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Understanding the Spatiotemporal Pattern of Crimes in Changchun, China: A Bayesian Modeling Approach

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Abstract: Chinese cities have been undergoing extraordinary changes in many respects during the process of urbanization, which has caused crime patterns to evolve accordingly. This research applies a Bayesian spatiotemporal model to explore and understand the spatiotemporal patterns of crime risk from 2008 to 2017 in Changchun, China. The overall temporal trend of crime risk, the effects of land use covariates, spatial random effects, and area-specific differential trends are estimated through a Bayesian spatiotemporal model fitted using the Integrated Nested Laplace Approximation (INLA). The analytical results show that the regression coefficient for the overall temporal trend of crime risk changed from significantly positive to negative after the land use variables are incorporated into the Bayesian spatiotemporal model. The covariates of road density, commercial and recreational land per capita, residential land per capita, and industrial land per capita are found to be significantly associated with crime risk, which relates to classic theories in environmental criminology. In addition, some areas still exhibit significantly increasing crime risks compared with the general trend even after controlling for the land use covariates and the spatial random effects, which may provide insights for law enforcement and researchers regarding where more attention is required since there may be some unmeasured factors causing higher crime trend in these areas.

Keywords: spatiotemporal pattern; crime trend; Bayesian hierarchical model; INLA; China



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1. Introduction

During recent decades, most cities in China have been undergoing extraordinary changes in many aspects, such as demographic characteristics, socioeconomic status, land use and building environments, which are often proven to be associated with the spatial pattern of crimes in the urban environment in the literature on environmental criminology [1–3]. Meanwhile, the crime control effort by law enforcement agencies, which provide official guardianship to deter crime, has also greatly intensified in recent years. For example, security cameras have been installed at most road intersections, and more police officers have been deployed on roads to control crime, especially in the inner parts of cities. Consequently, the patterns of criminal activities in Chinese cities may evolve along with such intense changes, especially in long-term trends. Unfortunately, due to limited access to crime data, information on changes in the crime pattern in Chinese cities with the accelerating process of urbanization is largely lacking.

Recently, an increasing number of studies have emerged relating to the spatial and temporal patterns of crimes in Chinese cities as relevant data become available. The criminal activities in these cities have been found to concentrate or cluster in some areas and give rise to some hotspots [4–6]. Similar to the findings of studies conducted in Western

countries, the distribution of crimes or hotspots in some Chinese cities displays hourly, daily, weekly and seasonal variation, and some factors that may have impacts on the spatial and temporal pattern of crime have also been verified [7–10]. The applicability of western criminological theories, such as social disorganization theory [11] and routine activities theory [12], have also been demonstrated by studies conducted in Chinese context [13–15]. Nevertheless, few of these studies have focused on long-term changes in crime patterns in China.

In this study, we first compare the different spatial patterns of crime rates at the police precinct level in Changchun, the capital city of Jilin Province in Northeast China, between 2008 and 2017. As a typical large city in the inner area of China, Changchun has been undergoing a dramatic change in the urban space during the process of urbanization. For example, more farmland has been developed for real estate, roads, industrial entities, etc., especially in the peripheral areas of the city. The demographic characteristics in different areas have also changed during these years, which may have caused evolution in terms of the spatiotemporal pattern of crime. In addition, different areas may display area-specific trends of crime risks compared with the general trend. To further explore and understand the spatial and temporal variation of crime risks as well as the underlying drivers of the changes in both dimensions, a Bayesian spatiotemporal modeling approach is introduced in this study. As indicated by other studies [2,16], land use may be associated with crime patterns, and some land use variables collected in both years are selected as the covariates incorporated in the model. In addition, the spatial effect (often referred to as spatial dependence or spatial autocorrelation) is incorporated in the model, which has been suggested by many relevant studies in terms of crime analysis when dealing with spatial data [17,18]. The general trend across the two years studied and the differential time effect (reflecting a varying trend that is different from the general trend for each region) are also included in the spatiotemporal model. All the models are fitted using the Integrated Nested Laplace Approximation (INLA) proposed by Rue et al. [19], which was completed in R using the R-INLA package. As an alternative to the conventional method of Markov chain Monte Carlo (MCMC), the INLA method are effective in reducing computational time and retain reliable parameter estimates [20–22].

Compared with the traditional frequentist method, Bayesian modeling has some intrinsic advantages. For example, Bayesian models can estimate trends using two or more years of data in the same model and can incorporate random effect terms that overcome methodological problems such as overdispersion and the small number problem [23–25]. Taking advantage of crime mapping tools, it is also convenient to identify the hotspots of crime, which reveal areas having relatively higher crime risks compared with the general trend, after adjusting the effects of covariate variables such as land use based on the results of the Bayesian spatiotemporal model. These hotspots not only draw attention from law enforcement but also have the potential to reveal underlying and unmeasured factors that could contribute to the spatiotemporal pattern of crime.

This study begins with a literature review pertaining to spatial and temporal patterns of crime in the long term as well as the application of crime studies using the Bayesian approach. Then, the study area, study unit and spatiotemporal Bayesian models are introduced. Next, the spatial patterns of crime rates in Changchun in 2008 and 2017 are compared. The results of the Bayesian spatiotemporal model are presented, visualized and explained based on the specific context of Changchun city during the study period. Finally, the theoretical, analytical and practical implications are discussed, followed by the conclusion, limitations and insights.

