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Meteorological Determinants Of Mosquito Populations In Connecticut

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Abstract:

As climate change continues at an alarming rate, it is important to quantify and characterize its wide-ranging impacts at both the global and more localized scales. This study aims to build on this body of evidence that details the local impacts of climate change that have already begun to and will increasingly harm human health. The study explores time trends in Connecticut's mosquito abundance, as well as potential meteorological determinants of abundance for one key species. Secondary analysis using computational techniques was performed on mosquito abundance data provided by the Connecticut Agricultural Experiment Station (CAES). Simple linear regression was performed on 27 mosquito species connected to viruses that cause human disease in the state of Connecticut. It was determined that the population sizes of 12 mosquito species are increasing in the state while 2 appear to be decreasing. The *Culex pipiens* mosquito was selected *a priori* for further analysis because of its strong connection to West Nile Virus in the state. A multiple linear regression model with an autoregressive time series function to control for temporal correlation between collected mosquito counts from year to year was fit and evaluated. This study concludes that the abundance of the *Cx. pipiens* is positively associated with both temperature and precipitation variables. As climate change continues to warm our planet and have impacts such as higher yearly temperatures and heavier rainfall, we can expect the abundance of certain mosquitos species to increase in Connecticut.

Table of Contents

List of Figures:

List of Tables:

INTRODUCTION

Climate change and all efforts to comprehend the burden its consequences will impose is an inherently interdisciplinary discourse that demands research at all points of intersection. This particular study aims to address the intersection between climate change and health focused on changing environmental conditions and the potential for the spread of disease. It begins with an examination of changes in mosquito abundance for species related to health in the state of Connecticut and then explores the impact of meteorological variables on the abundance of the selected *Culex pipiens* species. This analysis sheds light on how meteorological determinants associated with a changing climate can create conditions that result in a greater abundance of mosquitos, thus increasing the potential for the spread of vector borne diseases.

Surveillance programs, such as the Mosquito Management Program in Connecticut, are integral components of state level public health programs. The surveillance data and accompanying analyses are used to determine the need for public health interventions as well as evaluate the effectiveness of existing programs. However, research in this field further contributes to a better understanding of the severity of climate change and its associated consequences. In a general sense, there is no shortage of information or lack of motivation for research on this subject. Scientists are in consensus that the planet is warming as a result of human activity bringing about changes that impact our health. Despite this work, though, there remains an impasse for the collective concrete steps needed to mitigate the warming of the climate globally and to reduce the adverse impacts of climate change through adaptation. As such, there is a need to study and detail the local, seemingly small-scale impacts that have already begun to and will increasingly harm human health. This study aims to build on this body of evidence through an exploration of the state of Connecticut's most important mosquito vectors.

The results presented here further pave the way for more in-depth modelling on the drivers of changes in mosquito abundance, virus isolations, and disease prevalence in Connecticut. It is critical to first work towards examining and quantifying any changes to vector abundance through an analysis of trends over time within selected species. Through the study of these particular vectors, researchers can further understand the scope of climate change and implications for harsher consequences in the areas they inhabit. Since the connection between climate change and its consequences, specifically when discussing health, can be difficult to clearly see, this research works to draw these connections more explicitly. As such, the complex realities of climate change are broken down into more understandable components that can guide adaptation efforts in the short term and inform long term solutions to a newer reality.

Background and Prior Studies

One of the most import health related impacts of climate change is the potential for increases in vector borne diseases. Mosquito abundance is one of the key factors that influences vectoral capacity and the basic reproductive rate for infections. A high abundance is also often a prelude to an epidemic (Roiz et al. 2014). Understanding the spread of vector borne diseases, though, must begin with the study of the vectors themselves. That is the primary objective of this study. Using measures of mosquito abundance is one way to demonstrate how climate change and health are interconnected as it reflects the extent to which changes in the environment impact human disease. Changing environmental conditions reflected through measured meteorological variables are embodied in the growth and decline of mosquito populations. Modeling these dynamics plays an important role in further understanding the transmission of mosquito-borne arboviruses (Walsh et al. 2008).

In order to understand how the populations of vectors themselves are being impacted in the face of changing environmental conditions, we can look to meteorological variables that reflect these changes. Temperature and precipitation, and various iterations of each of these variables, can achieve this goal. These are the primary weather-related measures that reflect the impact that climate change has on our environment. Furthermore, it has been demonstrated that both high temperatures and higher rainfall are positively associated with mosquito abundance (Roiz et al. 2014).

