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EPPS 6356 Data Visualization Final Report

Climate Change and Crime: A Comparative Study between Texas and New York

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Introduction

Climate change refers to the change in the long-term weather conditions e.g., temperature, precipitation etc. of a place. Since the beginning of the century, changes in the climate have been discussed from global to local scale due to the ongoing rapid change in temperature. According to NOAA, during the second half of 2023, each of the months reached the hottest temperature recorded and it was also declared the hottest year ever recorded (NOAA, 2024). Some researchers have found correlations or likelihood in violent crime with high ambient temperatures (Trujillo & Howley 2021; Hsiang et al, 2013) while others explored the relationship between crime and precipitation (Ranson, 2014). Crime and precipitation portrayed a mixed relationship where some studies reported relationships between robberies and rain (Ranson, 2014). There is little doubt that the climate is changing. It could also be said that the crime rate is dynamic. There are a lot of factors that can influence the crime rate instead of natural phenomena e.g., the law enforcement, political conditions and so on. However, as established in previous research, natural phenomena also influence crime related activities of a place. Robert Agnew (2011) suggested that changing climate will facilitate social conflict and will help increase crime opportunities. According to him, climate change will be one of the major driving forces in the upcoming years. The purpose of this project is to explore the relationship between changing climate and the crime rate. The relationship between crime and climate change is not fully understood yet. To facilitate a better understanding of the relationship between climate change and crime, we picked two states in the United States of America of different climatic conditions. The climate data has been collected from the National Oceanic and Atmospheric Administration (NOAA) and the crime data has been collected from the Federal Bureau of Investigation (FBI) United Crime Rate (UCR).

Objective:

i. Explore the relationship between climate change and crime rate.
ii. Compare the relationship between climate change and crime for different climatic conditions.

Literature Review

There has been a lot of studies trying to address the existence of any relationship between climate or climate change with the level of crime, crime rate and occurrences of crime incidents. Despite the decrease in the global crime rate the researchers have found that crime and climate are related to each other. Most of them have found a positive relationship between temperature increase and the increase in violent crimes. Robert Agnew (2012) speculated that the changes in climate e.g., the rising temperature, the rising sea levels or extreme weather, the changing patterns of precipitation will lead to habitat change and have negative health effects on people. It will also contribute towards the food/water shortage, loss of livelihood, migration and social conflicts. All these can lead to increase strain, reduce control and social support and increase the opportunities of crime as well as social conflict and ultimately higher level of crimes.

i. **Crime forecast due to Climate Change**

Ranson (2014) forecasted that between 2010-2099, there will be an additional of 22, 000 murders and 1.2 million aggravated assaults because of climate change. Mares et al, (2019) suggests that for 1°C increase in the temperature, on an average the number of crimes will increase by 100,000 annually.

ii. Seasonality in Crime

Monthly temperature anomalies for warmer months are linked to higher number of homicides. In case of other crimes e.g., rape, the relationship is stronger with colder months.

iii. Climate Change-Temperature-Crime Hypothesis (CC-T-C)

Lynch et al, (2020) used the term in their article which refers to the concept that temperature and level of crime will increase which has been stressed by the green criminologists.

iv. Geographical Scope

These studies have covered several places across the globe. The scale of the studies also varies. Some researchers looked into this at a larger scale and others at a local scale. For example, Ranson (2014) studies the topic based on almost a continental scale. He studied 49 states of the continental Unites States at the county level (Ranson, 2014). Research showing the type of place e.g., urban or rural has also been conducted. Lynch et al, (2022) focused on 15 major cities in the US while Mares (2013) only focused on St. Louise. At a global level, many other countries have also addressed the issue. Australia, Taiwan, Beijing and Tangshan have also been targeted by some researchers to study the association between crime and climate change and/or extreme events (Churchill, 2023; Xiaofeng et al, 2017; Shen et al, 2020; Chin-Hsien et al, 2017).

Methodology

i. Study Area

The study area of this project is two prominent states in the continental United States of America with different characteristics. These are Texas and New York.

Rationale of the Choice

Texas and New York states are different from one another in several aspects e.g., land area, climate, population density, culture, economy etc. The pervious literature has established a connection between higher temperatures and violent crimes. Our objective is to explore that connection in different geographic and climatic settings. The purpose was to choose one state from warmer regions and another from colder regions. According to previous studies, warmer regions should have higher crime rates. Having higher annual average temperature than New York, Texas ranks 12th with a crime index of 1962 while New York ranks 41st (crime index: 1194) among all the states in the United States of America (USA.com, Accessed: Dec 2024). The previous hypothesis is upheld by these statistics. However, the level of association between climate change and crime as well as population as a factor in different climatic conditions is explored in this project.

