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Comparing the Spatiotemporal Patterns of Crime Incidents based on Time Series Analysis: A Case Study of Austin, Texas

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Abstract: As urban populations continue to expand, understanding the patterns of urban crimes becomes increasingly important for public safety and prevention strategies. This study uses spatiotemporal autoregressive integrated moving average (STARIMA) and geographical random forest (GRF) models to explore and compare the dynamics of two distinct categories of crime as classified by the Federal Bureau of Investigation: crimes against persons (e.g., assault, rape) and crimes against property (e.g., burglary, vandalism). While STARIMA is a well-established method for capturing linear spatiotemporal dependencies, GRF integrates spatial heterogeneity and nonlinear relationships through local weighting. Our results show that GRF consistently outperforms STARIMA across both crime types, particularly for property crimes, where broader temporal trends and spatially variable patterns play a stronger role. This work demonstrates the importance of disaggregating crime by type and selecting modeling approaches that accommodate the unique spatial and temporal characteristics of each. The results provide a deeper understanding of crime prediction and guidance for data-driven policing strategies.

Keywords: Crime Prediction, STARIMA, Geographical Random Forest, Spatial-Temporal Modeling

1. Introduction

Urban crime remains a persistent concern in modern cities as it influences public safety, local economics, and the allocation of policing resources (Hess et al., 2014, LeClerc and Savona, 2017, van Koppen et al., 2010). As urban environments grow more dynamic and complex, the need for timely and accurate prediction of crime patterns becomes increasingly urgent (Neuilly et al., 2011, Wolff and Asche, 2009). The pattern of crime is inherently spatiotemporal in nature, which emerges from the interaction of social behaviors, environmental contexts, built environment, and routine human mobility patterns (Alexander and Xiang, 1994). Thus, understanding the spatial and temporal dynamics of crime is essential for effective intervention strategies and long-term urban planning (Ratcliffe, 2004, Weisburd et al., 2004).

A wide variety of analytical approaches have been developed for crime prediction. Traditional statistical methods such as regression analysis have been widely used to examine the correlation between crime rates and socio-demographic or environmental variables (Anselin et al., 2000, Boggs, 1965). Kernel density estimation and other hotspot mapping techniques are commonly employed to visualize concentrations of criminal activity across space (Chainey and Ratcliffe, 2005, Rennison and Hart, 2019). However, these methods often neglect the temporal dimension or treat time as a static factor.

To address crime's dynamic nature, temporal prediction methods based on time series analysis have been adopted and refined for crime predictions. For example, the autoregressive integrated moving average (ARIMA) model and its seasonal variants have been applied to crime count data to capture recurring temporal trends and cycles (Anderson, 1985, Gorr and Harries, 2003, Yuan, 2017, Yuan and Wylie, 2024). Among the more spatially grounded methods, the spatiotemporal autoregressive integrated moving average (STARIMA) model provides a structured framework for incorporating both spatial autocorrelation and temporal dependency (Kamarianakis, 2006, Liu and Lu, 2019). STARIMA has been effectively used in fields such as traffic forecasting (Min et al., 2009), climate monitoring (Munandar et al., 2023), and crime analysis (Liu and Lu, 2019).

More recently, machine learning models such as decision trees, random forests, support vector machines, and deep learning architectures have gained popularity for their ability to handle large-scale and high-dimensional datasets (Shah et al., 2021, Wang et al., 2013). These approaches offer high predictive performance but are sometimes criticized for their limited interpretability and lack of integration with spatial theory or geographic context (Perry et al., 2013). A machine learning approach to addressing these challenges is the geographical random forest (GRF) model, which combines regular random forests with spatially varying coefficients (Georganos et al., 2021). The spatially-aware nature of the approach allows the model to capture how crime patterns vary depending on local factors, such as socioeconomic status, infrastructure, and population density; therefore, it has been proven effective in several studies (Sun et al., 2024, Wu et al., 2024).

However, although spatially aware models like STARIMA and GRF are effective in predicting space-time series, most crime-related applications of these models focus on overall crime counts or aggregate categories without differentiating between crime types. This lack of differentiation poses a significant limitation. Crimes against persons, such as assault or sexual violence, are often influenced by social interaction patterns and may display different spatial diffusion behaviors compared to crimes against property, such as burglary or vandalism, which may be more opportunistic and location-specific (Cohen and Felson, 1979, Groff and La Vigne, 2002). Aggregating these distinct types of crime into a single modeling framework may overlook important details and reduce predictive performance.

