreaks of West Nile Virus have increased the urgency for effective evidence-based surveillance in order to establish early detection. Through understanding surveillance data, a West Nile Virus risk map was plotted across the United States in 2003[7]. Similar studies have also been performed for other various mosquito borne illnesses. More time and effort, however, has been focused on mapping potential outbreak of mosquito-borne viral diseases rather than establishing efficient surveillance methods to maximize information gained through surveillance[6]. There is very limited literature on the concept of optimizing mosquito surveillance networks for higher efficiency levels. Efficient surveillance networks, however, will decrease time lost retrieving surveillance data, reduce expenses, and optimize the information attained.

This report studies and analyzes the mosquito surveillance network in St. Tammany Parish, Louisiana. The parish is 854 square miles and has a human population of 233,700 as of 2010. St. Tammany Parish, Louisiana experienced a major outbreak of West Nile Virus in 2002 as 40 human cases and 4 deaths were reported[8]. Consequently, the outbreak led to a large operational budget increase for St. Tammany Parish Mosquito Abatement District (STMAD) to establish a more vigorous mosquito surveillance network to better predict mosquito outbreaks. STMAD is an agency in St. Tammany Parish, Louisiana which was established 30 years ago to reduce the nuisance from mosquitoes. Today it has become the leading agency in controlling mosquito-borne viral diseases, while continuing its original mission. STMAD is experienced in advanced mosquito surveillance and control, has staff of about 20 persons (including 2 entomologists), and a veritable arsenal of surveillance and control equipment. It has also collected data for decades about the ecology of mosquito species in the region[9].

One method of mosquito surveillance STMAD performs is through a system of gravid traps across the area. Gravid traps are portable, battery-powered traps for collecting species. The trap attracts females by means of an oviposition medium (attracts females to deposit their eggs) contained in a pan below the trap. In particular, the gravid traps selectively capture for the *Culex* species mosquitoes[6]. Gravid traps are used because in Louisiana, *Culex quinquefasciatus* is the main mosquito vector for West Nile Virus[8].

The STMAD has divided the parish into 75 surveillance zones. STMAD has established a mosquito surveillance network based on these zones by placing a gravid trap in each zone. Each gravid trap is subject to change positions within in each zone. From these gravid traps, STMAD retrieves mosquito counts from a particular zone where a single zone is visited approximately once every two to three weeks. The mosquito counts are then identified by species, zone location, and date of retrieval to create an extensive data set of the mosquito count observations in the St. Tammany Parish.

A literature search indicates that almost no work has been done in applying optimization to the problem of mosquito control (Dimitrov et al. on malaria is an exception)[10]. Therefore, this study is one of the first of its kind to apply optimization to mosquito surveillance. This paper first discusses the methods taken to seek possible trends to predict West Nile Virus outbreaks. After thorough analysis of the data, it was discovered that optimizing the surveillance network of traps would greatly benefit St. Tammany Parish. An optimization model is currently being developed by my collaborators at the University of Texas at Austin and Tulane University. They are focusing on improving surveillance operations to reduce costs, improve the quality of surveillance for mosquito density and arbovirus prediction, and increase the lead time to alert for the emergence of arbovirus outbreaks.

METHODS

Data Set

STMAD has provided the data set for the mosquito surveillance network. The data set includes gravid trap mosquito counts for a total of 75 zones in the St. Tammany Parish. The gravid traps were placed outdoors at known sites (pools, tires, ditches). STMAD has also provided other mosquito surveillance data including CDC light traps, but only the gravid trap data has been analyzed for this paper because they are most sensitive to *Culex quinquefasciatus*.

The gravid trap data set spans from February 23rd, 2006 to August 13th, 2012. A total of 11,788 measurements were taken in all. A measurement is specified with zone location, species type, total number of female counts, and total number of male counts. Only female measurements were analyzed here. Females require the nutrition of blood, hence, influencing the spread of West Nile Virus among humans and animals. The mosquito species of interest in the data set was solely *Culex quinquefasciatus* as it is the predominant mosquito carrier of West Nile Virus in the Louisiana area.

Mapping St. Tammany Parish

STMAD provided a hand-drawn diagram of the region divided into 75 zones. They also provided the human population for each of these zones. The longitude and latitude coordinates for the region were obtained. Using GIS (Geographic Information System) software, Justin Davis and Alexander Gutfraind were able to successfully convert the hand-drawn map to a computer generated map. All bodies of water throughout the region were also plotted on the map. GIS software was then used to compare the mosquito count densities with the human population densities. As a general rule, densely human populated zones are smaller, likely because in densely-populated zones it is more important for STMAD to obtain accurate data on the mosquito.