Texas

The state of Texas is the second largest in the United States of America by population and land area. The total area of Texas is 268, 820 square miles (Bullock Texas State History Museum, Accessed: Dec, 2024). This means the state is more than 5 times in size than New Work. The average climate of Texas varies from humid marine to semi-arid savanna. Texas has been divided into 10 climate zones according to the National Climatic Data Center. The average temperature in this state ranges between 52°F to 68°F (Texas Water Development Board, 2012).

New York

Situated in the east coast of the United States, New York was its leading state till 1960 in almost all the indices (e.g., population, economic and cultural) (Brittanica, Accessed: Dec 2024). The state of New York comprises 49,576 square miles of land and water. The population of the state of New York is approximately 20.2 million (US Census Bureau, Accessed: Dec 2024). It is located between the latitudes of 42°N to 45°N and longitude of 73.5°W to 79.75°W. The elevation of 40% of the state is more than 1000 feet above sea level. The climate of the state can be distinguished as humid continental. The average annual temperature of the state ranges between 40°F to 55°F from Adirondacks to New York City area respectively. During summer the of 90°F can occur from May to mid-September.

ii. Data

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The analysis of this paper is based on a few different datasets with the goal being to measure the relation between climate and crime monthly between the years 1985 and 2023 for Texas and New York. These states were chosen as they are quite disparate in climate but still have large populations and major urban centers. The data for this comes from the Federal Bureau of Investigation (FBI) Unform Crime Reporting (UCR) dataset and the National Oceanic and Atmospheric Administration (NOAA), both of which report at the county and monthly level.

a) Crime

The FBI UCR is the major US crime data which contains monthly reports on crime dating back to 1985 or possibly to 1960s. These reports are submitted from monthly from participating agencies via two collection datasets, a) Summary Reporting System which was retired in 2021 and b) the National Incident-Based Reporting System (NIBRS) which replaced it. As of 2023, 95.2% of US law enforcement agencies (FBI) participate in the program covering approximately 94.3% of the US population. These agencies report 8 types of crime to the database divided into two categories. These being, violent crimes: aggravated assault, robbery, rape, and murder and property crimes: arson, larcen-theft, burglary, and motor vehicle theft. For those incidents where multiple offenses were committed that may fall into multiple types, only the most serious of the crimes are reported as part of the Hierarchy Rule (FBI).

b) Climate

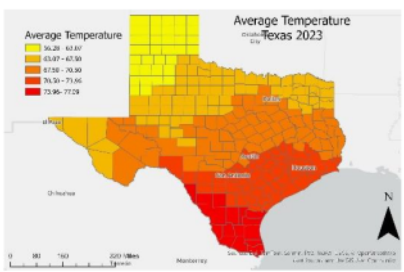
Regarding the weather data, this was gathered from NOAA, the main agency within the US for climate and weather data. This study uses two datasets gathered by NOAA, the main one being the US Climate dataset which contains monthly data by county for all of the US going back to 1960s. From this database, we drew data on average temperature, maximum temperature, minimum temperature, precipitation, cooling degree days, heating degree days, Palmer Drought Severity Index (PDSI), Palmer Hydrological Drought Index (PHDI), Palmer Modified Drought Index (PMDI), and the Palmer Z-index. The other being the Storm Events Database, containing records of severe weather events going back to 1950, these are recorded by the county affected, the damage incurred, and the dates of the beginning and end.

c) Population

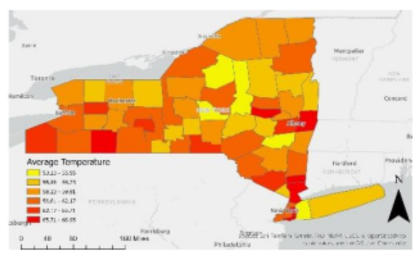
Annual Estimates of resident population data were collected from Census Bureau at county level for both Texas and New York for the corresponding years.

iii. Analysis

Exploratory Data Analysis



a



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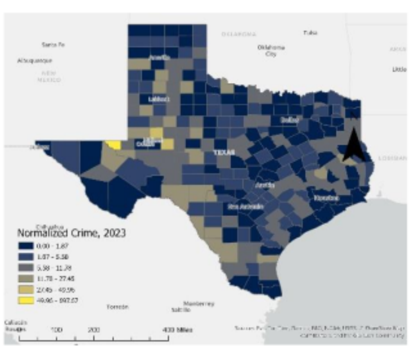

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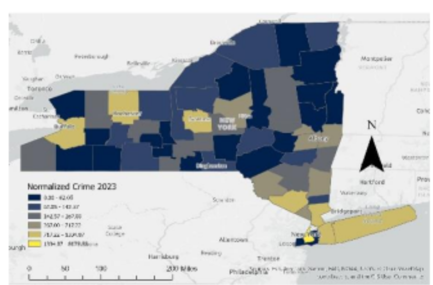

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Figure 1: Average Temperature and Normalized Crime Per 1000 in Texas and New York for the year 2023. a) Average temperature in Texas in 2023; b) Average temperature in New York in 2023 c) Normalized Crime in Texas in 2023 and d) Normalized Crime in New York in 2023.

