# Climate Change: A Ticking Lyme Bomb

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## ABSTRACT

Background

The most common vector-borne disease in the United States is Lyme disease. Its causative bacterium *Borrelia burgdorferi* uses the blacklegged tick as its vector. Each stage of the tick's lifecycle is dependent on ambient temperature and relative humidity. Indicators of climate change such as increasing temperature, rainfall, and extreme weather events may impact tick prevalence, leading to downstream changes in LD incidence. Prior national analyses have confirmed an association between climatic variables and LD incidence, but those analyses have yet to be repeated at the state level in Michigan. This study uses 20 years of county-level data to determine if increasing LD incidence in MI is associated with climate change.

Methods

Fixed-effects, longitudinal panel regression is used to model the relationship between LD and average temperatures, rainfall, and extreme weather events, using publicly available county-level data for MI.

Results

Higher population counties in MI have an inverted U-shaped positive relationship with average temperature and incidence, in line with national analyses. Counties with lower populations had significant positive relationships with incidence and extreme precipitation events. The state as a whole shows a significant negative relationship between extreme heat days and LD ($p<0.001$).

Conclusions

Increasing tick-borne illness is a significant public health concern, and results from this report support further analysis into climate change impacts on tick abundance, and tickborne illness incidence. Better understandings of these relationships will inform LD interventions targeted towards communities most impacted by climate change.

## Introduction

Lyme disease is the most common vector-borne disease in the United States.[1] The spirochete bacterium *Borrelia burgdorferi*, Lyme disease's causative agent, is transmitted to humans via its vector the blacklegged tick.[1,2] Approximately 30,000 cases of Lyme disease are reported nationally per year, but CDC estimates the true incidence up to 10x higher.[1,2] Lyme disease is characterized by three distinct stages, sometimes followed by a long-term postdrome syndrome.

The stages of infection are characterized as follows:[1,2]

i) Stage 1 is defined by localized *B. burgdorferi* skin infection at the site of the tick bite. A characteristic 'bullseye' rash develops around the bite, forming red rings which grow outwards over a period of days or weeks.
ii) Stage 2 begins when the infection disseminates and symptoms of systematic involvement such as fever, fatigue, malaise, and neurological problems can occur. In some instances, it may impact the cardiovascular system.

iii) Stage 3 is characterized as a persistent infection. Individuals develop episodes of significant pain and swelling in major joints, coined 'Lyme arthritis'. This may persist even if/when the infection is caught and treated with antibiotics.
iv) Post-Lyme disease syndrome may develop in individuals whose infection resolved without the use of antibiotics. Individuals may develop symptoms mimicking chronic fatigue syndrome or fibromyalgia, or other generalized neurological symptoms.

*B. burgdorferi*'s preferred hosts are wildlife mammalians such as deer and mice.[4] Humans are rarely bit enough to transmit the infection back into the tick – as such they are considered a dead-end host for the bacterium. Geographic land changes caused by human activity may have an impact on *B. burgdorferi* preferred-host habitats, leading to changes in tick abundance and further downstream changes in Lyme disease incidence.[2,3,4] In addition, each stage in the life cycle of the tick depends on ambient temperature and relative humidity.[4] According to the literature, ambient temperature increases tick survival and development.[4-5] Subsequently, seeking behavior of unfed ticks increases with relative humidity. As a consequence, an individual's risk of exposure to an infected tick may depend on climatic factors.[1,4-5]

National studies have found associations between indicators of our changing climate and the incidence of Lyme disease and other tick-borne illnesses.[5] State level analyses describing this relationship have yet to be done in Michigan. Lyme incidence is increasing in Michigan – the state reported 2,398 cases of Lyme disease between 2000-201, which equates to a 20-year incidence rate of 25 cases per 100k people per year.[6] According to CDC estimates, the true incidence could be as high as 250 cases per 100k people per year. In addition, the yearly Michigan Lyme incidence rates grew 20x higher in 2019 than in 2000.