Motivated by this gap, the present study applies the STARIMA and GRF models to separately analyze and compare the spatiotemporal patterns of crimes against persons and crimes against property in Austin, Texas. Drawing on two years of detailed incident-level crime data from 2022 to 2023, we aim to evaluate how well these two predictive models perform for each crime category and whether distinct spatial or temporal structures emerge. Our study seeks to provide better insights into the dynamics of urban crime and inform more effective prevention strategies.

2. Background

Although much research modeling spatiotemporal crime patterns includes all crimes or calls for police service without disaggregating by offense type (Catlett et al., 2019, Yi et al., 2018), other studies have examined different types of crime separately (Alghamdi and Al-Dala'in, 2024). There are several reasons why at least crimes against persons and property should be considered separately. First, research has shown that different types of crime often follow different seasonal and long-term trends (Andresen and Malleson, 2013, Baumer et al., 2018, Prieto Curiel, 2023). For example, Andresen and Malleson (2013) showed how assaults peaked in the summer months, while thefts appeared to be most prevalent later in the year. When examining long-term trends, the data shows that trends for homicide and burglary, the most serious violent and property offenses, respectively, are "similar but not identical" (Baumer et al., 2018: 41).

Second, the public is disproportionately worried about crimes against persons, such as homicide, assaults, and sexual offenses (Lee et al., 2020). This has been attributed, at least in part, to the psychological and physical harms associated with violent crime (Langton and Truman, 2015). Because crimes against persons are much less prevalent than crimes against property, when we consider both crime types together, any patterns in the former—the crimes demanding the most urgent response—get obscured.

Lastly, responses to crimes against persons and crimes against property can be very different from each other, which also warrants their independent examination. Law enforcement strategies, resource allocation, community interventions, and even policy frameworks are often tailored according to offense type (National Institute of Justice, 2025). For example, preventing assaults may focus on situational interventions in nightlife districts or domestic violence prevention, whereas burglary prevention might prioritize environmental design and neighborhood surveillance programs. Failing to distinguish between them in predictive modelling could lead to generalized strategies that are ill-suited to address the specific drivers and consequences of each crime type.

3. Research Design

3.1 Data

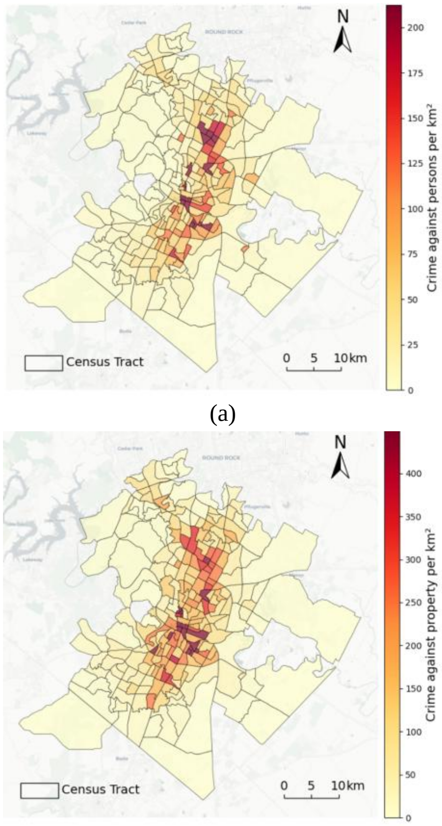
The dataset used in this study was provided by the Austin Police Department (APD). It contains detailed records of reported crime incidents within the city of Austin, covering a multi-year period from January 2022 to December 2023. Each record includes spatial, temporal, and categorical attributes associated with individual crime events. Key attributes in the dataset include anonymized incident identifiers ('IncidentID'), and crime types such as 'Homicide', 'Assault', 'Robbery', 'Burglary', and others. For the purpose of analysis, we grouped the incidents into crimes against persons (e.g., assault, rape) and crimes against property (e.g., burglary, vandalism) based on the guidelines from the Federal Bureau of Investigation (2019).

The dataset also includes spatial information through coordinate fields ('X', 'Y'), which represent the geolocation of incidents based on address-level data. Temporal characteristics are thoroughly documented, with fields such as 'DateTime_From' and 'DateTime_To' indicating the time window during which the incident occurred. For the time series analysis, we derived the middle point of the recorded incident duration to use as the time point of the incident.