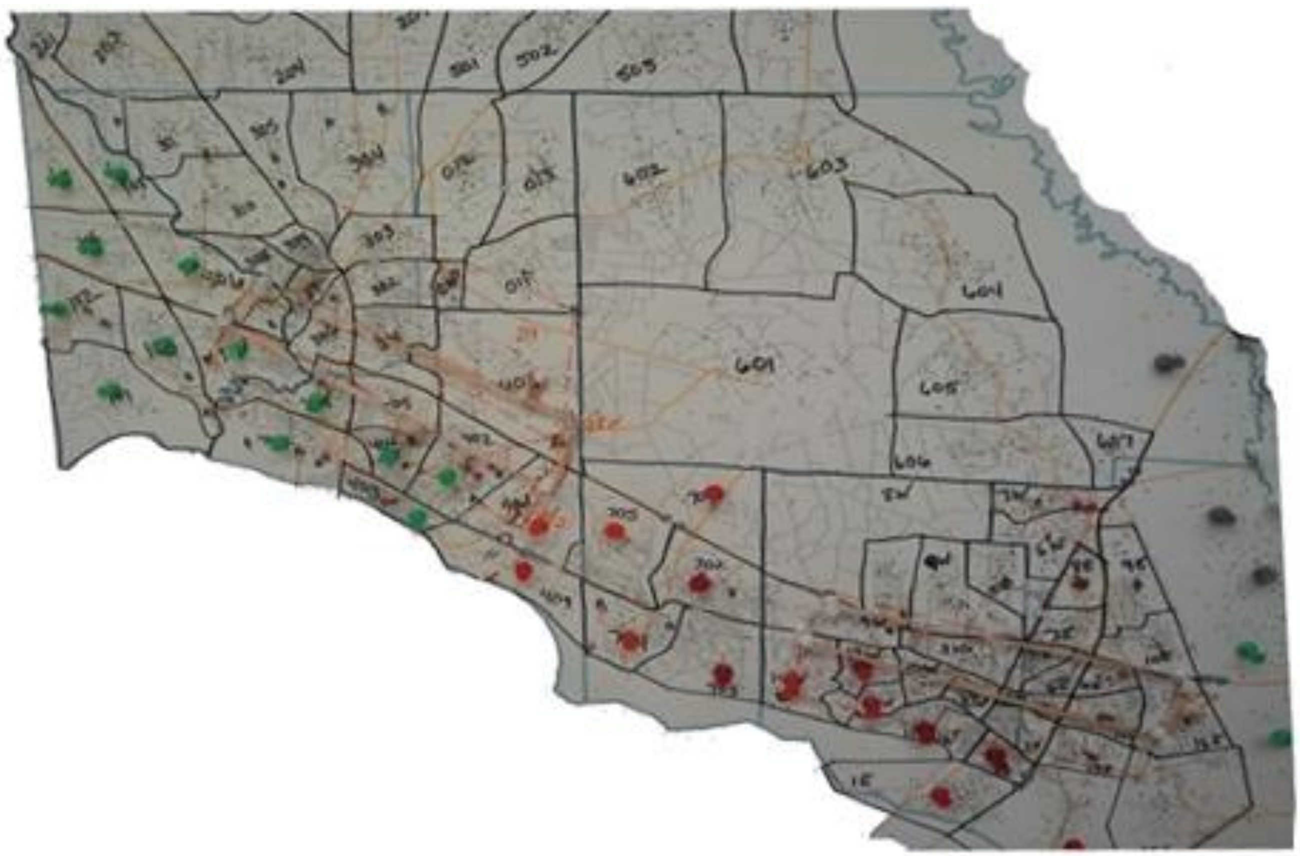

Figure 1: Map of St. Tammany Parish, Louisiana from the STMAD operations room The region is divided into 75 different zones. The longitude and latitude coordinates for each zone were obtained and this map was then computer generated.

Precise longitude and latitude coordinates for the gravid traps were not provided. The gravid traps were only identified by which zones they were located in. As a result, it was assumed that each gravid trap was located at the geographical centroid of the zone.

Linear Interpolation

R, the free software statistical and graphing program, was used to analyze the data set. Upon initial analysis, it was seen that the data was very noisy. Certain traps were visited consistently while other traps were entirely neglected. To gain a better understanding of the mosquito counts trends, the data was linearly interpolated. The mosquito counts were grouped into weeks. If a trap was not visited in that particular week, then the empty measurement was calculated using the average of the total weekly mosquito counts before and after that particular week. . No conclusions were drawn from interpolated data, but it did provide a stronger understanding of the mosquito count tendencies.

Cross Correlation

The weekly number of mosquito counts for each zone was determined. Consequently, each zone had an associated time series of mosquito counts. To illustrate time lags between zones, a pair of zones was compared to see if the rise or fall of mosquito counts in one zone indicated a rise or fall of mosquito counts in another zone in the same week, a week later, two weeks later, and so on. Cross correlations were performed with every pair of zones in the St. Tammany Parish to determine the existence of time lags. The cross correlation function in R is similar to any cross correlation function—Suppose there is a relationship between two time series (y_t and x_t), the series y_t may be related to past lags of the x-series. The sample cross correlation function (CCF) in R is helpful for identifying lags of the x-variable that might be useful predictors of y_t. In R, the *sample CCF* is defined as the set of sample correlations between x_{t+h} and y_t for $h = 0, \pm1, \pm2, \pm3$, and so on. A negative value for h is a correlation between the x-variable at a time before t and the *y*-variable at time *t* [11]. The cross correlation was only applied to weekly mosquito counts if and only if each of the specified zones were visited at least once during the same week.

Cumulative Probability Distribution

The cumulative probability distribution function in R describes the probability that a real-valued random variable *X* with a given probability distribution will be found at a value less than or equal to a number *x*. This function was used to summarize the cross correlation values.

Objective Function

The objective of this project was to construct an effective surveillance system for the mosquito vectors of West Nile Virus. Effectiveness is defined based on the amount of information the surveillance system provides on the mosquito population, while considering its impact on the human population. To be specific, the surveillance system's effectiveness is a product of the variance about a zone, and the human population in it:

$$\mathrm{S(A)} = \sum_{z\ in\ Zones} \mathrm{h_z v_z}\,(A) \quad [EqObj]$$

Where $\mathrm{h_z}$ is the human population in zone z, and $\mathrm{v_z(A)}$ is the variance about the mosquito population at zone z, as a function of the surveillance network A.

The variance function was written by Justin Davis at Tulane University. The code for the variance summary runs a hierarchical model and determines the variance in mosquito counts when a set number of zones are placed in the surveillance network. The more zones added to the surveillance network increases the total number of mosquito counts and hence reduces the variance, as seen with most normal distributions.