According to the maps the average temperature in Texas ranged from 56º-77ºC while for the counties in New York, it ranged from 53º-68ºC. The spatial pattern in Texas is clearly visible with the counties in the south experiencing higher temperatures than northern parts of Texas. Spatial autocorrelation is visible in the map of Texas.

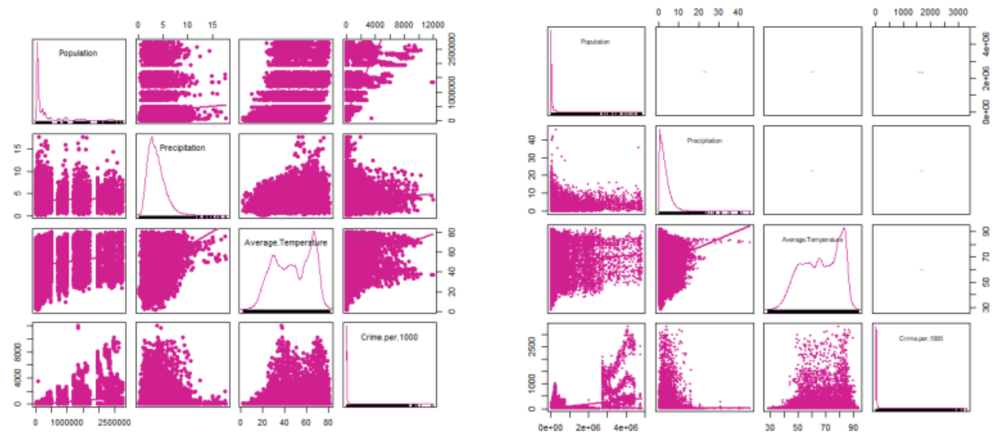
At first glance, counties in New York show a random pattern. The highest normalized crime per 1000 people in Texas is observed in three counties but it ranges from 49-700 while for New York, the normalized crime per 1000 people goes up to more than 8000 in 2023. The number of counties at the higher end is also more than the number of counties with high crime in Texas.

Table 1: The Average temperature, average crime per 1000 people and average population in New York and Texas

Decade	Average Temperature	Average Crime per 1000	Average Population	State
1980	46.29	122.05	288447	New York
1990	47.06	67.68	297794	New York
2000	47.30	69.23	308805	New York
2010	48.00	63.92	321834	New York
2020	49.04	30.35	319370	New York
1980	64.47	5.75	65299	Texas
1990	65.25	5.56	73896	Texas
2000	65.69	5.84	89551	Texas
2010	66.21	4.10	106705	Texas
2020	66.85	2.25	117450	Texas

Table 1 shows that the average crime per 1000 people has decreased even though the temperature has increased in both New York and Texas. The contrasting characteristics of Texas and New York, in case of climate and crime as well as the contrasting initial findings in our part are the reasons these two states were chosen.

Figure 2: Scatterplot matrix of population, precipitation, average temperature and crime per 1000 people in New York and Texas.



New York   Texas

The scatterplot matrix for New York and Texas do not show much information.

Choosing the Correct Model for Spatio-Temporal Data

The spatio-temporal data considers both space and time simultaneously. Creating models with this type of data could provide incorrect result in case of population data as the sample is one per location. To address this issue, Bayesian Hierarchical Model could be utilized. The Integrated Nested Laplace Approximation (INLA) has more computational efficiency than the traditional Markov Chain Monte Carlo (MCMC) method and it also decreases the time required for computation for Bayesian inference. It allows the utilization of hierarchical Bayesian methods which allows specifications for nested structures with spatio-temporal data.

There is great flexibility provided by the INLA in model ranges and the integration of it in R as the R-INLA can provide an accessible interface to researchers. This is also compatible with large datasets and the accuracy of the approximation is great.

Advantages of using Spatio-Temporal Data

One of the most important advantages of spatio-temporal data is that there is the presence of autocorrelation and that can help with estimating missing data as well as predictions. INLA can handle the missing data naturally while imputing data for unobserved locations. Disease mapping, environmental pollution monitoring and social science research has already seen application of real world spatio-temporal problems using INLA. The high-dimensional data with latent variables can also be made suitable for analysis by incorporating INLA.

Bayesian Modelling Approach using INLA

The spatio-temporal data has spatial and temporal autocorrelation that needs to be addressed. These are the advantages of Bayesian model that were taken into consideration for choosing a model.

- **Enhanced Predictive Modeling**

Leverages spatial and temporal autocorrelation to estimate missing data, improve predictions, and provide robust decision-making under uncertainty.

- **Explicit Uncertainty Modeling**

Bayesian approaches like INLA deliver credible intervals for predictions and insights into result reliability, ensuring transparency in uncertainty quantification.