2. Literature Review

2.1. Changing Pattern of Crime over the Long-Term Period

As clearly indicated by routine activities theory [12] and crime pattern theory [26], both space and time matter for the identification of any crime pattern. In the literature, the spatial pattern of crimes and the factors impacting the formation of the pattern of crime

continue to draw attention from researchers in the field of environmental criminology. In particular, driven by the increased availability of informative crime data with spatial information and the advances in analytical technology in the area of crime analysis, a large body of studies has emerged regarding the spatial analysis of crime in recent years [27–29]. However, the temporal analysis of crime patterns has not kept pace with the expansion of the spatial analysis of crime [30,31]. Moreover, studies that consider both space and time are even more rare [32]. During the last decade, an increasing number of studies have focused on the changing spatial pattern of crime, integrating the dimensions of both space and time. Researchers have found that different types of crime patterns vary by hour, day, month, season and year [32–37]. Among the different temporal scales of resolution, studies pertaining to the annual variation in crime patterns remain a branch of the study of crime patterns in both space and time. A comparison and analysis of crime patterns over years are conducted to address some essential questions, such as whether the level of crime concentration and the crime hotspots are stable in the long term. For example, after a long-term observation of the distribution of delinquency in the city of Chicago, Shaw and McKay found early on that the crime pattern remained relatively stable and advanced social disorganization theory [11]. Similarly, routine activities theory was originally developed to explain the changes in crime rates over a long period after the Second World War in the United States [12]. In recent years, it is worth mentioning trajectory analysis, introduced by Weisburd et al. They examined the changes in crime patterns over a 14-year period on street segments in Seattle by grouping the street segments according to their developmental trajectories and found that there was a high degree of stability during this period. In subsequent studies using the same method of trajectory analysis at smaller units, researchers went a step further in assessing the stability and variability of crime patterns in different cities over a relatively long time [38,39]. However, as stated by Law et al., trajectory analysis does not allow for small areas to exhibit unique crime trends and does not identify hotspots through statistical testing of the difference between area-specific crime trends and overall crime trend [23]. Another way of examining the changing patterns of crime over a long-term period is the use of the spatial point pattern test (SPPT), first proposed by Andresen [40]. By conducting the test and analyzing the results of the S-indexes, researchers were able to investigate the stability and changes in the spatial patterns of crimes over years [41,42]. Nevertheless, the spatial point pattern test is not capable of accommodating covariates and is only suitable for measuring the similarity of two datasets at the area scale.

2.2. Traditional Modeling Methods for Analyzing Crime Patterns

To further analyze and understand the spatial and temporal patterns of crime, regression models are often used to explore the relationships between crime and influential factors based on theories such as social disorganization theory and routine activities theory. The most common factors that may have impacts on crime risks are usually quantified by variables representing the socioeconomic, demographical and land use characteristics across different analytical units [1,2,13,43]. As the data (crime data or other relevant data) are usually available as counts for small areas (e.g., census tracts and neighborhoods), the modeling of crime needs to take into account spatial or spatiotemporal autocorrelation effects, which may result in biased parameter estimates if ignored [44]. In reality, the phenomenon of crime concentration or clustering, often identified as crime hotspots, has been quantified by many studies in the area of environmental criminology [45]. The spatial dependence in small-area analysis is often modeled traditionally in the frequentist statistical approach in the form of a spatial lag model or spatial error model [46]. However, these traditional spatial regression methods have some limitations. For example, both types of models are designed to model continuous variables (e.g., crime rates) following a normal distribution, while this assumption is often invalid for real crime data. Although generalized linear models, such as Poisson, logistic and negative binomial regression models, can be used as an alternative way to solve the problems of nonnormal

data, the method would become excessively complex when it incorporated spatially and temporally autocorrelated effects [22,44]. Furthermore, traditional (frequentist) spatial regression methods are incapable of addressing the small number problem, which arises when unstable estimates occur because of low counts of events in small areas and high sampling variation [47]. If the data were available at the area level for more than one time period, integrating all the information over different times would be a difficult issue for the traditional regression model.

2.3. Bayesian Modeling Approach

The Bayesian spatiotemporal model is capable of overcoming the aforementioned limitations of the frequentist approach. In contrast with the traditional frequentist approach, Bayesian models treat data as fixed but consider the parameters of the model to be random variables for which the researchers can specify prior probability distributions, enabling quantification of parameter uncertainty. By using Bayesian models, it is convenient to process data collected over more than one time period, integrating spatial, temporal, and spatiotemporal interaction information as well as some measured covariates. By incorporating the spatial random effects term expressed in terms of a conditional autoregressive model, the Bayesian model can capture the spatial autocorrelation unaccounted for by the independent variables in the regression model. In other words, the spatial random effects can act as surrogates for spatial structure that is unexplained due to, for instance, measurement errors or missing or unmeasured covariates that have spatial structure [47]. Additionally, by borrowing strength from neighboring areas, the Bayesian spatiotemporal model can stabilize risk estimate (e.g., crime risk) areas and address the small number problem [23]. The Bayesian model can be used to not only analyze continuous outcome variables such as crime rates but also model discrete outcome variables that follow Poisson or binomial distributions. What is particularly appealing is that the Bayesian model could be fitted more conveniently with the advancement of computational algorithms. In addition, identifying and mapping the areas with greater relative risks of the outcome variable than the mean trend based on the results of the Bayesian spatiotemporal model could yield more insights into the areas requiring more attention, which might be ignored by frequentist techniques [23]. The Bayesian spatiotemporal model has been widely applied in epidemiological studies and disease mapping [48]. Crime studies employing this model have also emerged in Western literature [21–23,47,49–52]. However, very few crime studies applying the Bayesian approach have been conducted in a Chinese context, except for several case studies in Wuhan, China [25,53,54]. To fill this research gap, we employed the Bayesian modeling in this research to examine the long-term changing pattern of crime in a large Chinese city that is experiencing a rapid process of urbanization. A further novelty or contribution of this research is the inclusion of some covariates of land use into the Bayesian model to explain the variation of crime risks in a long run and help identify areas with significantly higher risks than the overall trend.

