A Spatio-Temporal Analysis of College Crime in the USA

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Abstract
College crime is one of the most alarming social problems in the USA. To investigate important factors that are associated with college crime, we collect spatio-temporal datasets for both states of California and Texas from publicly accessible sources. In addition to an exploratory data analysis, a temporal autoregressive modeling procedure is applied in the statistical analysis for each state. Stepwise procedures are used to select the best set of predictors, with the validity of spatial stationarity taken into account. The final models for California and Texas both show a strong autoregressive effect of the college crime rate. They also demonstrate substantially different sets of most predictive factors between the two states.

Key Words: Markov Chain Monte Carlo, Bayesian Hierarchical Modeling, Clery Act, Uniform Crime Reporting

1. Introduction

Universities and colleges, where students receive higher education, are important for the prosperity and stability of a country. Therefore, it is crucial for a government to monitor incidents on university and college campuses, conduct in-depth research to study important factors, and propose effective methods for crime prevention. In the USA, a landmark effort by the federal government is the Clery Act, which was signed into law in 1990. The Clery Act requires all universities and colleges which participate in federal financial aid programs to report and disclose their crime statistics based on the Uniform Crime Reporting (UCR) definitions by the Department of Education, and civil penalties and/or suspension from participating in federal financial aid programs may be imposed for violations.

Since the Clery Act was signed, research studies on campus crime and related factors have been growing. One of the first studies was conducted by [22], who presented features related to campus crime types, determined latent variables using factor analysis, and fitted a multivariate regression. [21] found that aggressive acts in a relationship promote dating violence, but serious actions such as the use of a gun or a knife rarely happen. They concluded their study by a regression analysis of a survey dataset from a group of students. [12] found that 27 percent of the students are aware of campus crime disclosures and even fewer read annual crime reports, but most students feel safe in their campuses. [13] concluded in another study that the Clery Act has a minor effect on students' behaviors.

Other studies aim to examine the impact of social learning and social control theories on college crime. [19] argued that both theories have a strong association with college crime, which is agreed by [7] who justified that students who have less connection to classes and campuses are the risk for crimes. Likewise, as [6] pointed out, the questionnaires from 2,230 female students showed that the increase of their attachment to campus life and the frequency of their party attendance tend to enlarge

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the possibility of their sexual victimization. [9] focused on the intentional homicide crime rate and found that youth unemployment rate is statistically significant.

Despite the popularity in other fields, such as climate science and ecology, the use of spatial and spatio-temporal methods has been void to analyze crime data until very recently. [18] mapped on- and off-campus crimes in a large southeastern university in the USA and obtained predictive factors for the incidents in terms of a spatial analysis and a binary logistic regression. [15] applied a spatial regression model to study property crimes in Ottawa, Canada and concluded that universities are significant factors, which indicates the entanglement of city and university crimes. [23] fitted a spatio-temporal generalized additive model to predict the possibility of a crime when a specific time and location is given in Charlottesville, Virginia, USA, where predictors that represent ethnicity were included in the modeling. [16] performed a Bayesian hierarchical model to investigate the spatio-temporal pattern of police calls of incidents in Waterloo, Canada. Similarly [1] studied the city level crime trends in Philadelphia over time using Bayesian modeling approaches based on neighborhood information, including economic and demographic characteristics. Unfortunately, apart from these works, the application of spatio-temporal methods in college crime research remains inadequate. Moreover, the spatio-temporal pattern of college crime at the state level has never been investigated.

To the best of our knowledge, this paper is the first attempt to model the spatio-temporal pattern of the USA college crime at the state level. Inspired by prior work on crime data, we synthesized data from three public databases and obtained college crime data, university and college information (e.g., tuition per capita, proportion of undergraduate students, etc.) and each institution's neighborhood information (e.g., local unemployment rate, city-level crime rate, etc.). Due to several limitations of the data sources, we only focused on two states, California and Texas, in this paper, However, our procedures are readily applicable in regions where better data sources are available or after the three public databases in the USA are improved in the future. Motivated by an exploratory data analysis, temporal autoregressive models were fitted under the Bayesian hierarchical modeling framework. At the present of a large number of predictors, we performed stepwise model selection procedures and identified the most important ones for each state. To decide the optimal model, we checked the validity of spatial stationarity assumed by the autoregressive modeling.

The main contribution of this paper to college crime studies is threefold. First, our analysis identifies a significant temporal autoregressive effect of the annual college crime rate and demonstrates distinct sets of key predictors for the crime rate between different states, which provide novel insights on the understanding of college crime in the USA. Moreover, the integration of Bayesian hierarchical modeling, model selection and stationarity validation adopted by this paper is new in the research on college crime and is promising for a wide use by researchers within or beyond this area. Finally, this paper identifies the limitations of the three public databases of which improvements will benefit future studies of college crime.