- **Versatile Applications Across Fields**

Applicable to disease mapping, environmental monitoring, and social science research; INLA also manages high-dimensional data with latent variables, accommodating complex spatio-temporal challenges.

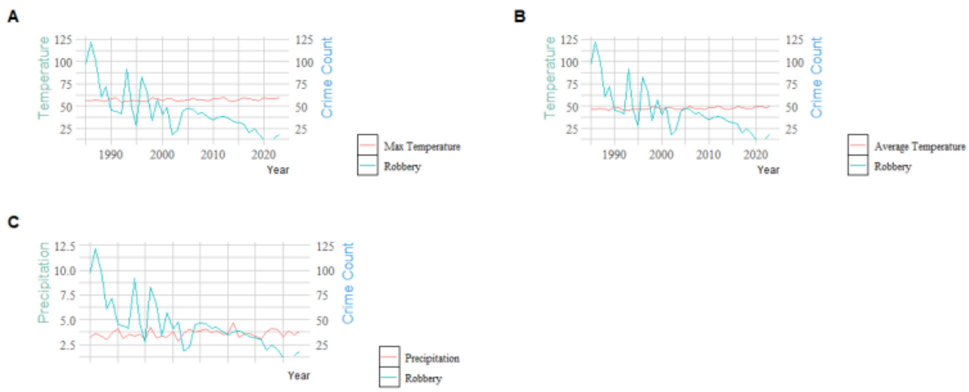
Results

Trend in Changes in Specific Crime and Climate Variables

Robbery

The total number of robberies went down drastically over the years, but the maximum and average temperature did not follow the same trend. Precipitation fluctuated a lot because of seasonality.

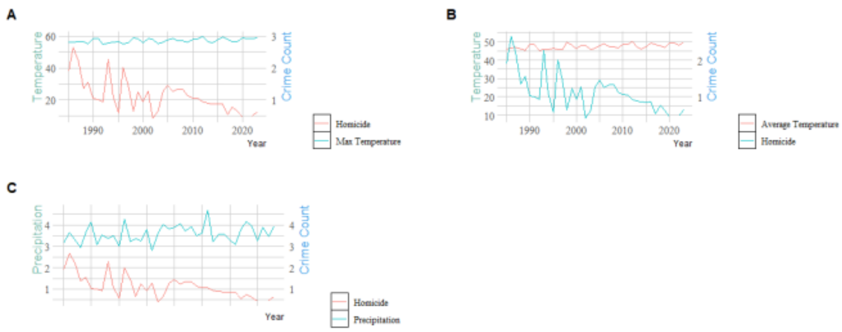
Figure 3: Trend in maximum temperature, average temperature, precipitation and robberies per 1000 people.



Homicide

The total number of homicides went down drastically over the years, but the maximum and average temperature did not follow the same trend. Precipitation fluctuated a lot because of seasonality.

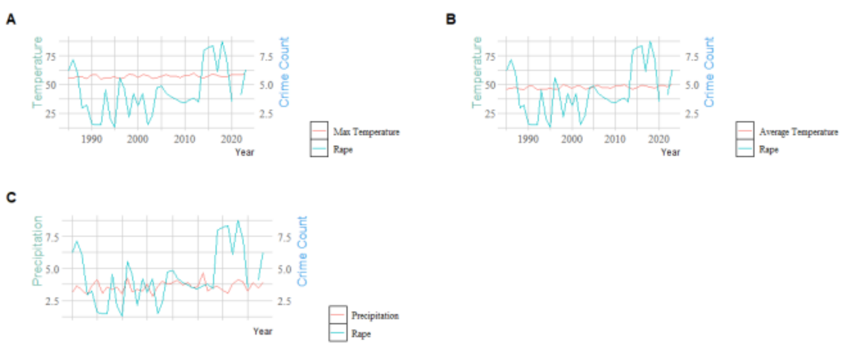
Figure 4: Trend in maximum temperature, average temperature, precipitation and homicide per 1000 people.



Rape

The total number of rapes went down drastically over the years, but the maximum and average temperature did not follow the same trend. Precipitation fluctuated a lot because of seasonality.