3. Study Area and Data

Changchun city is the capital city of Jilin Province, located in Northeast China. Because of the differences between urban areas and rural areas in terms of land use, population density, socioeconomic activities, and crime patterns, we chose the inner city of Changchun as the study area, excluding the surrounding rural areas that are far away and have a quite low level of urbanization, although they are administered by the Changchun government. Changchun city is the economic, financial, cultural and transportation center of Jilin Province, and it has undergone a continuous process of urbanization in recent years. According to the statistics of the registered population from the Public Security Bureau of Changchun, there were approximately 2.86 million and 2.97 million inhabitants in the study area in 2008 and 2017, respectively, indicating an apparent concentrating trend of the population in this metropolitan area. Furthermore, the land use, transportation system and

distribution of commercial and service entities also experienced dramatic changes during this period [55].

The crime data for 2008 and 2017 provided by the Public Security Bureau of Changchun are aggregated to 82 police precincts within the study area, and the total number of crimes (including all violent crimes and property crimes) is available for each precinct in both years. Since detailed crime incident-level data with address information were not available, the 82 police precincts (or named police station service area) were used as the basic units. The whole study area is about 1372.17 km² and the mean size of a police precinct is about 16.73 km². Although the analytical unit is relatively large and might obscure the heterogeneity across micro units, choosing this meso-level unit is still capable of capturing some key, broader effects of the social and physical environment, as well as the social control exercised by the local police [56]. The land use data and the transportation system data in 2008 and 2017 were collected for the covariates from the Changchun Institute of City Planning and Design. In the land use maps in both years, land blocks in the inner city of Changchun are classified into different land types such as residential land, commercial land, industrial land, etc. It means each block possesses its own specific main function. For example, the commercial and recreational land blocks mainly contain the buildings for shopping, business, entertainment and so on. The educational and scientific land blocks mostly involve schools, universities, scientific institutes and so forth. The medical and healthy land blocks are largely composed of hospitals, departments of health and epidemic prevention, etc. The transportation system data for the two years are maps with different types of lines representing roads with various functions, such as arterial roads, sub-arterial roads and ordinary roads. The geocoding process of these maps was implemented in the GIS software ArcGIS10.5, and the crime data and all the covariates were extracted as the attributes for each police precinct.

4. Methodology

As proposed by Bernardinelli et al. [57], a Bayesian spatiotemporal model was first built to simulate the spatial and temporal process of crimes in Changchun during the two years using Equations (1)–(4):

$$Y_{it} \sim \text{Poisson}(\lambda_{it}) \quad (1)$$

$$\lambda_{it} = E_{it} \times RR_{it} \quad (2)$$

$$\log(RR_{it}) = \eta_{it} \quad (3)$$

$$\eta_{it} = b_0 + s_i + u_i + (g + \delta_i) \times t \quad (4)$$

For the i -th ($i = 1, \dots, 82$) police precinct in year t (where $t = 1, 2$ denote 2008 and 2017, respectively), the number of crime cases Y_{it} was assumed to follow a Poisson distribution conditioned on the expected parameter λ_{it} , which can be calculated as a product of E_{it} and RR_{it} . E_{it} denotes the number of expected cases of crimes for each police precinct in year t , which is proportional to the population size for each police precinct. Specifically, E_{it} can be obtained by multiplying the overall crime rate for the entire study area by the population for each police precinct for a specific year t . RR_{it} is the corresponding area-specific relative risk in year t , the logarithm of which (η_{it}) is determined by a linear combination of an intercept b_0 , spatial random effects ($s_i + u_i$), a linear overall temporal trend (g) and a spatiotemporal interaction term (δ_i). The intercept b_0 and the overall temporal trend g are the two fixed effects. The spatial random effects include the spatially structured random effects s_i and the spatially unstructured random effects u_i , accounting for spatial autocorrelation and overdispersion, respectively [58]. The spatiotemporal interaction term δ_i represents the difference between area-specific trends and the overall time trend. This allows for a measurement of the specific departure in each area from the global temporal trend (g). When $\delta_i > 0$, the area-specific trend is steeper than the overall trend, while when $\delta_i < 0$, the area-specific trend is less steep than the overall trend [57].

