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Applications of Geospatial Modeling to Improve Public Health Surveillance and Control of West Nile Virus

A dissertation submitted in partial satisfaction of the requirements for the degree Doctor of Philosophy in Environmental Health Sciences

by

Bryan Moy

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ABSTRACT OF THE DISSERTATION

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Professor Hilary Godwin, Chair

The overarching goal of the work described herein is aimed at increasing the translation and application of geospatial research to improve real-world West Nile virus surveillance and mitigation activities. We first conducted a case study in Los Angeles County to demonstrate how geospatial methods can be used to identify factors supporting WNV hotspots. Through our analysis, we determined that catch basins provide a link between drought conditions and increased WNV prevalence of vectors and humans in the county. We then focused on public health and vector control agencies involved in WNV control and investigated the barriers and challenges in implementing geospatial modeling for use in WNV surveillance and mitigation. Barriers were largely dependent upon what stage agencies had implemented geospatial modeling. Additionally, stand-alone vector control and public health agencies faced a greater number of barriers compared to combined agencies. Following our analysis of identifying barriers to

implementation, we sought to identify best practices in geospatial modeling for use in WNV control. We examined how four vector control and public health agencies have used geospatial modeling to: (1) elucidate the vector ecology of mosquito species; (2) bolster mosquito source reduction efforts; (3) develop predictive risk assessment models; and (4) increase vector control agency worker utilization. Taken together, these studies provide important insights into how geospatial modeling can be used to applied and implemented in practice to improve the surveillance and control of WNV throughout the United States, and identifies how these practices can be applied to address threats by newly emerging and re-emerging vector-borne diseases.

The dissertation of Bryan Moy is approved.

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2016

To my amazing family and friends for their unyielding support, generosity, and encouragement

TABLE OF CONTENTS

LIST OF FIGURES AND TABLES

For Chapter 2 (manuscript submitted for publication to *Emerging Infectious Diseases*):

For Chapter 3 (manuscript submitted for publication to the *Journal of Environmental Health*):

For Chapter 4 (manuscript submitted for publication to *Applied Geography*):

For APPENDIX 1:

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Adelaine, S., **Moy, B.W**., Rhaman, T., Sokolow, S., Watson, T. (2016), Rhoades, E.; Bellomo, A.; Godwin, H., *One Size Doesn't Fit All: Determining Priorities for Climate Action Planning at the Neighborhood Level in Los Angeles*. [In preparation]

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*An Assessment of Malaria Interventions in Six Districts in Botswana: Controlling for the Influences of Climate Variability***. Moy, B.W**., Thompson, M.

CHAPTER 1

Introduction and Overview to the Dissertation

Since it was first identified in New York in 1999, West Nile virus (WNV) has continued to be a serious threat to public health in the United States (1, 2). West Nile virus is an arbovirus commonly transmitted between *Culex* mosquito vectors, bird reservoir hosts (primary transmission), and secondary transmission occurring among humans and horses (3-4). In most human cases, WNV infection is asymptomatic or causes a mild febrile illness known as West Nile fever, which is characterized by increased body temperature, headaches, fatigue, skin rash, swollen lymph glands and eye pain (5). More severe infections can result in neurological disorders known as 'West Nile encephalitis' and 'West Nile meningitis,' which, if left untreated, can result in death. These significant public health threats posed by WNV are further compounded by a lack of vaccines or antivirals for the virus (6). The lack of available treatment and prevention options make vector surveillance and control an important public health weapon in the prevention of the disease in the United States and abroad (1).

One way to increase the effectiveness and capacity of vector control efforts is to use geospatial modeling and geographic information system (GIS) tools. Geospatial modeling allows for the visualization, analysis, and interpretation of data to understand spatial relationships, patterns, and trends (www.esri.com). When applied to vector control, geospatial modeling can be used to gain insights into mosquito ecology and disease hotspots in a spatio-temporally explicit manner (7-11). For example, geospatial models have been developed to allow vector control agencies to incorporate local vector ecology information into their mosquito control prevention efforts (12), identify areas of high human risk (13), and target those areas for public outreach and intervention efforts. Unfortunately, significant gaps exist between the state of the research and the use of these tools by practitioners to inform and improve WNV surveillance and mitigation activities.

In an effort to improve the translation of geospatial modeling for use in WNV control practice, I sought to answer the following questions: (1) How can geospatial modeling be used to enhance WNV control in a WNV hotspot, such as Los Angeles County, CA? (2) What are the current barriers and limitations of public health and vector control agencies in implementing geospatial modeling for WNV control at the national level? (3) For agencies that have successfully implemented geospatial modeling, how has geospatial modeling helped to improve WNV control and how can geospatial modeling be applied to inform the control of newly emerging and reemerging mosquito-borne diseases? These questions are addressed sequentially in **Chapters 2-4** of this thesis.

To begin, **Chapter 2** demonstrates how geospatial modeling can be applied to evaluate the role catch basins against other known predictors of WNV prevalence in Los Angeles County, California, a known WNV hotspot. To identify the significance of catch basins in supporting WNV prevalence in both *Culex* vector and in humans, a number of environmental and demographic predictors were evaluated through ecological niche modeling software and machine learning algorithms. Modeling revealed that warm, dry conditions, such as those during periods of drought, are a significant predictor for WNV prevalence in vectors, while catch basins are a significant predictor for WNV disease in humans within Los Angeles County. The application of geospatial modeling demonstrated herein provides critical information for vector control and public health agencies to develop more effective WNV programs and prevention efforts within Los Angeles and other jurisdictions with similar environmental conditions.

Chapter 3 focuses on identifying barriers restricting the implementation of geospatial modeling for WNV control at the national level. Standardized interviews were conducted with public health and vector control agencies in states with the highest cumulative human WNV cases. The barriers that were identified from this study were dependent on the current level of implementation of geospatial modeling used for WNV control. Agencies that were interested in applying geospatial modeling techniques to their WNV program described barriers related to their *initial implementation and support*. By contrast, agencies that were using geospatial modeling *internally* for their WNV program reported barriers related to *surveillance and mitigation*. Additionally, the agencies that had already integrated geospatial modeling into their WNV program both *internally* and *externally* discussed barriers related to *communication and outreach*. Recommendations are provided to address each challenge to improve the application of geospatial modeling for WNV control.

Chapter 4 is aimed at identifying best practices in the use of geospatial modeling methods to improve mosquito control efforts in different regions in the United States. In-depth interviews were conducted with four public health and vector control agencies identified in the study reported in **Chapter 3** as being particularly successful in using geospatial modeling for WNV control. Best practices include the use of geospatial modeling by agencies to: (1) elucidate the vector ecology of mosquito species; (2) bolster mosquito source reduction efforts; (3) develop predictive risk assessment models; and (4) increase vector control agency worker utilization. Identifying best practices currently used in practice can inform public health and vector control agencies about how geospatial modeling is currently being used to reduce WNV prevalence and how these practices can be applied to address newly emerging and reemerging mosquito-borne disease threats in the future. **Chapter 5** concludes with overarching conclusions for these studies as well as recommendations for future studies that could improve the translation of geospatial modeling for enhanced mosquito control.

As agencies attempt to reduce the burden of WNV, understanding the available tools, barriers, and best practices of effective mosquito control is critical to reducing the burden of WNV and other vector-borne diseases as well. The information provided herein demonstrates how geospatial modelling can be applied to help provide insight into the role of predictors supporting WNV prevalence in vectors and humans in hotspot locations. Additionally, the identification of key challenges and limitations preventing further application of geospatial modelling can help to enhance mosquito control of WNV and other vector-borne diseases. Lastly, highlighting best practices in geospatial modelling for WNV surveillance and control efforts can provide insight into how geospatial resources can be applied to address newly emerging and re-emerging mosquito-borne diseases.

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CHAPTER 2

Adapting to a Changing World: The Role of Urban Infrastructure and Drought in Facilitating West Nile Virus in Los Angeles County

(a modified version of this chapter was submitted as a manuscript to *Emerging Infectious Diseases* on August 13, 2016)

ABSTRACT

Los Angeles County, California continues to be a hotspot for West Nile virus (WNV) within the United States, despite the occurrence of an ongoing drought. Given these conditions, we sought to examine the role of artificial water sources, such as catch basins, against known predictors of WNV prevalence. To assess the significance of catch basins in supporting WNV prevalence in both *Culex* vectors and human hosts within the county, we tested a number of predictors using ecological niche modeling software and machine learning algorithms. We found that a combination of warm, dry conditions, due to meteorological drought, were significant predictors in explaining WNV prevalence in vectors. Additionally, analysis of human WNV hotspots identified catch basins as a potential mechanistic link providing suitable habitats for *Culex* vectors during dry conditions. This study provides critical findings into how public health and vector control agencies can improve current and future WNV surveillance and control within Los Angeles County.

INTRODUCTION

Los Angeles County, California remains a top priority region for improved control of West Nile virus (WNV). Following the initial identification of WNV in Los Angeles in 2003, the county has recorded positive mosquito and human cases every year, with some of the highest human WNV incidence in the United States (1, 2). Within the past year (2015), Los Angeles County alone accounted for 13% of all human WNV cases within the United States (2). The risk of WNV to the county as a public health concern is amplified by the lack of available WNV vaccines, which to date have proven unsatisfactory and cost-prohibitive (3). The limited available treatment and prevention options makes vector control and personal protection the primary defense mechanisms against the spread of WNV in Los Angeles County and the greater United States.

The control of WNV in Los Angeles County is an enormously challenging task. Responsibility for the surveillance and control of WNV lies with the Los Angeles County Department of Public Health (LACDPH) and the County's five vector control districts (Antelope Valley Mosquito and Vector Control District, Greater Los Angeles County Vector Control District, San Gabriel Vector Control District, Compton Creek Mosquito Abatement District, and Los Angeles County West Vector & Vector-borne Disease Control District). These vector control districts serve over 10 million residents and have a combined jurisdiction over an area of approximately 12,310 km^2 (i.e., larger than the states of Delaware and Rhode Island combined) (4). The surveillance of human WNV cases falls under the jurisdiction of LACDPH, while the region's five vector control agencies are responsible for conducting surveillance and control of local WNV vectors, such as *Culex quinquefasciatus* and *Cx. tarsalis,* (1, 4, 5). Despite these efforts, Los Angeles County has continued to experience high WNV incidence, with high number of human cases occurring in 2004 (294), 2008 (169), 2012 (169), 2013 (159), 2014 (257), and most recently, 2015 (252) (2).

To improve the control of WNV, researchers have attempted to identify the biotic and abiotic drivers supporting the spread of WNV. A number of studies have identified links between elevated temperatures and decreased precipitation, conditions found during droughts, to increases in WNV disease in both *Culex* vectors and humans in California as a whole, and in Southern California in particular (6-8). While these findings are significant given California's ongoing meteorological drought, the mechanism(s) supporting the exceptionally high rates of WNV transmission in Los Angeles have not been well characterized to date. In studies conducted in other parts of California and the greater United States, researchers have identified artificial water sources, such as storm drain catch basins, as playing a significant role in contributing to vector breeding and viral amplification of WNV (9-16). Thus, we hypothesized that during drought conditions, the availability of catch basins (curbside drains used to capture urban runoff) could support the transmission of WNV prevalence by providing suitable microhabitats for the survival of *Cx.* vectors in Los Angeles County.

Here, we investigated the importance of catch basins compared to other known environmental and socio-demographic predictors of WNV prevalence in mosquito and human populations for Los Angeles County, between the period 2004–2014. Using machine learning algorithms, we assessed whether catch basins may better explain WNV prevalence in mosquitoes throughout the county compared to other environmental and socio-demographic predictors. We then conducted a similar analysis using ecological modeling software to examine the importance of catch basins in explaining human cases of WNV disease using observed positive WNV presence data and their relationship to the current environmental and socio-demographic landscape.

METHODS

Within our analysis, we sought to examine the importance of catch basins against a range of known environmental and socio-demographic predictors identified within the literature to be associated with WNV prevalence in vectors and humans. All data was processed using ArcMap 10.3 (17). Environmental and socio-demographic data layers were clipped to adhere to the Los Angeles County boundary, and measured to ensure cell sizes were consistent at 1km resolution, an estimate of the nightly range of *Cx. spp.* (18). We then used the statistical framework *R* (19) and the ecological modeling software package Maxent (version 3.1.0) (20) to analyze and develop predictions for WNV in both *Culex* mosquitoes and in humans in Los Angeles County.

West Nile virus data

Confirmed WNV positive human case data with geo-locations were compiled and provided by the Los Angeles County Department of Public Health (LACDPH) for the years 2004-2014. The Los Angeles County Department of Public Health only included confirmed cases of WN neuroinvasive disease, WN fever, and positive blood donors. In addition, only those cases for which the infections were believed to have occurred in Los Angeles County (as opposed to one where infection was believed to have occurred during travel to another region) were included in the data set. Cases for which no geo-locations was available (e.g., cases involving transient or homeless individuals) were excluded from the study.

Culex vector data was provided between 2004-2014 by the Greater Los Angeles County Vector Control District (GLACVCD). The GLACVCD is the largest of Los Angeles County's five vector control districts covering an area of 3,471 km^2 and serves over 6 million out of the 10 million residents in the county (21). Vector data from the remaining four vector control agencies were not available at the time of the study and were therefore excluded from our analysis. For the years 2004-2014, we included trapping sites that were surveyed more than 15 times during the WNV season (defined as May-November each year), resulting in over approximately ~100 sites sampled across Los Angeles County. Mosquitoes were collected using gravid traps and CO_2 traps to capture the potential dominant WNV vectors (*Cx. quinquefasciatus* and *C. tarsalis*), and individual mosquitoes were then pooled to test for WNV (mosquito pools were defined as batches of ~50 mosquitoes). For each mosquito pool, we calculated the Maximum Likelihood Estimate (MLE) of positive mosquitoes to represent WNV prevalence (16). MLE was used as a proxy for prevalence of WNV in mosquitos, where larger MLE values correspond to higher overall WNV prevalence in mosquito samples. In addition to MLE, mosquito abundance was obtained by calculating the total number of mosquitoes divided by the number of trapping nights.

Environmental data

A number of studies have identified relationships among WNV prevalence in mosquitoes and humans and environmental factors including precipitation (22) and temperature (7, 23, 24), vegetation (8, 25), and elevation (8). To incorporate aspects of climate into our model, we began with 19 bioclimatic layers developed by the WorldClim group at 1km resolution (26). Each bioclimatic layer was derived using monthly mean temperature and rainfall data, and represented annual trends, seasonality, and temperature extremes. To avoid multicollinearity among the variables, we removed variables with an *r* correlation value greater than 0.5, resulting in a final suite of four bioclimatic variables (mean annual temperature, annual precipitation, precipitation seasonality, and temperature seasonality) for use within our analysis. Elevation was found to be highly correlated with the bioclimatic variables for Los Angeles County during the time period studied and was therefore excluded from further analysis.