This objective function allows one to determine which surveillance zones provide the most amount of information for a given surveillance budget. We believe (but have not proven) that this objective function is submodular in the set of zones with surveillance. Submodularity means that adding another zone to a small surveillance network of zones will enhance performance far greater than adding a zone to a very large surveillance network. For optimization, submodularity of the objective functions is a very useful property. In a now classic result, Nemhauser et al. have shown that maximization of an increasing submodular function of set could be approximated efficiently using a greedy algorithm. This is numerically equivalent to our case where we are minimizing a function whose value is decreasing. The greedy algorithm is expected to find a solution who performance is no less than $(1 - 1/\mathrm{e})$ of the best possible performance, i.e., at least 63% of the optimum[18].

Greedy Algorithm

Based on the objective function, a greedy algorithm was applied to select the zones to minimize $EqObj$. The greedy algorithm follows these steps:

1. Let *Z* be the entire pool of surveillance zones, and let *A* be the zones that have already been selected in the surveillance network. Let *f(A)* by the submodular function in *A*. The model begins with zero surveillance zones in *A.*
2. Let *x* be a zone in *Z* and not in *A* such that *x* minimizes *f(A+x) – f(A).*
3. Add *x* to *A* until *b* zones are selected.

Hence, the greedy algorithm selects *b* zones that best optimize the surveillance network to provide the most amount information about public health concerns with mosquito populations in the St. Tammany's Parish. The greedy algorithm selects a zone that most effectively predicts mosquito counts, weighted by the variance. The greedy algorithm only selects zones that minimize the objective score.

Population, Random, and Trap Visit Algorithms

The greedy algorithm was compared to three other algorithms in determining a surveillance network. The population algorithm selects zones for the surveillance network based on which zones have the highest human population. The random algorithm randomly selects zones for the surveillance network based equal probability of selecting any one particular zone. Lastly, the trap visit algorithm selects zones for the surveillance network by selecting zones with the most trap visits first.

RESULTS

Mapping St. Tammany's Parish

After analyzing the mosquito trap data and human population data through R and GIS, a risk-map of St. Tammany's Parish for high threat areas for West Nile Virus was created. The mosquito population density was calculated by totaling the number of female mosquitoes caught and dividing by the number of trap visits at each zone. Zones that did not have at least 10 trap visits at these zones were removed from the data set as they did not have enough data to be analyzed. The mosquito count density was then overlaid with the human population density using GIS to portray how human population density related to mosquito count density.

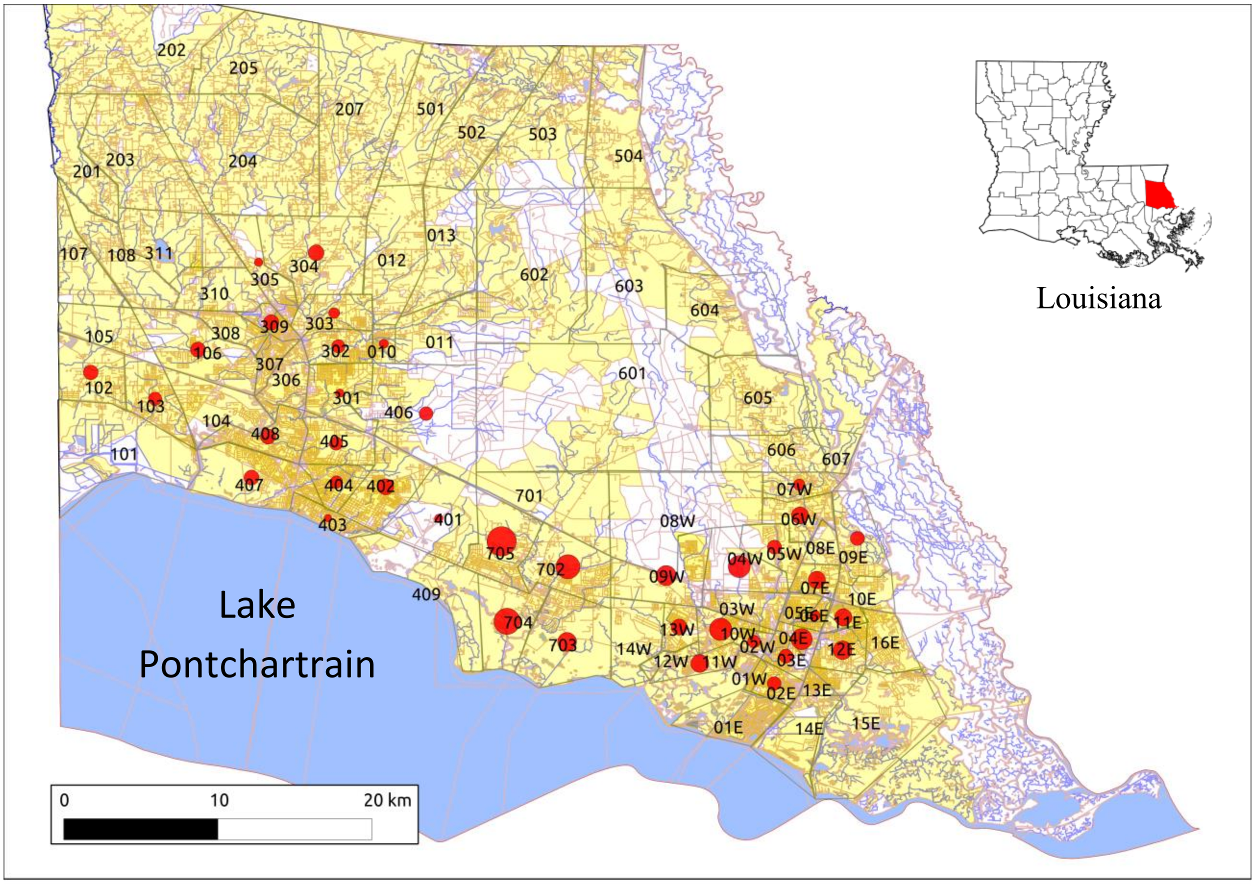

Figure 2: Map of St. Tammany's Parish comparing human population density with mosquito count density across various zones in the area. The yellow indicates the human population density. The red circles show the female mosquito count density. The larger the diameter of the circle, the larger the mosquito count density.