Studies have demonstrated that both off-season meteorological variables and variables during the same collection timeframe impact the population size of mosquitos. Warmer winter temperatures, as well as warmer temperatures in March and April independently, have been demonstrated to lead to larger summer populations, which aligns with the Connecticut Agricultural Experiment Station (CAES) collection season (Walsh et al. 2008). Additionally, extreme temperatures measures, such as in minimum and maximum, have also demonstrated an impact on mosquito abundance during collection season, particularly in the *Cx. pipiens* species (Paz and Albersheim 2008).

Documenting and further examining any changes occurring in the state of Connecticut will allow for more informed approaches to protecting public health. In addition to a greater understanding of how meteorological variables could impact the size of the mosquito population, it is also important to consider how an increased abundance may prompt mosquito control and environmental management efforts as well. While the connection between climate change, mosquito abundance, and disease transmission remains controversial, it is known that mosquito abundance is a key factor in disease transmission. This is of particular concern when considering the arboviruses that affect Connecticut.

With this in mind, understanding the overall changes within a state is an important first step in characterizing the potential harms faced. It is hypothesized that changing meteorological variables, such as variations of temperature and precipitation, leads to an increase in the collected counts of mosquito species reflecting a larger species population in the state resulting in conditions that foster increased infection of diseases that affect public health.

Prior studies in Connecticut that make use of the robust mosquito surveillance data from the CAES detail topics relating specifically to human health through the study of the viruses transmitted and mosquitos studied. Work has been done to properly communicate the usefulness of monitoring virus activity in the state through lab analysis of collected mosquitos and focused on vectors in relation to the viruses they carry (Armstrong et al. 2011; Armstrong, Andreadis, and Anderson 2015; Andreadis et al. 2004). However, the topic of climate change and its effect in the state has also recently been considered in relation to range expansion of the invasive species *Aedis albopticus*. The *Ae. Albopictus* is an important vector for viruses such as dengue (DENV), chikungunya (CHIKV), and Zika (ZIKV) (Armstrong et al. 2017). Its establishment in Connecticut due to changing environmental conditions has significant implications for what the effects of climate change may look like in this state. This study attributes warming winter temperatures to the expansion of the species into the northern limits of its range and establishes a baseline for monitoring this species as climate change and its impacts intensify.

Looking beyond the limits of the state, there have been a number of studies outside of Connecticut that have looked more generally at the impact of meteorological variables on mosquito abundance as well as studies that have connected an increased mosquito abundance to an increased mosquito infection rate (MIR) (Chaves et al. 2011). Studies that examine variations in mosquito abundance have worked to establish a set of common variables that are important to consider in explaining any changes in abundance. Among these are temperature and precipitation variables as discussed above (Reisen et al. 2010; 2008; Poh et al. 2019).

Researchers have relied on models to help understand the drivers of any observed changes in abundance of mosquito species. Studies have made use of mixed effects modelling and autoregressive time series modelling to avoid bias that may be introduced as a consequence of mosquito surveillance structure and temporal correlation (Yoo et al. 2015; Roiz et al. 2014). Much of the model-based research to predict changes in mosquito population size has relied on meteorological and environmental contributors in the time preceding trapping of mosquitos while other studies begin to look at off-season meteorological factors (Walsh et al. 2008). These studies demonstrate the need for additional research on different factors influencing important disease vectors.

METHODS

Mosquito Sampling and Data

The mosquito count data analyzed was provided by the CAES from active mosquito surveillance as part of the Connecticut Mosquito Management Program. CAES conducts active mosquito surveillance and virus testing yearly across the entire state of Connecticut and maintains an active database (Armstrong et al. 2019). Trapping begins in June and goes through October each year. Across the state, there are 92 trapping stations that are maintained with locations displayed in Figure 1 (“Map Mosquito Testing Sites 2018” n.d.). CAES maintains 91 of these with an additional site maintained by the US Navy in Groton. Trapping at these sites is set on a ten-day rotational basis. Sites are set up in both rural areas and urban/suburban sites. As such, sites range from permanent swamps and marsh areas to horse stables and neighborhood parks. There are three main trap types that are used in collection methods: the CO_2-baited CDC miniature light trap, the CDC gravid trap, and in certain locations the BG-Sentinel Trap (McMillan, Armstrong, and Andreadis 2020). This study relied on statewide data collected through such methods for the years 2001 to 2019.