To include vegetation within our model, we used the Normalized Difference Vegetation Index (NDVI), which is a vegetation index that uses visible light and near-infrared radiation to identify vegetation abundance and biomass (27, 28). NDVI values range from +1.0 to -1.0, with high NDVI values corresponding to denser vegetation and lower values indicating bare soil. For our study, we obtained mean NDVI data at 1 km resolution using NASA's Moderate Resolution Imaging Spectroradiometer (29).

To assess the role of catch basins within our study, we obtained the geo-locations of all catch basins throughout Los Angeles County (n = ~168,000) from the Los Angeles County Department of Works (30). Catch basins were defined as curbside drains used to capture urban runoff. To develop a usable layer for our analysis, we used the 'Spatial Analyst' tool in ArcMap 10.3 to calculate the density of catch basins for each grid cell within a 1km radius.

Socio-demographic variables

In addition to the listed environmental variables, prior studies have identified economic conditions and population density to be predictors of WNV prevalence in humans for other regions within the United States. (16, 31) To evaluate for these socio-demographic predictors, we obtained 'per capita household income' and 'mean population density' for Los Angeles County from the U.S. Census 2014 American Community Survey (32). 'Per capita household income' is generally considered to be a good descriptor of the economic variation in residential areas, and 'mean population density' was included to assess whether WNV prevalence was correlated with population distribution throughout the county. Data was obtained at the block group level, which contains between 600– 3000 people (32). To process the socio-demographic data, U.S. Census data tables for Los Angeles County were first assigned to their corresponding block group shapefiles in ArcMap 10.3, and then converted from feature data to 1km cell raster grids for our analysis.

Importance of variables for WNV prevalence in mosquitoes

To assess the importance of each variable in explaining WNV prevalence in vectors, we used random forest models in *R*. Random forest models are well suited for this analysis, as this analysis can help capture any complex, non-linear relationships that may exist between the predictor variables and the response variable (here, *Culex* MLE). Random forest models use binary recursive partitioning procedures to measure the amount of variation in a response explained by each predictor used in the model (33). Predictor input for the model corresponded to vector abundance and the extracted environmental (NDVI, annual precipitation, mean annual temperature, and density of catch basins) and socio-demographic (per capita income and population density) data for each grid cell at the mosquito sampling location (both positive and non-positive sites). Ten thousand iterations were run with 50% of the data set aside; the remaining data were set aside and later used to test predictions generated from the random forests models.

Modeling the spatial distribution of human and vector hotspots in Los Angeles County

Because only positive WNV human cases (not human WNV prevalence data) were available, a random forest regression approach (which requires continuous data) could not be used to model human WNV data. Instead, we used Maxent, a machine learning algorithm to model the human cases and assess the relative importance of variables in predicting human WNV hotspots. To ensure that any differences observed between predictors for mosquito prevalence and human cases did not arise from using different modeling approaches for the two data sets, we also performed the Maxent analysis on vectors in addition to the random forest models run on these data (**See Appendix 1**). For our analysis, we used the geo-locations of positive human WNV cases as the outcome variable, and ran them against the generated layers of the environmental and socio-economic predictor variables at 1km resolution. Similarly, to assess the spatial distribution of WNV hotspots in vectors, we ran the environmental and socio-demographic predictor layers against the geo-locations of positive mosquito surveillance sites provided by GLACVCD. For the human case analysis, data from 2010 was excluded from the model due to the low human case count in LA County for that year (n = 4). By contrast, data for all years were used in data analyses on vectors. Default Maxent settings were used (10,000 background points; regularization multiplier = 1.0; maximum iterations = 500; convergence threshold = 0.00005).

RESULTS

For the period 2004-2014, the number of confirmed human WNV cases per year in Los Angeles County as a whole roughly mirrored trends observed in the Maximum Likelihood Estimate (MLE) of positive mosquitoes sampled by the GLACVCD during the same calendar year ($\rho = .619$, $p = .1153$) (**Figure 2.1**). As has been reported previously both for California and for other regions of the United States, significant year-to-year variation in overall human case counts were observed during this period (2).

Analysis of WNV mosquito data in Los Angeles County using random forest models revealed that at least 20% of the variation in WNV prevalence in *Cx.* vectors could be explained for the years 2004-2007, and in 2013. The amount of variation in WNV prevalence in *Cx.* vectors that can be explained using environmental and socio-demographic factors was highest in 2004 and 2005, with a maximum of 33% and 39%, respectively, of the variation explained in these years. Models for the years 2006, 2007, and 2013 explained 27%, 22%, and 25% (respectively) of the variation in WNV prevalence in *Cx.* vectors in those years. Random forests models did not, however, explain high amounts of variation between 2008-2012 and 2014. (Only ~17% of the variation was explained for 2012 and only ~20% was explained for 2014; even less variation was explained in 2008, 2009, and 2011).

For the years where the amount of variation in WNV prevalence in vectors that could be explained by the random forest models was over 20% (i.e., 2004-2007 and 2013), the predictors that consistently explained the largest amount of variation in WNV are 'mean annual temperature' and 'annual precipitation' (**Figure 2.2**). Inspection of the relationship for 'mean annual temperature' and 'annual precipitation' revealed that higher MLE levels in vectors were consistently associated with temperatures between 22-28°C, and annual precipitation between 200-300 mm. Similar results were also obtained from the Maxent analysis of positive WNV surveillance sites (See **Appendix 1** and **Figure A1.1**), and are consistent with previous studies that have linked warm, dry climates (e.g., those observed during drought conditions) to increases in the frequency and transmission of WNV (22, 23).

Our models of the spatial distribution of WNV infections in humans using Maxent revealed that catch basins consistently explain the highest amount of spatial variation of WNV infections in humans with the exception of 2004 (**Figure 2.3**). The percent of the observed variability attributed to catch basins was highest in 2005 (75.8%) and lowest in 2014 (46.4%).

Population density was the second highest contributing factor for the years 2007 and 2011-2013. All other predictors contributed less than 20% for each year. Interestingly, we observed that vector abundance did not significantly explain WNV prevalence for all years, suggesting that amplification dynamics may play an important role in determining the rate of WNV transmission. Furthermore, predictive maps generated by Maxent for both human cases (**Figure 2.4A)** and vectors (**Figure A1.2**) both identified the San Fernando Valley as an area supporting high human risk for WNV, with low WNV hotspot predictions occurring within the northern high desert region.

DISCUSSION

The findings from our analysis indicate that warm, dry conditions support WNV prevalence in vectors and human cases within Los Angeles County (**Figure 2.4**). For *Cx.* vectors, our results indicate that mean annual temperatures between 22-28°C and low rainfall between 200-300 mm supported higher WNV prevalence in mosquitos. Although these environmental conditions are consistent with the average annual temperature (~24°C) and rainfall (375 mm) for Los Angeles County as a whole during the period investigated, it is important to note that Los Angeles County comprises a broad range of microclimates and that both average temperature and rainfall are highly variable across the region (see **Figures 2.4C** and **2.4D)**. Additionally, spatial analysis of WNV human case data revealed that the density of catch basins (**Figure 2.4B**) is an important predictor of the location of human WNV cases in Los Angeles County. This result, combined with the lack of association to vector abundance, suggests that catch basins may play a role in the survival and development of WNV in adult *Cx*. vectors, thereby contributing to increases in secondary human cases (**Figure 2.4A**).

The presence of warm mean daily temperatures (between 22-30°C) within the WNV season may support WNV prevalence in vectors by accelerating the growth of WNV within Cx. mosquitoes (known as the extrinsic incubation period, or EIP) (23, 34) (**Figure 2.4C**). Decreases in the EIP due to warmer temperatures may increase the probability that mosquitoes will survive long enough to become infectious (35). This theory is supported by our data showing that temperatures between 22-28°C contributed to higher WNV prevalence for all years except 2006. Additionally, while our findings may be explained by increases in vector abundance (given identified relationships between warmer temperatures and higher rates of oviposition (13, 16, 36-38), there were no significant associations between vector abundance and daily temperatures within our study (**Figure 2.2**). This suggests that amplification dynamics among adults vectors and hosts may be primarily driven by warmer temperatures, rather than due to increases in the vector abundance.

For periods of unsuitable conditions for Cx. vectors (e.g., low rainfall or high temperatures), catch basins may facilitate WNV prevalence for three reasons. First, as *Cx. tarsalis* and *quinquefasciatus* are nocturnally active, they may rest within sheltered conditions, such as catch basins, during the day. Since catch basins receive constant urban runoff and are subterranean, they can provide cooler, humid microhabitats for adult *Cx.* mosquitoes to rest during unsuitable high daily temperatures, and allow them to return to the surface to feed in the evenings when temperatures subside (39). The increased persistence and survivability of adult female *Cx.* in catch basins may allow recently infected female WNV *Cx*. mosquitoes to become infectious and capable of transmitting the disease. The high number of infectious WNV positive mosquitoes around populated areas can help to drive WNV infections in humans at times when conditions may be normally hazardous for the survival of adult *Cx.* mosquitoes. The lack of human population and limited number of catch basins may help explain why our predictive maps did not identify the northern high desert region as a hotspot of disease for both humans and vectors, despite having extremely high temperatures and very low rainfall (**Figure 2.4A and A1.2**).

Second, during periods of low rainfall or persistent drought, WNV amplification may increase as *Cx*. vectors and common competent urban avian hosts, (e.g., house sparrows or crows) (40) congregate around anthropogenic or limited natural water sources, such as catch basins or reservoirs. The forced interaction between *Cx.* mosquitoes and primary avian hosts can provide an ideal environment for the rapid epizootic amplification of WNV throughout arid regions (22). Such may be the case in the San Fernando Valley, which receives low rainfall throughout the WNV season (**Figure 2.4D**) (5), maintains a high abundance of consistent avian hosts, and contains a number of man-made water sources, including catch basins, that can facilitate interactions between WNV vectors and hosts for WNV transmission. These findings are consistent with those reported in Orange County, California, which revealed that neglected swimming pools within low socioeconomic areas were associated with higher WNV amplification in vectors (16).

A third, albeit less likely, explanation for how catch basins may support the persistence of WNV during drought conditions is through their role in providing suitable ovipositing habitats for *Cx.* mosquitoes, as has been found with other water sources across the United States. The constant presence of eutrophic water found within and around catch basins provides ideal breeding habitats to support high densities of immature mosquitoes during extremely dry periods. These high mosquito densities have been associated with increases in WNV outbreaks, as more mosquitoes may increase the risk of people being bitten by WNV positive mosquitoes

(41-43). However, as noted, there were no significant associations between mosquito abundance and WNV prevalence, which is consistent with results conducted in neighboring Orange County (16). The lack of association between mosquito abundance and WNV prevalence indicates that the persistence and survival of adult WNV positive female *Cx.* mosquitoes may serve as the primary driver for WNV amplification and transmission to secondary human hosts within Los Angeles County.

Public Health implications for surveillance and mitigation of WNV in Los Angeles

The identification of how drought conditions support WNV prevalence in vectors and humans can aid public health and vector control agencies in reducing the overall burden of disease within the county. For regions within the county that may experience warm, or unseasonably high temperatures or dry conditions during the WNV season, vector control and public health agencies should focus their efforts on bolstering WNV preparedness, surveillance, and control within these regions to reduce the burden of WNV in *Cx*. vectors. Additionally, in addition to ongoing larvicide applications, vector control agencies should consider the application of *adulticides* to catch basins in populated areas to help reduce mosquitoes that may be resting or breeding. Furthermore, the identification of the San Fernando Valley as a consistent WNV hotspot for human cases and *Cx*. vectors warrants the need for vector control and LACDPH to provide increased surveillance and control in this region. Overall, the control of *Cx*. vectors during these conditions can help to reduce the transmission and occurrence of WNV to secondary human cases.

LIMITATIONS AND FUTURE RESEARCH

Our analyses in identifying predictors of WNV prevalence within Los Angeles County had several limitations that should be acknowledged. First, the outcome variables used within the study may not accurately represent the true spatial distribution of positive WNV mosquito pools and WNV human cases throughout the county. Although we were able to obtain comprehensive mosquito surveillance data from GLACVCD, the largest vector control agency in Los Angeles County, we were not able to obtain mosquito surveillance from the four other vector control agencies that operate in Los Angeles county, and hence did not have complete coverage for all geographic areas in the county (**Appendix Figure 2.1**). The lack of vector control data from the four other vector control districts limits our ability to accurately identify other spatial variations supporting WNV disease in vectors.

Additionally, it should be acknowledged that our use of WNV human cases may be influenced by media attention and how frequently medical practitioners test suspected patients for WNV (44). For example, in years were WNV epidemics are promoted in the general media more frequently (such as 2012 or 2014), medical practitioners may be more likely to test for WNV, thereby potentially identifying more WNV cases (**Figure A1.3**). Such variations in reporting may bias our data away from truly identifying potential human risk factors for WNV. To adjust for this, future research should consider correcting for this bias by implementing analyses of sentinel chicken sites alongside estimates of human WNV prevalence (45).

Additionally, in this study, temporal trends were downplayed to better capture spatial aspects related to identifying predictors. As a result, our analysis may not have picked up dynamic changes in environmental conditions that occurred throughout the duration of our study. Lastly, our models focused on examining the likely drivers of WNV in secondary cases, without examining primary avian hosts. To fully understand the mechanisms of WNV within the county, it will be important for future studies to examine the role of avian hosts, particularly for years where our models did not explain significant variation in our models. We suspect that one factor that we were not able to examine that may contribute to the variation is variation in immunity among avian hosts as a function of time, which would in turn influence WNV transmission and the overall WNV prevalence in humans over time (14).

The research presented herein provides important information to help researchers prioritize future studies. Ideally, future research should focus on developing methods to capture surface water sources at the neighborhood-level, such as pools and reservoirs, to identify how these sources may contribute to the amplification of WNV within the county. Furthermore, the observation that WNV amplification in vectors in Los Angeles County is driven by above average temperatures and limited rainfall may be applicable to other parts of the Southwestern United States. As a result, it will be important to conduct larger regional studies to identify how these climatic conditions influence WNV prevalence in mosquitos and human WNV cases.

CONCLUSIONS

The findings presented herein provide critical insights into how WNV has persisted throughout the recent drought in Los Angeles County and provides important insights into how both microenvironments and social dynamics contribute to the spatial distribution of WNV in Los Angeles. These findings are important for the surveillance and control of WNV for several reasons. First, climate change is anticipated to result in hotter and drier conditions in California in the coming decades (46), suggesting that WNV will continue to pose a significant threat in this region. Our study also provides insights into how catch basins may play a role in supporting

WNV prevalence in *Cx*. vectors during periods of drought. The results of this study suggest that, to reduce WNV infection in humans, vector control agencies should consider applying *adulticides* to catch basins to target and reduce WNV positive mosquito populations that may be sheltering in the catch basins during otherwise unfavorable climatic conditions. Lastly, our predictions identifying the San Fernando Valley as an area of high WNV risk in both humans and *Cx*. mosquitoes can allow the LACDPH and vector control agencies to prepare for future outbreaks of WNV within this region, and also improve community resilience to WNV through public health communication and outreach. These findings not only provide important ramifications for improving WNV surveillance and control within Los Angeles County, but may also be applied to improve the prevention of other mosquito-borne diseases as well.