Mosquito Count Time Series

The *Culex quinquefasciatus* female mosquito counts from gravid traps of two zones were plotted to observe how mosquito counts fluctuate over the seven years from 2006 to 2012. The mosquito counts for Zone 705 and Zone 704 were totaled for each week over the entire 346 weeks of the data set. The weekly counts were linearly interpolated in order to fill in large gaps in the data set.

Lastly, the logarithm of these weekly counts was then taken to better visualize how mosquito counts increase in the summer months and decrease in the winter months.

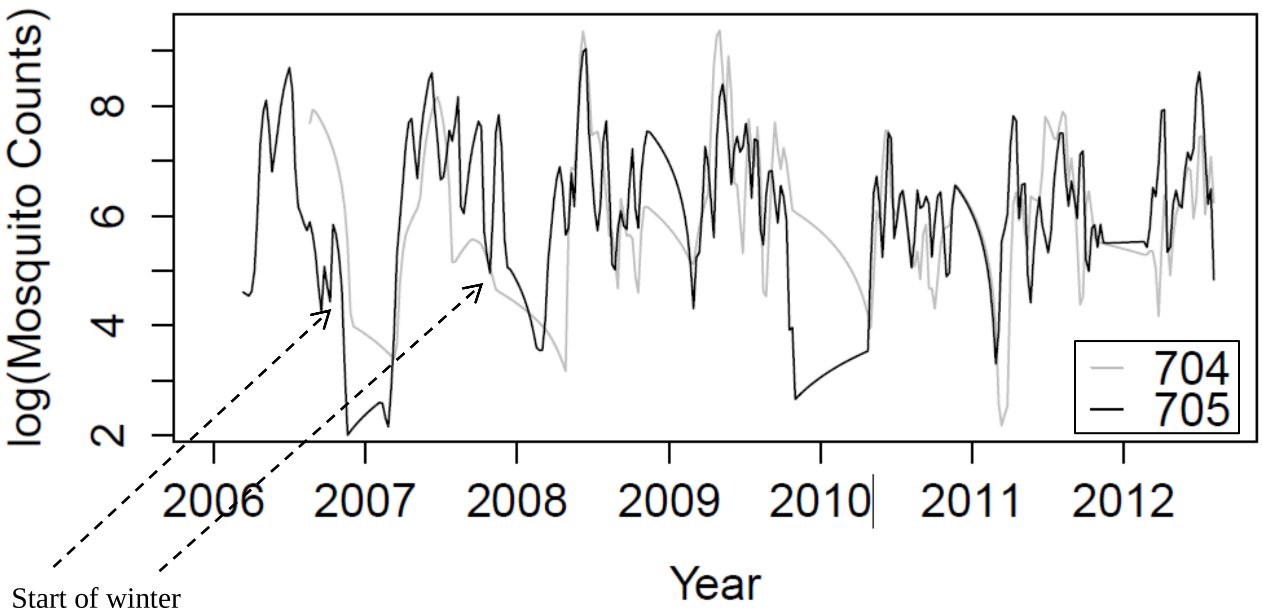

Figure 3: Number of female *Culex quinquefasciatus* trapped in two adjacent surveillance zones (704 and 705). Each measurement takes the logarithmic value of the total number of female counts for a particular week. The data are linearly interpolated for weekly female counts if a trap was not visited in a particular week. The cyclicity of mosquito counts are easily visualized in this graph. It can be seen exactly how mosquito populations rise in the summer and faller during the winter months.

Sampling Effort

The number of trap visits per zone was computed in order to better understand the surveillance network. Using R, it was determined if a particular zone was visited in a two week interval across the entire timeframe from February 2006 to August 2012.

