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Effect of Climate Change on Lyme Disease Cases in 4 New Jersey Counties

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CHAPTER 1: INTRODUCTION

Vector-borne diseases occur when a living organism, known as a vector, transmits infectious pathogens to humans. According to the World Health Organization (WHO), vector-borne diseases account for more than 17% of infectious diseases worldwide. Lyme disease (LD) is a vector-borne disease which was first identified in 1977 when a group of people in Lyme, Connecticut reported uncommon arthritic symptoms. Today, LD is one of the most common reported vector-borne diseases. LD is caused by the bacterial spirochete Borrelia burgdorferi. The main vector of LD is Ixodes scapularis, otherwise known as the “black-legged tick”. This tick is predominantly found in the northeastern region of the United States.

Since its discovery more than 40 years ago, there has been an increasing occurrence of LD. Previous research has examined what factors may be causing this up-rise in Lyme cases. Multiple factors have been hypothesized for the increase in ticks. Studies have shown that environmental factors play an important role on the life cycle of ticks and therefore, with climate change such as increasing temperatures and humidity, comes changes in the life cycle of ticks. Due to the complexity of environmental changes as well as the life cycle of different tick species, the variety of factors that could influence the increase in LD can be different depending on tick species and region. Since LD is predominantly found in the northeast, analyzing the effects of climate change on different regions in the northeast would be warranted.

This study looked at different regions in the state of New Jersey. New Jersey has one of the highest reported number of annual LD cases. However, the number of reported LD cases differ depending on each New Jersey county. Therefore, this project aimed to investigate environmental factors and their possible effects on LD cases in different regions of the same state. Specifically, the purpose of this study was to compare counties with the most reported cases to other counties with the least reported cases and to evaluate whether certain extrinsic
factors, climate change and the ticks’ reservoir hosts, are affecting the different counties in the same manner.

The overall purpose of this study was to conduct exploratory analyses on the similarities and differences between four counties in a highly LD state. The study examined trends in annual temperature, precipitation, and deer populations. The white-tailed deer of North America is a known reservoir host of the *Ixodes* tick species and therefore, examining the possible association between LD and deer populations was included in this examination. The study also aimed to explore whether there is an association between these factors and reported LD cases and to test whether any association(s) between predictors and outcome is similar across each county.

LD is a public health concern because if left untreated, LD can cause chronic issues that can affect the joints, heart and the nervous system. With the rise of LD cases, using public health resources to help minimize the burdensome effects of LD is crucial. “Understanding when and where cases are most likely to occur is key to the efficient targeting of limited public health resources to times and places it will have most impact” (Eisen et al, 2016). Different counties within New Jersey may require tailored plans to reduce LD incidences.

**CHAPTER 2: BACKGROUND**

The Center for Disease Control (CDC) reported tickborne diseases reached record numbers in 2017. Tick populations and cases of LD are also expanding outside of the northeastern region of the United States. Ticks can also carry other bacteria other than *Borrelia burgdorferi* that can cause serious illness and even death. For this reason, increases in LD and other tick-borne diseases are a serious public health concern. However, the reasons for the expansion of LD and other tick-borne illnesses are not completely understood. Studies have shown that the cause behind the increase in tick-borne diseases appears to be a multi-faceted
problem. The life cycles of ticks are complex and dynamic and therefore, factors that affect these life cycles would also be considered complex and dynamic.

Research such as a review by Dantas-Torres, 2015 has suggested that there are a variety of factors that contribute to tick distribution and abundance. Some of these factors include “vegetation coverage, host availability, moisture and temperature conditions, photoperiod and human activities” (Dantas-Torres, 2015). Other research such as Süß et al, 2008 highlights the importance of humidity and temperature in the role in the life cycle of ticks. Specifically, an increase in temperature and humidity will lead to acceleration and longer duration of ticks’ life cycle. This would cause an increase in tick population and a shift in geographic areas where ticks will become more prominent. While there are a multitude of factors that contribute to tick distribution and abundance, there may be some factors such as humidity and temperature that play a bigger role.