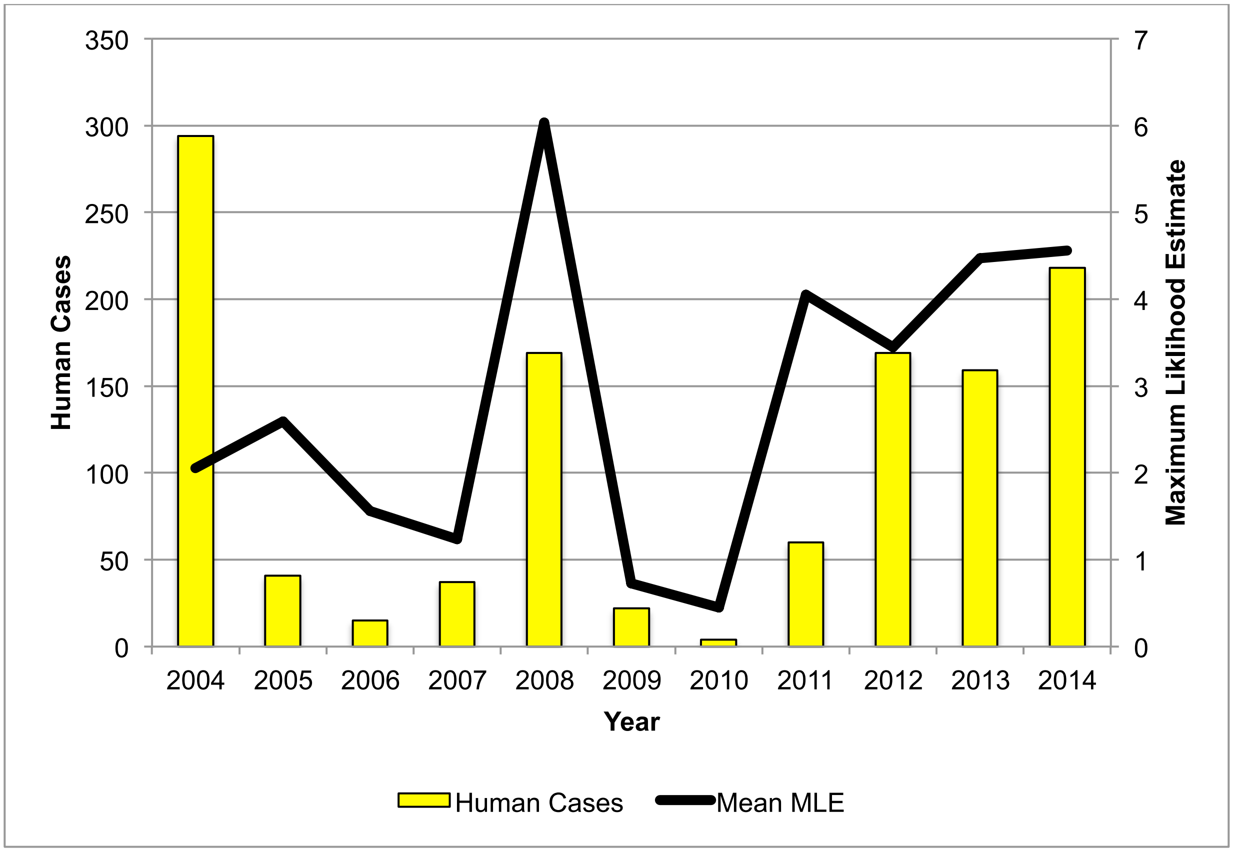

Figure 2.1. During the period 2004-2014, the total confirmed human WNV cases per year (bars) in all of Los Angeles County roughly mirrored the mean *Culex* WNV Maximum Likelihood Estimate (MLE) (line) reported by the Greater Los Angeles County Vector Control District (GLACVCD) (ρ = .619, p = .1153).

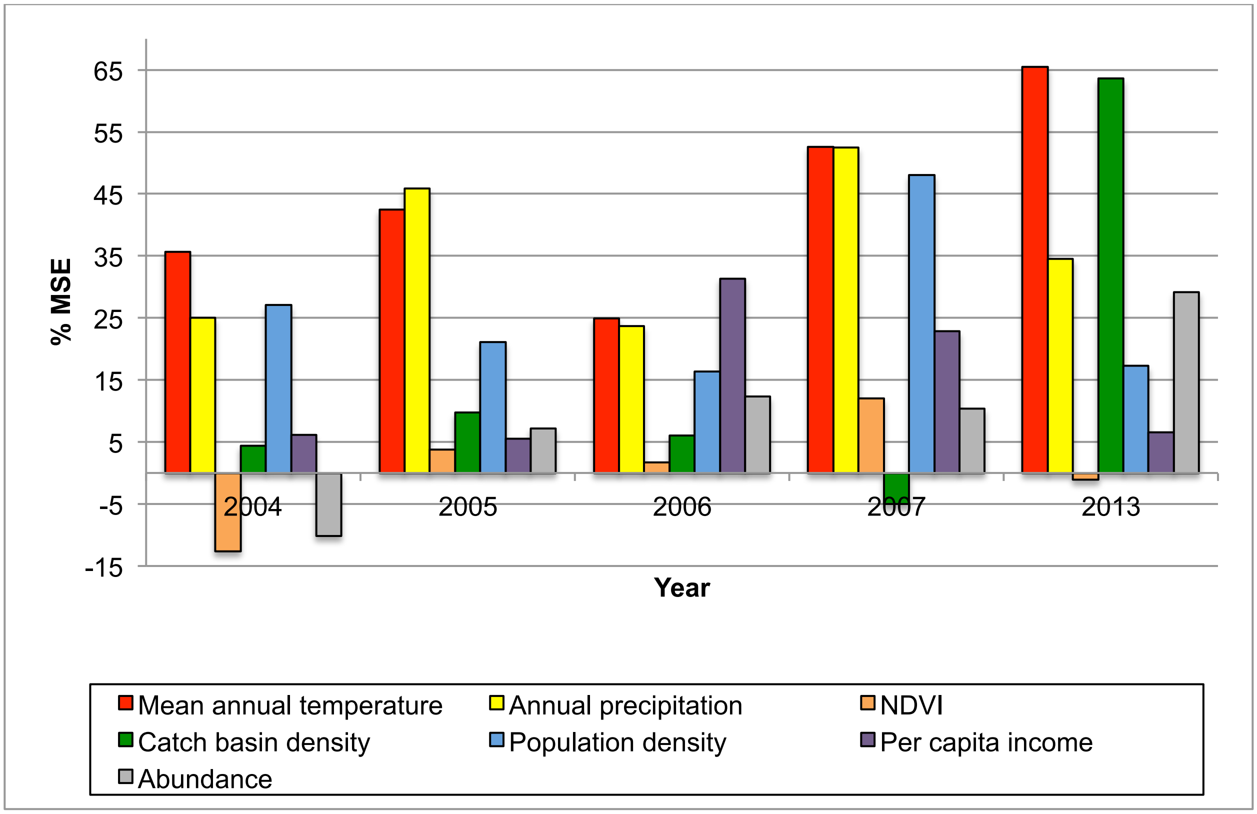

Figure 2.2. Importance scores (% mean square error) obtained from random forest models for potential environmental predictors (mean annual temperature, annual precipitation, NDVI, catch basin density), demographic predictors (population density, per capita income), and vector abundance of WNV virus prevalence in Los Angeles County. Negative changes in percent mean square error indicate poor predictors, while positive changes indicate good predictors. The variables that explained the largest amount of variation in WNV prevalence in vector populations were mean annual temperature and annual precipitation. Data for the years 2008-2012 and 2014 performed poorly within our random forest models and were excluded from the analysis.

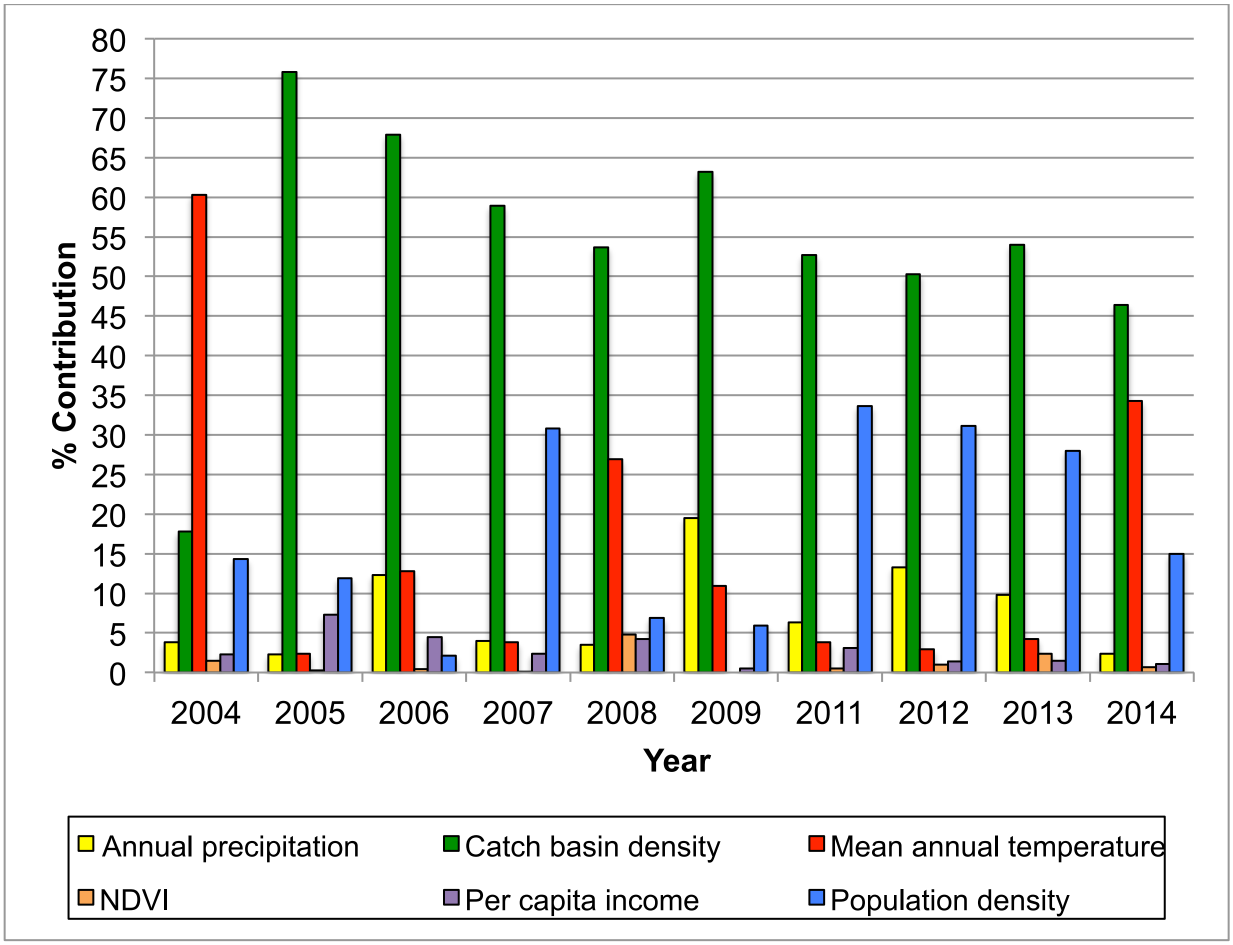

Figure 2.3. Percent contribution to spatial variability of human WNV cases in Los Angeles County obtained from Maxent models for environmental predictors (mean annual temperature, annual precipitation, NDVI, catch basin density) and demographic predictors (population density, per capita income). A higher percent contribution indicates that the variable is able to explain more of the model compared to lower percent contributions. Data for 2010 was excluded from our Maxent model due to low human case data (n = 4) for that year.

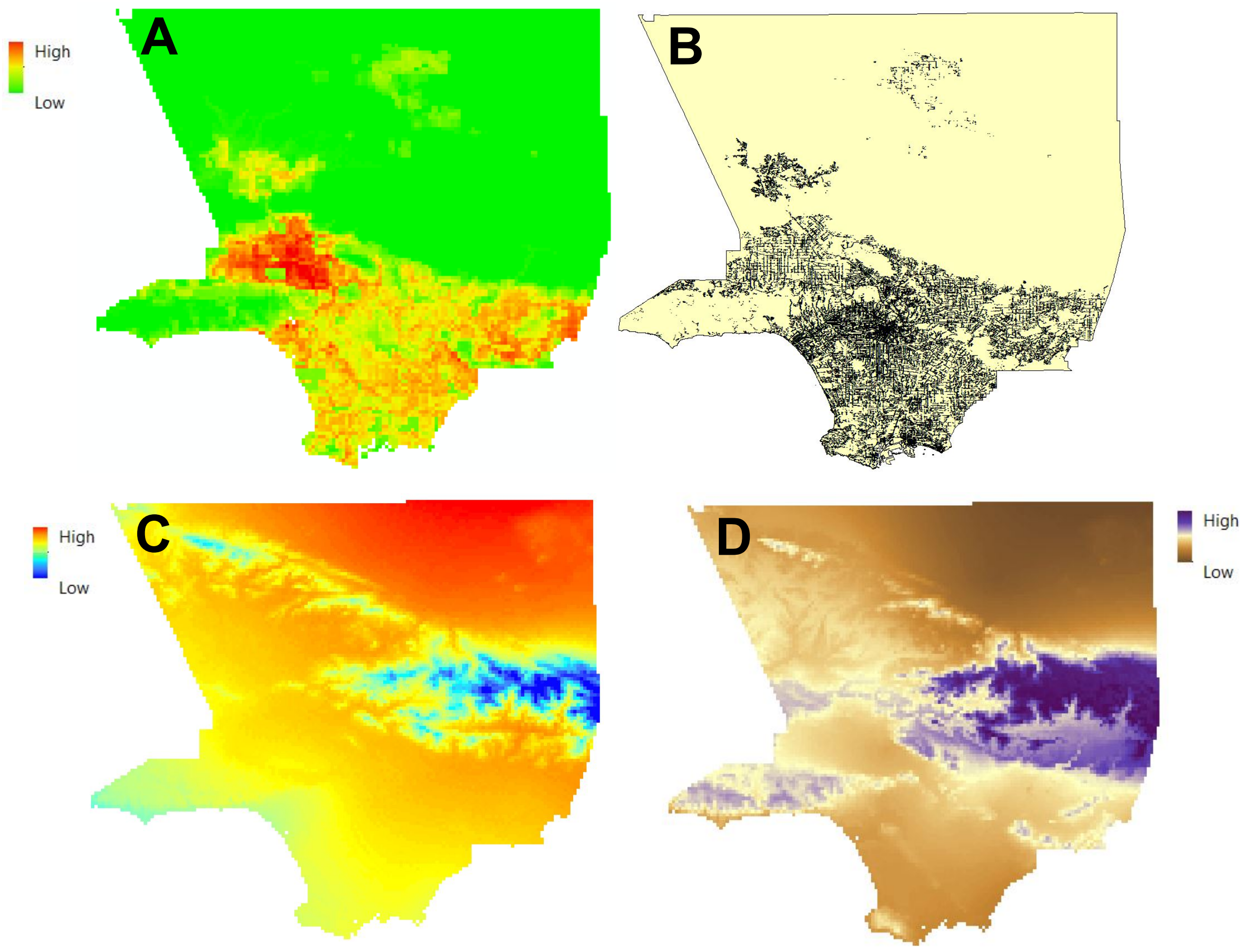

Figure 2.4. The cumulative presence of WNV in humans (A) during the period 2004-2014 was the density of catch basins (B). The best predictors of the spatial distribution of the prevalence of WNV in *Cx.* vectors during the same time period were mean annual temperature (C) and annual precipitation (D). Information displayed in (A): spatial distribution of risk of WNV prevalence in humans for the years 2004-2014 derived from Maxtent model. Data displayed in (B): distribution of catch basins provided by the Los Angeles County Department of Public Works. Data displayed in (C): spatial distribution of mean annual temperature for the time period 1960-2000. Data displayed in (D): spatial distribution of annual precipitation for the time period 1960-2000.