The rest of this paper proceeds as follows. Section 2 introduces data sources and variables. An exploratory analysis is given in Section 3 to visualize crime rates and their associations with other variables. Section 4 provides the details for the spatio-temporal modeling of college crime rate and model selection procedure. Results are given in Section 5 and Discussion in Section 6 concludes the paper.

2. Data and Variables

The data were extracted from three public data sources in the USA. The sources include the UCR Program (https://www.fbi.gov/services/cjis/ucr/) of the Federal Bureau of Investigation (FBI) provides crime statistics in the universities and cities. The National Center for Education Statistics (NCES, https://nces.ed.gov) provides many detailed information of universities and colleges, such as tuition per capita, proportion of undergraduate students, etc. The Bureau of Labor Statistics (BLS, https://www.bls.gov/lau/) provides local economic information, e.g., unemployment rate in each county.

In view of substantial differences among states, we opted to study each state separately. Due to the limitation that the UCR program does not provide crime information of all universities and colleges in every state, we only focused on California and Texas in this paper. Over the time period from 1997 to 2012, the two states have many more institutions of which crime information is available on the UCR program website than the other states: 32 institutions in California and 39 in Texas.

The three data sources have more than one thousand variables in total. Suggested by the literature, we selected a subset as predictors, e.g., city crime rate, and further removed some due to too many missing values or multicollinearity. The resulting predictor list is given in Table 1. All variables but one are the same to study both California and Texas. The variable *hsi* was included only for California while *control* was used for Texas only. Our ultimate goal is to find the best model to predict the annual crime rate of each university or college defined by

$$\text{crime rate} = \frac{\text{crime counts}}{\text{enrollment}} \times 1,000,$$

which is similar to the personal victimization rate defined in the Bureau of Justice Statistics' National Crime Victimization Survey (https://www.bjs.gov/index.cfm?ty=dcdetail& iid=245).

Table 1: The list of the predictors used in the exploratory and statistical analyses.

	Variable Name	**Type**	**Explanation**
Local Information	unemp_rate	Continuous	Unemployment rate in the associated county
	cpi_scalar	Continuous	Consumer price index (CPI)
	city_crime	Continuous	City crime rate
University Information	hsi (CA)	Categorical	Hispanic-serving institution (CA)
	control (TX)	Categorical	Publicly or Privately controlled (TX)
	tuition	Continuous	Average tuition revenue per student
	gom	Continuous	Gross operating margin
	undergrad	Continuous	Proportion of undergraduate students
	amin	Continuous	Proportion of American-Indian students
	asian	Continuous	Proportion of Asian students
	black	Continuous	Proportion of black students
	hisp	Continuous	Proportion of hispanic students
	white	Continuous	Proportion of white students
	nonres	Continuous	Proportion of nonresident students

3. Exploratory Analysis

This section provides an exploratory analysis of the data, including graphical visualizations and descriptive statistics. First, bubble graphs were used to visualize both spatial and temporal patterns of the crime rate. Figure 1 illustrates the crime rates of the 32 institutions in California from 1997 to 2012. The position of a bubble signifies the location of its corresponding university, and a bigger and darker bubble represents a higher crime rate. It shows that overall the crime rate declines from the late 1990s to 2012, but the variability across institutions is high in California. Among the 32 institutions, Santa Rosa Junior College is one of the safest universities, while the University of California, San Francisco, and California State University, Monterey Bay have the highest crime rates. The bubble plots were created by using two R packages `ggmap` and `ggplot2` [14]. The bubble plots for Texas were similarly created and are shown in Figure 2, which also demonstrates a decreasing trend of the crime rate over time. Among the 39 institutions in Texas, Rice University, Trinity University and University of North Texas Health Science Center are the most dangerous universities while Central Texas College and South Plains College are the safest.

Next, to present time-dynamic patterns of the crime rate more effectively, we averaged the crime rates over institutions in each state every year and created a line chart for the yearly average crime rate over time. The line charts for California and Texas respectively are both given in Figure 3. As observed in the bubble plots, the crime rate generally declined from 1997 to 2012 for both states except for a substantial increase in 2000 and 2001 in California. Figure 3 indicates a strong temporal autoregressive pattern of the crime rate and its collinearity with year, so we opt not to include year as a predictor in the subsequent modeling. In comparison, in the same year the institutions in California on average have a higher crime rate than those in Texas.

Finally, to explore marginal associations between the response and predictors, we calculated the Pearson correlation coefficient between the college crime rate and each continuous predictor given in Table 1, ignoring temporal and spatial dependencies among observations. The correlation coefficients are given in Table 2, together with their p-values for testing zero correlations. Table 2 shows that at the significance level 0.05 the sets of significantly predictors for California and Texas are almost identical. Explicitly, the college crime rate in both states is significantly correlated with the city crime rate, tuition, gross operating margin, and proportion of Asian students positively, and with the CPI, proportion of undergraduate students, and proportion of Hispanic students negatively. The unemployment rate in the associate county and proportion of nonresident students are only correlated with the college crime rate in Texas but not California while the proportion of black students is only correlated with that in California. Note that Table 2 merely reflects marginal associations of predictors ignoring the autoregressive patten of the response revealed in Figure 3, so their significances may change when the subsequent modeling procedures takes into account the autoregressive effect.