A review by Odgen & Lindsay, 2016 focused more into the effects of climate and climate change on vectors and vector-borne diseases. The authors anticipate that certain aspects of climate change such as increasing temperatures, changes in precipitation, greater climate variability and extreme weather events may be key factors in driving the increase in vectors and vector-borne diseases. The authors review laboratory studies that show that survival of vectors depends on certain temperature zones, with too high or too low of temperatures increasing the vectors’ mortality rates. Furthermore, humidity affects the vectors’ host and/or meal seeking activities. Low humidity decreases such activities. The authors also point out that reproduction rates of vectors are influenced by the amount of rainfall. Too little or too much precipitation is associated with the vector’s reproduction rates.
In Moore et al 2014, the researchers looked further into the meteorological influences and aimed to show how climatic factors affect the seasonality of LD. The research showed how temperature affects tick population dynamics, specifically, that an increase in temperature positively affects the emergence of tick nymphs in spring.

The effects of meteorological influences on the seasonality of LD was further studied in Levi et al, 2015. The authors discuss the life cycle of *Ixodes* species and described how climate plays a role in the life cycle. The authors analyzed the effects of climate change on the peak activities of *Ixodes* species, specifically, the nymphal life stage because transmission of pathogens to humans occurs predominantly during nymph stage of the *Ixodes* life cycle. Results showed that climate warming was associated with timing of nymph peak activity that occurred 3.7 ± 1.5 days earlier. Model predictions suggest that there will be an increase in mean annual temperature by 2050 which could lead to an advancement in nymph activity by 8-11 days sooner. This research suggests that earlier activity could have public health impact because earlier activity will lead to earlier and longer time for ticks to transmit disease to humans.

A study by Subak, 2003 found that moisture levels two years prior to disease incidence were most significant. This study compared seven states with the highest reported annual LD incidences. When comparing each of the states, the study discovered that some states were more linked to temperature and LD incidences than other states. This would suggest that variations in weather and geographic location can affect states differently.

Dumic & Severnini, 2018 point out that certain temperature zones seem to be related to the number of LD cases whereas other temperatures were not significant in predicting number of cases. Their results showed that a sharp increase in cases occur when the annual temperature is 5-11°C, those with an average temperature of 5°C or below was not significant, and there was a
drop in the number of cases with a temperature 11°C or above. This suggests that there is a more specific temperature range that causes a proliferation in ticks. Temperatures that are too cold or too hot may be inversely related to the number of LD cases.

Süss et al, 2008 reviewed the effects of climate change on the developmental life cycle and expansion of ticks in Germany. The authors noted basic criteria that make a suitable environment for ticks, which are humidity >85%, temperatures between 6-7°C and competent blood hosts. In addition to these criteria, the authors noted the importance of certain ecosystems, specifically, the microclimate conditions of the tick’s habitat. Researchers used a statistical regional climate model to predict the future expansion and occurrence of tick-borne diseases in Germany. The authors conveyed the important aspect that an increase in temperature will surely cause an acceleration of the ticks’ developmental life cycle, an increase in egg production and population density.

However, Stone et al, 2017 suggests that land coverage is also an important factor in the drive behind tick expansion and abundance. While LD expansion has occurred throughout the United States, the authors looked at the different regions where LD expansion may be different due to certain factors. In the northeast, where LD is most prominent, expansion has quadrupled in the last decade. LD is also appearing in areas where just 10 years ago there were no cases, such as the Midwest. Modeling studies suggest that the Midwest has been traditionally too dry and possesses inadequate habitats for tick survival. However, in recent years, several tick-borne diseases have been detected. This review also outlined several factors that may be driving the expansion of LD. The ideal habitat of I. scapularis was traditionally viewed to be in deciduous and mixed forests in specific humidity and temperature zones. However, recent expansion has suggested that this habitat may not be the only habitat suitable for ticks’ life cycles. Other
habitats such as coniferous forests, grasslands and pastures may also be suitable for sustaining
the life cycle of *Ixodes* species.

Gern, Cadenas & Burri, 2008 further explains that land coverage may be an important
factor. This study assessed the effects of altitude, temperature and humidity on ticks’ questing
activities in two different regions in Switzerland. The study compared two different altitudes
where temperature and humidity differ. The study observed that tick questing activity was
highest at the region with the lowest altitude. The study also observed that tick questing activity
was affected by high saturation deficit since ticks need to actively absorb water from the
atmosphere. In areas with higher saturation deficits, ticks have to more frequently venture to
lower ground to rehydrate causing them to exhaust energy that they would otherwise use for
questing. Favorable saturation deficits are >5 mmHg with the most questing activity observed
between 2-7 mmHg.