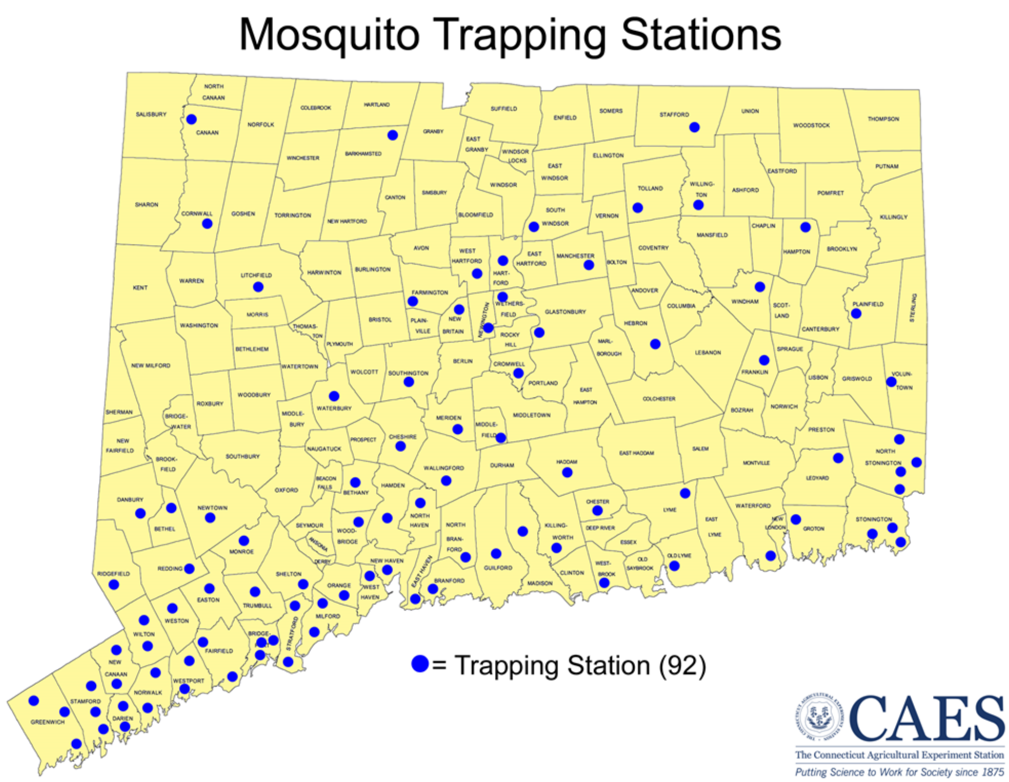

Figure 1: Mosquito Trapping Locations in Connecticut

Species Selection

Though CAES routinely collects 35 of the 52 known mosquito species in Connecticut, only 27 of these species were selected for analysis regarding time trends in abundance. These species were selected because they are known vectors of arboviruses that can result in human disease. These arboviruses are Cache Valley (CV), Eastern equine encephalitis (EEE), Jamestown

Canyon (JC), Trivittatus (TVT), Western equine encephalitis (WEE), and West Nile Virus (WNV) (Andreadis, Thomas, and Shepard 2005). Each species and isolated arboviruses are depicted in Table 1 below.

The *Cx. pipiens* was selected for further analysis in the development of an individual model to explain any changes in its abundance. Selection of this specific species was made *a priori* because of its strong connection to WNV, which was introduced to the United States in 1999. The *Cx. pipiens* is one of the species that accounts for the majority of WNV transmission in the Northeast United States (Hayes et al. 2005). In Connecticut, the preponderance of mosquito WNV isolations are from the *Cx. pipiens (*Andreadis et al. 2004*)*. From the years 1999 to 2018, 70% of WNV isolations from mosquito pools have been the *Cx. pipiens* (Armstrong et al. 2019). It is further important to note that the abundance of competent mosquitoes and the prevalence of infection in mosquitoes are the primary factors that determine the intensity of WNV transmission further highlighting the importance of the population size of the *Cx. pipiens* in Connecticut (Hayes et al. 2005).