Climate change is here. Temperatures in Michigan rose 2.3 degrees F between 1951 and 2017, and annual precipitation rose 14% in that same period.[7] Data from 2000-2019 show significant increases in extreme weather events alongside average rainfall.[8] The data fail, however, to show a significant change in temperature in the 20-year period. It may be that the study period is not sufficiently long enough to show the rising temperature in Michigan.

Analysis of Lyme disease incidence and climatic variables at the state level is a worthwhile endeavor.[3] Associations may lead to insight that could be used to inform public health interventions for the reduction of disease moving forward.[4-5] Changes in disease burden are among many complex impacts of our changing climate, impacts which disproportionately harm disadvantaged communities.[4,11] It is vitally important to understand these impacts – for instance, if the risk of infected tick exposure increases alongside the environmental changes of climate change, targeted public education campaigns must be developed for communities at risk. More funding will be required for such interventions moving forward.[11]

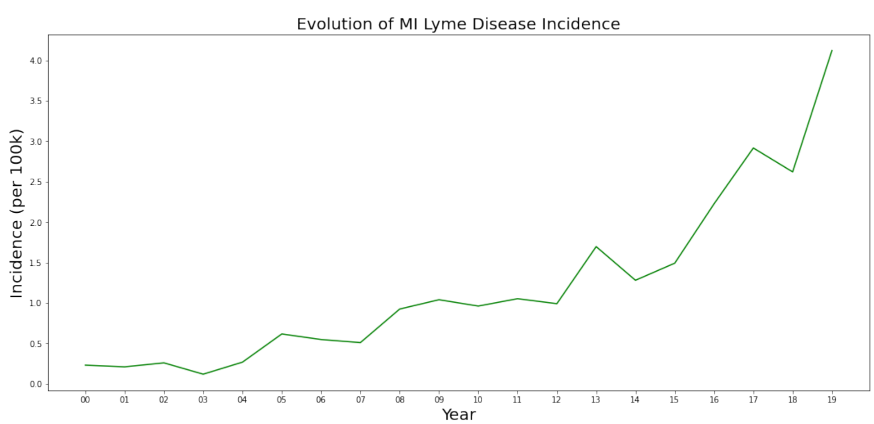


**Fig. 1**: The incidence rate of Lyme disease in Michigan is growing. Prior studies at the national level have shown associations between factors of a changing climate and increased rates of Lyme disease. Could this be occurring at the state level?

## Methods

This report will review results from standard fixed-effects panel regression modelling with climatic, geographic, population, and Lyme disease incidence data at the county level in Michigan between 2000-2019. Panel regression is a linear regression technique used with longitudinal data formatted into panel form.[5,9,10] Confounding caused by unmeasured characteristics of individual counties are controlled for with this technique, insofar as those traits are time-invariant.[5,9] The model takes the form:

$$\mathbf{Y_{it} = \beta C_{it} + \gamma Z_{it} + \mu_i + \theta_t + \varepsilon_{it}}$$ [4,5,10]

Where:

$\mathbf{Y}$ represents the outcome of interest (Lyme incidence) for county i and time t,
$\mathbf{\beta C_{it}}$ represents unobserved weather effects on climatic variables C,
$\mathbf{\gamma Z_{it}}$ represents common time trends,
$\mathbf{\mu_i}$ absorbs the unobserved effects of geographic characteristics for county i,
$\mathbf{\theta_t}$ absorbs common trends at time t, and
$\mathbf{\varepsilon_{it}}$ reflects error for county i and time t.

Data are controlled for changing forest coverage per county, as well as for geographic land-area. State results are reported, as well as results stratified by population. Average annual temperatures and rainfall are used as climate indicators, as well as annual extreme precipitation (absolute threshold over 1 inch) and extreme heat (over 90 deg F) days. These data were obtained from the MDHHS MiTracking program. Average monthly temperatures and total precipitation data were calculated from the NOAA National Centers for Environmental Information database. CDC provided the county-level Lyme disease incidence data via the NNDSS public use database. The CDC data was the limiting factor for the time period examined by this report, although data from years prior to 2000 are available upon request.