The theory that ticks in different regions may be affected by factors differently is further
exposed in Eisen et al, 2016, where the study examined both *Ixodes scapularis* and *Ixodes
pacificus* tick species. *I. scapularis* is predominantly found in the northeastern part of United
States and *I. pacificus* is found predominantly in the western states. The study outlined the
climatic factors that affect the developmental life cycles of both species. The study also indicated
that *I. scapularis* and *I. pacificus*’ activities were dependent on specific temperature and
humidity ranges. This study also looked at how the impact of seasonality of ticks due to climate
variation affects disease transmission to humans and concluded that the least efficient
transmission happens when larval stages of ticks feed earlier in the year than their nymph
counterparts, suggesting that the more immature the ticks are earlier in the year, we see a decline
in efficient disease transmission. However, due to an increase in the number of nymph populations can lead to a greater source of infection.

Climate variation and the geographic location of ticks may also affect the tick’s behavior. A study by Tomkins et al, 2014 suggested that geographically separated *I. ricinus* populations have variation in their questing initiation. With the environmental threshold model, researchers were able to determine that there is a difference in ticks’ “switch point” in geographically separated ticks. This study also mentions that time is another factor when determining switch points. In other words, the temperature must reach a certain degree and stay at that level for a specific period of time before the tick initiates questing. Their study showed that ticks from cooler climates had initiated questing at lower temperatures compared to tick in warmer climates.

It is also pertinent to point out the complexities in ticks’ life cycles and its relationship with the complex life cycle of their reservoir hosts, specifically the white-footed mouse, *Peromyscus leucopus* and the white-tailed deer, *Odocoileus virginianus*. While the previous research mentioned above just looked at climatic variables’ effects on vector-borne diseases, climatic factors can also affect reservoir hosts. Research conducted by Roy-Dufresne et al, 2013 showed that climatic factors causing shorter milder winters in Quebec has caused a northward expansion of *P. leucopus*. The researchers projected that by 2050, the white-footed mouse will have expanded its geographic locations by 3° latitude. With the shifting northward distribution of the white-footed mouse, the study has shown the northward expansion of ticks.

Through previous research we see that certain factors such as humidity, temperature and reservoir hosts may all play important roles in the life cycle of tick species and thus the efficient transmission of tick-borne diseases to humans. We see that tick species located in the Midwest United States are affected by these factors differently than tick species located in the Northeast.
Research has also shown that even altitude can affect the ticks’ life cycles. However, there seems to be a gap in the research when it comes to comparing the different possible factors that affect ticks within closer areas of a highly endemic LD state. Are environmental factors affecting different areas of the same state in the same manner?

New Jersey is known to have one of the highest annual reported LD cases in the United States. However, from the more deciduous forested regions of the north to the salty dry beach regions of the south, one wonders if the tick populations are being affected by environmental factors to the same degree or in the same way. Some counties in New Jersey have reported annual LD cases in the hundreds but other counties only have reported annual LD cases in the teens. So, what makes this small state so diverse in the tick populations? Since the tick populations are already so diverse in such a small area, are the tick populations being affected by environmental factors in the same manner? Conducting research into such questions would be important for public health. If tick populations of two close areas are being affected by these factors in the same way then we will know that is important to begin building public health tick awareness and tick-borne disease prevention in areas where there may be less education and prevention plans currently.

**CHAPTER 3: DATA & METHODS**

This descriptive retrospective study looked at LD cases in four New Jersey counties between the years of 1997 to 2017. This quantitative study collected secondary data from public access sites. All LD cases collected were obtained from the New Jersey Department of Health’s official records. Meteorological data was secondary data obtained through the National Centers for Environmental Information (NCEI) by Rutgers University and the National Oceanic and
Atmospheric Association (NOAA). Population density was obtained for each county from the U.S. Census Bureau starting in 1997 to 2017.

The study human population was any reported cases of LD within four New Jersey counties in the United States. The four counties were Camden, Union, Hunterdon and Sussex, (Figure 1). The two counties with the highest annual incidence of LD cases were Hunterdon and Sussex County. The two counties with the lowest annual cases are Union and Camden County. The inclusion criteria were all residents (regardless of age, gender, race etc.) who tested positive for LD within the four counties. LD cases were collected for each county for two decades starting from 1997 to 2017.