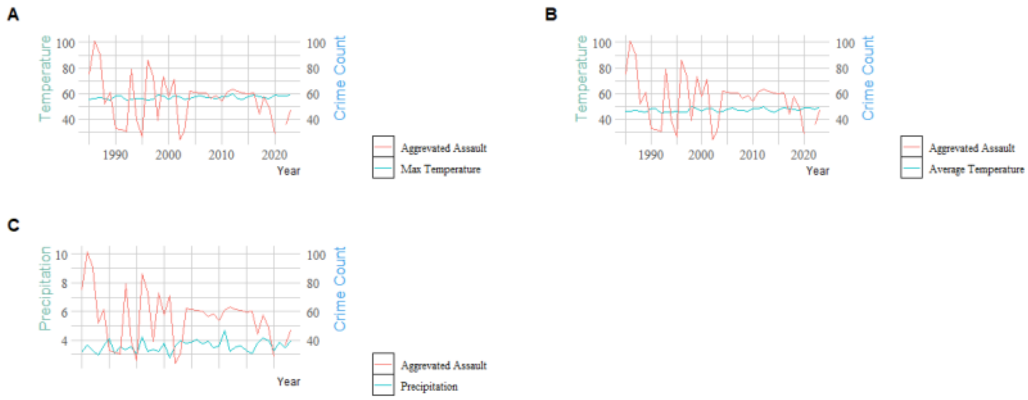
Figure 5: Trend in maximum temperature, average temperature, precipitation and rape per 1000 people.



Aggravated Assault

The total number of aggravated assaults went down drastically at the same time it fluctuated a lot over the years, but the maximum and average temperature did not follow the same trend. Precipitation fluctuated a lot because of seasonality.

Figure 6: Trend in maximum temperature, average temperature, precipitation and aggravated assault per 1000 people.



Comparison of the relationship between climate change and crime

- **Model variable settings**

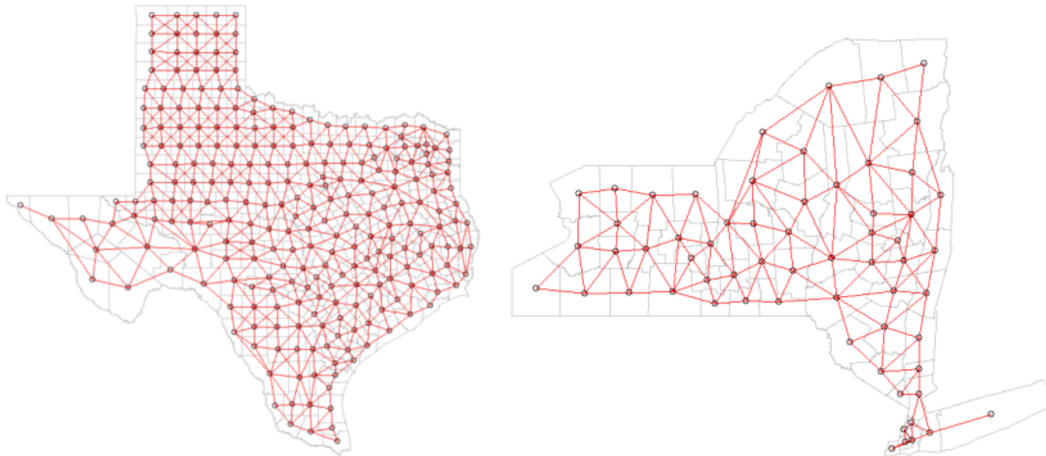
The table provides a detailed summary of variables used in a spatio-temporal analysis of monthly crime rates spanning from January 1985 to December 2023. The dependent variable is the monthly crime rate, log-transformed for normalization and expressed as events per 1,000 persons, making it suitable for statistical modeling and comparison across different contexts. The independent variables include multiple socio-environmental factors. The monthly mean temperature, measured in Fahrenheit, is included for the entire study period (1985–2023) to capture potential seasonal or climatic effects. The monthly unemployment rate, available from January 1990 to December 2023 and expressed as percentages, reflects economic conditions that may influence crime trends. Additionally, annual resident population density estimates, measured every July 1st from 1985 to 2023 in persons per square kilometer, provide insights into demographic influences on crime rates. The spatial component is defined through an adjacency matrix constructed using the queen contiguity method. This method accounts for spatial relationships by identifying neighbors based on both shared edges and corners of geographic units, with a binary representation (1 for adjacency, 0 for non-adjacency). This ensures the model captures spatial dependence accurately. The temporal component introduces an autoregressive structure to account for temporal dependencies in crime rates. Specifically, an autoregressive order of 1 is applied for Texas, while New York uses an order of 2, reflecting differences in temporal patterns and dynamics between the regions. This framework ensures a comprehensive integration of spatial, temporal, and contextual variables, enabling robust modeling of crime patterns over time and across geographic areas while addressing potential biases and dependencies inherent in spatio-temporal data.

To be specific, the variable average temperature, representing monthly mean temperature, is included to capture its influence on the crime rate. Similarly, the monthly unemployment rate is used to reflect the impact of economic conditions on crime trends. Additionally, annual population density in persons per square kilometer is included to account for demographic pressure.