Field Name	Value
IncidentID	A1234xxxxx
X	30xxxxx.5
Y	100xxxxx.2
Category	Assault
DateTime_From	6/18/2022 0:30
DateTime_To	6/18/2022 6:30

Table 1. Example data records (only fields related to this research are included)

The density plot in Figure 1 shows that both crimes against persons and crimes against property in Austin are highly concentrated in the central and near-east tracts of the city, with densities gradually decreasing toward the outer suburbs. However, crimes against property exhibit a broader spatial spread and higher overall density levels compared to crimes against persons, which appear more clustered in specific hotspots.



(a)

(b)

Figure 1. Density plots for crime incidents in Austin: (a) Crime against persons; (b) Crime against property.

3.2 Methodology

3.2.1 *STARIMA*

The STARIMA model extends the classical ARIMA framework by incorporating spatial dependencies through spatial lag operators (Kamarianakis, 2006), which makes STARIMA particularly suitable for modeling incidents that are autocorrelated in both space and time, such as urban crime patterns.

The STARIMA model is denoted as STARIMA (p^r, d, q^s), where p^r represents the autoregressive (AR) component, with p indicating the number of temporal lags, r representing the number of spatial lags in the AR term, and q^s term corresponds to the moving average (MA) component, where q is the number of temporal lags and s denotes the number of spatial lags in the MA term. The parameter d refers to the order of differencing required to achieve stationarity. For example, STARIMA (1^1, 1, 1^2) has an AR term with 1 temporal lag and 1 spatial lag, a first-order differencing to ensure stationarity, and an MA term with 1 temporal lag and 2 spatial lags. In this research, we construct the STARIMA models following the steps below:

- *Stationarity Check and Differencing*:

  We first tested the stationarity of the weekly crime incident data using the standard Augmented Dickey-Fuller (ADF) test. For non-stationary series, differencing is applied to achieve stationarity:

  $$Y_{t'} = Y_t - Y_{t-1} \tag{1}$$

  where $Y_{t'}$ represents the differenced value at time t, Y_t is the original value at time t, and Y_{t-1} is the value at the previous time point. This process removes trends and helps identify the *d* parameter in STARIMA.

- *Parameter Selection*:

  After achieving stationarity, STARIMA models can be modelled by the STARMA (space-time autoregressive moving average) package in R. In our analysis, we chose the census tracts as the spatial unit. The spatial structure in STARIMA was encoded using a contiguity-based spatial weight matrix *W*, where neighboring geographic units (e.g., grid cells or administrative boundaries) were assigned non-zero weights. This ensures that spatial lags accurately reflect local spatial interactions.

  A grid search procedure was conducted to identify optimal values for all parameters, which help balance temporal and spatial lags. Candidate models were evaluated based on the Bayesian Information Criterion (BIC) and the highest Log-Likelihood to avoid overfitting.

This methodological framework can effectively link spatial patterns with temporal trends to better capture the inherent complexities in urban crime data and improve prediction accuracy.

3.2.2 *GRF*

GRF is a spatial extension of the traditional random forest algorithm capable of modeling the spatial heterogeneity in geographic data. It combines the predictive power of ensemble machine learning algorithms with the spatial awareness of traditional spatial statistical methods (e.g., geographically weighted regression or GWR) (Georganos et al., 2021).

GRF incorporates geographic distance into the model process, where observations closer to a given location have a higher impact on predictions than distant observations. This allows the model to capture spatially varying relationships in the data, which makes it particularly useful for predicting the spatiotemporal patterns of crime incidents. GRF creates both global and local models (Georganos et al., 2021). The global model captures general relationships across the entire study area. The local model accounts for spatial variations specific to individual locations. The combined model integrates both global and local components using a weighting parameter.

In this research, the GRF implementation uses the PyGRF python package (Sun et al., 2024), as described below:

- *Spatial Weighting*:

  For each census tract, nearby observations receive higher weights based on a bisquare kernel function and optimal bandwidth parameter determined using the incremental spatial autocorrelation (ISA) method. The ISA method ensures the fitted models are not too localized or too generalized by identifying the distance at which spatial autocorrelation peaks.

- *Model Training and Prediction*:

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We then train the random forest models for each census tract using weighted observations. The prediction process combines global and local components: the former uses a standard random forest trained on all observations, whereas the latter trains spatially weighted models based on the distance from a given location.