Since the spatial and temporal pattern of crime might be associated with land use, as mentioned before, the pure spatiotemporal model can be extended by incorporating the covariates (Equation (5)), where X_{ft} denotes the covariates and β_f indicates the corresponding parameters. In this study, the land use covariates were calculated based on the sizes of different types of land use and the lengths of the roads in each area divided by the corresponding population size or the total size of each unit. For example, the residential land per capita in units of m^2 per person is calculated by dividing the total area of residential land by the population in each police precinct. The road density in units of km per square kilometers is calculated by dividing the total length of roads in each area by the total size of the corresponding unit. The descriptive statistics for the crime counts and the covariates are presented in Table 1. The final model for analysis drops the variables that are statistically insignificant:

$$\eta_{ti} = b_0 + \sum_f \beta_f X_{ft} + s_i + u_i + (g + \delta_i) \times t \quad (5)$$

Table 1. Descriptive statistics of crimes and covariates for police precincts in Changchun ($n = 82$).

Variables	2008		2017	
	Mean	Std.	Mean	Std.
Number of crime cases (number)	213.73	157.18	185.21	126.68
Crime rate (per 10,000 inhabitants)	62.89	46.24	54.12	41.66
Dens_R: Road density (km/km^2)	5.14	4.23	5.58	3.92
Com_R_P: Commercial and recreational land per capita (m^2 per person) (same below)	6.57	8.8	9.1	11.32
Res_P: Residential land per capita	30.25	23.58	46.12	37.77
Adm_P: Administrative land per capita	1.58	1.67	1.7	1.98
Indu_P: Industrial land per capita	33.80	57.24	34.96	66.05
Green_P: Green land per capita	6.77	10.32	10.09	15.1
Edu_Sc_P: Educational and scientific land per capita	9.89	14.97	10.54	17.07
Med_H_P: Medical and healthy land per capita	0.75	1.72	0.9	1.78

To fit the models within a Bayesian framework, it is necessary to set prior distributions for the unknown parameters. For the fixed effects, including the intercept b_0 , the overall trend g and the coefficients of the covariates β ($\beta_1, \dots, \beta_f$), a vague prior normal distribution with mean 0 and variance 10^6 was specified. For the spatial random effects s_i and u_i , we assume a Besag-York-Mollie (BYM) specification [59], in which the spatially structural random effect s_i is modeled using an intrinsic conditional autoregressive structure (ICAR) and u_i is modeled by a Gaussian distribution $N(0, \sigma_u^2)$. The ICAR model is defined as:

$$s_i | s_{j \neq i} \sim N \left(\frac{1}{n_i} \sum_{j \sim i} s_j, \frac{\sigma_s^2}{n_i} \right) \quad (6)$$

where n_i is the number of neighbors of area i . $j \sim i$ means all units j that share boundaries with unit i , and σ_s is the standard deviation parameter. The matrix used to define the neighbors for each unit i can be obtained from the shapefile of the study region using the R packages `maptools` and `spdep`, as referred to in Blangiardo and Cameletti [60]. The spatiotemporal interaction term δ_i is assumed to follow an i.i.d. Gaussian distribution $N(0, \sigma_\delta^2)$.

Regarding the hyperparameters σ_u^2 and σ_s^2 , by default, a minimally informative prior logGamma distribution is specified on the logarithm of the two precisions, which means that $\log(1/\sigma_u^2) \sim \log \text{Gamma}(1, 0.0005)$ and $\log(1/\sigma_s^2) \sim \log \text{Gamma}(1, 0.0005)$. In addition, a default log Gamma (1, 0.00005) prior in R-INLA is specified on the logarithm of the precision $1/\sigma_\delta^2$.

To test the sensitivity of the results to the alternatives of the hyperprior distributions, a Gamma (0.001, 0.001) distribution is assigned as the prior for the precisions of hyperparameters σ_u^2 , σ_s^2 and σ_δ^2 .

The deviance information criterion (DIC) evaluated by INLA was used to compare the performance of the models [61], which is a generalization of the Akaike information criterion for Bayesian hierarchical modeling. Models with smaller DIC values (by 5 or more) are usually considered better fitting models.

5. Results

5.1. Variation in the Quantitative and Spatial Patterns of Crimes in Changchun

Overall, the total crime counts in the study area undergo an obvious decrease between the two years. The total crime counts in 2008 and 2017 are approximately 17.5 thousand and 15.2 thousand, respectively, with an approximately 15.4% decrease. As shown in Table 1, the average crime counts decreased from 213.73 in 2008 to 185.21 in 2017. The standard deviation also experienced a decrease from 157.18 to 126.68, which indicates a smaller dispersion of the crime numbers in 2017. Since the population in each unit also changed during the same period, it is necessary and more meaningful to compare the variation in the crime rates between the two years. As reported in Table 1, the average and the standard deviation of the crime rates also showed a decreasing trend, from 62.89 to 54.12 and from 46.24 to 41.66, respectively. In regard to the spatial pattern of crime rates, a clear variation is displayed, as shown in Figure 1.