Table. Variables and its properties

Parameter	Properties	Unit
Dependent	Monthly Crime rate from Jan 1985 to Dec 2023 (log transformed values)	Events per 1,000 persons
Independent	Monthly Mean temperature Jan 1985 to Dec 2023	Fahrenheit
	Monthly unemployment rate from Jan 1990 to Dec 2023	Percentage
	Annual estimates of resident population density on every July 1st from 1985 to 2023	Persons per sq. km
Spatial component	Adjacent matrix using queen method (define neighbors shared with edge and corners of its geographical shape	Binary
Temporal component	Autoregressive order 1 for Texas and 2 for New York	NA

Figure. Spatial structure of study area, Texas (left), New York (right)



- **Model parameter settings**

The fixed effects in the model include the intercept, which represents the baseline level of the dependent variable (log-transformed crime rate) across all observations. For random effects, the spatial component incorporates a spatial random effect using the Besag model. This spatial structure is based on an adjacency matrix that captures spatial autocorrelation by identifying neighbors through shared edges and corners (queen contiguity method). This approach ensures the model accounts for spatial dependencies in crime rates. The temporal component adds a temporal random effect modeled as an autoregressive process of order 1 (AR1) for Texas and order 2 (AR2) for New York, capturing temporal autocorrelation. This ensures that crime rates for a given period depend on values from the preceding period. Regarding data and family, the input dataset contains observations for counties in Texas and New York, structured in a long format suitable for spatio-temporal modeling. The Gaussian family is specified, assuming a normal distribution for the log-transformed crime rates, which is appropriate for continuous outcome variables. Finally, the control parameters configure the computation to enable posterior sampling and efficiently generate credible intervals for the model's estimates.

The parameters model used offer several strengths and features. It explicitly captures spatio-temporal dependencies. This enhances predictive accuracy and facilitates a more nuanced interpretation of underlying patterns. Through the use of a Bayesian hierarchical framework, the model leverages INLA for computationally efficient Bayesian inference, allowing for precise parameter estimates and credible intervals.

The model is highly flexible, capable of handling complex data structures and relationships, including cases with missing data, thanks to its hierarchical setup. Furthermore, it integrates fixed effects, such as monthly average temperature, monthly unemployment rate, and population density, to estimate global influences, while random effects capture localized variations and dependencies, ensuring a comprehensive and robust analysis. Also, these fixed effects enable the model to account for overarching trends and relationships while the random effects capture localized variations and dependencies. This combination ensures the model is well-suited for understanding both global and context-specific drivers of crime rates, with strengths in handling spatio-temporal complexities efficiently.

- **Model results for Texas**

Table. The results of four models with different independent variables for Texas

Model for crime rate	Model 1: Null	Model 2: Climate	Model3: Climate + Economic	Model 4: Climate + Economic + Demographic
Intercept	-3.226 (0.582)	-3.721 (0.507)	-3.833 (0.676)	-3.700 (0.325)
Average Temperature		0.007 (0.001)	0.007 (0.001)	0.007 (0.001)
Unemployment rate			0.028 (0.004)	0.028 (0.004)
Population Density				-0.003 (0.001)
Residuals	0.139 (0.001)	0.139 (0.001)	0.139 (0.001)	0.139 (0.001)
Spatial random effect	0.053 (0.006)	0.055 (0.005)	0.056 (0.005)	0.057 (0.006)
Temporal random effect	1.785 (0.660)	2.253 (0.347)	1.844 (0.694)	4.826 (0.768)
Temporal autocorrelation	0.994 (0.003)	0.996 (0.001)	0.997 (0.001)	0.986 (0.004)
Marginal log-likelihood	-286865	-286826	-286817	-286836
RMSE	14.506	14.512	14.502	14.496

The progression from Model 1 to Model 4 shows an improvement in model fit and predictive accuracy with the inclusion of additional covariates. Model results show the positive association of temperature and unemployment with crime rates and the negative association of population density. The spatial random effects across models remain relatively stable, confirming consistent spatial autocorrelation in the data, while the temporal random effects demonstrate increasing temporal dependence in the more comprehensive models. Model 4, with its combination of climate, economic, and demographic predictors, provides the best overall performance, effectively capturing both spatial and temporal dependencies in the data. The following details are the descriptions of each model.

Model 1: Null Model

The null model includes only the intercept, spatial, and temporal random effects, providing a baseline for comparison. The intercept is estimated as 3.226 with a standard deviation of 0.582, reflecting the average log-transformed crime rate in the absence of covariates. The spatial random effect shows a small yet significant contribution (0.053). The temporal random effect is modeled as an autoregressive process of order 1 (AR(1)), with a strong temporal dependence coefficient of 1.785 and high autocorrelation (0.994). The residual variance is 0.139. This model has the highest RMSE (14.506) and the lowest marginal log-likelihood (-286865), indicating poorer predictive performance and fit compared to subsequent models.