The prediction is computed using Equation (2).

$$y_p = (1 - w) * g + w * l \quad (2)$$

where y_p is the predicted value, w is the local weight assigned to the local prediction (a value between 0 and 1), g is the global prediction from the global model, and l is the local prediction from the local model.

3.2.3 *Model Performance Comparison*

To compare the predictive performance of STARIMA and GRF models, we applied both models separately to the two aforementioned crime categories: crimes against persons and crimes against property. For each model, we first trained and validated on the same temporal range (January 2022–April 2023) and used a consistent testing period (May 2023–December 2023). We then evaluated model performance using R^2 and Root Mean Square Error (RMSE). This allowed us to assess not only how STARIMA and GRF perform within each crime type but also to compare their overall effectiveness across crime categories.

Figure 2 shows a methodological flow chart of our analysis, including the processing, model construction, and evaluation steps.

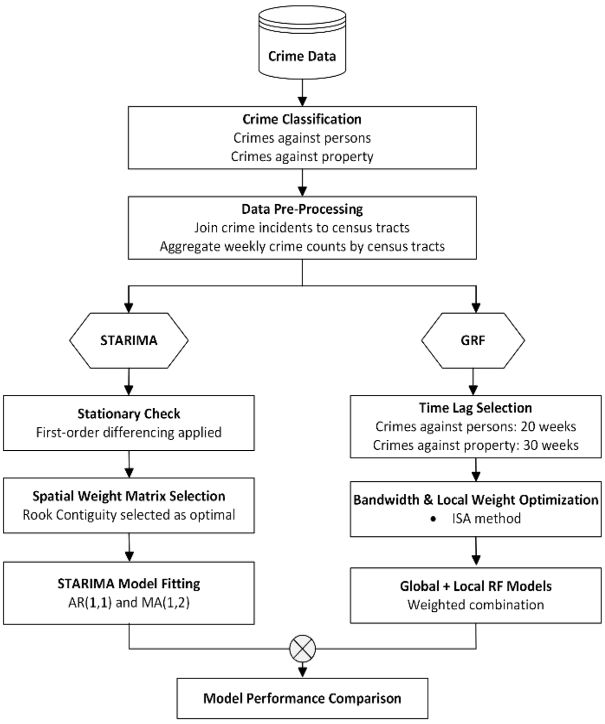


Figure 2. Methodological flow chart.

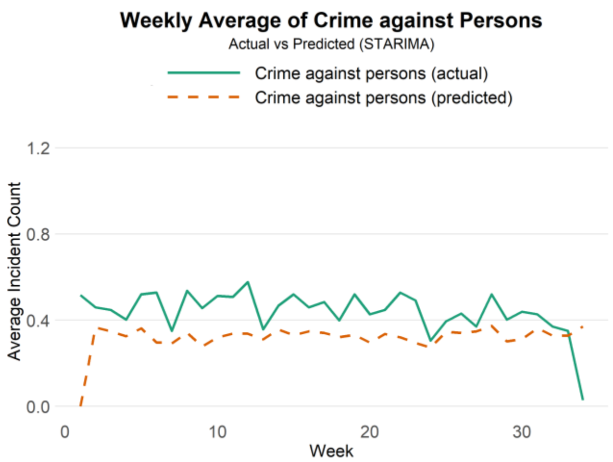
4. Results and Discussion

4.1 STARIMA Results

The STARIMA model was applied separately to the weekly time series of crimes against persons and crimes against property to evaluate spatiotemporal dynamics and predictive performance. After confirming non-stationarity in both time series, first-order differencing was applied to meet the stationarity assumption required for STARIMA modeling. The model STARIMA(1^1,1,1^2) was selected as the best-fitting structure for both crime categories based on the BIC and Log-Likelihood values. It includes one temporal and one spatial lag in the AR component, and one temporal and two spatial lags in the MA component. This configuration effectively captures short-term temporal autocorrelations as well as spatial spillover effects across neighboring census tracts.

The evaluation of the models showed that STARIMA performed better in modeling crimes against persons than crimes against property. STARIMA achieved a lower BIC (54,732.29) and a higher Log-Likelihood (-27,341.76) for crimes against persons, compared to a BIC of 74,687.64 and Log-Likelihood of -37,319.44 for crimes against property. In addition, for crimes against persons, the model reached a test R^2 of 0.38 and RMSE of 1.13, while for crimes against property, the respective values were 0.30 and 2.21. The results suggested that crimes against persons may demonstrate more structured spatiotemporal patterns, which makes them more suitable for STARIMA's assumptions (c.f. Figure 3).