Species Name:	**Arbovirus Isolation:**
Aedes cinereus	CV, EEE, JC, WNV
Aedes vexans	CV, EEE, JC, WNV
Anopholes punctipennis	CV, EEE, JC, TVT, WNV
Anopholes quadrimaculatus	CV, EEE, WNV
Anopholes walkeri	CV, EEE, JC, WNV
Coquillettidia perturbans	CV, EEE, JC, TVT, WNV
Culex pipiens	EEE, WNV
Culex restuans	EEE, JC, WNV
Culex salinarius	EEE, WNV
Culex territans	EEE
Culiseta melanura	CV, EEE, WEE, WNV
Culiseta morsitans	EEE
Ochlerotatus abserratus	JC
Ochlerotatus aurifer	JC
Ochlerotatus canadensis	CV, EEE, JC, WNV
Ochlerotatus cantator	CV, EEE, JC, WNV
Ochlerotatus communis	JC
Ochlerotatus excrucians	JC
Ochlerotatus provocans	JC
Ochlerotatus sollicitans	CV, EEE, JC
Ochlerotatus strictus	CV, EEE, JC, TVT, WNV
Ochlerotatus stimulans	JC
Ochlerotatus taeniorhynchus	CV, EEE, JC, WNV
Ochlerotatus triseriatus	CV, EEE, JC, WNV
Ochlerotatus trivattatus	CV, EEE, JC, TVT, WNV
Psorophora ferox	CV, EEE, JC, TVT, WNV
Uranotaenia sapphirina	EEE, WNV

Table 1: Species Selected and Arboviruses Isolated

Meteorological Variables

Publicly available meteorological data used as explanatory variables in model building was downloaded and cleaned from NOAA Northeast Regional Climate Centers Applied Climate Information System (http://scacis.rcc-acis.org/). Station data are interpolated and made available on a county basis making use of the Natural Neighbor Method (ESRI n.d.). The variables downloaded were monthly values for each county during the years 2000 to 2019 for average daily temperature and average daily precipitation, the maximum and minimum recorded temperature, and the number of days that over one inch of precipitation was recorded. Values from 2000 were used to account for the 1-6 month lag transformations for the year 2001 to each variable. Variable names and details for downloaded and derived variables are depicted in Table 2.

Variable:	Explanation:
1. Average Temperature	Monthly averaged daily temperature (to 0.1 degree F)
Average Winter Temperature	Average of monthly averaged daily temperatures for winter months December through March
Average Temperature with Lags	Average Temperature lagged by 1,2,3,4,5, and 6 months
2. Average Precipitation	Monthly averaged daily precipitation (to 0.01 inch) for the 24 hours
Average Precipitation with Lag	Average Precipitation lagged by 1,2,3,4,5, and 6 months
3. Maximum Temperature	Maximum recorded temperature per month (degree F)
Maximum Temperature with Lag	Maximum Temperature lagged by 1,2,3,4,5, and 6 months
4. Minimum Temperature	Minimum recorded temperature per month (degree F)
Minimum Temperature with Lag	Minimum Temperature lagged by 1,2,3,4,5, and 6 months
5. Precipitation > 1 Inch	Number of days per month with over 1 inch of recorded precipitation

Table 2: Meteorological Variables and Explanation

Dataset Compilation

Data from CAES were provided via separated Microsoft Excel files and downloaded and cleaned in R version 3.6.1 (2019-07-05). The original dataset contained 295,681 observations for all 27 mosquito species. The compiled datasets were cleaned to filter for months of active surveillance (only June through October) and remove data from stand-alone measures in months outside the collection season. Columns such as “Town”, “Trap Type”, and “Comments” were also removed for analysis in this thesis. Finally, aggregating counts by month for each year in each county of the state resulted in a final mosquito dataset that contained 13,569 observations. Additionally, the meteorological datasets obtained here were transformed into additional variables used in model building for predictive analysis (Table 2). All temperature and precipitation variables were lagged 1-6 months to account for the impact that prior months had on counts for the month in question. Additionally, the average temperatures for the months December through March were averaged together to create an “Average Winter Temperature” variable for each year. All meteorological variables and their transformations were merged into the mosquito count dataset matched by year and county to create a complete dataset for further analysis. Analysis of each species was completed by sub-setting each species from the complete dataset.

Statistical Analysis

Mosquito counts for each individual species of interest, 27 in total, were plotted against the year collected from 2001 to 2019. A simple linear regression was fit and this line was superimposed on all graphs to visually represent the trend and assess its general direction over the 19-year period. The response variable that is mosquito counts represents the number of mosquitos of that species that were collected and identified from all traps aggregated across all counties in the state. County level mosquito counts were examined for any variation in the number of mosquitos collected but all species were plotted on a statewide basis. Regression results for each species were compiled into a table displaying the coefficient, standard error, and p-value.