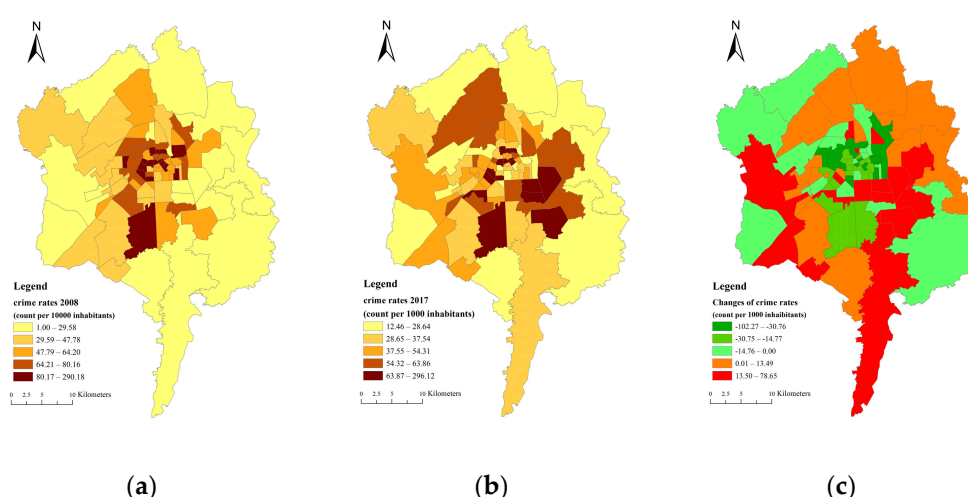


Figure 1. Crime rates in Changchun in 2008 (a) and 2017 (b) and the variation between the two years (c).

For a better comparison of the spatial pattern of crime rates in different years, maps were made based on the quantile classification method. Figure 1a depicts the distribution of crime rates in 2008, which shows that areas with higher crime rates are mostly concentrated in the central city area. In 2017, a more dispersed pattern of areas with higher crime rates appears in the outlying parts of the city, as demonstrated in Figure 1b. Some areas, in particular some police precincts in the eastern and southeastern parts of the city, show higher crime risks. Figure 1c captures the changes in the crime rates between the two years. The areas in green are ones in which the crime rates decreased in 2017 compared with the crime rates in 2008, most of which are located in the central area. The orange and red areas experienced an increase in crime rates during this period, and these mostly appear in the peripheral area of the city.

5.2. Results of Bayesian Spatiotemporal Models

We chose the models with the alternative prior Gamma (0.001, 0.001) for the precision of hyperparameters as the analytical models due to the smaller DIC, although sensitivity

testing reveals that the results of the models are robust to the selection of different hyperpriors (the DICs have a difference of less than 2.0, and the regression coefficients are nearly identical).

Table 2 presents the estimates of all fixed effects for the pure spatiotemporal model, the models incorporating all the land use covariates and the final model with the nonsignificant covariates dropped. The posterior mean of the intercept is significantly negative, indicating a lower basic relative risk for all police precincts. The overall temporal trend estimated by the pure spatiotemporal model is statistically significantly positive (posterior mean of $g = 0.054$, with 95% CI: 0.027, 0.082), indicating that the relative risk of crime during the study period increased by approximately 5.55% on average ($\exp(0.054) = 1.0555$). When the diverse land use covariates are incorporated into the model, some of the variables show significant associations with the relative risk of crimes, while some of the relationships are statistically insignificant. The final spatiotemporal model is obtained after dropping the nonsignificant covariates. The parameters of all the covariates as well as the DIC values of different models are presented in Table 2.

Table 2. Posterior estimates of fixed effects for the Bayesian spatiotemporal models.

	Pure Spatiotemporal Model Mean (0.95 Credible Interval)	Mean of the Model with All Covariates Mean (0.95 Credible Interval)	Final Model Mean (0.95 Credible Interval)
<i>Intercept</i>	−0.251 (−0.306, −0.197) *	−0.690 (−1.000, −0.388) *	−0.686 (−0.983, −0.396) *
<i>Den_R</i>	NA	0.072 (0.014, 0.132) *	0.074 (0.016, 0.133) *
<i>Com_R_P</i>	NA	0.022 (0.013, 0.031) *	0.021 (0.012, 0.029) *
<i>Res_P</i>	NA	0.003 (0.000, 0.006) *	0.003 (0.000, 0.006) *
<i>Adm_P</i>	NA	0.035 (−0.012, 0.083)	NA
<i>Indu_P</i>	NA	−0.002 (−0.004, 0.000) *	−0.001 (−0.003, 0.000) *
<i>Green_P</i>	NA	0.000 (−0.007, 0.007)	NA
<i>Edu_S_P</i>	NA	−0.003 (−0.013, 0.007)	NA
<i>Med_H_P</i>	NA	−0.024 (−0.098, 0.049)	NA
<i>Overall Trend</i>	0.054 (0.027, 0.082) *	−0.076 (−0.133, −0.019) *	−0.074 (−0.129, −0.019) *
DIC	1463.59	1462.39	1462.30

* 95% credible interval excludes 0, indicating the correlation is statistically significant at the 0.05 level.

Although the DIC of the final model is not remarkably smaller than that of the pure spatiotemporal model, indicating that they have the same fitting ability, some of the covariates are proven to be significantly associated with crime risks (0 is not in the 95% credible interval), including the four variables of road density (*Den_R*), commercial and recreational land per capita (*Com_R_P*), residential land per capita (*Res_P*), and industrial land per capita (*Indu_P*), which provides some insights for explaining the overall spatiotemporal pattern of crime risks. It is especially interesting and noteworthy that the estimated coefficient of the overall time trend in the final model changes to a significantly negative sign from a significantly positive one in the pure model; we will conduct some analysis of this in the next discussion section. Regarding the land use covariates, the strongest association is found between road density and crime risk, which means that an increase of 1 unit in road density is associated with an increase of approximately 7.7% in the relative risk of crime ($\exp(0.074) - 1 \approx 0.0768$). In a similar way, an increase of 1 unit in commercial and recreational land use per capita and in residential land use per capita is weakly associated with an increase of approximately 2.12% and 0.30%, respectively, in crime risk. However, an increase of 1 unit in industrial land per capita is very weakly related to a decrease of approximately 0.10% in crime risk ($1 - \exp(-0.001) \approx 0.0010$).