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CHAPTER 3

Building Capacity to Support the Use of Geospatial Modeling for Vector-borne Disease Control: West Nile Virus as a Case Study

(a modified version of this chapter was submitted as a manuscript to the *Journal of Environmental Health* on December 14, 2015)

ABSTRACT

We surveyed public health and vector control agencies in the United States to identify barriers restricting the implementation of geospatial modeling for West Nile virus (WNV) control. We conducted standardized interviews (n=18) with public health and vector control agencies in states with the highest cumulative human WNV cases. Agencies were categorized according to their stage of implementation of geospatial modeling (either *Initial, Internal, or Internal and External*) and thematic analysis was used to identify barriers and best practices. *Initial Implementation* agencies reported funding and educational barriers, while *Internal Implementation* agencies reported surveillance data challenges and mistrust of geospatial modeling as limiting factors for geospatial modeling use. Agencies involved in *Internal and External Implementation* reported policy guidelines and lack of public interest as barriers to using geospatial modeling for WNV control. To overcome these challenges, we identified the use of unified resource programs, local data repositories, and multi-stakeholder taskforces as best practices to improving overall WNV control.

INTRODUCTION

The use of geospatial modeling technologies for vector surveillance, control, and prediction have rapidly increased within the last decade. Myriad geospatial modeling tools implemented in QGIS (1), R(2), and ArcGIS (3), have allowed researchers to examine vector presence, abundance, and biodiversity for a variety of vector-borne diseases (VBDs) with respect to time and space (4-8). These advances should ideally allow public health agencies to effectively use limited operational funds, increase their flexibility and response, and improve coordination with other stakeholders. Despite these advances, most public health agencies continue to use traditional empirical methods of VBD surveillance and control, with limited integration of geospatial modeling techniques to enhance these methods.

The gap between the potential use of geospatial modeling and actual practice for VBD control is evident in the case of West Nile virus (WNV) in the US. In response to the emergence and spread of WNV in the United States starting in 1999, the Centers for Disease Control and Prevention (CDC) collaborated with public health departments and academic institutions to develop WNV surveillance and mitigation guidelines (9, 10). These guidelines serve as the foundation for a national arbovirus program and outline public health and vector control efforts to monitor WNV infections in humans, birds, mosquitos, and other vertebrate hosts (11). These guidelines continue to be used for WNV control efforts across the US, with minor variations dependent on the specific agency features and access to local resources (12).

In addition, the US government has invested significant research dollars examining factors contributing to the distribution of WNV. For example, within the past five years, the National Institutes of Health have invested more than $250 million aimed at understanding and improving the ability to model and predict WNV transmission (13). As a result of these studies, a growing body of literature has demonstrated that geospatial modeling techniques can be used to examine a variety of facets such as the spatial heterogeneity of vectors and hosts, and applications into predictive modeling (5, 14-18). Unfortunately, very little of this progress has been translated to current CDC WNV surveillance and mitigation guidelines (12).

As CDC guidelines focus primarily on traditional surveillance and mitigation approaches, we hypothesized that a majority of public health and vector control agencies do not optimally use geospatial modeling techniques within their WNV control efforts, and that barriers may prevent further implementation of geospatial modeling efforts. Exploring these factors could provide insights into improving public health practice within this arena. To test this hypothesis, we conducted structured interviews with individuals at public health and vector control agencies in regions of the United States with the highest WNV human cases. We sought to assess how geospatial modeling techniques are currently used to support WNV control efforts, and what barriers may exist to greater use of geospatial modeling for WNV control. Based on our analysis of these interviews, we provide recommendations for how building capacity can expand the use of geospatial modeling capabilities by public health agencies, and how that could translate into better use of existing funds, improve response to outbreaks, and engender greater support from agencies and stakeholders for vector control activities.

METHODS

To focus our efforts in areas with significant WNV case burden, we reviewed cumulative human WNV count data from the US Geological Survey (USGS) Disease Mapper (19) for each of the 50 states for a 10-year period from 2004 to 2013. We selected 11 states based on a combination of regional distribution and highest WNV cumulative human case counts (**Table**

3.1). For these 11 states, we used the CDC's county-level ArboNET data to identify counties with the highest WNV human case activity. Within these counties, we identified local public health and vector control agencies involved in West Nile virus control efforts through a series of internet searches and agency referrals. In selected counties which lacked local public health or vector control departments, (n = 3), state-level health departments were included. The resulting agency sampling frame (n = 22) consisted of 8 stand-alone public health agencies, 7 stand-alone vector control agencies, and 6 combined vector control/public health agencies. Potential interviewees (n = 24) in each of these agencies were identified after speaking with individuals in these departments to identify staff involved in WNV control activities.

Once potential interviewees were identified, they were sent a recruitment email followed by a phone call from a member of the research team. This resulted in an interview pool of 18 individuals, representing 7 stand-alone public health departments (both state and local), 6 combined public health and vector control programs, and 5 stand-alone vector control agencies. All interviews were digitally recorded and transcribed using the software program *Transcribe* (20).

The structured interview guide consisted of questions regarding current WNV surveillance and mitigation practices and specifically whether their WNV control program used geospatial modeling techniques (**See Appendix 2**). For agencies not using geospatial modeling techniques, we asked open-ended questions to elucidate why their agency was not employing these methods and what barriers prevented them from using these tools. Agencies that indicated using geospatial modeling techniques were asked further questions about how their program uses these techniques to enhance their WNV activities.

Interview data was analyzed through the qualitative data analysis program, *Dedoose*, using a thematic analysis approach (21, 22). Thematic codes (n = 91) were used to identify underlying concepts that linked recurrent statements about WNV control priorities and challenges, and benefits and barriers with regard to implementation of geospatial modeling techniques. Emergent themes were then refined and a comparative approach was used across agencies to identify connections between concepts(22). Coding and analyses were conducted by researchers to ensure consistency in coding and authors discussed thematic coding results for relevancy, followed by further recoding and redefining of appropriate themes.

RESULTS

Based on these interviews, barriers reported by agencies correlate with the category at which the agency was using geospatial modeling for their WNV programs. (**Tables 3.2-3.4**.) Agencies that were interested in applying geospatial modeling techniques into their WNV program typically described barriers related to their *initial implementation and support*. Agencies that were using geospatial modeling *internally* for their WNV program generally described barriers related to *surveillance and mitigation*, while agencies that had already integrated geospatial modeling into their WNV program both *internally* and *externally* discussed barriers related to *communication and outreach*. Below, we examine the main barriers reported within each of these categories.

Initial Stage: Barriers Related to Implementation and Support

Individuals from 28% of all agencies interviewed reported being in the early stages of geospatial modeling. All but one stand-alone public health agency within this category reported insufficient funding as a primary barrier restricting the application of geospatial modeling within their WNV programs. Individuals reported the high upfront cost to obtain and maintain software licenses for geospatial programs such as ESRI's ArcGIS, and geocoding devices prevented their agencies from using geospatial modeling within their WNV programs. Additionally, budgetary constraints related to hiring geospatial modelers were also cited. Furthermore, funding was consistently cited as a barrier among agencies within the later stages of geospatial modeling implementation for their WNV programs.

The second barrier reported by agencies within this category was the high learning curve required to use previously mentioned programs such as ArcGIS or QGIS. These software programs often require individuals to take multiple courses or tutorials to gain familiarity with the management of geospatial data. Interestingly, this barrier was frequently reported by local public health agencies that were unable to allocate the time and resources necessary for geospatial modeling proficiency. By contrast, state-wide public health agencies (20%) did not report challenges to learning geospatial software, possibly indicating that more geospatial modeling resources and training opportunities exist at agencies at the state level.

Internal Stage: Barriers Related to Surveillance and Mitigation

Individuals from 39% of the agencies reported that their agencies were using geospatial modeling for surveillance and mitigation of WNV. All but one of the stand-alone public health departments interviewed expressed challenges associated with using avian surveillance, such as dead bird reporting, as a predictor for identifying WNV risk. Literature on the use of dead bird surveillance as early indicators for WNV activity has been inconsistent among researchers (23-

25), though many agencies reported decreasing utilization of avian surveillance for predicting WNV risk. One particular public health agency adequately explained:

> *"We don't do dead bird surveillance anymore. What ended up happening is that we'd get WNV positive humans before we would get birds or horses or anything like that. It just wasn't all that useful for us and we've grown out of that."*

The decrease in avian surveillance efficacy may be attributed to several factors, such as increasing avian resistance to WNV (26), biases among birds sampled (26-28), and the decreasing public reporting of dead birds within their neighborhoods(23, 24, 29). Additionally, once an area has become endemic for WNV, avian surveillance loses much of its scientific interest and control programs may shift their efforts towards other WNV surveillance mechanisms (30). Despite this, current CDC WNV guidelines (12) draw attention to the use of the Dynamic Continuous-Area Space-Time (DYCAST) program (31), which uses geospatial modeling of dead bird reports to predict WNV risk. Unfortunately, given the aforementioned problems with dead bird surveillance, the efficacy of the DYCAST program has decreased over time (32), highlighting how existing efforts should be refocused to identify robust data sources for predicting WNV risk.

A second challenge within this category was a perceived inability to conduct geospatial analyses using mosquito surveillance data due to inconsistent spatial coverage. Individuals from both stand-alone public health and vector control agencies within this category believed inadequate mosquito surveillance prevented them from conducting geospatial analyses. This perception is concerning, as a primary strength of geospatial modeling is its ability to help elucidate environmental factors correlated with WNV prevalence in mosquitos, thereby helping in situations where surveillance data is incomplete (5, 14-18). By contrast, none of the combined public health agencies within this category reported limitations related to using WNV mosquito surveillance data for geospatial analyses.

A third challenge reported within this category was the perception that geospatial modeling is better suited for research. Both stand-alone public health agencies within this category and 39% of *all* stand-alone and combined public health agencies within the study believed that more advanced geospatial modeling techniques were unreliable and better suited for research purposes than for practice. For example, when questioned if their agency uses advanced geospatial modeling techniques such as predictive mapping of WNV human cases (7), one public health agency stated:

> *"We are the Department of Health, and we have goals. We don't do research. I think that's a good idea that somebody from academia do it."*

Despite this outlook, certain public health agencies have made efforts to *predict* the risk of WNV transmission to humans (34). For example, the California Mosquito-borne Virus Risk Assessment relies on passive surveillance data to predict overall WNV risk. Similarly, many geospatial modeling techniques also use WNV passive surveillance data as the basis for their analyses. Public health agencies may perceive geospatial modeling techniques to be less reliable for assessing overall WNV risk, despite results being derived from the same data sources. In these cases, the distance between research conducted by public health agencies and academia may be more perceived than real, and future work should work to unify efforts from groups with the same ultimate goals.

The fourth barrier reported within this category were challenges of stand-alone vector control agencies in using the home address of confirmed WNV human cases as a proxy for exposure site. Despite CDC guidelines requiring public health agencies to obtain a four week travel and exposure history for cases prior to disease onset, public health agencies typically report the home address of the individual, as cases may be subject to recall bias or simply forget where they were possibly bitten (9, 12). One individual from a stand-alone vector control agency in this category explained:

> *"Human cases are tricky when you use the home address because people are very mobile and so they're going from place to place. Unless that person doesn't leave their house, there's a good chance that you won't know where they were exposed, which makes it less reliable for us to use."*

While having the home address may be useful for public health outreach programs, the lack of known exposure sites can be troublesome for WNV mitigation efforts, as agencies may be missing potential WNV hotspots. This demonstrates an absolute necessity to link human case data with mosquito and avian surveillance, as these combined datasets can allow agencies to identify legitimate or "false" hotspots (areas in which only human cases occur, but where the virus is not present vectors or other hosts) in real-time.

External Stage: Barriers Related to Outreach and Communication

Individuals from 33% of the agencies surveyed reported using geospatial modeling for both internal decision-making and external outreach to stakeholders. Among the agencies represented, two primary barriers were identified: (1) intra-agency communication challenges due to the Health Insurance Portability and Accountability Act of 1996 (HIPAA) (35); and (2) maintaining public interest in WNV activities.

HIPAA-related intra-agency challenges were reported by stand-alone vector control agencies, which receive WNV human case data from stand-alone public health agencies. While HIPAA provides safeguards to protect electronic health information, the Privacy Rule allows for disclosure of health information needed for patient care (35). However, stand-alone vector control agencies within this category reported that the spatial-level at which positive WNV human cases are reported is at the discretion of their associated public health agency. An individual from a stand-alone vector control agency in this category noted:

> *"Due to HIPAA laws, if someone tests positive for West Nile virus, all I can find out from my local public health department is that it's somewhere in the county. Other departments here have been able to get within a square mile or township range, but it's dependent on how you can get your health department to work with you."*

Unfortunately, the specificity of WNV human case locations appears challenging for stand-alone vector control agencies, which must use this data to perform mosquito mitigation. Conversely, both combined and stand-alone public health agencies did not report challenges with communication to stand-alone vector control agencies. This discrepancy suggests that public health agencies may be unaware of the problems experienced by stand-alone vector control agencies, and that enhanced intra-agency channels of communication are needed for effective WNV control activities.