4. Statistical Analysis

In this section, we introduce the procedures of our statistical analysis. We first specify an autoregressive modeling framework that can capture the spatio-temporal structure of our data. Due to a large number of predictors, we present a criterion for model assessment, together with stepwise model selection procedures based on such criterion. At last we propose a strategy to check spatial stationarity, an essential assumption of the autoregressive models, which will help us further with selecting the final model.

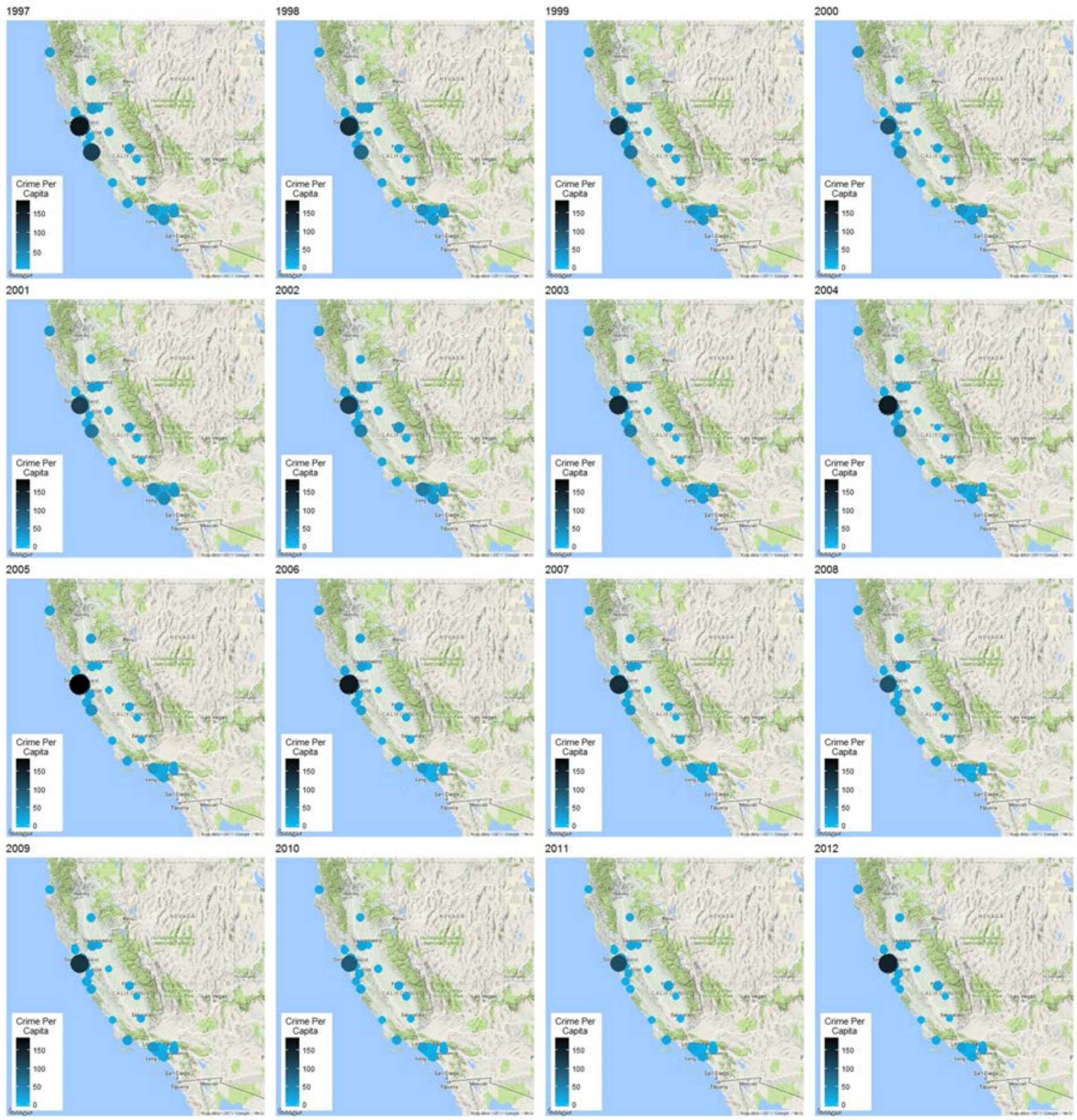

Figure 1: Bubble plots for crime rates of the 32 institutions in California from 1997 to 2012.