After all data were merged into a *pandas* dataframe, the climatic data were formatted into indicator bins of equal frequencies for the model – similar to the methodology in the national study.[5] Population data were also binned accordingly for the population level analyses and comparisons. Linear regressions of the four parameters against time were performed for each county using the *Leaspy* python library, and then combined to determine significant trends. Average rainfall, extreme heat days, and extreme precipitation days increased significantly over the twenty-year period. Notably, average temperatures of Michigan counties did not increase significantly in the studied timeframe.

Using the python library *linearmodels,* several panel regressions were run in order to determine the number of parameter bins for each variable that would create the best-fitting model. The models with four bins for each climate parameter performed the most reliably. Notably, splitting the population data into nine bins showed interesting differences between high and low population counties.

## Results

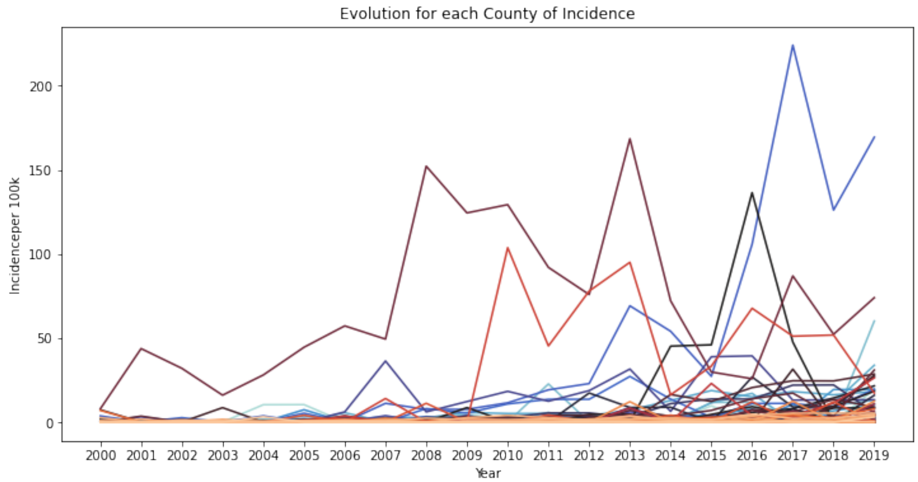


**Fig. 2**: Of the 83 counties in MI, 73 experienced increases in Lyme incidence.

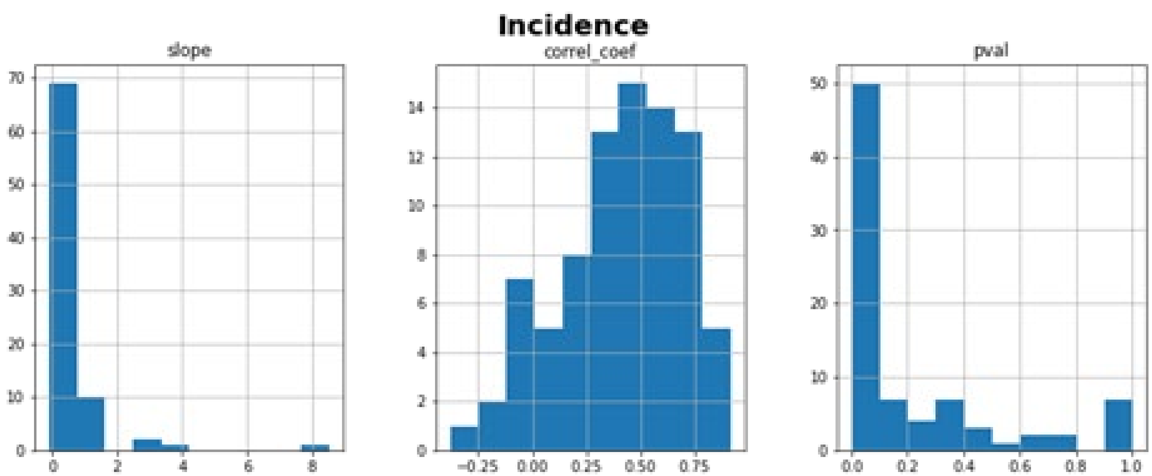


**Fig. 3**: Linear regression of each county's Lyme disease incidence against time

This report attempts to replicate results from the national study in which a positive relationship between Lyme incidence and average temperature was determined.[5] Indeed, higher population counties in Michigan (109k-208k) mirror the inverted u-shaped association between temperature and incidence seen at the national level. When compared to counties with average temperatures below 44 deg F, counties between 44–46 deg F saw an additional 2.2 cases of Lyme disease per 100,000 population. After this initial jump, however, the positive relationship declines down to 1.5 additional cases per 100,000 in the 46–48 deg F group, and then to 1.2 cases per 100,000 in counties with average temperatures over 48 deg F.