By contrast, both combined and stand-alone public health agencies reported challenges in maintaining public interest in WNV activity, despite providing real-time WNV geospatial human case data and intensive public health messaging. Despite public projects such as the previously mentioned USGS Disease Mapper, public health agencies reported drawbacks to having such data available during observed periods of low WNV presence (11, 36). One individual from a public health agency in this category explained:

> *"People will see that we only have a few cases in our county of West Nile virus one year, even though we [public health] know that it's largely underreported. This reduces West Nile virus as a threat, and people become accustomed to not taking precautionary measures during the West Nile virus season."*

To counteract the lack of public WNV preparedness, public health agencies reported spending considerable resources on public education programs, only to be met with disinterest. Lack of public interest in WNV presents a substantial challenge for WNV programs, which must provide WNV control despite declining public interest and decreasing availability of funds. This became a substantial issue during the 2012 WNV season, in which a lack of public interest combined with decreased government spending for WNV contributed to an unprecedented number of WNV human cases (n=5674) in the United States since the initial WNV outbreak

(19). Furthermore, the 2012 WNV season highlights a larger systematic need for public funds to reflect current public health risks such as WNV. To begin to address these issues, new approaches to public communication may be required in order to balance the fine line between community awareness and message oversaturation, while still bolstering WNV resiliency among communities.

DISCUSSION

To develop recommendations to overcome these barriers, we identified best practices within the interviewed agencies for each of the three stages of implementation. These recommendations aim to improve the implementation of geospatial modeling efforts for WNV control activities.

Unified Sharing of Geospatial Modeling Resources

Within the *Initial Stage: Barriers Related to Implementation and Support* category, combined public health/vector control agencies reported fewer budgetary and learning constraints compared to stand-alone public health agencies. This suggests that stand-alone public health agencies within this category could benefit from working with stand-alone vector-control agencies within their jurisdictions to share geospatial training and resources (such as hardware). Additionally, resource sharing would have the co-benefit of fostering more robust intra-agency communication and partnership development. While we recognize that stand-alone public health and vector control agencies have distinct data collection roles with regard to WNV surveillance, unified geospatial training sessions would allow for greater appreciation for the challenges experienced by their partner agencies.

Development of Local Shared Data Repositories

To address barriers related to use of geospatial modeling within the *Internal Stage: Barriers Related to Surveillance and Mitigation* category, agencies would benefit from developing local shared data repositories that include both human and non-human WNV surveillance data, similar to the CDC's national ArboNet platform (11). However, agencies need access to real-time shared data at a *local* scale in order to effectively perform geospatial analyses of WNV risk factors. Additionally, increased accessibility to local geospatial WNV surveillance data would increase agency response time and flexibility to changing conditions.

Furthermore, increased application of geospatial modeling can help remove the spatial and resource limitations associated with mosquito surveillance. An abundance of literature supports the use of geospatial modeling techniques to enhance spatial coverage for areas not currently surveyed due to resource or personnel limitations (5, 6, 17, 37-40). Thus, for agencies currently using geospatial modeling for internal purposes, the creation of shared local WNV surveillance data repositories could facilitate optimal use of limited surveillance resources.

Creation of Multi-Stakeholder Taskforces

To address barriers within the *External Stage: Barriers Related to Outreach and Communication* category, we recommend that agencies hold regular meetings of multi-stakeholder taskforces, which include stakeholders associated with WNV control. This best practice was identified among some of the combined public health/vector control agencies:

"Funding has been a major gap for us, but through constant communication with the City Council, Mayor, and Commissioner of Health, they're providing us assistance and funding and we're trying our best to do what we can for the city."

Multi-stakeholder taskforces are an important mechanism for facilitating partnerships between agencies involved in WNV control and other government agencies that can support these efforts. Additionally, further benefits reported were greater support for WNV spraying initiatives, increased funding, and greater public awareness. More localized planning, transparency, and outreach among agencies can help empower communities to be more vigilant with regard to WNV precautions and emphasize the need for WNV mitigation efforts. Furthermore, regularly scheduled stakeholder meetings can allow for more rapid information transfers, such as for human case data between stand-alone public health and vector control agencies, as well as decrease the reluctance associated with HIPAA constraints.

LIMITATIONS AND FUTURE RESEARCH

Our analyses on the use of geospatial modeling for vector control had several limitations that should be acknowledged. First, potential sample bias may be present, as participants were only from states with the highest WNV cumulative human case counts for the 2004-2013 period. Given this, participants were likely to be from well-developed WNV programs, which may have influenced their views on the use of geospatial modeling. In this sense, we predict that these examples are ones of a "best-case" scenario, and it is possible that smaller or less-funded agencies face these or even greater limitations in their WNV control efforts.

Secondly, another limitation within our study could be recall bias among the interviewees, which could work for or against the barriers identified in this study. For example, given the amount of senior positions interviewed, some interviewees may have aggrandized their WNV control programs in a more positive tone for fear of seeming underprepared or outdated. Conversely, given the confidential nature of this study, certain agencies may have over-emphasized the extent to which their agencies could be improved (*e.g.,* with the goal of trying to drive more resources nationally to their field of expertise).

CONCLUSIONS

This study highlights the barriers facing agencies in implementing geospatial modeling techniques for WNV control. Despite an abundance of literature supporting the use of geospatial modeling efforts for WNV control, the barriers reported by agencies is largely dependent on the category at which they use geospatial modeling within their agency. These results suggest that combined public health agencies experience fewer challenges in using geospatial modeling for WNV. The barriers articulated by agencies and their best practices highlight the need to increase sharing of geospatial modeling resources across agencies, create locally shared repositories of surveillance data, and create regional multi-stakeholder taskforces to improve communication between agencies and with external stakeholders. These insights provide important ramifications for translating geospatial research into practice not only to improve WNV control, but for improved prevention of other vector-borne diseases as well.

Table 3.1. Number of agencies in which interviews where conducted in each region of the United States and the number of states in that region that were covered by the interviews.

Region	Agencies interviewed	States included
Midwest	5	4
Northeast	2	1
South	4	2
West	7	4
TOTAL	18	11

Table 3.2. Barriers reported by interviewees at agencies that were in the initial stages of implementation of geospatial modeling (n = 5).

	Number of each type of agency reporting barrier			
Barrier reported	**Stand-alone public health (n = 4)**	**Stand-alone vector control (n = 0)**	**Combined public health and vector control (n = 1)**	**% of all agencies in this category reporting barrier**
Budgetary constraints	3	N.A.*	1	80%
High learning curve	2	N.A.*	1	75%

*N.A. indicates that no agency of this type fell within this stage of implementing geospatial modeling.

Table 3.3. Barriers reported by interviewees at agencies that were already using geospatial modeling for internal purposes (n = 7).

	Number of each type of agency reporting barrier			
Barrier Reported	**Stand-Alone Public Health (n = 2)**	**Stand-Alone Vector Control (n = 2)**	**Combined Public Health and Vector Control (n = 3)**	**% of all agencies in this category reporting barrier**
Ineffective Avian Surveillance	1	2	3	86%
Spatially Incomplete Mosquito Data	2	2	0	57%
View Geospatial Modeling as Research*	2	0	0	29%
Home used as Proxy for Exposure Site	0	2	0	29%

*39% of all stand-alone and combined public health agencies believed geospatial modeling to be unreliable.

Table 3.4. Barriers reported by interviewees at agencies that were already using geospatial modeling for both internal and external purposes (n = 6).

	Number of each type of agency reporting barrier			
Barrier reported	**Stand-alone public health (n = 1)**	**Stand-alone vector control (n = 3)**	**Combined public health and vector control (n = 2)**	**% of all agencies in this category reporting barrier**
HIPAA Constraints	0	3	0	50%
Lack of Public Trust	1	3	2	50%

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CHAPTER 4

Applied Geospatial Modeling to Improve Control of Current and Future Mosquito-borne Disease Outbreaks

(A modified version of this chapter has been submitted as a manuscript to *Applied Geography* on June 10, 2016)

ABSTRACT

The use of geospatial modeling methodologies has the potential to significantly improve the control of mosquito-borne diseases and reduce the risk of these diseases to public health. Despite the availability of these methodologies, many vector control agencies continue to rely on traditional methods of surveillance and control. To identify how geospatial modeling methods can be used to improve mosquito control efforts, we conducted in-depth interviews with four public health and vector control agencies that currently use geospatial modeling applications within their mosquito control programs. Best practices include use of geospatial modeling by agencies to: (1) elucidate the vector ecology of mosquito species; (2) bolster mosquito source reduction efforts; (3) develop predictive risk assessment models; and (4) increase vector control agency worker utilization. This study provides critical lessons on practical ways that public health and vector control agencies can use geospatial modeling to more effectively mitigate the threats posed by new and reemerging mosquito-borne diseases.

INTRODUCTION

The need to implement enhanced methods to proactively combat mosquito-borne viruses has never been more apparent, with threats of West Nile, Chikungunya, dengue, and the recently introduced Zika virus (Zika) in the Americas. Within the past year, Zika rapidly spread throughout South America, Central America, and the Caribbean, with thousands of locally acquired, annual cases of Zika expected to occur in Puerto Rico alone (1). Although not particularly fatal in healthy adults, Zika has been linked to microcephaly, a serious birth defect resulting in abnormally small heads in newborns, and other congenital abnormalities in infants of pregnant women infected with the virus (2). Associations have also been found between Zika infection in adults and Guillain-Barré syndrome (1). The significant public health threats posed by Zika to fetuses and adults is further compounded due to sexual transmission of the disease and the lack of vaccines or antivirals for this virus (3). The lack of available treatment and prevention options make mosquito control and personal protection the primary defenses to reduce the spread of Zika and other mosquito-borne diseases in the United States and abroad.

One way to bolster the efficacy and cost-effectiveness of mosquito control efforts is to use geospatial modeling and geographic information system (GIS) tools to gain insights into mosquito ecology and disease hotspots with respect to space and time (4-8). The use of geospatial modeling tools for mosquito control can improve the effectiveness of vector control efforts by allowing agencies to incorporate local vector ecology information into their mosquito control prevention efforts. Geospatial modeling techniques can also allow vector control agencies the ability to identify areas of high human risk and target those areas for public outreach and intervention efforts. Despite these capabilities, most public health and vector control agencies currently use geospatial modeling tools in a limited capacity. (See **Chapter 3** of this thesis.)

The limited use of geospatial modeling techniques for mosquito-borne virus surveillance and control efforts is well illustrated by the case of West Nile virus (WNV) control practices in the U.S. Following the arrival of WNV in New York City in 1999, the National Centers for Disease Control and Prevention (CDC) established guidelines encouraging state and local public health agencies to adapt existing empirical methods of other mosquito-borne diseases to use in monitoring WNV (9). Unfortunately, most agencies in the United States still face challenges in managing WNV (**Figure 4.1**). The majority of vector control agencies continue to rely on traditional methods for WNV control, despite the increasing availability of geospatial modeling resources to enhance existing methods of WNV surveillance, management, and mitigation (5, 10-15). In interviews with U.S. public health and vector control agencies involved in WNV control, less than a third of agencies surveyed acknowledged using geospatial modeling to predict, manage, or prevent WNV. (See **Chapter 3** of this thesis.) Here, we explored how agencies that are successfully using geospatial modeling tools for WNV control can provide crucial insights into how other agencies might implement geospatial modeling within their own jurisdictions to mitigate threats posed by new and reemerging mosquito-borne diseases.

METHODS

Through previously conducted interviews (n = 18) with vector control and public health departments in states with high cumulative human WNV cases, we identified 13 agencies in the U.S. that currently use geospatial modeling resources in some capacity in their WNV control efforts. (See **Chapter 3** of this thesis.) From these unique 13 agencies, seven potential interviewees were selected to best represent the geographic range and spectrum of geospatial modeling practices used within their WNV programs. Each of the seven potential interviewees were sent a recruitment email, followed by a phone call from a member of the research team. Following this process, four of the seven individuals from different vector control and public health agencies responded, comprising the final interview pool. These four individuals were located in the Northern Great Plains, Southern California, Southwestern United States, and Southern United States. (See **Figure 4.2.**)

Each structured case interview consisted of questions regarding the use of geospatial modeling in the agency's WNV program, benefits that the agency perceived resulted from using geospatial modeling, and how/whether geospatial modeling could be applied to address other mosquito-borne diseases (**See Appendix 3**). The implementation questions also focused on how the agency had initiated their use of geospatial modeling within their WNV programs and whether geospatial efforts had included other agencies or organizations. Questions about the agency's current geospatial modeling practices focused on how geospatial modeling methods were being used by the agency (e.g., whether geospatial modeling was being used in a limited project-based capacity or as part of an integrated program within the agency's WNV control efforts). Follow-up questions focused on whether agencies had observed any noticeable improvements to their WNV control efforts or impacts to their local WNV prevalence after having implemented geospatial modeling techniques, and how/whether their geospatial modeling practices could be adapted to address newly emerging or reemerging mosquito-borne diseases. All interviews were digitally recorded and transcribed using the software program *Transcribe* (16).

Lessons learned: best practices for incorporating geospatial modeling into vector control programs

The ways in which vector control programs used geospatial modeling to inform their WNV surveillance and mitigation practices varied dramatically between the four agencies that were interviewed. Here, we begin each case study by introducing how that particular agency used geospatial modeling techniques to address gaps in their current WNV control programs, and provide details on how these techniques were implemented. Next, we summarize how the application of geospatial modeling applications has enhanced each agency's WNV program. Finally, we explore how lessons learned from each case study can be applied by other agencies beyond the scope of WNV to address the threat of emerging and reemerging mosquito-borne diseases (**Table 4.1**).

Elucidating the vector ecology of Culex *spp. in the Northern Great Plains*. To improve current WNV programs in the Northern Great Plains, vector control agencies, public health departments, and research institutions have conducted joint geospatial modeling projects to gain insights into the vector ecology of the *Culex tarsalis*, the local vector for WNV in that region (17-19). These geospatial modeling projects allowed collaborators to identify suitable abiotic and biotic environmental conditions for *Cx. tarsalis*, which allows local WNV programs to provide more targeted mosquito surveillance and control efforts (5, 20-23). For example, collaborators at the U.S. Geological Survey's Earth Resources Observation Center and South Dakota State University, reported conducting geospatial analyses with GIS software such as ESRI's ArcGIS (24), to combine traditional mosquito surveillance data with a variety of climate forecast models, and remote sensing data, and U.S. Census data to identify landscape-level features and climatic influences affecting the local *Cx. tarsalis* ecology, human activity, and avian host communities (25-27).

The results from these projects have helped to enhance current *Cx.* surveillance and mitigation efforts in the Northern Great Plains. Benefits recognized by the interviewees include the ability to re-focus mosquito trapping sites to accommodate *Cx.* ecology data and the identification of new *Cx. tarsalis* habitats outside the scope of current surveillance sites. These analyses allow vector control agencies to conduct more effective source reduction and ground spraying efforts, thereby saving resources and reducing unnecessary chemical spraying. Furthermore, project collaborators are now using the information generated from their geospatial modeling efforts to develop long-lead forecasting systems for WNV outbreaks based on overwintering and springtime climate anomalies (28). The aim of these forecasting systems is to provide vector control agencies ample time to prepare for potential disease outbreaks and conduct appropriate mitigation activities (12, 29, 30).