Deer population data was obtained from New Jersey Division of Fish & Wildlife deer harvest reports, which reflect the annual number of deer collected by hunters per county. Since deer population is not an annually recorded statistic, annual deer harvest reports were used as an indirect measure of deer population, with higher counts of deer harvested as a surrogate for a
higher count of deer population. Total harvests were collected on an annual basis from 1997 to 2017 for each county.

The variables obtained in this study include temperature, precipitation, deer harvests, population, land area and deer harvests per square mile. The meteorological variables data included the average (TAVG), maximum (TMAX) and minimum (TMIN) temperature per county. Temperature was measured in degrees Fahrenheit (°F). Precipitation (PRCP) was collected for each county per year. Precipitation was measured in inches (in). Population density (POP) was measured by persons per square mile. Deer population (DEER) data was also a count measure reflecting that each deer harvest counted as one deer, deer population data was collected from 1997-2017 for each county. Each county’s land size (AREA) was collected and measured in square miles (miles²). Each county’s land size remained the same for all years between 1997-2017. Each county’s land size was included to calculate the rate of deer harvested per square mile (DEER_AREA) of each county per year.

The outcome variables used in this study were LD cases and rate of LD cases per 100,000 population. LD cases (LD_CASES) was a count measure reflecting that each case counted as one LD case. LD case rate (RATE) was calculated by the incidences of new cases per year per county divided by the total population at risk per year per county.

Descriptive data was performed to visualize each county’s variables and analyses were used to explore any similarities or differences between each of the four counties. Analysis of variance (ANOVA) with Tukey comparison was conducted to determine if there are significant differences in the variables among the four different counties.

Multiple linear regression was also used to evaluate the possible association between climatic factors and deer harvests on the incidence of LD cases using the RATE variable. Testing
for interactions was performed by dropping variables and re-running linear regression procedure. Correlation tests were conducted to test for collinearity among variables. An all-four counties regression model was conducted using all four counties combined and additional linear regressions were conducted for each of the counties in order to describe individual effects in each county.

CHAPTER 4: RESULTS

While precipitation is relatively similar across the region, temperature, LD cases and deer population widely vary between counties. Hunterdon and Sussex counties have a similar profile whereas Camden and Union counties are similar to each other. Both Camden and Union have higher overall temperatures per year than does Hunterdon and Sussex counties, (Figure 2). The descriptive data also shows that LD rates are widely different across Hunterdon and Sussex, but appear to be similar in Camden and Union counties, (Figure 3).

Descriptive data was further used to examine the two counties with the highest annual reported LD rates, Hunterdon and Sussex, and the two counties with the lowest annual reported LD rates, Camden and Union. Using the percent difference formula listed, there is a 30.68% LD rate difference, (Figure 4), and a 0.69% average temperature difference between the two decades in Hunterdon County (Figure 5). For Sussex county, we see a 61.15% difference in LD rates, (Figure 6), with an average temperature difference of 2.05% between the two decades, (Figure 7). We can compare these results with the two lowest LD incidence counties, Camden and Union. For Union county, we see a 97.00% LD rate difference (Figure 8), with a 1.20% average temperature difference between the two decades (Figure 9). For Camden county, we see an
126.96% LD difference, (Figure 10), with a 0.58% average temperature difference between the two decades, (Figure 11).

It was also important to note that the annual deer harvests per year for the last two decades has been on the decline for both Hunterdon and Sussex County but has remained relatively steady in both Union and Camden county, (Figure 12).
Figure 4: LD rates (LD cases/population x 100,000) per year in Hunterdon County, showing a 30.68% difference between the two decades.

Figure 5: Average temperate (°F) per year in Hunterdon County, showing a 0.69% average temperature difference between two decades.
Figure 6: LD rates (LD cases/population x 100,000) per year over 20 years in Sussex County, showing a 61.15% LD rate difference between two decades.

Figure 7: Average temperate (F°) per year in Sussex County, showing a 2.05% average temperature difference between two decades.
Figure 8: LD rates (LD cases/population x 100,000) per year in Union County, showing a 97.00% difference in LD rates between two decades.