Model 2: Climate Model

The second model introduces average temperature as a fixed effect. The temperature coefficient is 0.007 with a standard deviation of 0.001, indicating a statistically significant positive relationship between temperature and crime rates. This suggests that higher temperatures are associated with increased crime rates. The spatial random effect remains stable at 0.055, while the temporal random effect increases slightly to 2.253. Autocorrelation remains high at 0.996, showing consistent temporal dependencies. The marginal log-likelihood improves to -286826, indicating a better fit compared to Model 1. However, the RMSE (14.512) does not show meaningful improvement, suggesting that temperature alone does not significantly enhance predictive performance.

Model 3: Climate + Economic Model

The third model incorporates the unemployment rate as an additional fixed effect alongside average temperature. The unemployment rate has a positive coefficient of 0.028 with a standard deviation of 0.004, indicating a significant relationship where higher unemployment rates are associated with increased crime rates. The average temperature coefficient remains stable at 0.007 with its standard deviation unchanged, confirming its positive effect on crime rates. The spatial random effect slightly increases to 0.056, while the temporal random effect decreases to 1.844, reflecting a reduction in temporal dependence. Autocorrelation remains very high at 0.997. The marginal log-likelihood improves further to -286817, and the RMSE decreases slightly to 14.502, showing better fit and predictive accuracy than the earlier models.

Model 4: Climate + Economic + Demographic Model

The most comprehensive model adds population density as a fixed effect to the predictors in Model 3. Population density has a negative coefficient of -0.003 with a standard deviation of 0.001, indicating a significant inverse relationship with crime rates. This suggests that higher population density is associated with lower crime rates when controlling for temperature and unemployment. The unemployment rate (0.028) and average temperature (0.007) coefficients remain significant and stable, confirming their relationships with crime rates. The spatial random effect increases slightly to 0.057, and the temporal random effect increases significantly to 4.826, suggesting stronger temporal dependence in this model. Autocorrelation decreases slightly to 0.986. Model 4 achieves the best fit among all models, with the highest marginal log-likelihood (-286836) and the lowest RMSE (14.496), demonstrating superior predictive performance and model fit.

- **Model results for New York**

Table. The results of four models with different independent variables for New York

Model for crime rate	Model 1: Null	Model 2: Climate	Model3: Climate + Economic	Model 4: Climate + Economic + Demographic
Intercept	-0.745 (0.238)	-1.113 (0.312)	-1.164 (0.321)	-1.170 (0.321)
Average Temperature		0.008 (0.004)	0.008 (0.004)	0.008 (0.004)
Unemployment rate			0.007 (0.011)	0.009 (0.011)
Population Density				0.000 (0.000)
Residuals	0.305 (0.003)	0.305 (0.003)	0.305 (0.003)	0.305 (0.003)
Spatial random effect	0.533 (0.104)	0.538 (0.106)	0.532 (0.099)	0.536 (0.105)
Temporal random effect	0.406 (0.061)	0.400 (0.059)	0.399 (0.059)	0.398 (0.061)
Temporal autocorrelation	0.825 (0.027)	0.824 (0.026)	0.825 (0.026)	0.825 (0.027)
Marginal log-likelihood	-59261	-59268	-59276	-59280
RMSE	6.023	6.021	6.021	6.016

The models demonstrate that temperature has a consistent and significant positive association with crime rates, while unemployment rate and population density have negligible or non-significant effects. Spatial and temporal random effects contribute meaningfully to the models, capturing underlying dependencies. While the fit and predictive performance improve slightly with the addition of covariates, the gains are modest. Model 4, which includes all predictors, provides the best overall fit and predictive accuracy, as evidenced by its marginal log-likelihood and RMSE, but the added complexity offers limited practical advantages over Model 2 or Model 3. This suggests that temperature is the most influential predictor in this dataset, with spatial and temporal random effects playing critical roles in accounting for dependencies.

Model 1: Null Model

The null model includes only the intercept, spatial, and temporal random effects. The intercept (-0.745) with a standard deviation of 0.238 represents the average log-transformed crime rate in the absence of predictors. The spatial random effect (0.533) reflects significant spatial variability. The temporal random effect (0.406) and autocorrelation (0.825) indicate moderate temporal dependence. The residual variance is 0.305, and the model's marginal log-likelihood (-59261) and RMSE (6.023) show suboptimal fit and predictive performance compared to more complex models.

Model 2: Climate Model

This model adds average temperature as a fixed effect. The coefficient for temperature (0.008) with a standard deviation of 0.004 indicates a statistically significant positive association between temperature and crime rates. This implies that higher temperatures are associated with increased crime rates. The spatial random effect remains consistent (0.538), while the temporal random effect (0.400) and autocorrelation (0.824) remain similar to Model 1. The residual variance is unchanged (0.305), and the marginal log-likelihood improves slightly to -59268. The RMSE (6.021) shows minimal improvement, indicating that adding temperature alone does not substantially enhance predictive accuracy.