The success and versatility of this project highlights how geospatial analyses and GIS software could be used more broadly to address emerging and reemerging mosquito-borne viruses within the U.S. Because there is significant ecological diversity in the U.S., vector control agencies would benefit from using geospatial analyses to characterize how/whether their local environment might support new mosquito-borne disease vectors, such as *Aedes* mosquitoes, which can transmit Zika, dengue, and Chikungunya. Following the introduction of *Aedes* mosquitoes into new areas, vector control agencies should conduct vector ecology studies to develop targeted surveillance and control efforts to help reduce the potential for human cases to occur. Furthermore, combining geospatial analyses with traditional mosquito surveillance efforts can provide the foundation for the development and implementation of predictive forecasting systems aimed at controlling the spread of Zika and other mosquito-borne diseases.

Mosquito source reduction in the Southern United States. Vector control agencies in the Southern U.S. have employed geospatial modeling tools to address the abundance of WNV positive mosquitoes breeding in abandoned swimming pools in the aftermath of Hurricane Katrina in 2005 (31). Originally, field technicians would identify abandoned swimming pools through observation during their daily rounds, which was both time consuming and resource intensive. However, the addition of geospatial modeling tools, such as aerial surveillance photos and mobile GIS devices, allowed field technicians to significantly improve source reduction efforts of *Culex* mosquitoes. Through aerial surveillance photos provided by local County Assessors, vector control agencies have been able to identify the location of permanent swimming pools within their jurisdictions. Following the identification of pools, field technicians then "ground-truth" pool locations, assess the condition of the pools, and apply appropriate control measures for treatment. Given the success of the source reduction program, it has been expanded to include other suspected breeding sites such as tire piles and leaking pipe runoff pools (32, 33).

The use of aerial surveillance and GIS hardware for source reduction efforts has largely improved local vector control capacity to identify and control *Culex* breeding sources and increases the flexibility of field technicians to address new breeding sites as they appear. The application of geospatial modeling tools and techniques has allowed field technicians the ability to; 1) rapidly assess potential *Culex* breeding sources; 2) prioritize trapping and planning efforts; 3) manage previously identified and treated sites; and 4) provide more targeted source reduction efforts. Furthermore, the addition of mobile GIS platforms have further enhanced the ability of field technicians by allowing them to spatially manage, prioritize, and record treatment sites for follow-up in real-time, and allow for the quick mobilization of field teams when needed.

This use of geospatial modeling to enhance source reduction efforts can also allow vector control agencies to more effectively address the challenges across a much broader range of diseases and vectors, such as the introduced *Ae. aegypti* and *Ae. albopictus* (34). Both *Ae. aegypti* and *Ae. albopictus* present challenges for source reduction efforts given their ovipositing preferences for small water sources or small objects, such as funeral urns, water jugs, and tires (35). Additionally, differences in vector competency for mosquito-borne viruses such as Zika, may require vector control agencies to conduct different source reduction strategies for each *Ae. spp*. (36). For example, *Ae. ageypti* has been suggested to be a more competent vector than *Ae. albopictus* for both Zika and Chikingunya transmission, though both species maintain distinct, but overlapping ecological niches (34). However, combining geospatial photos and GIS hardware with traditional mosquito surveillance methods can allow vector control agencies to survey and manage multiple *Ae. spp*., including competent native arboviral vectors, such as *Ae. triseriatus*. Through these enhanced source reduction programs, vector control agencies can increase the flexibility and timeliness needed to address the current and future disease outbreaks that likely depend on reducing the availability of suitable habitats for ovipositing, competent vectors throughout the U.S.

Predictive risk assessment in Southern California. In Southern California, individuals from vector control agencies have collaborated with researchers from local academic institutions to use geospatial modeling to develop regional predictive risk assessment models in an effort to reduce future WNV human cases. Predictive risk assessment models can be used to identify environmental, climatic, or socioeconomic predictors of mosquito-borne diseases, and can be used to provide lead-time for WNV control efforts. To develop these models, collaborators used GIS software (24) and machine learning and statistical software, including Maxent (37) and R (38) to combine local topographical, environmental, climactic, and socio-demographic layers to risk factors for WNV human cases across the region (21). Results from these models can then be used by vector control agencies to identify other suitable areas where future WNV human cases may occur and to more effectively target their control and outreach efforts.

The addition of predictive risk assessment models has helped vector control agencies overcome many of the challenges facing WNV control in Southern California. For example, since the abundance of the most locally prevalent WNV vector, *Cx. quicifaciatus*, does not serve as an accurate predictor for WNV human risk, vector control agencies have used predictive risk assessment modeling to identify suitable conditions for where WNV hotspots may occur. In Southern California, identified risk factors supporting WNV hotspots have been the density of abandoned swimming pools and regions of low per capita income (21). Using this information, vector control agencies have been able to decrease their response time between surveillance and control efforts, verify suspected breeding sources, perform targeted WNV control efforts, and conduct educational outreach programs in identified high risk areas.

In the future, predictive risk assessment modeling could also be used to identify areas of high risk for emerging and reemerging mosquito-borne disease threats. For example, leveraging the associations between Zika and microcephaly, and low socioeconomic conditions and high birth rates, can yield predictive risk assessment models for use in Zika virus disease control. Preliminary models can already be generated using a combination of *Aedes* niche preferences, local pregnancy rates, and socioeconomic conditions to roughly estimate the risk of Zika infection to pregnant or soon-to-be expecting women within a region (1, 35, 39). Additionally, the data required to develop these predictive risk assessment models presents an opportunity for increased collaboration and data sharing between separated vector control and public health agencies. Lastly, results generated from predictive risk assessment models can be used to target high-risk populations for increased education and outreach efforts in order to bolster community resilience to future threats posed by emerging and reemerging mosquito-borne viruses.

Increasing vector control capacity in the Southwest. In the Southwestern U.S., where suitable conditions may support prolonged WNV activity, vector control agencies have partnered with the geospatial technology company Environmental Systems Research Institute (ESRI) (24), to increase the productivity and effectiveness of their WNV control efforts. Through such partnerships, some vector control agencies have obtained a variety of fully customized GIS programs and GIS applications to support their WNV surveillance, control, and management activities. For surveillance purposes, cloud-based applications have allowed field technicians to: 1) enter and directly send data to central databases for manager processing; 2) observe historical records of all previously surveyed sites; 3) identify and route next surveillance sites; and 4) flag potential high risk or suitable breeding sites for future mosquito surveillance. For control efforts, these applications have allowed field technicians to quickly identify treated sites to reduce reapplication of pesticides, prioritize areas for treatment, and determine the chemical concentration and amount of pesticides needed to address an area designated by the field technician. At the management level, the development of GIS applications provides supervisors the ability to track field technicians in real-time to assess performance within the field and adjust workloads when necessary.

To analyze WNV data, GIS software, and freeware such as QGIS (40) and packages within the statistical program R (38), can allow vector control agencies to expand their department's geospatial modeling capabilities without significantly increasing financial costs or the number of personnel. The addition of these programs can allow supervisors to rapidly observe positive mosquito trends, identify where control activities should occur, and rapidly mobilize staff for treatment as needed. Furthermore, by providing supervisors with real-time updates of data and fieldwork, supervisors are able to rapidly organize data and personnel to decide best management decisions. Overall, the addition of GIS software and applications for WNV control efforts has allowed vector control agencies in the Southwest to overcome the year-to-year variations in vector control budgets and increase WNV surveillance and control activities without the need to increase personnel or demands on current employees.

Cloud-based geospatial modeling approaches could also be effective tools to address the emergence of other new or reemerging mosquito-borne viruses. As previously mentioned, differences in the vector ecology for certain mosquitoes, such as *Ae. spp*, their range, and other potential mediating factors, will require vector control agencies to increase their overall capacity to perform rapid surveillance and control. During periods when vector activity may extend beyond the normal breeding season or when resources may be limited, the application of geospatial tools and applications can increase the efficiency, productivity, and response of vector control agencies in controlling vectors. Furthermore, these tools can help facilitate the transfer of data, increase communication efforts between entities involved in mosquito control, and provide transparency to external stakeholders regarding the work being conducted by vector control agencies.

DISCUSSION

The identification of best practices from years of surveillance and control efforts for West Nile virus provide important insight into how geospatial modeling hardware, software, and analyses can be used to improve the effectiveness and efficiency of surveillance and control methods for new and re-emerging mosquito-borne diseases. (**Table 4.1**) For surveillance of emerging threats such as Zika and other anthroponotic viruses, applying geospatial methods, in combination with traditional control and mitigation efforts, will be essential for understanding the local vector ecologies of non-native mosquito species such as *Ae. aegypti* and *Ae. albopictus*, along with the particular conditions that increase the risk of the diseases they transmit. Furthermore, predictive risk assessment models can aid vector control agencies in bolstering preparedness efforts by identifying new areas where hotspots of disease may occur. For active mosquito control efforts, resource-limited vector control and public health agencies can use aerial photos and mobile GIS devices to help rapidly identify, mitigate, and manage mosquito breeding sources. Lastly, to effectively manage the mounting workload and demand of vector control and public health agencies in dealing with current and new mosquito-borne viruses, cloud-based GIS applications can be used to expand the capacity of field technicians, managers, and lab workers to effectively perform their duties without the need for additional resource investments.

CONCLUSION

Overall, the application of geospatial modeling resources in tandem with traditional surveillance and control methods can allow agencies to develop and implement effective, adaptive, and flexible vector control programs that are capable of addressing threats posed by current and emerging mosquito-borne diseases. For vector control programs with limited resources, the use of geospatial modeling tools to develop preventative measures for mosquito surveillance and control can be substantially more cost-effective in the long-run compared to potential disease case management and coverage of follow-up costs. The case studies presented herein suggest that it will be increasingly necessary to think outside the purview of traditional vector control activities and embrace the incorporation of geospatial modeling resources to address the growing threat posed by current and emerging mosquito-borne diseases.

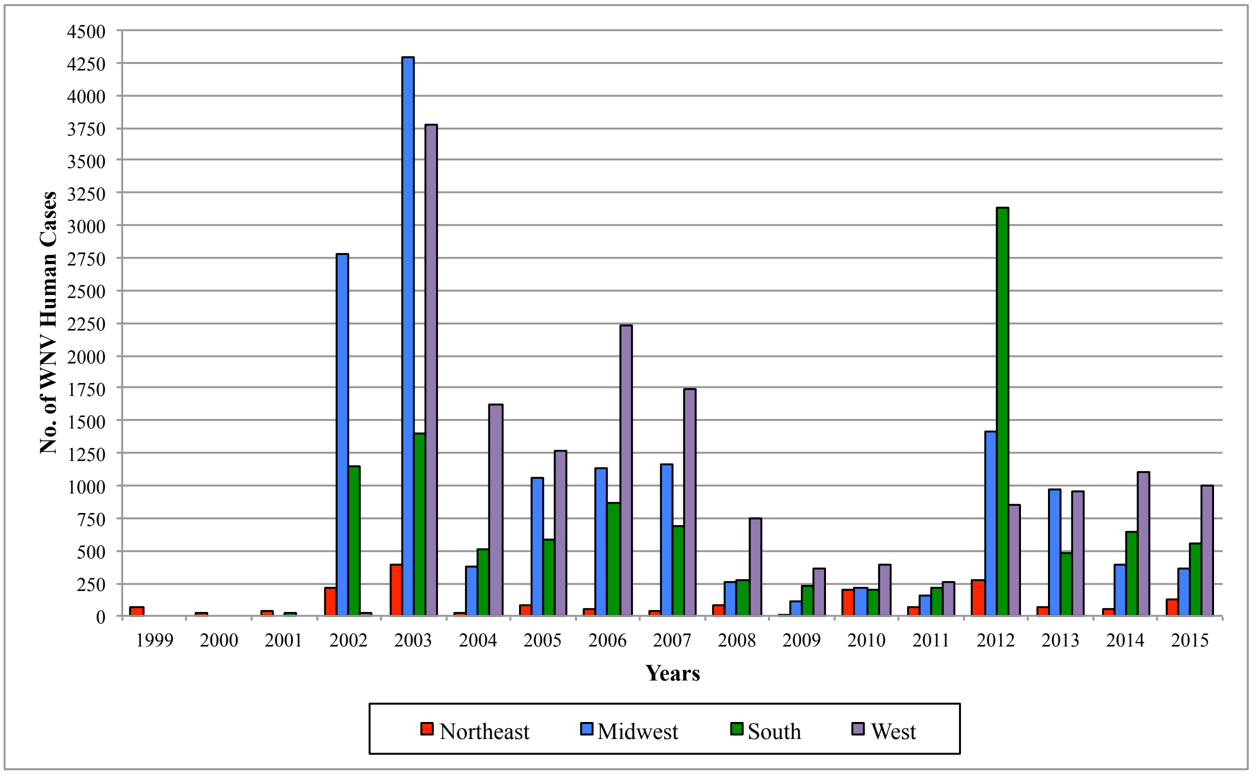

Figure 4.1. Yearly human WNV cases from 1999-2015 for the Northeast (red), Midwest (blue), South (green), and Western United States (purple), the regions of the US that have consistently shown the highest human WNV case counts. Annual variations of human WNV cases by region highlight the limited success of vector control efforts in addressing WNV.