Figure 9: Average temperate (F°) per year in Union County, showing a 1.20% average temperature difference between two decades.
Figure 10: LD rates (LD cases/population x 100,000) per year in Camden County, showing a 126.96% LD rate difference between two decades.

$$\frac{|3.76 - 16.83|}{\frac{(3.76 + 16.83)}{2}} \times 100$$
$$= \frac{|-13.07|}{\frac{20.59}{2}} \times 100$$
$$= \frac{13.07}{10.295} \times 100$$
$$= 1.26955 \times 100$$
$$= 126.955\% \text{ difference}$$

Figure 11: Average temperature (°F) per year in Camden County, showing a 0.58% average temperature difference between two decades.

$$\frac{|55.29 - 54.97|}{\frac{(55.29 + 54.97)}{2}} \times 100$$
$$= \frac{|0.32|}{\frac{110.26}{2}} \times 100$$
$$= \frac{0.32}{55.13} \times 100$$
$$= 0.00580446 \times 100$$
$$= 0.580446\% \text{ difference}$$
Running an Analysis of Variance, this study looked at the different variables and how they compare across each county. The ANOVA procedure suggests that the difference in precipitation among the four counties is not significant, (Figure 13), whereas the difference in average, maximum and minimum temperature, LD case rate and deer populations are all significant. A Tukey comparison test was performed to identify which counties were significantly different from the rest of the counties, (Figures 13-18).

Figure 12: Deer harvest rates (Deer harvest/mile²) per year in each county, over the last 20 years.
Figure 13: Comparison of precipitation (inches) records from 1997 to 2017 across four New Jersey counties.

Figure 14: Comparison of average temperature (°F) from 1997 to 2017 across four New Jersey counties.
Figure 15: Comparison of maximum temperature (°F) from 1997 to 2017 across four New Jersey counties.

Figure 16: Comparison of minimum temperature (°F) from 1997 to 2017 across four New Jersey counties.
Figure 17: Comparison of LD rate (LD cases/population x 100,000) from 1997 to 2017 across four New Jersey counties.

Figure 18: Comparison of deer harvests per land area (deer harvests/mile²) from 1997 to 2017 across four New Jersey counties.
A multiple linear regression model was run to investigate the possible relationship between the predictor variables and the outcome variable, LD case rate, with all four counties included. Based on diagnostic tests, there appeared to be some violations to the linear regression assumptions. Using Box-Cox analysis, the suggested data transformation for the model as a whole was by $\lambda = 0.25$ on LD case rate. After data transformation, the assumptions appear to be met and the linear regression shows that deer populations and average temperature are statistically significant in predicting LD case rate, see final model with diagnostics, (Figure 19).

A multiple linear regression was also performed for each county separately. For Hunterdon County, regression assumptions did not appear to be met. After data transformation (RATE by $\lambda = 0.25$), the final model showed only the deer population variable is statistically significant in predicting LD case rates, (Figure 20). When running a linear regression on Sussex county, no variable appears to be statistically significant. The linear regression model for Union County showed that only deer population is slightly statistically significant. The assumptions appeared to be met so no data transformations were performed. The final model for Union with just deer population as a predictor is below, (Figure 21). Camden’s linear regression shows that deer population is statistically significant predictor. The linear assumptions appear to be met so no data transformation was performed. Removing all non-significant predictors, the final model is as follows, (Figure 22).
Figure 19: All counties final multiple linear regression model of significant predictors affecting LD rates.

Figure 20: Hunterdon County's linear regression model with diagnostics of DEER_AREA (deer/mile\(^2\)) affecting RATE (LD cases/population x 100,000).
Figure 21: Union County’s linear regression model with diagnostics of DEER AREA (deer/mile^2) affecting RATE (LD cases/population x 100,000).

Figure 22: Camden County’s linear regression model with diagnostics of DEER AREA (deer/mile^2) affecting RATE (LD cases/population x 100,000).
CHAPTER 5 DISCUSSION

Certain locations seem to have higher incidences of vector-borne diseases than others. LD is a serious vector-borne disease found mostly in the northeast United States. Previous research has explored the associations between certain environmental factors on the incidences of LD. Previous research has shown that certain factors can affect LD rates differently in each northeastern state but there is a gap in research when examining LD cases within the same state. This study aimed to narrow in on one state and compare LD rates by each county. In New Jersey, there are some counties that highly contribute to New Jersey’s overall LD rate statistics while other counties contribute very little. This study compared four counties of New Jersey, two counties with the highest annual incidences of LD and two counties with the lowest annual incidences of LD. The study explored the differences and similarities on LD rates between the four counties and aimed to identify a common association between certain predictor variables and LD rates.