A multiple linear regression model with an autoregressive time series function to control for temporal correlation between collected mosquito counts from year to year was fit and evaluated for the species *Cx. pipiens* (Harrell, Jr. 2015). The response variable, *Cx. pipiens* counts, was natural-log transformed and predictors tested to develop a final model were the county-specific meteorological variables as well as various iterations of each of these including the average winter temperature and 1-6 month lags on each variable. The procedure for model selection was based upon improvement to the Akaike Information Criterion (AIC) using a combination of forwards and backwards stepwise selection processes. The initial model tested included Year, Month, and County as predictor variables and adjusted for temporal correlation of repeated measurements. Through a backwards selection process with only these variables, it was determined that Year should be removed. To this model, the forwards element of the stepwise selection process was introduced where one variable group at a time was added. Then, through a backwards stepwise elimination process, the variable(s) within that variable group that improved the model most were selected. There are five total variable groups as identified in Table 2. If more than one variable from each group was beneficial to the model, all were included. To this model, the next variable group was added and the process was repeated until the most predictive iterations of each variable group was selected from each variable group.

A near-final version of the model included three different precipitation measures: average precipitation for the current month, average precipitation for the month prior, and average precipitation from two months prior. We then tested the effect of simplifying this model by combining these three variables into a singular 3-month average. This model was selected as the final model due to having the lowest AIC and its relative parsimony. All coefficients were statistically significant. The model was verified for normality and homoscedasticity through the inspection of a residuals versus normal quantile and fitted values plots. All data management, analysis, and plots were created in R.

RESULTS & DISCUSSION

Time Trend Analysis in All Selected Species

Results from the simple linear regressions performed on the 27 selected mosquito species to explore time trends in population size are displayed in Table 3. Each species is listed with the results of the linear regression (coefficient, standard error, and p-value). Also listed is the total count of mosquitos collected through trapping from 2001 to 2019 to help illustrate the magnitude of estimated change in each species' abundance. There is a statistically significant association between mosquito counts and calendar time in 14 species, identified in bold.

Species Name:	Coefficient	Standard Error	P-Value	Total Mosquitos Collected
Aedes cinereus	1.98	3.61	0.58	255417
Aedes vexans	9.94	8.36	0.23	436873
Anopholes punctipennis	**4.23**	**0.98**	**<0.001**	**72706**
Anopholes quadrimaculatus	**1.52**	**0.39**	**<0.001**	**16445**
Anopholes walkeri	**8.06**	**1.7**	**<0.001**	**65871**
Coquillettidia perturbans	**65.96**	**15.24**	**<0.001**	**832586**
Culex pipiens	**19.9**	**9.74**	**0.042**	**393770**
Culex restuans	**7.43**	**3.34**	**0.027**	**186583**
Culex salinarius	**35.6**	**8.36**	**<0.001**	**358979**
Culex territans	**0.28**	**0.09**	**0.0016**	**3226**
Culiseta melanura	**13.68**	**3.27**	**<0.001**	**227578**
Culiseta morsitans	-0.065	0.1	0.52	2519
Ochlerotatus abserratus	3.43	3.98	0.39	54955
Ochlerotatus aurifer	**10.93**	**4.33**	**0.012**	**62588**
Ochlerotatus canadensis	**34.49**	**15.69**	**0.028**	**630871**
Ochlerotatus cantator	3.4	3.41	0.32	74786
Ochlerotatus communis	-0.091	1.14	0.94	948
Ochlerotatus excrucians	0.53	0.59	0.37	12639
Ochlerotatus provocans	1.26	4.15	0.76	3031
Ochlerotatus sollicitans	-5.32	3.39	0.12	27986
Ochlerotatus strictus	**-13.12**	**5.48**	**0.017**	**83791**
Ochlerotatus stimulans	-1.24	1.13	0.27	28484
Ochlerotatus taeniorhynchus	25.55	22.46	0.26	182531
Ochlerotatus triseriatus	**-2.36**	**0.7**	**<0.001**	**44523**
Ochlerotatus trivattatus	-8.82	5.56	0.11	217995
Psorophora ferox	**12.85**	**5.54**	**0.021**	**170491**
Uranotaenia sapphirina	1.26	1.35	0.35	72070

Table 3: Simple Linear Regression Results

Of the species examined, 12 demonstrate a statistically significant positive association between mosquito counts and calendar time, indicating that the population size of that species is increasing. Only two species examined demonstrate a statistically significant negative association between mosquito counts and calendar time, indicating a declining abundance of that species.