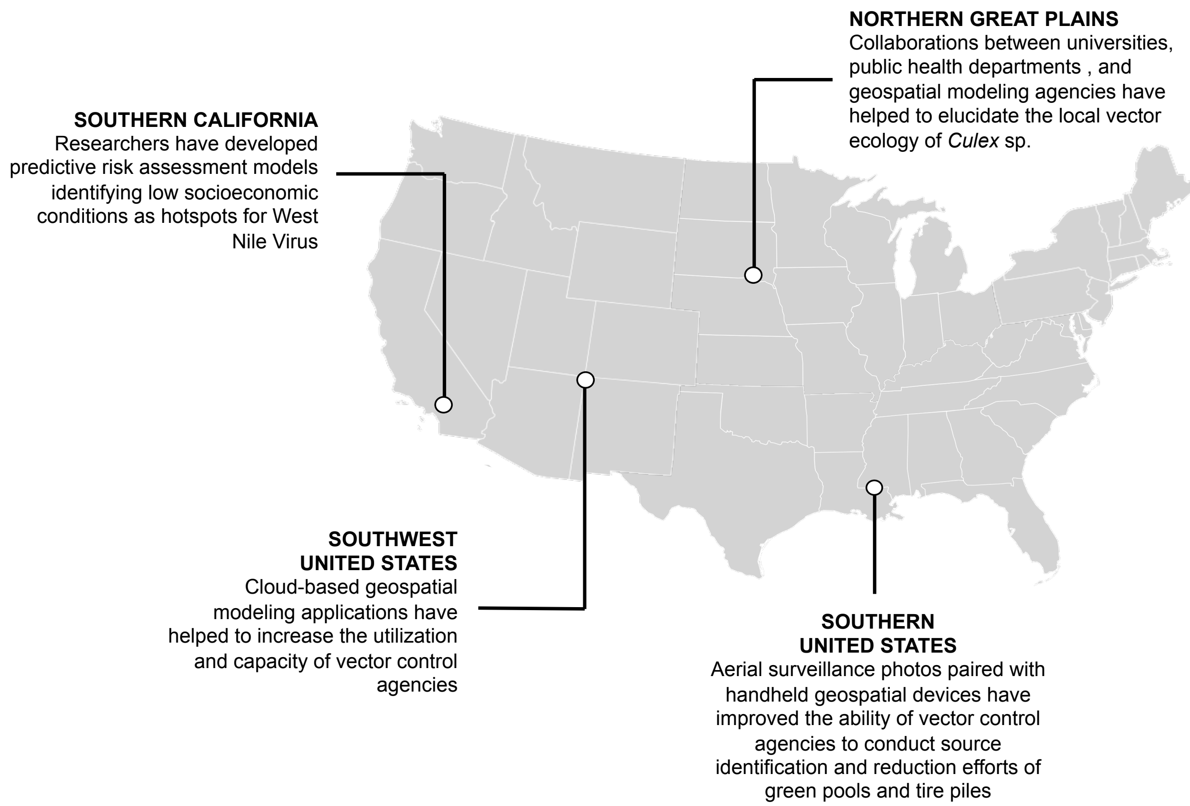

Figure 4.2. Case study areas used in this study and summaries of the geospatial modeling efforts used for mosquito control and disease prevention by the "best practice" agency interviewed each of these areas. Case studies were selected to address how geospatial modeling resources have been used to help overcome distinct problems experienced using traditional vector control methods.

Table 4.1. Case study areas, aims, available tools and approaches, and identified improvements

Case Study	Aim	Available tools and approaches		Identified Improvements
		Traditional	Geospatial	
Northern Great Plains	Understand local vector ecology of *Culex* spp.	Scientific literature	Remote sensing layers	Greater understanding of local vector ecology of *Cx*. Tarsalis in the Northern Great Plains
		Mosquito surveillance*	Climate forecast models	Able to explore alternative data sources to improve mosquito forecasting efforts
		Technical collaborations	Geospatial modeling software	Developed seasonal forecasting approaches for mosquito-borne diseases
				Increased mosquito surveillance *
Southern United States	Source identification and reduction of mosquitos	Larval dips	Aerial surveillance photos	Increased in the number of breeding sites identified
		Field technician observations	Mobile geospatial devices	Faster response time for source reduction efforts
				Greater flexibility in mitigating new breeding sites
		Civilian complaints/reports	Geospatial modeling software	Improved management of field technicians and operations
				Extended source identification range outside of current larval dipping sites
Southern California	Risk assessment and disease hotspot analysis	Mosquito surveillance*	Remote sensing layers	Improved verification of known disease hotspots
		Mosquito infection rates	Ecological niche modeling software	More targeted mosquito surveillance, control, and public education efforts
		Human case follow-up	Machine learning techniques	Increased mosquito surveillance*
		Non-human surveillance	Geospatial modeling software	
Southwest United States	Increase vector control employee utilization	N/A	Cloud-based mobile applications	Increased productivity of managers and field technicians to perform mosquito surveillance and control
				Improved management and tracking of pesticide applications
			Geospatial modeling software	Greater response of field operations through improved identification of virus risk
				Increased confidence of field technicians

*Includes both adult mosquito surveillance and larval dips

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CHAPTER 5

Overarching Conclusions and Recommendations for Future Studies

Geospatial modeling as an integral tool in the identification of factors supporting West Nile virus prevalence

The analyses applied and implemented in **Chapter 2** demonstrates the power of geospatial modeling in identifying predictors supporting WNV hotspots in vectors and humans. We identified environmental predictors for WNV using geospatial layers, such as temperature, precipitation, elevation, and socio-demographic features, with machine learning algorithms to identify any complex, non-linear relationships that may exist between variables and WNV prevalence. Through this approach, we were able to obtain significant insights into the drivers of WNV in Los Angeles County and provide guidance on how local vector control and public health agencies can leverage these results to anticipate when suitable climatic conditions are present that may support the spread of WNV. Additionally, these insights can help identify target hotspots within the county and develop new approaches to mitigating the spread of WNV. This study demonstrates that geospatial modeling analyses of mosquito-borne diseases can provide valuable insights for vector control agencies, particularly those that cover areas with heterogeneous landscapes, jurisdictions, or climates. This study suggests that future research should be conducted to assess how these methods could be used to improve surveillance and mitigation of other vector-borne diseases such as Lyme disease, typhus, or Zika.

Public health and vector control agencies face different barriers depending on their stage of implementation of geospatial modeling for West Nile virus control

The findings presented in **Chapter 3** highlight the barriers that public health and vector control agencies face in implementing geospatial modeling techniques for WNV control. The barriers reported by agencies are highly dependent on the stage at which the agency is at in implementing geospatial modeling. We termed these stages as: (1) *Initial Implementation,* (2) *Internal Implementation,* and (3) *Internal and External Implementation*. Our results suggest that stand-alone public health and vector control agencies face the greatest number of barriers at all stages of implementation, and that combined public health and vector control agencies experience fewer challenges in using geospatial modeling for WNV. This study suggests that agencies falling within the *Initial Implementation* stage would benefit from sharing geospatial modeling resources with other local agencies. By contrast, agencies that fall within the *Internal Implementation* stage would most likely benefit more from creating repositories of surveillance data that are shared with other agencies in their jurisdiction. Lastly, agencies in the advanced stages of geospatial modeling use (*Internal and External Implementation*), would benefit from regional multi-stakeholder taskforces to improve communication between agencies and with external stakeholders. These insights provide important ramifications for translating geospatial research into practice not only to improve WNV surveillance and mitigation, but for improved prevention of other vector-borne diseases as well. Going forward, to obtain a holistic national perspective of barriers preventing the implementation of geospatial modeling, future studies should seek to examine barriers within non-WNV hotspots.

Though limited, geospatial modeling resources are currently being used to enhance the surveillance and control of West Nile virus Across the United States

In **Chapter 4,** we identified best practices from agencies that are already using geospatial modeling to improve their effectiveness and efficiency of their surveillance and control methods for WNV. This study provides specific examples of how geospatial modeling hardware, software, and analyses are currently being used to improve the effectiveness and efficiency of surveillance and control methods for WNV, and how they can be applied to other new and re-emerging mosquito-borne diseases. For surveillance of emerging threats such as Zika and other vector-borne viruses, geospatial analyses combined with traditional surveillance techniques can provide critical insights into the local vector ecologies of non-native mosquito species such as *Cx. tarsalis* and *Ae. aegypti*, and can also help to identify environmental conditions that increase the risk of the diseases they transmit. Additionally, combinations of geospatial software and machine learning algorithms can help vector control agencies to improve their effectiveness by identifying new areas where hotspots of disease may occur and allowing agencies to target mitigation activities at those sites. For active mosquito control efforts, resource-limited vector control and public health agencies should consider using aerial photos and mobile GIS devices to help rapidly identify, mitigate, and manage mosquito breeding sources. Lastly, the availability of cloud-based GIS applications can aid vector control agencies in effectively managing the mounting workload and demand of dealing with current and new mosquito-borne viruses.

The application of geospatial methods demonstrated in **Chapter 2**, combined with the identification of barriers and best practices in geospatial modeling (**Chapters 3** and **4**), provide a holistic perspective into how geospatial modeling can be applied to improve vector control and public health practice of WNV and mosquito-borne diseases. Overall, these findings suggest that, as the field of vector control advances, it is becoming increasingly necessary to think outside the purview of traditional vector control activities and embrace the incorporation of geospatial modeling resources to address the growing threat posed by current and emerging mosquito-borne diseases.

APPENDIX 1

Supporting Information for Chapter 2

SUPPLEMENTAL METHODS

To assess whether differences in predictors identified by vectors (through random forest models) and human cases (through Maxent) varied due to research methodologies, we used Maxent to assess the relative importance of variables in predicting positive WNV surveillance sites. For this analysis, we ran the environmental and socio-economic predictor variables layers against the outcome variable of geo-locations of positive WNV surveillance sites provided by GLACVCD. Data for all years were included in the model, and default Maxent settings were used (10,000 background points; regularization multiplier = 1.0; maximum iterations = 500; convergence threshold = 0.00005).

SUPPLEMENTAL RESULTS

Across all years, the most significant predictors for WNV prevalence in vectors was mean annual temperature, annual precipitation, and density of catch basins (**Figure A1.1**). Mean annual temperature contributed the most to explaining WNV prevalence during the years 2004-2005, 2008, and 2011-2014. Of these years, mean annual temperature explained above 60% for the years 2013 (64.7%), 2008 (62%), and 2014 (60.5%), with over 45% explained for all other years in this category except for 2004 (39.3%). For the remaining years where mean annual temperature did not contribute to explaining WNV prevalence (2006-2007 and 2009-2010), annual precipitation was the largest contributor. During 2009 and 2010, annual precipitation explained above 80% of the WNV prevalence in vectors, and explained above 35% for 2006-2007. Lastly, while the density of catch basins was not the most significant predictor for WNV prevalence in vectors, it did explain over 20% for the years 2005, 2008, and 2011-2014.

These findings are highly concordant with those from the random forest models for WNV prevalence. The regression trees for WNV prevalence in vectors identified that mean annual temperature and annual precipitation consistently explained the most variation of any predictor variable across the study years. Other variables were also included in the regression trees, but these only explained a relatively small amount of the variation, and were not consistent across years. Interestingly, the years where annual precipitation was the highest contributor to WNV prevalence were also years with the lowest average MLE among sites. This could potentially indicate that complex transmission dynamics were at play for these years, atypical from years with higher WNV prevalence where mean annual temperature may help drive WNV transmission in vectors.

The spatial predictive maps generated using the WNV positive surveillance sites (**Figure A1.2**) were also highly concordant with those generated from the human WNV cases (**Figure 2.4A**). Within these maps, the San Fernando Valley has been identified as a hotspot for the disease, with noticeable hotspots in the southeast, within the San Gabriel Valley. In the north, the high desert has not been identified as potential hotspot, which can be explained given the extremely high temperatures, minimal rainfall, and possible lack of microhabitats (e.g. catch basins), which may support vectors during extreme conditions.

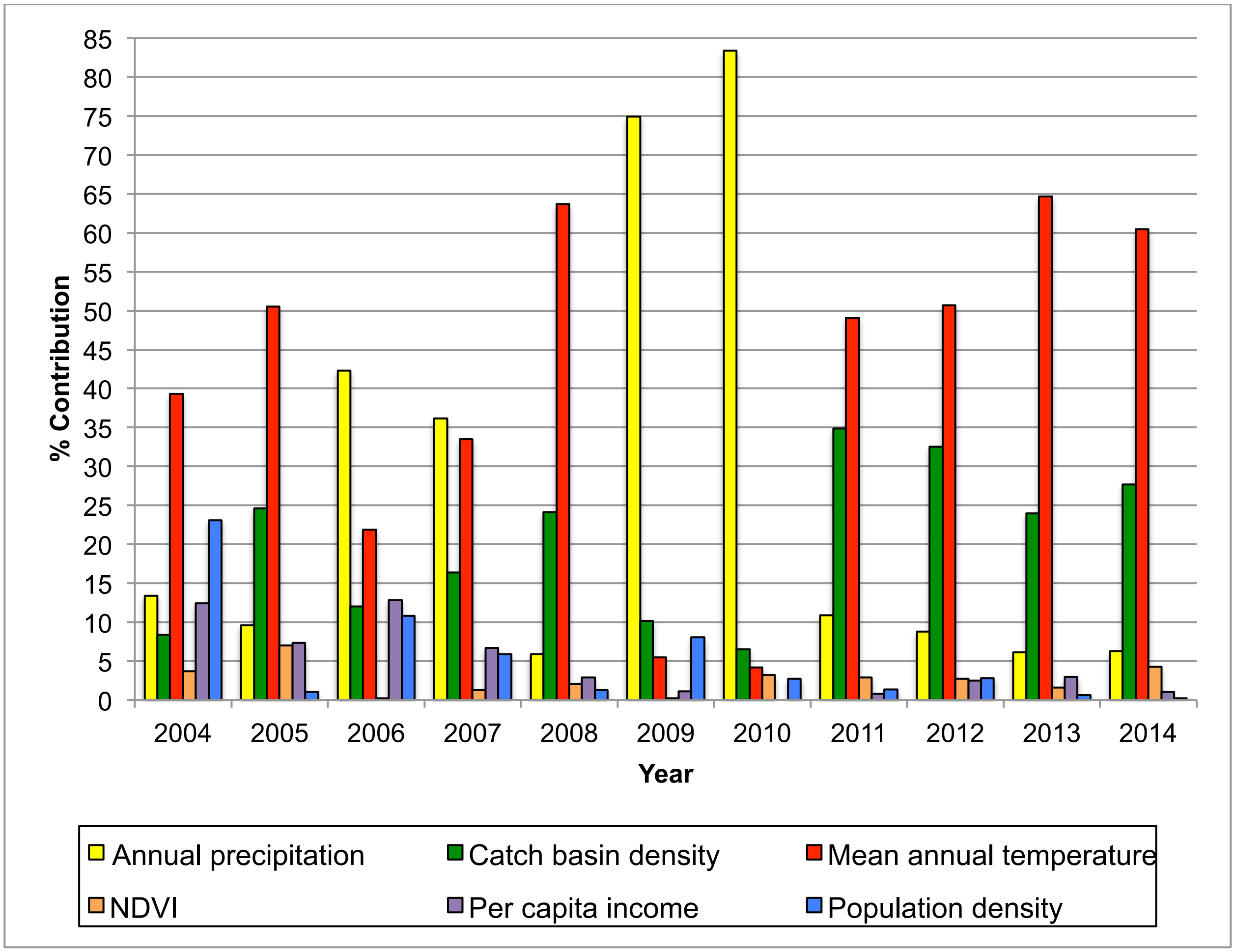

Figure A1.1. Percent contribution to spatial variability of WNV positive mosquito surveillance sites in Los Angeles County obtained from Maxent models for environmental predictors (mean annual temperature, annual precipitation, NDVI, catch basin density) and demographic predictors (population density, per capita income). A higher percent contribution indicates that the variable is able to explain more of the model compared to lower percent contributions.