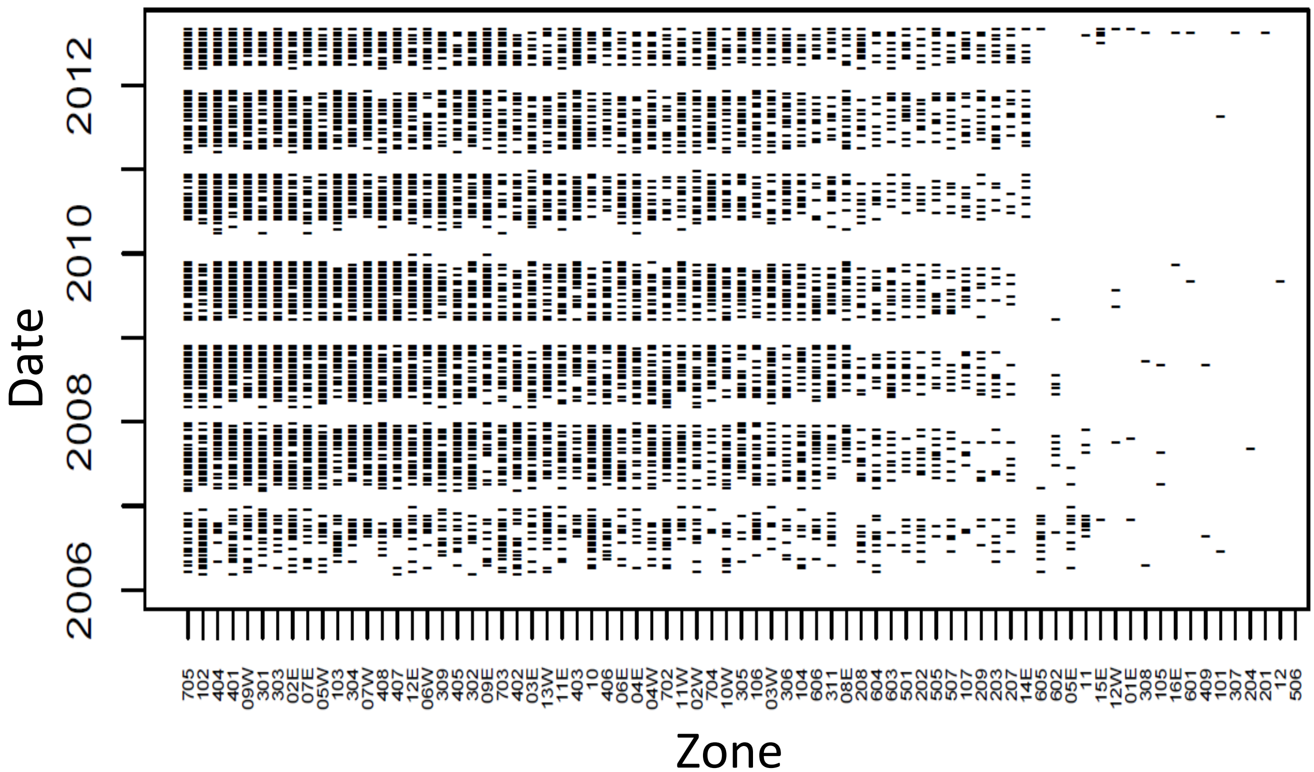

Figure 4: Trap visits for each zone in two week time intervals. A dash on the plot represents that the trap at that specific zone was visited at least once during that two week interval. The plot is also sorted such that with the zones with the most two week time interval visits are on the left and the zones with the least two week time interval visits are on the right. This figure portrays which zones are consistently visited and which zones are hardly visited.

Cross Correlation

A cross correlation plot was created for a pair of zones to determine if the two zones were correlated with time (i.e. mosquito count fluctuations in one zone will indicate fluctuations in mosquito counts at another zone two weeks later).

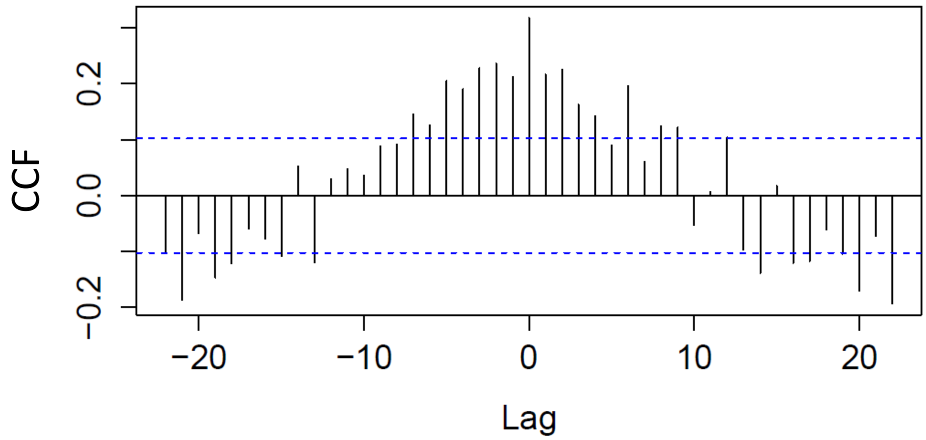

Figure 5: Cross correlation data between Zones 102 and 301. The lag time is in weeks so a +1 lag indicates the correlation between the two zones with the counts of one zone comparing the counts of another zone one week ahead. The low cross correlation of about 0.3 is rather weak. This demonstrates there is low predictability in the fluctuations in mosquito counts among these two zones.

The cross correlation of weekly female *Culex quinquefasciatus* mosquito counts was calculated for every pair of zones in St. Tammany Parish. Zones that did not overlap with at least one trap visit for at least 10 matching weeks were eliminated due to lack of data. After several cross correlation plots it was evident that a time lag did not exist between zones. Hence, the next step was to look simply at the correlation values at zero time lag to see if mosquito counts fluctuate together in zones. A cumulative probability distribution of the cross correlation values for all pairs of zones at zero time lag was plotted.

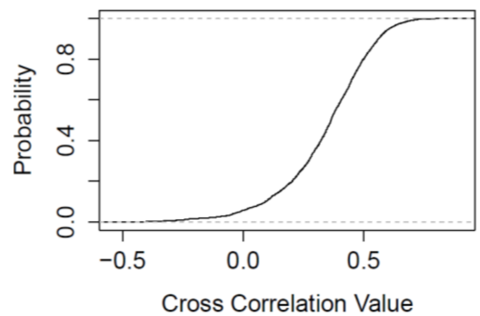

Figure 6: Cumulative probability distribution for the cross correlation values between all zones. The cross correlations were calculated for all pairs of zones at zero time lag. The cumulative probability distribution at 50% yields a cross correlation value of 0.423. This portrays that there is very low predictability in the fluctuations in mosquito counts among all the zones.