According to Equation (5), in addition to the fixed effects, the area-specific random effects composed of the spatially structured random effects, the spatially unstructured random effects and the differential trends (spatiotemporal interactions) were estimated in the model fitting results.

Usually, differential trends draw more attention from researchers because they can be used to capture the difference in an area between the global trend and the area-specific

trend [23]. Using ArcGIS 10.5 software, we mapped the posterior means of the spatiotemporal interactions ($\delta_i s$) fitted by the final model (Figure 1a). Additionally, as interest often lies in the areas with significantly higher crime risks, which are sometimes called hotspot areas [23,47], we also compute the posterior probability of each area possessing a spatiotemporal interaction larger than 0 using R-INLA as proposed by Blangiardo et al. [20], and we identify the areas with a larger than 95% probability of being a hotspot, as shown in Figure 2b.

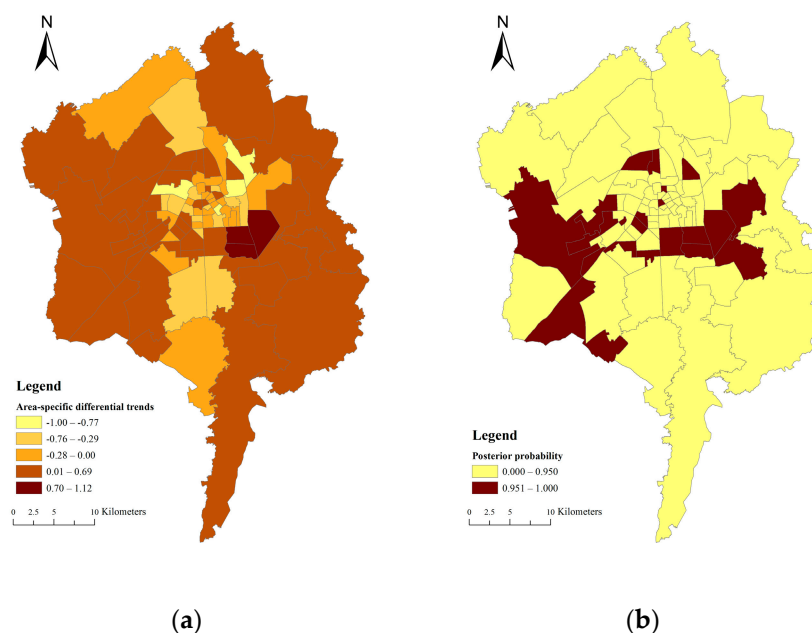


Figure 2. Posterior mean of area-specific differential trends (a) and the posterior probability of being a crime hotspot (b) according to the final Bayesian model.

Based on the spatial distribution of the posterior mean of the area-specific differential trends, the areas with increasing area-specific trends ($\delta_i > 0$) are mostly located in the surrounding part of the city. The police precincts with the greatest increasing area-specific differential trends are identified in the southeastern part of the city, all of which are within the Changchun Economic and Technological Development Zone. It is also worth noting that the areas with less steep area-specific trends than the overall trend ($\delta_i < 0$) are mostly located in the central city. In regard to the posterior probability of the areas having a significantly steeper area-specific trend than the overall trend, we are more certain that some police precincts possess steeper area-specific temporal trends from a statistical perspective. Generally, areas with higher increasing differential trends also have higher posterior probabilities of being greater than the overall trend, which is also found by Law et al. [23].

6. Discussion

As a typical rapidly growing city in Northeast China, Changchun has undergone an obvious change in terms of the spatial pattern of crime risks in recent years. Although both the average crime counts and crime rates decreased in 2017 compared with 2008, the areas with relatively high crime risks exhibit a more dispersed pattern. As shown in Figure 1, the crime rates in the two years show different patterns to some extent. The most prominent characteristic is that the outside areas present higher crime risks while most areas of the inner city experience a decreasing trend in crime risks. Interpretations of this phenomenon may be complicated since the crime data cover more than one period. For instance, the official guardianship from the law enforcement has been largely enhanced, especially in the inner city during these years. More surveillance cameras have been installed and more police officers have been deployed on the streets to deter crime. That is an important reason

why the total crime counts decreased obviously during these years. Nevertheless, the enhancement of guardianship are not distributed evenly across space, with more deployed in the inner part and less in the outskirts. The increase of crime rates in some outside areas may be partly related to the insufficiency of the guardianship. Although data explicitly quantifying the effect of guardianship are unavailable, it is reasonable to believe that guardianship did contribute to the changing spatial pattern of crime risks. There may be a general trend in all the areas, but different areas may also have a differential trend. Additionally, the covariates that may exert an impact on crime risks are changing. The spatial effects among neighboring areas should also not be overlooked since they may affect the estimations of the parameters. The Bayesian spatiotemporal model provides a useful framework to incorporate the multiple effects and overcome the small number problem. By including a spatiotemporal interaction term acting as a surrogate of the unmeasured changing factors, such as the changing guardianship during these years, the Bayesian model is able to obtain a more accurate estimate for the covariates and improve model fit. In addition, researchers and police officers could identify the areas where underlying factors possess more impacts on the change of the crime patterns (such as areas with insufficient official guardianship) through mapping the spatiotemporal interactions or so-called area-specific differential temporal trends.