4.1 Autoregressive Modeling

We applied an autoregressive (AR) model developed by [20] to our spatio-temporal data. The AR model indicates that the current value of the response depends on both its previous value in time and the current values of predictors. Let $Z(s_i, t)$ and $O(s_i, t)$ be the observed and true response, i.e., the college crime rate, respectively at location s_i and time t, $i = 1, ..., n$, $t = 1, ...T$. Denote $\mathbf{Z}_t = (Z(s_1, t), Z(s_2, t), ..., Z(s_n, t))^\top$ and $\mathbf{O}_t = (O(s_1, t), O(s_2, t), ..., O(s_n, t))^\top$. Let $\mathbf{X}_t$ denote the $n \times p$ design matrix for the predictors together with the intercept at time $t = 1, ...T$, and $\boldsymbol{\beta} = (\beta_0, \beta_1, ..., \beta_{p-1})^\top$ denote the regression coefficient vector. The number of locations, i.e., institutions, is $n = 32$ for California while it is $n = 39$ for Texas. For both states, $T = 16$ which ranges from

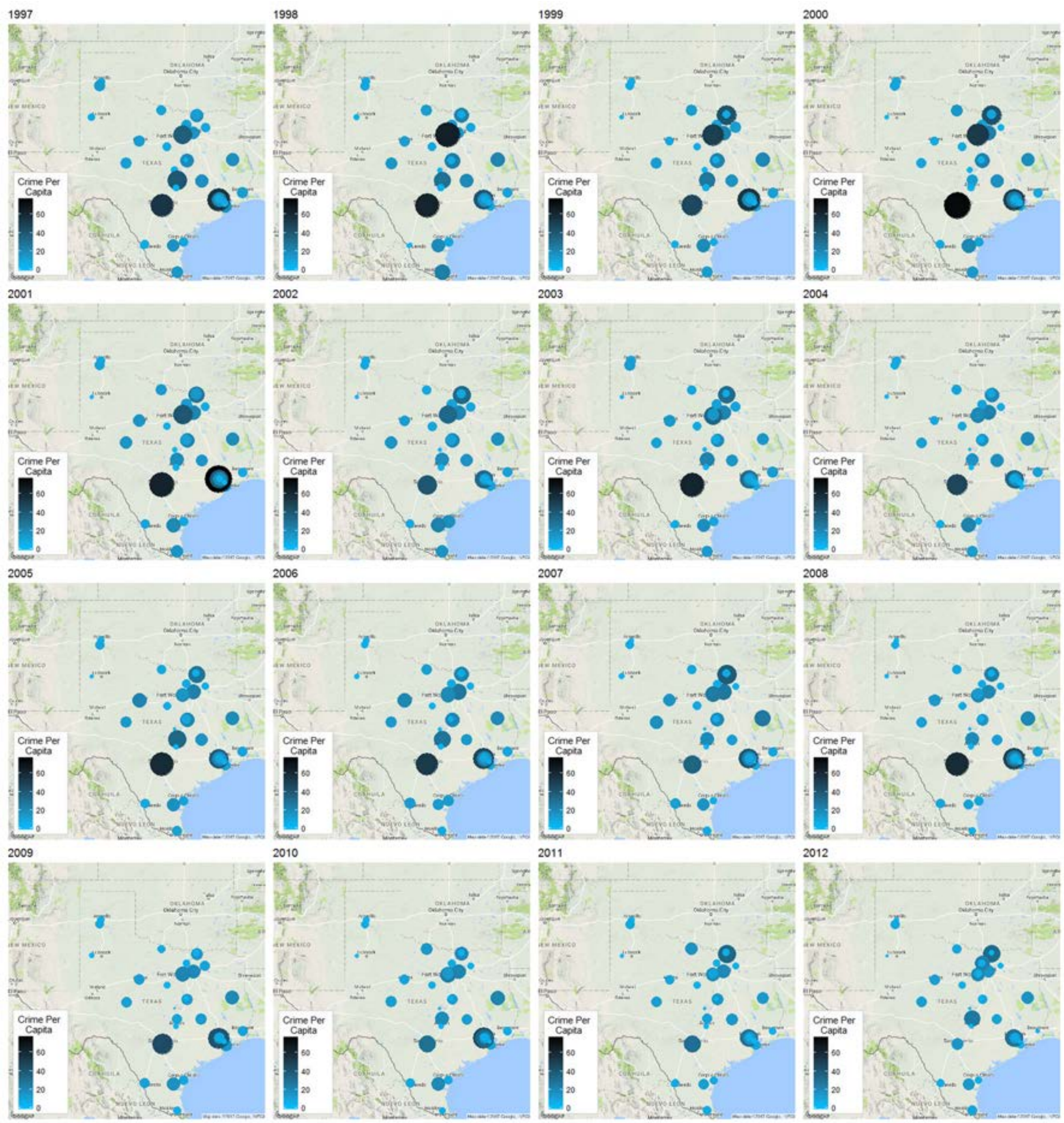

Figure 2: Bubble plots of crime rates for the 39 institutions in Texas from 1997 to 2012.

1997 to 2012.