Greedy Algorithm

The greedy algorithm was run with 65 zones. 10 of the 75 zones were removed from the data set based on the sampling effort plot (Figure 4) as these zones lacked substantial trap visits.

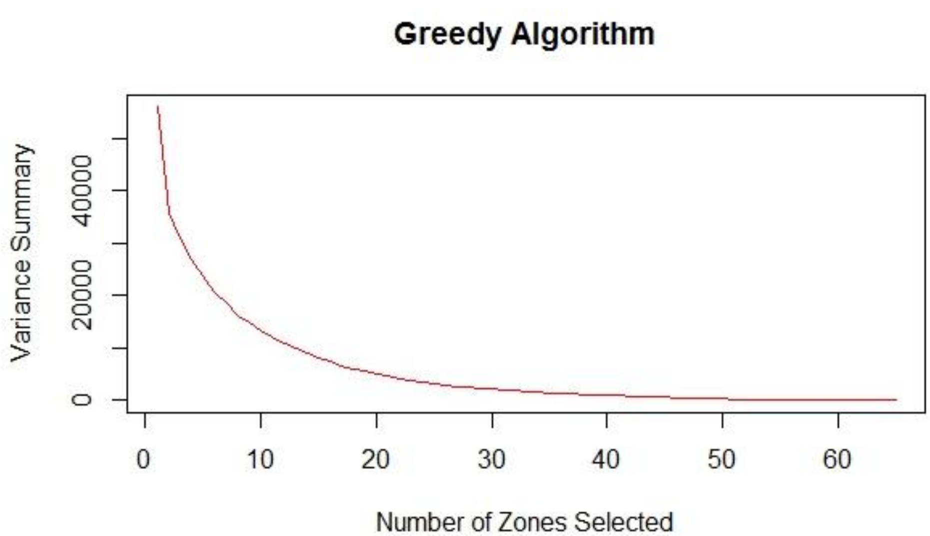

Figure 7: The number of zones selected by the greedy algorithm is plotted against the varaince summary. As more zones are selected into the pool of zones, more information about the

mosquito counts is obtained and consequentlly the variance of the data declines. Thus, the plot attains a minimum when all 65 zones are selected for.

	Selected Zone	Zone Population	Change in Objective Score	Objective Score
1	405	10278	NA	55901.46
2	06E	3838	-20254.69	35646.77
3	203	3039	-4657.69	30989.07
4	14E	8463	-4240.41	26748.67
5	407	8415	-3111.25	23637.41
6	402	11149	-2843.31	20794.11
7	301	13044	-2354.89	18439.22
8	09W	4829	-2221.80	16217.42
9	102	2471	-1513.27	14704.14
10	202	4757	-1486.40	13217.74
11	207	2488	-1165.61	12052.13
12	09E	2457	-1094.30	10957.83
13	15E	4979	-998.52	9959.31
14	404	11607	-908.31	9051.00
15	02E	6660	-893.89	8157.12
16	11E	9509	-781.76	7375.35
17	106	2836	-728.44	6646.91
18	705	1393	-599.65	6047.26
19	605	1076	-523.01	5524.25
20	311	2611	-481.23	5043.02
21	408	4896	-465.64	4577.38
22	16E	3200	-383.87	4193.51
23	703	1210	-353.15	3840.37
24	101	1736	-339.04	3501.32
25	05W	1815	-324.88	3176.45

Table 1: Greedy Algorithm results of the first 25 zones selected. The table displays the number of zones selected, the order of selected zones, the human population, the objective score after the zone was added to the surveillance network, and the change in objective score between before and after the zone was added to the surveillance network. This table identifies exactly which zones carry the most weight in the greedy algorithm and which zones should be in the surveillance network.