The coefficients and standard errors quantify the extent to which the mosquito abundance is impacted over time. The population of mosquitos collected is estimated to increase or decrease by the value of the coefficient +/- the standard error each year. The *Cx. pipiens*, for example, is estimated to increase by a count of 19.90 +/- 9.74 each year. However, the greatest estimated increase in population is observed in the *Coquillettidia perturbans* at 65.96 +/- 15.24 mosquitos per year. Though this species also has the largest overall abundance of all species examined, an estimated change of such magnitude should prompt the consideration of consequences that could stem from this change. It is further important to note that the *Coquillettidia perturbans* is an important bridge vector for EEE and all other arboviruses related to human disease have been isolated from this species (Shepard 2019; Andreadis, Thomas, and Shepard 2005). Looking to the two species displaying a negative trend in abundance over time, the *Ochlerotatus strictus* species demonstrates the greatest estimated magnitude of decline with an overall abundance that is one of the largest in the state. The statewide time trends for both the *Coquillettidia perturbans* and the *Ochlerotatus strictus* are displayed in Figure 2 below.

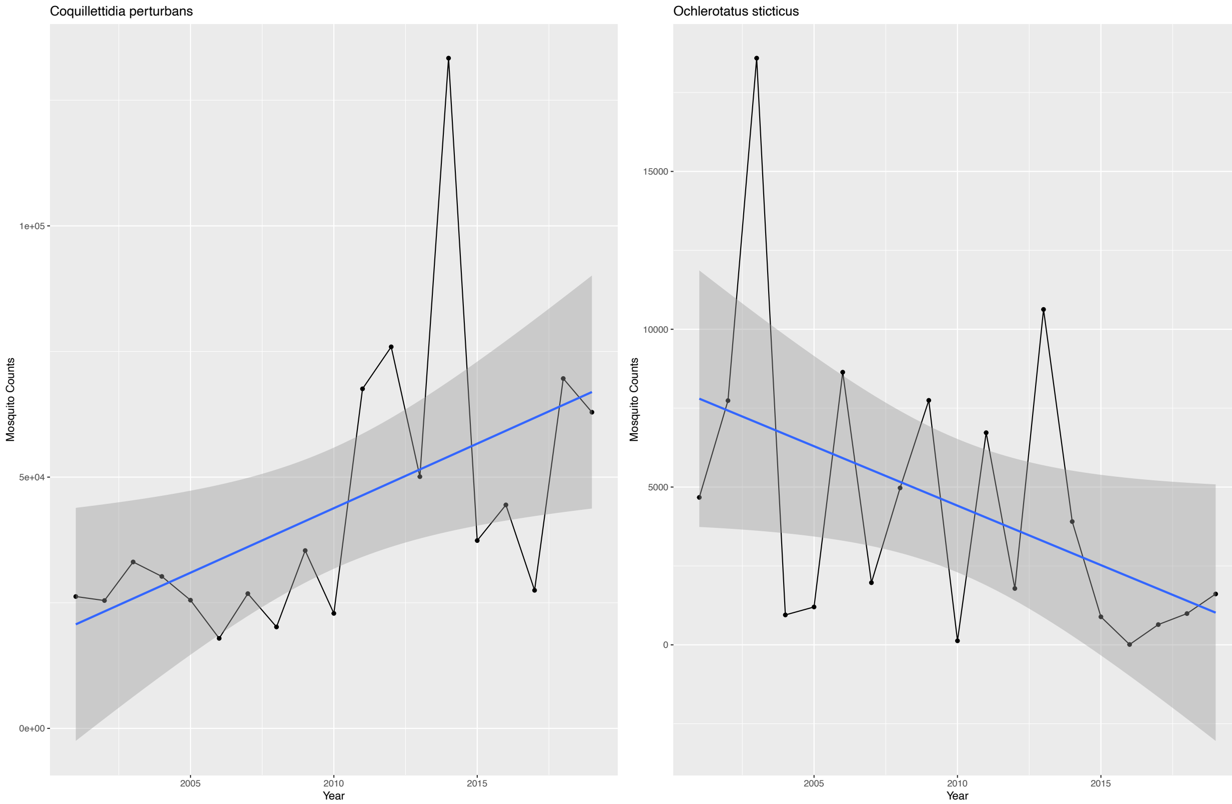

Figure 2: Coquillettidia perturbans and *Ochlerotatus strictus* Time Trends

Culex Pipiens Predictive Model

The results from the linear regression demonstrate that the abundance of the *Cx. pipiens* is estimated to be increasing over time. However, this predictive capability of the linear model is extremely limited in explaining this observed change. There are various factors to consider when examining the drivers of abundance for this species. As such, meteorological explanatory variables were introduced in a process of backwards and forwards stepwise selection to develop a final model that is a multiple linear regression. The covariates in the final model include the county variable and the following meteorological determinants: average temperature (of the same month), average winter temperature, maximum temperature recorded (of the same month), minimum recorded temperature (of the month prior), and the 3-month average daily precipitation (for the same month, the month prior, and two months prior). The natural log of the response variable, mosquito counts, was used in order to address skew in the data from differences in county to county measurements. All covariates, coefficients, standard error, and p-values are depicted below in Table 4.

This final model demonstrates that there is a statistically significant positive association between the number of *Cx. pipiens* mosquitos trapped and both temperature (each temperature variable) and precipitation. The coefficients are interpreted as follows. Each county coefficient represents the change in the natural log of mosquito count compared with Fairfield County. Since Fairfield county has the greatest number of mosquitos collected, every other county will have fewer counts, which explains the negative coefficients of the other counties. For all temperature variables, the coefficient reflects the magnitude of change in natural log of mosquito count per 1-degree Fahrenheit increase in temperature. Finally, the coefficient for the 3-month average daily precipitation is the change in natural log of mosquito count per 0.1-inch increase in average daily precipitation.