The AR model takes the following form:

$$\mathbf{Z}_t = \mathbf{O}_t + \boldsymbol{\epsilon}_t, \quad \mathbf{O}_t = \rho \mathbf{O}_{t-1} + \mathbf{X}_t \boldsymbol{\beta} + \boldsymbol{\eta}_t, \quad t = 1, \ldots, T, \tag{1}$$

where ρ is the autoregressive parameter, the error $\boldsymbol{\epsilon}_t = (\epsilon(s_1, t), \epsilon(s_2, t), ..., \epsilon(s_n, t))^\top$ is assumed to follow $N(0, \sigma_\epsilon^2 \mathbf{I}_n)$ with unknown variance σ_ϵ^2 and identity matrix $\mathbf{I}_n$, and the spatio-temporal random effect vector $\boldsymbol{\eta}_t = (\eta(s_1, t), \eta(s_2, t), ..., \eta(s_n, t))^\top$ is assumed to follow $N(0, \sigma_\eta^2 \mathbf{S}_\eta)$ with spatially invariant variance σ_η^2 and spatial correlation matrix $\mathbf{S}_\eta$.

We used two popular forms to model the spatial correlation matrix $\mathbf{S}_\eta$, the Matérn correlation and

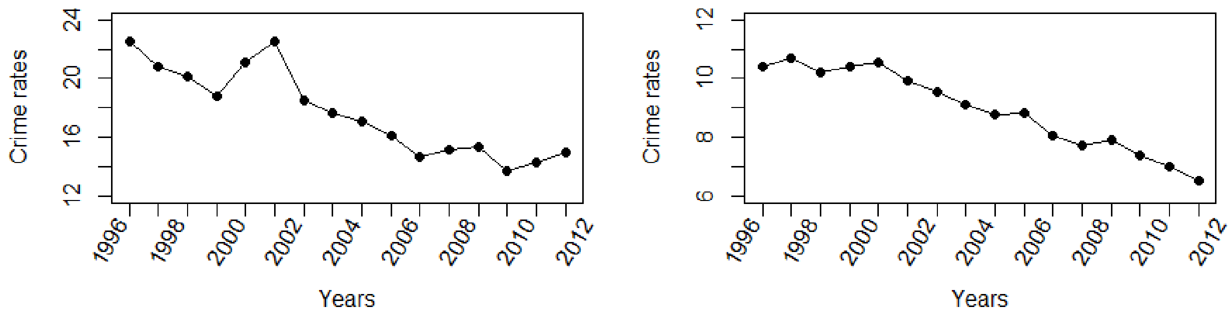

Figure 3: The line charts of the average crime rate over year for California (left) and Texas (right) respectively.

Table 2: Pearson correlation coefficient between the crime rate and each continuous predictor for California and Texas. Corresponding p-values are given in the parentheses.

		California	**Texas**
Local Information	unemp_rate	-0.0248 (0.574)	-0.124 (0.002)
	cpi_scalar	-0.122 (0.006)	-0.134 (0.001)
	city_crime	0.133 (0.003)	0.126 (0.001)
University Information	tuition	0.370 (< 0.001)	0.566 (< 0.001)
	gom	0.535 (< 0.001)	0.356 (< 0.001)
	undergrad	-0.691 (< 0.001)	-0.278 (< 0.001)
	amin	-0.004 (0.919)	-0.052 (0.192)
	asian	0.279 (< 0.001)	0.284 (< 0.001)
	black	-0.132 (0.003)	0.034 (0.388)
	hisp	-0.313 (< 0.001)	-0.241 (< 0.001)
	white	0.092 (0.036)	0.068 (0.088)
	nonres	0.047 (0.281)	0.282 (< 0.001)

exponential correlation. The Matérn correlation [17, 10, 11] has the form

$$\mathbf{S}_\eta(s_i, s_j; \phi, \nu) = \frac{1}{2^{\nu-1}\Gamma(\nu)}(2\sqrt{\nu}\|s_i - s_j\|\phi)^\nu K_\nu(2\sqrt{\nu}\|s_i - s_j\|\phi),$$

where $\Gamma(\nu)$ is the standard gamma function, K_ν is the second kind Bessel function with the order $\nu > 0$, and $\|s_i - s_j\|$ is the Euclidean distance between locations s_i and s_j. The decay rate for the correlation is controlled by the parameter $\phi > 0$ while the distance increases between two locations [2, 4].

The exponential correlation [e.g., 20] takes the form

$$\mathbf{S}_\eta(s_i, s_j; \phi) = \exp(-\phi\|s_i - s_j\|),$$

where $\phi > 0$ is the decay rate. Note that the use of either Matérn or exponential correlation implicitly assumes spatial stationarity, so we propose a strategy to check the validity of this assumption.

In the subsequent analysis which involves model selection, we found that the exponential correlation always leads to a better final model than the Matérn correlation in terms of the predictive model selection criteria values, which will be introduced in Section 4. Therefore in Section 5 below we only report the results where the spatial structure is assumed to follow the exponential correlation.

To fit each AR model of the form (1), we used the R package `spTimer` to obtain the posterior distribution of each parameter based on the Bayesian hierarchical modeling framework.