The results of the pure Bayesian spatiotemporal model indicate that the overall temporal trend is significantly positive, while the fitting results of the final model show that the overall temporal trend is significantly negative. This switch happens because of the integration of the land use covariates. Some of the variation in higher crime relative risks that occurs in some of the analytical units is explained by the covariates of land use in the final model. In other words, after controlling the impacts of these land use variables, the general trend should be decreasing rather than increasing, which justifies the incorporation of the land use variables to some extent. Additionally, the incorporation of the covariates changed the values as well as the spatial pattern of the area-specific differential temporal trends (spatiotemporal interactions). Figure 3 illustrates the spatial pattern of the posterior mean of δ_i (Figure 3a) and the posterior probability of areas being crime hotspots (Figure 3b) according to the results of the pure spatiotemporal model. Compared with this, we can see that the range and the pattern of the values estimated by the final model obviously change, as shown in Figure 2. For example, the range of the area-specific differential temporal trends in the final results shrink to -1.00 – 1.12 from -1.13 – 1.48 according to the pure model. The number of areas with higher values of δ_i clearly decreases, and the posterior probabilities of some areas being crime hotspots become insignificant, such as the police precincts in the northernmost, southernmost and easternmost parts of the city. The change in the spatial pattern of area-specific differential trends after incorporating the covariates indicates that some of the geographical variation in the area-specific trends can be explained by the land use variables, especially in the peripheral areas.

Based on the final Bayesian model, the regression parameters of the land use variables show that the relative risks of crime in Changchun are positively associated with three land use variables, road density, commercial and recreational land per capita, and residential land per capita, as expected. These associations can be interpreted largely from the perspective of routine activities theory, which states that the opportunities for criminal activity are determined by the convergence in space and time of three key elements: likely offenders, suitable targets, and the absence of capable guardians against crime [12]. A higher level of road density always means more pedestrian traffic and more vehicle traffic on the roads, which may increase the number of suitable targets and attract more potential offenders. Additionally, high road density implies that offenders have more escape routes to select after committing crimes and that effective guardianship is difficult to implement. The positive relationship between commercial and recreational land per capita and crime risk is also in accordance with routine activities theory. Many banks, markets and other businesses are concentrated in commercial and recreational areas. Furthermore, such areas draw more transient populations for working, shopping, and entertainment rather than

living. Taken together, there are usually more suitable targets as well as potential offenders in these areas. Meanwhile, guardianship in such areas is usually ineffective due to intense mobility. Residential land per capita is weakly positively associated with crime risk. In Changchun, the areas with higher residential land per capita usually correspond to newly developing neighborhoods. During the process of urbanization, land use for living has largely expanded following the high demand for better residential conditions. Meanwhile, the land resources in Changchun are relatively sufficient compared with those of other large cities, so housing developers in the newly developing neighborhoods tend to occupy more land to attract consumers. In newly developing areas with more residential land per capita, residents are usually unacquainted with each other, which might weaken the ability of social control to affect crime occurrences, so these areas may have higher crime risks, tracing back to social disorganization theory [11]. However, it should also be noted that newly developing neighborhoods are commonly gated or semiclosed, which may prevent some potential offenders from entering and hinder crime. This may explain why the association between residential land per capita and crime risk is weak to some extent. Finally, a negative association is found between industrial land per capita and crime risk, as expected. Areas with vast industrial land are nearly all located in the periphery of the city. In the peripheral areas of Changchun, the population density is usually small, and the degree of mixture is lower, which could bring down the number of potential offenders and targets and hence opportunities for crime [13]. Similarly, it is worth noting that the relationship between industrial land per capita and crime risk is also weak. This may be because industrial land is not a ubiquitous land type, and there are many areas that have very little or even no industrial land but have very low levels of crime risk for other reasons, which may weaken the general associations.

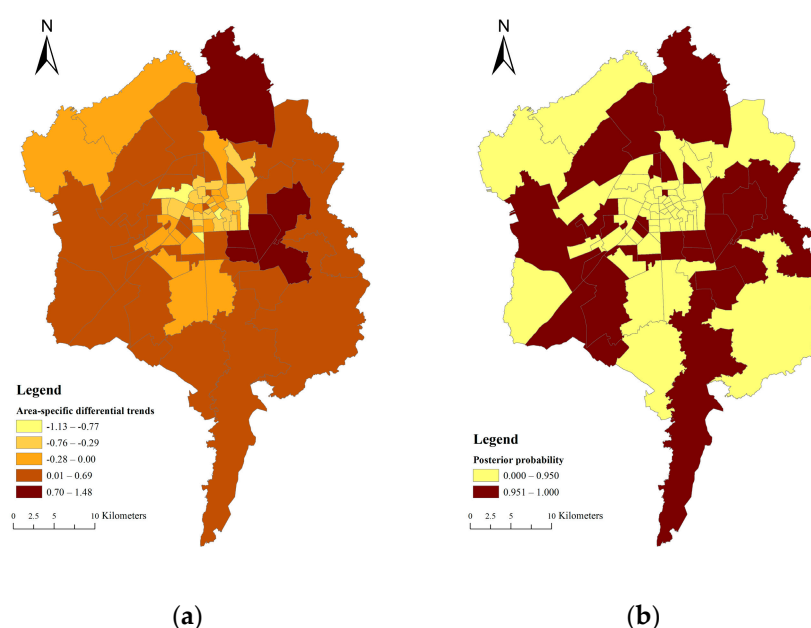


Figure 3. Posterior mean of area-specific differential trends (a) and the posterior probability of being a crime hotspot (b) according to the pure Bayesian model.