**Table 1**: Results of fixed-effects panel regression of Lyme incidence against binned climatic variables, of Michigan and of two population categories within Michigan.

| **Climate Change Indicators** | | **Overall** | | **Pop: 11k - 18k** | | **Pop: 109k-208k** | |
|---|---|---|---|---|---|---|---|
| | | Impact | P-value | Impact | P-value | Impact | P-value |
| Extreme Heat Days: | Reference < 10 days | 1.0 | 0 | 1.0 | 0 | 1.0 | 0 |
| Extreme Heat Days: | 10 -19 days | **-12.0 (-17.5,-6.5)**** | 0 | -1.5 (-13.8, 10.9) | 0.8163 | -0.4 (-1.1, 0.4) | 0.3541 |
| Extreme Heat Days: | 19 - 27 days | **-13.0 (-20.1, -5.9)**** | 0.0004 | 0.0 (-14.9, 15.0) | 0.9952 | -0.4 (-1.4, 0.7) | 0.4771 |
| Extreme Heat Days: | 27 - 58 days | **-13.5 (-21.6, -5.6)**** | 0.0009 | -3.2 (-20.3, 13.9) | 0.7113 | -1.0 (-2.1, 0.1) | 0.0883 |
| Extreme Precip. Days: | Reference < 3 Days | 1.0 | 0 | 1.0 | 0 | 1.0 | 0 |
| Extreme Precip. Days: | 3 - 4 days | 3.4 (-0.2, 7.1)* | 0.0631 | **7.8 (0.8, 14.7)**** | 0.0283 | 0.1 (-0.5, 0.8) | 0.7048 |
| Extreme Precip. Days: | 4 - 6 days | **3.7 (0.1, 7.2)**** | 0.0444 | **13.0 (5.3, 20.8)**** | 0.0011 | 0.5 (-0.1, 1.2) | 0.1112 |
| Extreme Precip. Days: | 6 - 13 days | **4.5 (0.2, 8.9)**** | 0.0425 | **13.9 (3.9, 23.9)**** | 0.0069 | 0.4 (-0.3, 1.1) | 0.2512 |
| Average Temperature: | Reference < 44 F | 1.0 | 0 | 1.0 | 0 | 1.0 | 0 |
| Average Temperature: | 44 - 46 F | -2.2 (-7.5, 3.1) | 0.4142 | -3.7 (-12.3, 4.8) | 0.3944 | 2.2 (-0.1, 4.5)* | 0.0562 |
| Average Temperature: | 46 - 48 F | -6.4 (-14.1, 1.3) | 0.1029 | -13.4 (-27.3, 0.5)* | 0.0588 | **1.5 (0.2, 2.8)**** | 0.0261 |
| Average Temperature: | 48 - 53 F | **-10.6 (-20.1, -0.3)**** | 0.044 | **-29.2 (-52.6, -5.7)**** | 0.0152 | **1.2 (0.1, 2.3)**** | 0.04 |
| Average Rainfall: | Reference < 2.6 in | 1.0 | 0 | 1.0 | 0 | 1.0 | 0 |
| Average Rainfall: | 2.6 - 2.9 in | 1.0 (-2.8, 4.9) | 0.5965 | -3.0 (-9.9, 4.0) | 0.4002 | -0.5 (-1.3, 0.3) | 0.2158 |
| Average Rainfall: | 2.9 - 3.2 in | 0.4 (-4.4, 5.2) | 0.8666 | -7.6, (-17.1, 1.9) | 0.1162 | -0.7 (-1.7, 0.3) | 0.1833 |
| Average Rainfall: | 3.2 - 4.2 in | 1.1 (-5.0, 7.2) | 0.7274 | -7.7 (-20.6, 5.2) | 0.2401 | -0.2 (-1.5, 1.1) | 0.7401 |
| | | R-square: 0.0215 | | R-square: 0.1425 | | R-square: 0.0933 | |