Covariates	Coefficients	Std.Error	P-Value
(Intercept)	-9.80	0.90	<0.001
County-Hartford	-1.60	0.28	<0.001
County-Litchfield	-5.11	0.29	<0.001
County-Middlesex	-3.83	0.28	<0.001
County-New Haven	-0.63	0.28	0.023
County-New London	-2.24	0.28	<0.001
County-Tolland	-4.55	0.28	<0.001
County-Windham	-4.34	0.28	<0.001
Average Temp	0.13	0.011	<0.001
Average Winter Temp	0.058	0.018	0.0016
Maximum Temp	0.046	0.013	0.00030
Minimum Temp	0.025	0.0056	<0.001
3 Month Average Precip	0.51	0.97	<0.001

Table 4: Culex Pipiens Regression Results

When interpreting the coefficients, it is important to note that the magnitudes of coefficients are not directly comparable and to consider the unit changes for each covariate associated with a change in mosquito counts. Thus, an increase of 1-degree Fahrenheit in temperature is not directly comparable to a 0.1-inch increase in precipitation. However, among the temperature variables, average temperature during the same month appears to have the greatest effect on *Cx. pipiens* abundance. The fact that the county variable remains in the model could simply reflect differences in the number or placement of trapping sites across counties or could indicate that there may be meteorological or other drivers of mosquito abundance within each county that are unaccounted for in this model.

CONCLUSION

Conclusions based on the study

Overall, this study concludes that the population sizes of 12 mosquito species that are vectors for viruses that cause human disease are increasing in the state of Connecticut while 2 appear to be decreasing. This discovery highlights the fact that there is a measurable change over time in abundance of various mosquito species in the state of Connecticut. Active surveillance and continued analysis of trends in mosquito abundance ought to continue.

More specifically, this study examined meteorological determinants of abundance of the *Cx. pipiens*. It is concluded that the observed increase in the *Cx. pipiens* counts is positively associated with temperature and precipitation. As such, we conclude that higher temperature and precipitation values are associated with a greater abundance of mosquitos. In a more general sense, the findings from this model support the conclusion that as climate change continues to warm our planet and have impacts such as higher yearly temperatures and heavier rainfall, we can expect the abundance of certain mosquitos species to increase in Connecticut.

Limitations of findings and other limitations of the study

While this study is exploratory in nature, it is important to consider the limitations in the study and its conclusions. First, the meteorological data used in the model is on a monthly basis. Weekly data would have aided in a more granular analysis and been more informative for a detailed winter months variable. Many of the previous studies that made use of temperature and precipitation variables demonstrated the impact of various iterations of a weekly temperature on mosquito populations (Paz and Albersheim 2008; Roiz et al. 2014; Walsh et al. 2008).