Descriptive data was utilized to visualize the differences in variables between each county. Camden and Union county appear to have similar climatic patterns and deer harvests, whereas Hunterdon and Sussex appear to have similar temperature variables, but Hunterdon and Sussex differ significantly in deer harvests. It is also clear that the change in LD rates and average temperature over the last two decades are different in each county. Running an ANOVA procedure, we see that precipitation is not significantly different among the counties, but all other variables are significantly different. In particular, average temperature and LD rates are similar between Union and Camden, but Sussex and Hunterdon are statistically different. When it comes to maximum temperature, only Sussex county is significantly different. With minimum temperature, Camden and Hunterdon are similar, Hunterdon and Sussex are similar, and Union and Camden are similar. Lastly, deer population is significantly different between all four
counties. This suggests that even though each county is from the same high LD incident state, environmental factors within each state differ by different degrees.

A multiple linear regression was performed to see if there is an overall association between these variables and LD rates. The all-four counties linear regression model suggests that deer population and average temperature are significantly associated with LD rate; individual county linear regressions in three counties (Hunterdon, Sussex and Union) suggest that deer population may drive this finding. However, individual regressions do not show that average temperature is significant in predicting Lyme rates. There could be a variety of reasons of why this could be but the most obvious reason could be simply that p-values can be affected by sample size as Dahiru, T. 2008 points out “the larger the sample the more likely a difference to be detected”. Combining all four counties’ data could be causing the detection that average temperature has significance. Individual effect size of each county may also be an explanation of why there is a difference between the all-county model and individual each county model.

Based on the data collected, we see that each county has different climatic factors and deer populations. Overall, using the all-four counties model to predict LD rates from climatic factors and deer harvests does not appear to be a good fit. Each county has its own special attributes that add to the complex life cycles of ticks and their reservoir hosts which all affect transmission of LD differently. As Gern, Cadenas & Burri, 2008 pointed out, different regions with different climatic and geographic factors is enough to apply evolution pressure on ticks to react differently to these factors. This research suggests that even close, nearby regions may possess differently evolved tick populations that react differently to environmental factors. Therefore, a slight temperature increase in southern Camden county New Jersey will have a
different effect on the ticks in its own region compared to the temperature increase in a more northern county like Sussex.

It is also important to point out that there were only some climatic factors included in this research. When reviewing Subak, 2003 we see that climate factors of previous years may play a role in the number of LD cases one to two years later. Furthermore, the study found that humidity was a main significant predictor on Lyme rates. Adding humidity as a climatic factor may have been warranted in this research. However, humidity was not a recorded historical data found in per county regions and therefore was a limitation in this study.

This study also did not account for another reservoir host that plays an important role in the life cycle of the black-legged tick; that is, Peromyscus leucopus and Peromyscus maniculatus, otherwise known as the white-footed mouse of North America. As Roy-Dufresne et al, 2013 points out in their research study, the increase in temperature has caused the P. leucopus species to expand northward in Canada. This study found that the northward expansion of P. leucopus has caused ticks to “hitch a ride” up north with them and in turn has caused a northward expansion of LD cases. Perhaps the ticks themselves are being affected by some climate change variables that impact the ticks’ ability to quest (Süss et al, 2008, Odgen & Lindsay, 2016, Dumic & Severnini, 2018, Eisen et al, 2016 and Gern, Cadenas & Burri, 2008) however, the reservoir hosts could also be affected by these climate change factors which indirectly affect ticks’ ability to transmit diseases onto humans. Ticks’ geographic expansion could also be explained by the geographic expansion of the tick’s reservoir hosts. Further research into other reservoir hosts and their role in LD transmission should be explored.