After considering the spatial effects and controlling for the land use covariates, we are still able to identify some police precincts possessing the greatest increasing area-specific differential trends in the southeastern part of the city. For example, the areas with the highest area-specific differential trends are all located in the Changchun Economic and Technological Development Zone, as shown in Figure 2. There is a necessity for further exploration of these areas, as the existence of hotspots indicates that there may be some unmeasured factors in these areas that cause the areas to suffer increasing crime risks compared with the overall trend. The results could provide relatively accurate crime trend

estimations and specific locations requiring more attention from law enforcement because the Bayesian model has already taken care of the covariates, the general trends, and the spatial effects that might affect the estimation of crime risks, which is difficult for the traditional frequentist approach.

The limitations of this study mainly derive from the lack of adequate data. For example, only two years of data are available, so the overall trend of the crime risks is assumed to be linear. If data for more time periods are obtained, a linear time trend may be found unsuitable. Additionally, due to the data accessibility, we can only use land use variables as covariates. As the DIC results show (Table 2), the final model with the covariates of land use does not show distinguishably better performance than the pure spatiotemporal model. Although the final model is also necessary to obtain insights into the impacts of land use on crime risks, as discussed above, the DIC results indicate that land use variables do not explain a considerable part of the variability in crime risks. There should be more underlying and unmeasured confounders, such as variables in terms of socioeconomic status, demographic characteristics or official and unofficial guardianship, and incorporating them in the model may improve the fit. Similarly, the crime rates and the expected numbers of crimes for each area are calculated using the registered population, which may not be the best choice. In recent years, ambient populations have been adopted more often in studies and have proven to yield better performance [62,63]. If appropriate data are available, it is worth using the ambient population to estimate the expected number of crimes in the Bayesian model and making a comparison with the results of this study. In addition, if incident-based crime data with detailed locational information were obtained in the future, it might be promising to conduct Bayesian spatiotemporal analysis to better explore the relationships between crime and influential factors at smaller units, such as regular grids that can be readily created using GIS tools [64]. Finally, different types of crimes may have specific spatial and temporal patterns as well as influential factors. Future research should consider analyzing certain types of crime to deepen the understanding of the spatiotemporal pattern of crimes.

7. Conclusions

During the process of urbanization over the years studied, the spatial pattern of crimes in Changchun has experienced an obvious change in the characteristics of more dispersed crime risks in the surrounding areas, although the total crime counts, the mean of the crime counts and crime rates across all the precincts present a clearly decreasing trend. To further capture and understand the change in the pattern of crime risks, this study used a Bayesian modeling approach to estimate the overall trend of crime risks, the coefficients of the land use covariates, spatial effects and area-specific differential trends. The results show that the sign of the overall crime trend changes from significantly positive to significantly negative after the land use covariates are incorporated into the Bayesian model. This means that some of the higher crime risks appearing in peripheral areas can be explained by the land use variables. In other words, some of the change in land use during these years may contribute to the change in the pattern of crime risks, especially in the surrounding areas. Four land use variables are found to be significantly associated with crime risks: road density, commercial and recreational land per capita, residential land per capita and industrial land per capita. All these associations can be explained by classic theories in environmental criminology, such as routine activities theory and social disorganization theory. In addition, the results of the Bayesian spatiotemporal model also highlight that some areas exhibit significantly higher crime risks than the general trend even after controlling for the land use covariates and spatial effects. The identification of these areas can provide insights for police officers regarding where to concentrate more effort to control increasing crime risks rather than concentrating on all areas. It is also necessary for researchers to pay more attention to these areas because the existence of these hotspot areas indicates that there may be some unmeasured factors causing higher crime risks other than land development for urban construction. This study represents an

early attempt of applying Bayesian modelling approach to analyze the long-term changing pattern of crimes in a typical large Chinese city during the intense process of urbanization. The Bayesian spatiotemporal method is able to incorporate data in different periods into the same model and address methodological concerns such as the small number problem, overdispersion and spatial autocorrelation, presenting advantages in many respects, such as flexibility and computational convenience. For instance, after considering the spatial effects, the results of the Bayesian model in this work reveal that more factors may have impacts on the crime pattern. If crime data and data of other relevant aspects in more years were available, they could be readily incorporated into the Bayesian model framework to generate more convincing results and insights, without making the computation more complex and time-consuming. Compared with the traditional crime analysis methods, the Bayesian model not only can verify the existence of unmeasured factors underlying the changes in crime risks but also has the ability of identifying spatial areas where these factors most likely locate. It is worthy conducting more researches using the Bayesian method in the area of crime analysis.

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