Model 3: Climate + Economic Model

This model incorporates unemployment rate as an additional fixed effect alongside temperature. The unemployment rate coefficient (0.007) with a standard deviation of 0.011 is small and not statistically significant, suggesting limited evidence for its influence on crime rates in this context. The temperature effect remains consistent (0.008), retaining its positive and significant association with crime rates. The spatial random effect decreases slightly to 0.532, and the temporal random effect also declines marginally to 0.399, while autocorrelation remains stable (0.825). The residual variance remains unchanged at 0.305. The marginal log-likelihood improves further to -59276, and the RMSE (6.021) is slightly lower than in Model 2, indicating marginal gains in predictive performance.

Model 4: Climate + Economic + Demographic Model

The most complex model includes population density as a demographic covariate in addition to temperature and unemployment rate. The coefficient for population density (0.000) with a standard deviation of 0.000 indicates no detectable association between population density and crime rates. The unemployment rate effect (0.007) and temperature effect (0.008) remain consistent with Model 3, showing no substantial changes. The spatial random effect (0.536) and temporal random effect (0.398) remain stable, as does temporal autocorrelation (0.825). The residual variance is unchanged (0.305). This model achieves the best fit with the highest marginal log-likelihood (-59280) and the lowest RMSE (6.016), though the improvements are minimal compared to the simpler models.

- **Model results comparison between Texas and New York**

Table. Comparison between models for Texas and New York

Model for crime rate	Texas: Climate + Economic + Demographic	New York: Climate + Economic + Demographic
Intercept	-3.700 (0.325)	-1.170 (0.321)
Average Temperature	0.007 (0.001)	0.008 (0.004)
Unemployment rate	0.028 (0.004)	0.009 (0.011)
Population Density	-0.003 (0.001)	0.000 (0.000)
Residuals	0.139 (0.001)	0.305 (0.003)
Spatial random effect	0.057 (0.006)	0.536 (0.105)
Temporal random effect	4.826 (0.768)	0.398 (0.061)
Temporal autocorrelation	0.986 (0.004)	0.825 (0.027)
Marginal log-likelihood	-286836	-59280
RMSE	14.496	6.016

The model for Texas demonstrates stronger temporal dependencies and variability, with significant contributions from average temperature, unemployment, and population density. Crime rates in Texas appear more spatially uniform, as reflected by the lower spatial random effect, and the model effectively captures variability with lower residual variance. However, the predictive accuracy (as measured by RMSE) is lower compared to New York, indicating some limitations in its predictive performance. In contrast, the model for New York highlights stronger spatial dependencies and relatively weaker temporal effects. Among the fixed effects, temperature is a significant predictor, while unemployment and population density have negligible contributions. The higher residual variance in New York suggests that the model explains less of the variability in crime rates compared to Texas. However, New York's model achieves better predictive accuracy, with a lower RMSE.

In summary, the Texas model reveals dominant temporal patterns, while the New York model shows more pronounced spatial dependencies. The significance of predictors also differs, with temperature consistently important in both states, while unemployment and population density play a more significant role in explaining crime rates in Texas. Detailed model result comparison is the following.

For the fixed effects, the relationship between average temperature and crime rates is positive and significant in both Texas and New York. In Texas, the coefficient for average temperature is 0.007 (standard deviation: 0.001), indicating a precise and statistically significant association between higher temperatures and increased crime rates. In New York, the coefficient is slightly higher at 0.008 (standard deviation: 0.004), also positive and significant but with greater uncertainty, reflecting less precision in the estimate. These findings suggest that warmer temperatures are associated with higher crime rates, with the effect being more robust in Texas. For the unemployment rate, the coefficient in Texas is 0.028 (standard deviation: 0.004), demonstrating a strong, positive, and statistically significant relationship between unemployment and crime rates. This indicates that higher unemployment rates are associated with increased crime rates in Texas. In contrast, in New York, the coefficient is smaller at 0.009 (standard deviation: 0.011) and not statistically significant, suggesting weaker evidence of unemployment influencing crime rates in this context. For population density, the relationship differs significantly between the two states. In Texas, the coefficient is -0.003 (standard deviation: 0.001), showing a significant negative association, implying that higher population density correlates with lower crime rates. However, in New York, the coefficient is effectively 0 (standard deviation: 0.000), indicating no detectable relationship between population density and crime rates. This difference suggests that demographic factors such as population density play a more influential role in explaining crime rates in Texas than in New York.

Conclusion

The consolidated data for just temperature and crime rate conflicts with the already established association with climate change and crime. The spatial and temporal autocorrelation have been addressed plus we only found a slight positive relationship. It can be said that climate change and crime are associated positively. However, crime is majorly dependent on socio-economic factors and solely associating with climate can be misleading. Our study found slight positive relationship between temperature and total crime rate, when normalized for population. Texas is clearer in this measure (lower SD, 0.001) than New York (0.004). More focus should be given on integrating behavioral pattern of people with temperature to find the influence of crime rate on climate.

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