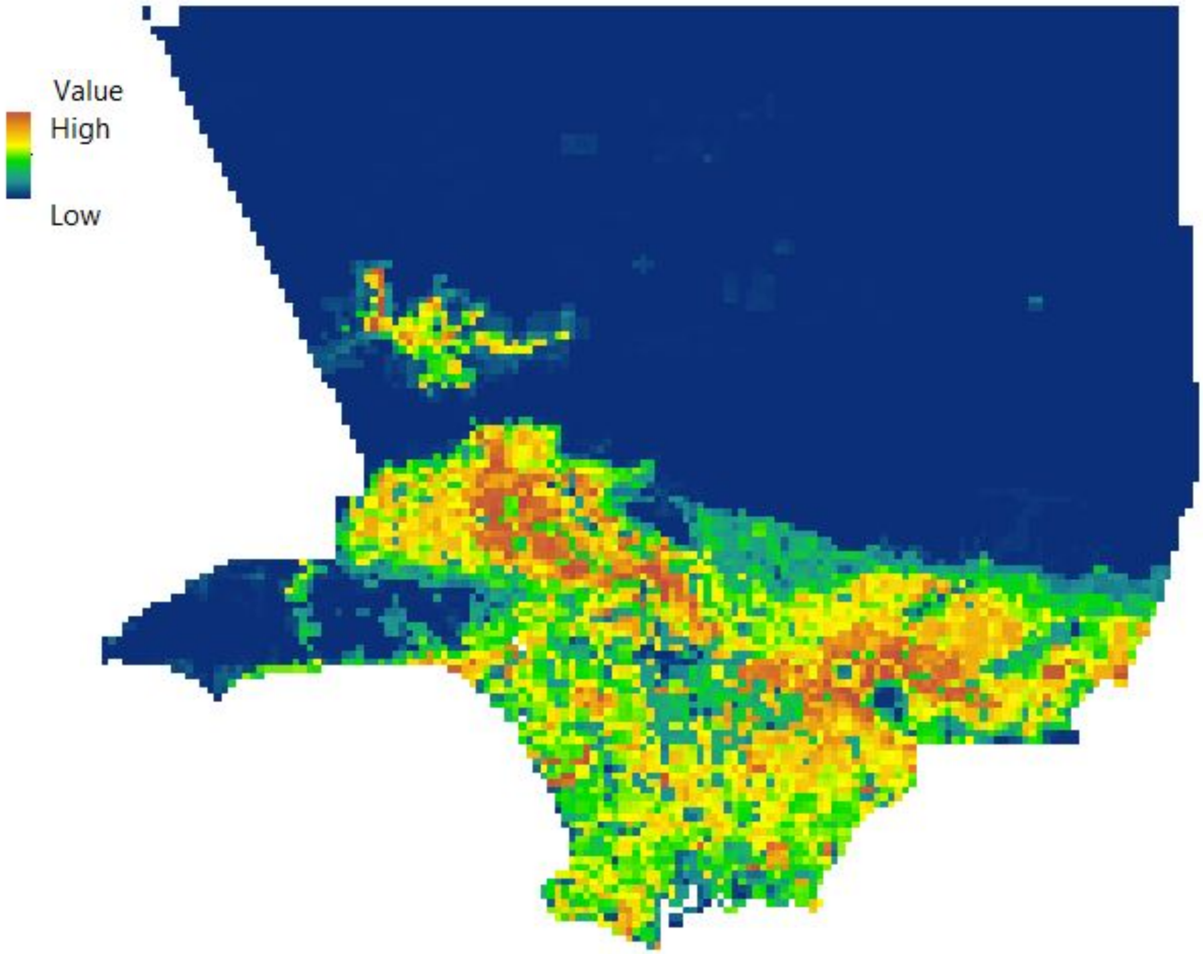

Figure A1.2. The cumulative presence of WNV in *Cx.* spp in positive WNV surveillance sites developed through Maxent models for the years 2004-2014.

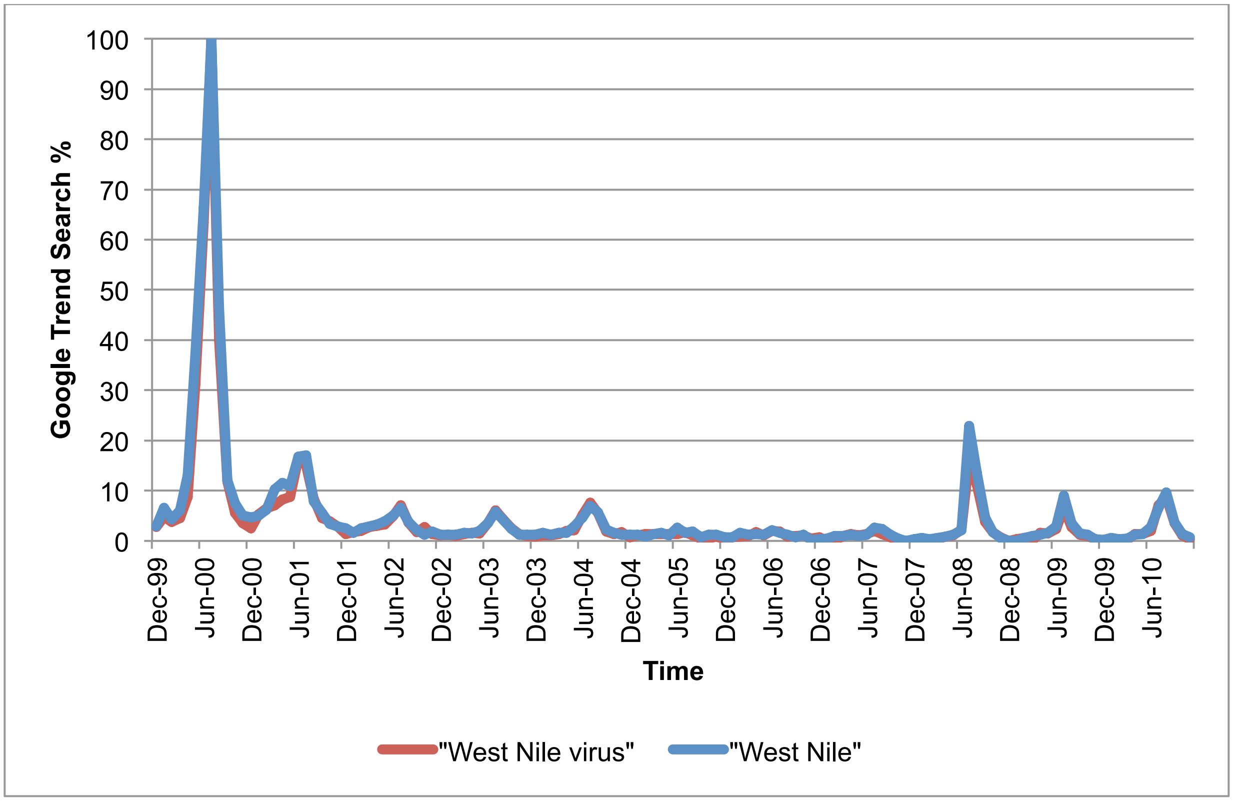

Figure A1.3. Google Trend searches for the keywords, “West Nile virus” and “West Nile” within Los Angeles County from 2004-2014. Search results are presented relative to the year with the highest amount of searches for the key words listed above (2004).

APPENDIX 2

Supporting Information for Chapter 3

<u>Interview Questions for West Nile Virus Surveillance Experts</u>

<u>Interview Format</u>: Non-schedule standardized narrative interviews

<u>WNV Prevalence</u>

1. Describe the WNV prevalence within your jurisdiction currently and for the past 10 years.

Prompts given participant response	a. What do you believe has attributed to the WNV prevalence within your jurisdiction?

<u>Current WNV Surveillance Techniques</u>

2. What are the current WNV surveillance techniques of non-human cases used by your agency/department?

Prompts given participant response	a. Describe how these techniques are conducted. b. How successful have these techniques been in identifying WNV hotspots within your jurisdiction? c. Can you identify any potential limitations or gaps with your current WNV surveillance program?

Use of Geospatial Modeling to Enhance Surveillance Activities

3. Has your agency/department used geospatial modeling as a tool for improving surveillance of any infectious diseases?

Prompts given participant response	a. Describe how you use geospatial modeling in your work; what are the inputs and outputs? b. Have you used geospatial modeling as a tool for improving WNV surveillance?

If Geospatial Modeling is used as a WNV Surveillance Technique

4a. You mentioned that your agency/department uses geospatial modeling for WNV surveillance. Approximately how long has your department been using GIS?

Prompts given participant response	a. How effective has GIS been in helping you to identify and predict WNV hotspots? b. Describe any benefits that have resulted from use of geospatial modeling in your WNV surveillance program. c. Describe any limitations your agency/department has experienced in using geospatial modeling for WNV surveillance. d. How was your agency able to integrate geospatial modeling into their WNV surveillance program?

If Geospatial Modeling is NOT Used as a Surveillance Technique

4b. I'm interested in examining the use of GIS in West Nile virus surveillance. How familiar are you with the use of geospatial modeling for WNV surveillance?

Prompts given participant response	a. Is your agency/department interested in implementing geospatial modeling into their WNV program? b. If YES: i. What are the potential barriers preventing this implementation? c. If NO: i. Why is your agency not interested in implementing geospatial modeling into their WNV surveillance?

<u>**Human Case Data**</u>

5. How are human WNV case data collected and communicated in your jurisdiction?

Prompts given participant response	a. Which agency in your jurisdiction is responsible for collecting WNV human case data? b. If not own agency, then do you have easy access to human WNV case data for your jurisdiction? c. Approximately how long is the lag between when a human case occurs and when your agency is notified of the case?

<u>**Abatement & Mitigation**</u>

6. How are WNV mitigation and abatement activities conducted in your jurisdiction?

Prompts given participant response	a. Which agencies in your jurisdiction are responsible for WNV mitigation and abatement activities?
	b. What mitigation/abatement techniques are being used?
	c. Describe how these techniques are conducted.
	d. How are intervention locations selected? Are human case data used to inform intervention locations?
	e. If human case data IS NOT used:
	    i. Why does your agency/department not use human case data to inform mitigation/abatement efforts?
	f. Is geospatial modeling used to inform abatement/mitigation efforts?
	g. If YES:
	    i. What types of data are used in your geospatial modeling?
	    ii. What types of correlations have you observed as a result of this modeling?
	h. If NO:
	    ii. Has your agency considered using geospatial modeling for abatement/mitigation efforts?
	i. If your agency HAS considered using geospatial modeling:
	    i. What are the potential barriers to implementing geospatial modeling into your intervention efforts?
	j. If your agency HAS NOT considered using geospatial modeling:
	    i. Why is your agency not interested in using geospatial modeling for WNV mitigation?

Helpful Documents

7. Do you have any suggestions for publically available documents that would be helpful for this work?

NOTE: If there are any individuals that you feel should be included in this study, we have created a flyer for this study that you may provide to them.

APPENDIX 3

Supporting Information for Chapter 4

UCLA FIELDING SCHOOL OF PUBLIC HEALTH

Applied Geospatial Modeling to Improve Control of Current and Future Mosquito-borne Disease Outbreaks

Bryan Moy, MPH | Department of Environmental Health Sciences

<u>Follow-up Interview Questions for West Nile Virus Surveillance Experts</u>

Email solicitation and explanation at beginning of interview:

Thank you for participating in the earlier interview with me about use of geospatial modeling of WNV amongst public health and vector control agencies. As a result of my interview with you and other practitioners, I have written a manuscript describing barriers to use of geospatial modeling for WNV in practice settings and how those barriers have been overcome by some agencies. The manuscript is currently under review at the *Journal of Environmental Health*, would you like me to share a copy of the manuscript with you?

Your agency was one of the few agencies surveyed that reported successfully incorporating geospatial modeling of WNV into their program. I am now in the process of developing some case studies about how geospatial modeling can be used to improve surveillance and mitigation of WNV by public health and vector control agencies. These case studies will be compiled into a report that will be made available to public health and vector control agencies to help disseminate best practices and will be included in my doctoral dissertation. Would you be willing to answer some follow up questions about how your organization has specifically incorporated geospatial modeling of WNV into your practice?

<u>Interview Format</u>: Non-schedule standardized narrative interviews

Current Geospatial Modeling Practices

a. Has your agency used geospatial modeling for West Nile Virus either specific short-term projects or more comprehensively as integral part of your surveillance and/or mitigation program?

    a. If short-term (e.g. project-based):

        i. Can you provide me with a more specific example of a short-term project in which your agency used geospatial modeling for WNV surveillance or mitigation?

        ii. Did your agency receive support from any outside organization(s) (such as universities, private companies, etc.) for the geospatial modeling component of this project? If yes, please describe what support they provided.

        iii. Has your agency noticed any improvements in your West Nile Virus surveillance and mitigation programs as a result of using geospatial modeling?

            1. Do you feel that your use of geospatial modeling has improved either the efficiency or cost-effectiveness of your WNV surveillance and/or mitigation program?

            2. Do you believe that your use of geospatial modeling has resulted in a decrease in the prevalence of West Nile Virus (mosquito, humans, etc.) in your area?

            3. Have you made any changes to your surveillance or mitigation strategies as a result of including geospatial modeling in this particular project?

b. If long-term (e.g. implemented use or program):

   i. Can you provide me with a more detailed explanation of how your agency has incorporated geospatial modeling for WNV into your surveillance and/or mitigation program(s)?

   ii. Did your agency receive support from any outside organization(s) (such as universities, private companies, etc.) for your geospatial modeling efforts? If yes, please describe what support they provided.

   iii. Has your agency noticed any improvements after using geospatial modeling for your West Nile Virus surveillance and mitigation?

   iv. Has your agency noticed any improvements in your West Nile Virus surveillance and mitigation programs as a result of using geospatial modeling?

      1. Do you feel that your use of geospatial modeling has improved either the efficiency or cost-effectiveness of your WNV surveillance and/or mitigation program?

      2. Do you believe that your use of geospatial modeling has resulted in a decrease in the prevalence of West Nile Virus (mosquito, humans, etc.) in your area?

      3. Have you made any changes to your surveillance or mitigation strategies as a result of including geospatial modeling in this particular project?

Geospatial Modeling Assessment and Evaluation Practices

a. Has your agency assessed or evaluated the impact of your geospatial modeling project/program for West Nile Virus on your surveillance or mitigation strategies?
    i. If yes:
        i. Was this assessment or evaluation either formal or quantitative?
        ii. Please describe who conducted the evaluation or assessment and what metrics if any they used to assess impact?
    ii. If no:
        i. Has your agency considered formally or quantitatively evaluating/assessing the impact of your geospatial modeling efforts on your WNV surveillance and/or mitigation program?
            1. If yes:
                a. What were you considered using as metrics to assess the impact?
                b. What were the barriers to conducting this evaluation?
            2. If no, would this be something your agency would be interested in? would you need assistance with this effort?

Helpful Documents

a. Do you have any suggestions about what information would be helpful to other practitioners who are considering implementation of geospatial modeling into their WNV surveillance and/or mitigation program?

b. What do you think is the most effective way to communicate this information to practitioners? (e.g., report, workshop, webinar, etc.)