Another limitation was the deer harvest variable because it may not be an entirely accurate estimation of deer population. Theories of how to take accurate deer population census
varies (Yamamura, K. et al, 2008, Patterson, B.R. & Power, V.A., 2002, Rosenberry, C.S., Diefenbach, D.R. & Wallingford, B.D., 2004, Grund, M.D. & Woolf, A., 2004). With the limited resources available on deer population, deer harvests were used for this study. Even though this study showed that deer population may affect Lyme rates, the exact relationship between deer population and Lyme rates may not be accurately defined in the linear regression models.

Another limitation of the deer harvest variable was in regards to the deer harvests reported in municipalities. Deer populations are not confined to one county and therefore, these reservoir hosts may be playing a role in different tick populations outside of municipality boundary lines. Overall, the complexities of these two reservoir hosts, white-footed mouse and white-tailed deer, shows just how complex evaluating ticks’ life cycles truly are.

Lastly, it is important to also mention the concept of medical influence. With the increase in LD over the last forty years has come an increase in public health awareness. More efficient testing and surveillance are becoming a standard in both prevention and detection of LD. This study did not take into account the improvement and changes in surveillance and diagnostics, but these may have affected the Lyme rate trends. A study conducted by Ertel, Nelson & Cartter in 2012, examined four different types of surveillance contributing to reported Lyme cases in Connecticut from 1996-2007. The study showed that reported cases were subject to variation depending on surveillance methods used and found that “changes in surveillance methods can cause changes in trends”. Changes in surveillance methods used to report LD cases in each four New Jersey counties was not included in this research but may have caused changes in LD trends.

This study showed that certain climate factors were not significant but deer populations may be significant in predicting Lyme rates in four New Jersey counties. Further progression of
this study would be to consider temperature and timing in the examination between the extrinsic factors and LD rates. Another progression to this study would be to evaluate all twenty-one counties within New Jersey. This would perhaps allow public health officials to gain a better understanding of why close tick populations may or may not be affected by environmental factors in the same way. By gaining a little more understanding on the niches of tick populations, public health officials may be able to more appropriately abate the growth in Lyme disease rates.

Although this study did not show statistically significant associations to most extrinsic factors examined in this study, we can still understand that each county, in the same high LD incident state, have their own attributes that may be contributing differently to the total amount of reported LD cases. Environmental factors could play a role differently in each region therefore, each county’s public health efforts may be more influential to reduce transmission of LD rather than whole state public health efforts. Each county may have their own unique group of tick populations residing in their county and thus, catered LD programs to each individual county could be more effective. One thing is clear, LD cases are on the rise and they will continue to rise. Public health efforts to increase awareness should continue and be strengthened to help improve prevention and early detection in these diseases.
References


Bibliography


Biography

Meredith Olson received her Bachelor of Science in Animal Science from Rutgers University. She is presently a Master of Public Health student in the Department of Epidemiology at the University of Nebraska Medical Center College of Public Health. Since March 2020, Meredith has been a part of the COVID-19 response efforts for the Hunterdon County Health Department in New Jersey. The COVID-19 response efforts include conducting case investigations and contact tracing as well being a Medical Reserve Corps volunteer. Meredith deeply values helping her community through her volunteer efforts at the Medical Reserve Corps and America’s Grow-a-Row. Her volunteer efforts had led her to pursue a degree in Public Health in hopes that she can do more to help the overall health and well-being of communities.
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EDUCATION

University of Nebraska Medical Center
Master of Public Health in Epidemiology
Cumulative GPA: 3.97

Rutgers University
Bachelor of Science in Pre-Veterinary Animal Science

Raritan Valley Community College
Associate of Science in Pre-Medical Science and Mathematics

PROFESSIONAL EXPERIENCE

Medical Reserve Corps volunteer
Hunterdon County Health Department
March 2020-Present
- Assisted county residents with COVID-19 FAQs, scheduled appointments for testing, vaccine point of distributions

COVID-19 Case Investigator/Contact Tracer
Hunterdon County Health Department
March 2020-Present
- Certified in contact tracing by John Hopkins University, conducted contact tracing and case investigations for Hunterdon County residents

Internship
Hunterdon County Health Department
September 2020-Present
- Created educational materials on COVID-19 FAQs, hurricane and shelter preparedness during a pandemic, COVID-19 school protocols and guidelines

CERTIFICATIONS/AWARDS

FEMA Incident Command System (ICS-100) certified
John Hopkins Certified in Contact Tracing
World Health Organization Global Outbreak and Alert Response Network (GOARN) Internship recipient