As already discussed above, the results from the simple linear regression are limited in their predictive capability. These results only demonstrate the trend over time as they do not account for any other predictor variables. However, they are still informative and can guide future studies that should include additional covariates not examined in this study. There are many factors in addition to the explanatory variables explored here that impact mosquito abundance in a state, such as humidity or landscape composition measures (Roiz et al. 2014; Chaves et al. 2011).

Finally, while this model selected demonstrated the best fit compared to other models tested in this study, the residual vs fitted values plots demonstrate slight heteroscedasticity as depicted below in Figure 3. This also calls on the need for additional explanatory variables to aid in the understanding of what is driving the changes observed in this species.

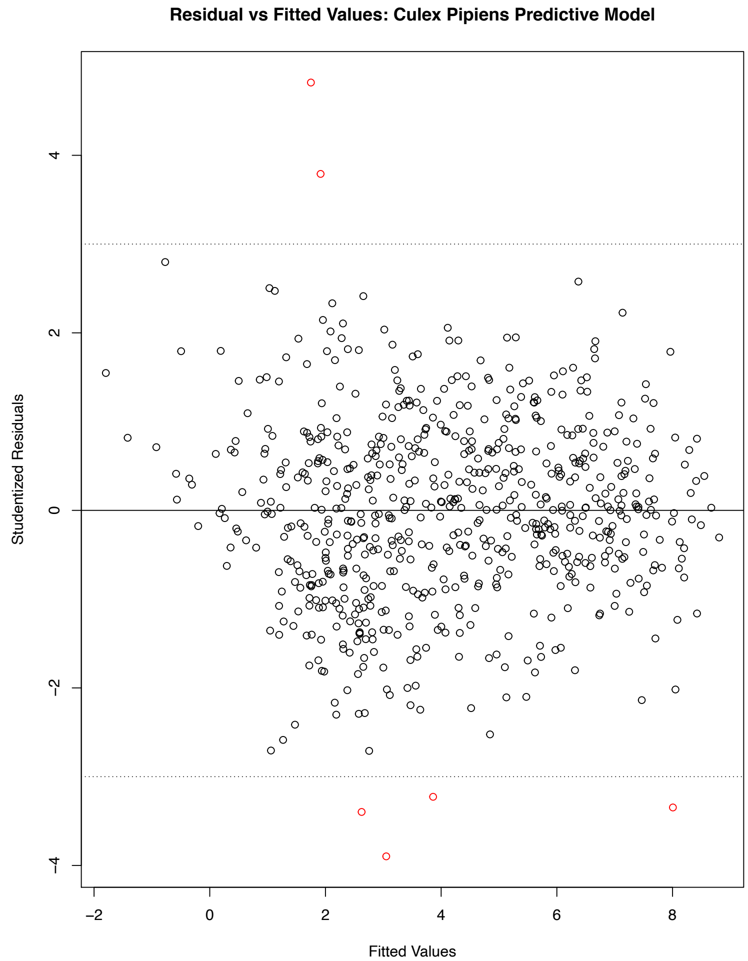

Figure 3: Culex Pipiens Model Residuals Plot

Future Directions

This study and its results lay the foundation for more in-depth analysis to be conducted on the *Cx. pipiens* as well as other species of interest in the state of Connecticut. As noted in the results, there are two species that appear to be declining in abundance over calendar time with statistical significance. Examining drivers of abundance of these species and then comparing with drivers of abundance of species with increasing trends (such as for *Cx. pipiens*) could yield greater insight on the impact of climate change on abundance of mosquitos connected to human health. Furthermore, species that showed a greater magnitude of change from the results of the simple linear regression (such as the *Coquillettidia perturbans*) ought to be examined to understand what is driving the observed changes. Other literature in this field further justifies this in demonstrating that the climate-mosquito abundance relationship is complex and species-specific (Roiz et al. 2014). As such, it is important to examine the impact of environmental and meteorological variables on different species in the state that are also important disease vectors.

The introduction of more complex explanatory variables that simultaneously account for scenarios such as a warmer winter followed by a wetter spring may also benefit the model. Meteorological variables considered in this model were all main effects. Interaction terms between covariates included in the model as well the introduction of new variables that address differences between counties may also improve the predictive capability of the *Cx. pipiens* model presented in this study.

Finally, while this study is centered on the idea of quantifying changes that could affect human health, examining the incidence of human disease in the state (such as WNV and EEE) in conjunction with changes in mosquito abundance would more directly establish this link.

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