4.2 Model Assessment and Model Selection

Due to a large number of predictors, we performed both forward selection and backward elimination to select the best set of predictors. To evaluate the quality of a fitted model in intermediate steps of each stepwise model selection procedure, we used the predictive model choice criteria [PMCC, 8],

$$\text{PMCC} = \sum_{i=1}^{n}\sum_{t=1}^{T} E\{Z(s_i,t)_{\text{rep}} - z(s_i,t)\}^2 + \sum_{i=1}^{n}\sum_{t=1}^{T} \text{Var}(Z(s_i,t)_{\text{rep}},$$

where $Z(s_i,t)_{\text{rep}}$ is a future replica of data $z(s_i,t)$. The first term reflects the goodness-of-fit (GoF) while the second is a penalty term for model complexity. The `spTimer` package can output the values of both terms for each AR model. For the college crime data studied in this paper, the GoF term always substantially dominates the penalty term, so we also used the GoF term in intermediate steps for model selection. The diagram of our model selection algorithm is illustrated in Figure 4.

For each candidate model selected by this algorithm, we check if the assumption of spatial stationarity is valid. The details for checking spatial stationarity will be introduced shortly in Section 4.3. If this assumption is valid for one candidate model but not for another one, then the former is preferred as the final model. If this assumption is valid for multiple models, the final model is the one with the smallest PMCC value among them.

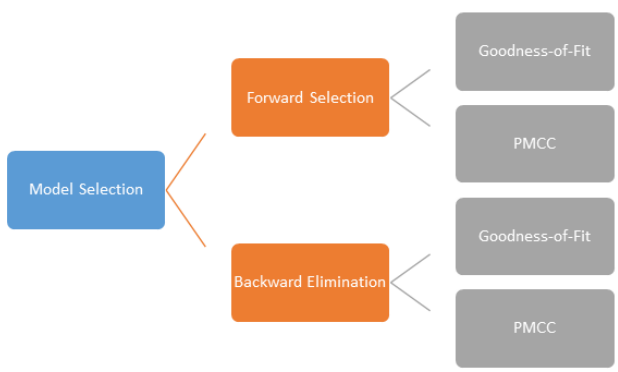

Figure 4: The diagram of forward and backward model selections with two selection criteria in intermediate steps.

4.3 Spatial Stationarity

The AR model (1) assumes spatial stationarity to ensure its applicability on the entire space. If spatial stationarity is violated, the results of the corresponding model are no longer trustworthy. Therefore, it is essential to check this assumption to guarantee the reliability of our results.

Our strategy to check spatial stationarity is motivated by Geographically Weighted Regression [GWR, 5]. The intuition of GWR is simple: If spatial stationarity holds on the entire space, then the global model fitted using data in the entire space is supposed to fit data in sub-regions well, so the parameter estimates obtained from the global model should be similar to those obtained from local models which are fitted using data in sub-regions [3]. We introduced this idea to our study as follows: For each global candidate model obtained as in Section 4 for each state, we chose two sub-regions of that state as shown in Figure 5, fitted two local models with the same set of predictors of the global model, and compared the posterior distributions of the parameter estimates of the three models. If their posterior distributions are similar, then spatial stationarity is considered as valid. If this assumption is invalid for all candidate models, then model selection procedures will be performed in sub-regions of each state.

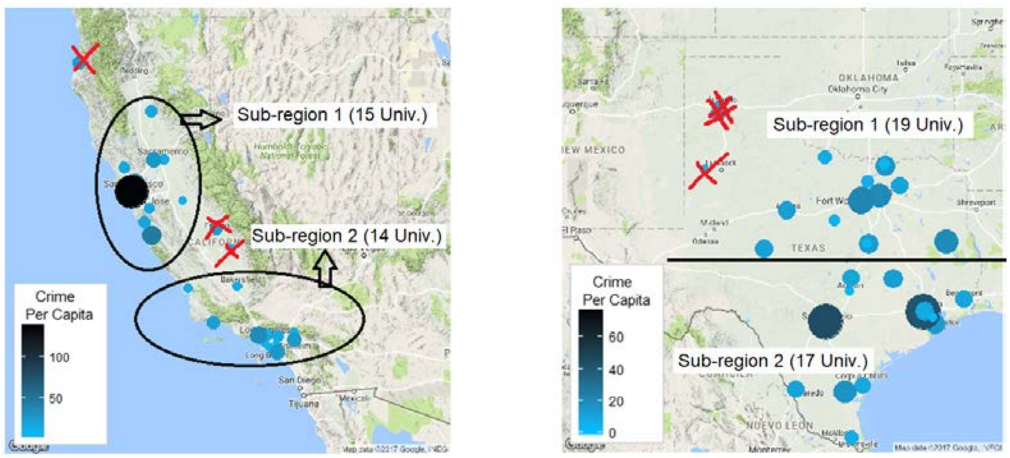

Figure 5: Sub-regions used to check spatial stationarity of fitted models for California (left) and Texas (right). Bubbles overlaid with red crosses refer to institutions excluded from sub-regions.