Population Algorithm

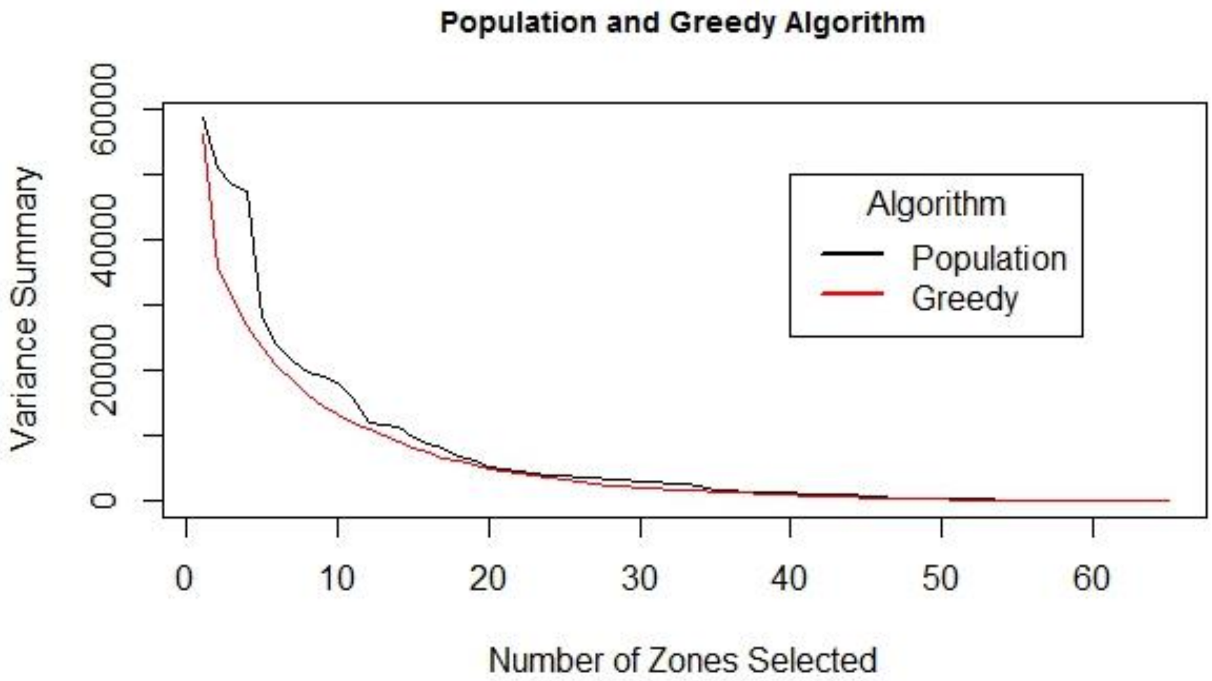

Figure 8: The population algorithm selects the zone with the largest human population first. Then the algorithm selects the zone with the second largest human population and so on until all 65 zones are selected. The population algorithm still maintains a minimum when all 65 zones are selected for. It can be seen that the greedy algorithm outperforms the population algorithm, especially when less than approximately 15 zones are selected for.

Random Algorithm

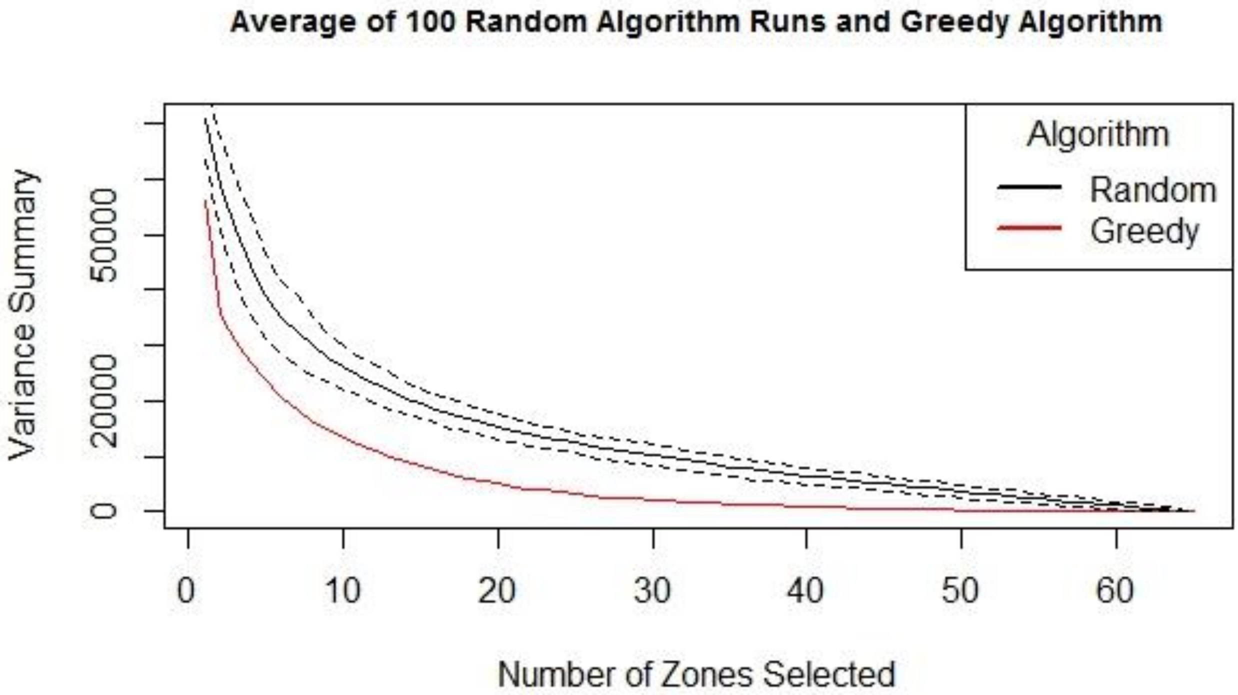

Figure 9: The random algorithm first selects one of the 65 zones with equal probabilty. Then it randomly selects another zone with equal probability from the remaining 64 zones and so on until all 65 zones are selected for. A total of 100 random algorithm runs were performed and the average variance summary of these random runs was calcualted. The mean of these runs is seen as the black solid line. The dotted lines inidicate one standard deviation above and below the mean. The greedy algorithm still outperforms the average random algorithm.