This pattern of impact may be explained by temperature influences on human behavior. As temperatures increase individuals spend more time outdoors, increasing their odds of infected tick exposure.[3,4] Outdoor activities decrease, however, as temperatures rise past a certain tolerable threshold.[4,5] The human element may also explain why counties with lower populations had decreased incidence rates as average temperature increased. Perhaps individuals living in those counties have different outdoor leisure hobbies, or perhaps they are more likely to utilize tick exposure reduction strategies.

Lower population counties (11k – 18k) were impacted more by frequencies of extreme precipitation days. This report uses extreme precipitation days and average monthly rainfall as proxies for humidity due to the difficulty of finding county level humidity data.[4,5] The strong positive relationship between extreme precipitation days and Lyme disease may be explained with the increase in 'seeking' behavior observed in unfed ticks within environments higher humidity environments.[4,5] This relationship is also seen at the whole-state level. Notably, average monthly rainfall had no impact on Lyme disease incidence.

The strong negative impact of extreme heat days on Lyme incidence in this reports results warrants further investigation. It could be that few ticks survive for extended periods of high heat. Perhaps extreme heat days are lower in relative humidity, making them a sort of negative proxy for humidity. It may be possible that extreme heat days have a significant negative impact on human outdoor activities. Future analyses may elucidate this relationship further.

## Discussions

The National Oceanic and Atmospheric Administration makes 100 years of weather data – down to the county-month level – publicly available. This report leaves significant room for further analyses of these data, and for further improvements on its regression model. The national study on which much of this report is based includes a quadratic variable alongside the linear parameters.[4,5] This is to account for trends which may change direction, such as varying funding expenditure patterns. Advanced panel regression modelling techniques, such as including nonlinear parameters, were outside the scope of this report due to limited time and resources. Advanced modelling could almost certainly improve this models r-squared and overall performance. The early and preliminary nature of this report supports the need for further analysis and model fine-tuning. Its results show significant promise for future studies.

## Conclusions

Tick-borne illness is steadily increasing at both the state and the national level.[1,2,3] In addition, climate change is now upon us.[8] As public health moves away from the prevention-only and towards the prevention *and* mitigation framework, it will be crucial to remain mindful of climate change and its disproportionate impacts on vulnerable communities.[11] Reports such as this are useful and important to tease apart many of the complex consequences of our changing climate, both present and future. Increasing risks of parasite exposure and infectious disease are not immediately apparent as downstream impacts of, for instance, summers with a few extra heavy rainfalls. The public health One Health perspective teaches us, however, that changes in one facet of nature almost certainly lead to changes in most other facets.

Disadvantaged communities suffer the most harm – and the earliest – from downstream impacts of climate change.[11] Armed with data from this report, public health practitioners in Michigan can develop tick-exposure risk management campaigns targeted towards communities most at risk of Lyme disease. One way to do this is to include seasonal tick forecasts on weather stations, based on climatic data paired with a more robust model than the one in this report. Programs which provide insect repellant alongside tick-check education pamphlets is another idea. Such interventions must be informed with sound scientific data. The data determined in this report are a good start for Michigan.

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