Sub-regions are ideal if they are sufficiently large to contain enough institutions to fit each candidate model, representative of the entire state (e.g., not all Hispanic-serving institutions), and optionally graphically interpretable (e.g., the San Francisco Bay Area). Following this guideline, we obtained two sub-regions for California as shown in Figure 5 (left), including 15 and 14 institutions respectively. The two sub-regions roughly center around San Francisco and Los Angeles respectively. Three institutions in California were excluded since one is up north of San Francisco, too far away from all others, and the other two are located in the middle of two sub-regions, which makes it difficult to assign them to either sub-region. As illustrated in Figure 5 (right), we also obtained two sub-regions for Texas following the same guideline. After removing three universities which are very far from the others, the first sub-region contains 19 institutions, while the second contains 17. There are no natural geographical landmarks the universities in Texas center around, so we used a latitude line to divide the state map.

5. Results

This section provides the results of the spatio-temporal modeling of the college crime data for California and Texas. For each state, we first obtained a few candidate models via the stepwise model selection procedures as in Section 4.2. Then we followed the GWR-type method as in Section 4.3 to check if spatial stationarity is valid for each candidate model globally with respect to its corresponding state. For either California or Texas, we were able to find one candidate model that satisfies spatial stationarity globally, so we designated it as the final model and did not need to perform model selection procedures within each sub-region. The interpretations of the two final models are given at the end of this section.

Table 3 lists five candidate models for California. Here we included the best two models selected by forward selection with the GoF term as the criterion in each intermediate step, corresponding to "Forward - GoF-1" and "Forward - GoF-2" respectively in Table 3, since their PMCC values are extremely close. Following Section 4.3, spatial stationarity can be considered valid only for Model 1 in Table 3, so it is selected as the final model for California. For the two coefficient estimates in Model 1, their posterior distributions for the entire state and two sub-regions are illustrated in Figure 6. The figures for the posterior distributions corresponding to the other four models are given in the supplementary material.

Table 3: Five candidate models for California, with their corresponding predictors and PMCC values.

Model	Predictors	PMCC
1: Forward - GoF-1	tuition, undergrad	88.15
2: Forward - GoF-2	hsi, tuition, gom, undergrad	88.08
3: Forward - PMCC	hsi, cpi_scalar, tuition, nonres	86.85
4: Backward - GoF	unemp_rate, tuition, asian, nonres	86.92
5: Backward - PMCC	hsi, tuition, amin, black, nonres	87.07

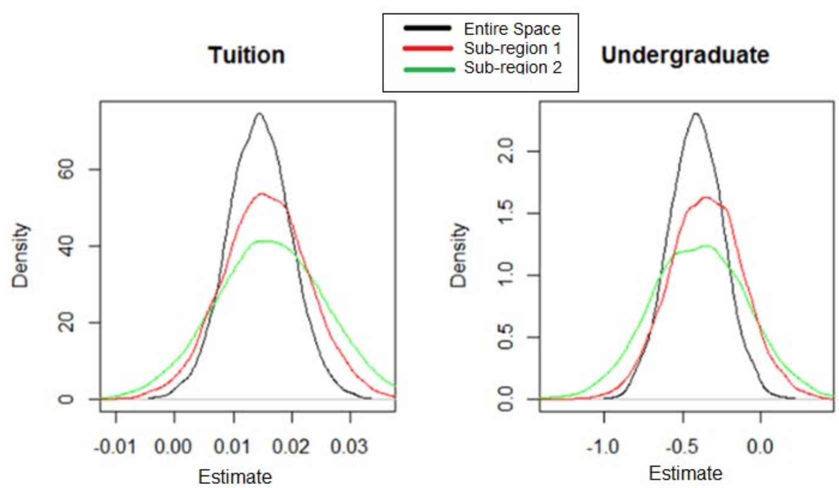

Figure 6: Posterior distributions of the parameter estimates in Model 1 for California.

The parameter estimates for the final model for California are shown in Table 4. It shows that tuition and the proportion of undergraduate students are highly associated with the college crime rate in California. As revealed by the posterior mean values, a higher tuition corresponds to a higher crime rate while a larger proportion of undergraduate students corresponds to a lower crime rate. These two posterior means are consistent with their marginal correlations with the response as in Table 2. Table 4 also shows that the college crime rate has a strong autoregressive effect, which indicates that the crime rate in a year is strongly and positively influenced by its value in the previous year. This result also echos our observations in Figure 3 (left).

Table 4: Posterior mean, standard deviation and 95% credible intervals for the parameter estimates in Model 1 for California.