Zone Visits Algorithms

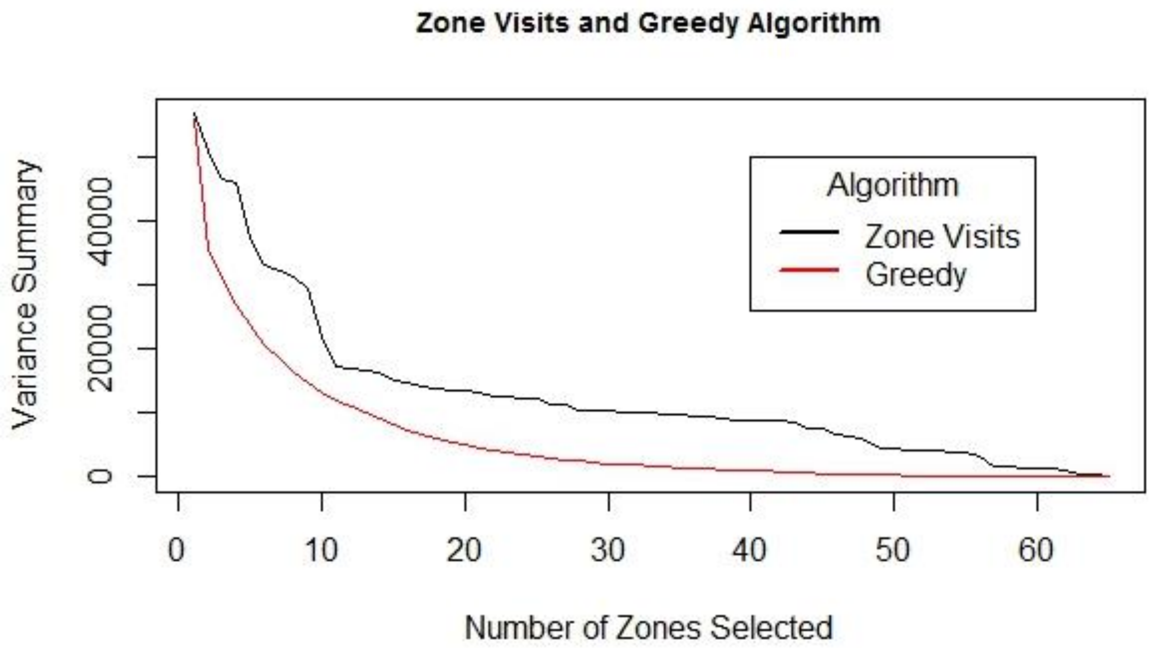

Figure 10: In this algorithm the zone with the most trap visits is selected first. The second zone selected is the zone with the second most number of trap visits. It can be seen again that the greedy algorithm yet again outperforms the zone visits algorithm.

DISCUSSIONS AND CONCLUSIONS

The risk-map of St. Tammany Parish (Figure 2) reveals which regions have high mosquito count densities. Zones near the Lake Pontchartrain and zones with high human population densities have the highest threat to West Nile Virus outbreaks. Zones 705 and Zone 704 lie very close to Lake Pontchartrain and are the two zones with highest mosquito count densities. The entire southeast and southwest regions of the parish have high human population densities and high mosquito count densities. These results are consistent with related literature as both water and human population heavily influence mosquito populations; water sources and human populations enable mosquitos to feed and reproduce. Hence, certain zones near Lake Pontchartrain and in the southeast and southwest regions should be included in the optimized surveillance network as they pose as high threat areas for West Nile Virus outbreaks.

The mosquito count time series (Figure 3) confirms that mosquito counts increase in the summer months and decrease in the winter months. Thus, in order to optimize the surveillance network, traps should be regularly observed from spring through the fall, but only sparsely visited throughout the winter.

The sampling effort for trap visits by STMAD is summarized in Figure 4. Generally each trap is visited about once every two to three weeks. Approximately 65 zones are visited consistently and 10 zones are hardly visited. This plot reassures that it is appropriate to remove these 10 zones from the greedy algorithm surveillance network.

Figure 5 is one of many cross correlation plots calculated for various pairs of zones. Every single cross correlation plot indicates a peak cross correlation at zero time lag. Hence, this means mosquito counts rise and fall together at the same exact time and no time lag exists between zones. Since the mosquito counts fluctuate at the same time, then the next step was to calculate correlation values. Figure 6 portrays the probability distribution of all the correlation values between all pairs of zones. Based on the probability distribution, the correlation values have a normal distribution with a mean value of 0.423. This is a relatively weak correlation value meaning zone mosquito counts do not necessarily all rise and fall together. Therefore, each zone provides a different amount of information. These results offer a better understanding of the data set and support the use of a greedy algorithm to determine which zones provide the most amount of information.

The greedy algorithm results are seen in Figure 7 and Table 1. The graphical display demonstrates how the objective is a decreasing function and attains a minimum when all zones are placed in the surveillance network. The greedy algorithm is submodular as the graph exhibits diminishing returns. Notice the characteristic knee in the algorithm between 5 and 15 zones (akin to an inflection point, if this was a continuous function). It corresponds to the point where diminishing returns set in; adding a zone to a small surveillance network greatly reduces the variance far more than adding a zone to a large surveillance network. Table 1 illustrates which zones should be part of the surveillance network. Ideally, about 20 to 25 zones should be included in the surveillance network. Adding more zones than this may lead to inefficiency as the small amount of additional information gained may not be worth the extra effort it takes to physically visit a trap.

The data from the multiple algorithms finds that the greedy algorithm is the best option for optimizing the surveillance system. In particular, the greedy algorithm outperformed the human population algorithm (Figure 8) indicating that human population density should not be the sole factor that determines which traps are in the surveillance network. The greedy algorithm also outperformed the random algorithm (Figure 9). This reassures that certain zones do in fact provide more information than others. Lastly, the trap visit algorithm is most representative of STMAD's sampling approach. The greedy algorithm yet again outperforms the trap visit algorithm (Figure 9). These results indicate that STMAD can improve their mosquito surveillance methods by establishing which zones provide the most amount of information based on the greedy algorithm results. This finding affirms the potential of optimization methods for mosquito surveillance and control of mosquito-borne infections in humans.

However, a limitation of our method is in the definition of the objective function for surveillance. The objective function is currently accounts for variance which is based on minimizing distance. In order for STMAD to be confident in the results, the objective function needs to be improved. A few ways of enhancing the objective function include adding more variables such as temperature, rainfall, geography, and other mosquito species' counts. Also adding known population data of animal hosts such as birds can improve the robustness of the objective function. Once a stronger objective function is complete then the greedy algorithm can be run again to determine a new surveillance network. In future extensions of this project, a spatial-temporal placement of traps model should be established. In this type of model, the selected traps are not fixed but instead the trap locations are changed from week to week.

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