	Mean	SD	95% CI
Intercept	0.6230	0.2018	(0.2244, 1.0160)
tuition	0.0145	0.0054	(0.0037, 0.0253)
undergrad	-0.4133	0.1736	(-0.7574, -0.0667)
rho	0.8998	0.0164	(0.8673, 0.9315)

Following the same model selection procedures, the resulting five candidate models for Texas are given in Table 5. Only Model 1 satisfactorily meets the assumption of spatial stationarity as illustrated by the posterior distributions in Figure 7, so it is selected as the final model for Texas. The figures for the other four models are given in the supplementary material. The parameter estimates of Model 1 are given in Table 6. Table 6 demonstrates a strong and positive autoregressive effect of the college crime rate in Texas, which is consistent with Figure 3 (right). However, neither of the two predictors, unemployment rate and the proportion of Asian students, is considered highly associated with the crime rate since the 95% credible intervals for their coefficients both contain zero.

Table 5: Five candidate models for Texas, with their corresponding predictors and PMCC values.

Model	Predictors	PMCC
1: Forward - GoF	unemp_rate, asian	121.76
2: Forward - PMCC	undergrad	124.74
3: Backward - GoF-1	control, gom, amin, nonres, city_crime	128.80
4: Backward - GoF-2	gom, amin, nonres	126.65
5: Backward - PMCC	control, cpi_scalar	124.93

In comparison of the final models for California and Texas, the college crime rate in both states has a strong and positive autoregressive effect, which indicates the importance of history in predicting college crime rate. Apart from the autoregressive effect, the two final models are very different. First, the two models do not share any common predictor. The predictors in the final model for California are highly related to the response, but those in the final model for Texas are not. These observations reflect the differences between California and Texas, which in return validates our decision to study the two states separately.

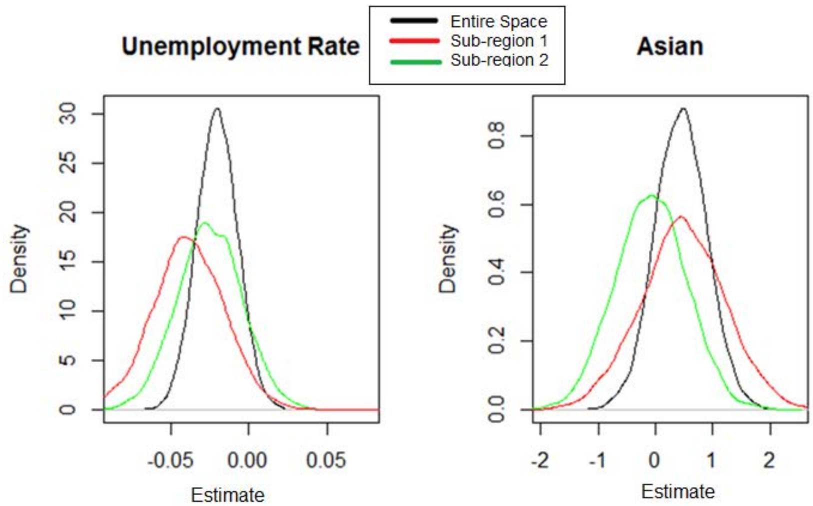

Figure 7: Posterior distributions of the parameter estimates in Model 1 for Texas.

Table 6: Posterior mean, standard deviation and 95% credible intervals for parameter estimates in Model 1 for Texas.

	Mean	SD	95% CI
Intercept	0.2908	0.0987	(0.0976, 0.4861)
unemp_rate	-0.0202	0.0131	(-0.0460, 0.0052)
asian	0.4434	0.4559	(-0.4585, 1.3410)
rho	0.9246	0.0164	(0.8928, 0.9566)

6. Discussion

In this paper we collected a dataset of the USA college crime from three public databases and studied the spatio-temporal patterns of the college crime rate in California and Texas. By stepwise model selection and GWR-type checking procedures, an autoregressive model with the optimal set of predictors is selected to predict the college crime rate of each state for which the temporal autoregressive effect of the response is captured and the spatial stationarity assumption is valid. Both models demonstrate a strong autoregressive effect of the college crime rate. They also reveal distinct optimal predictor sets for the two states, which indicates the heterogeneity of college crime patterns among different states. These results provide novel insights on understanding the USA college crime. To the best of our knowledge, this paper is the first to model the USA college crime rate at the state level and identify key predictors using spatio-temporal methods and model selection procedures. The application of spatio-temporal methods is new in the college crime studies and promising to be used by researchers within or beyond this area.

This paper has a few limitations mostly due to the public databases from which we collect the dataset. First, the NCES database has substantial missing values with respect to important university variables, e.g., the graduation rate, the numbers of students per faculty member, etc. Thus we had to delete numerous institutions and variables. Moreover, the crime data of many universities, especially private universities, are not provided by the UCR program or incomplete in many years. Hence the dataset analyzed in this paper is not satisfactorily representative, and the interpretations of each final model above may not be straightforwardly generalized to the entire higher education system in either California or Texas. However, our procedures are readily applicable in regions where relevant data sources do not have these drawbacks or after the three public databases in the USA are improved in the future.

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