Although the model effectively captured linear spatial-temporal interactions, residual diagnostics also indicated some remaining autocorrelation and non-normality in the residuals, particularly for property crime predictions. This suggested room for improvement by including more parameters in the analysis, such as demographic factors. However, STARIMA still demonstrates a promising capability for modeling urban crime patterns, especially in contexts where crimes are driven by shorter distances (inter-neighborhood) spatial factors.



(a)

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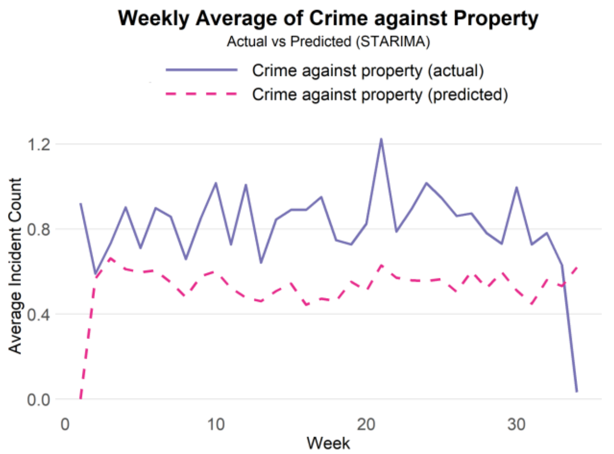
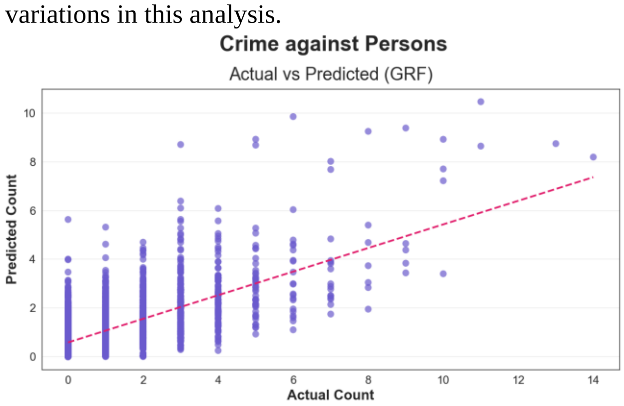


(b)

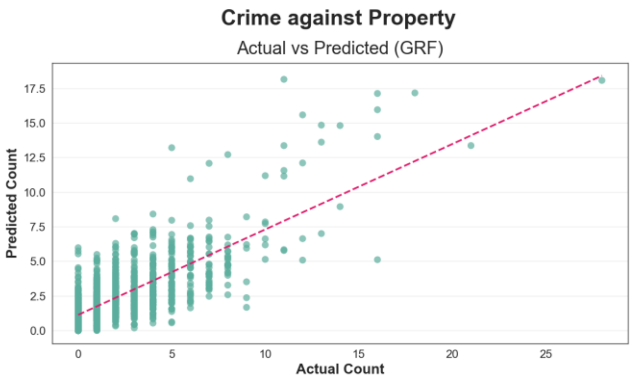
Figure 3. STARIMA model comparisons: (a) Crime against persons; (b) Crime against property.

4.2 GRF Results

The GRF framework was also tested on weekly crime datasets to evaluate its capacity to identify spatial variability in predictive outcomes. Distinct models were developed for crimes against persons versus crimes against property. The models integrated both global (broader trends) and localized (area-specific) factors. The trained models showed that, for crimes against persons, a 20-week lag and a local weight of 0.127 produced the best results. The model achieved an R^2 of 0.434 and an RMSE of 1.056 based on the testing subset. For crimes against property, the optimal lag was 30 weeks, and the model performed even better, with an R^2 of 0.545 and an RMSE of 1.832 (see Figure 4). In both cases, the global component of the model contributed more strongly to predictive accuracy than the local component, especially for crimes against property, suggesting that broader temporal trends and global spatial patterns were more influential than localized variations in this analysis.



(a)



(b)

Figure 4. GRF model comparisons: (a) Crime against persons; (b) Crime against property.

While the local models on their own showed modest performance, when combined with the global component, local models still helped improve the overall predictions. The contribution of the local model was more noticeable in areas with spatial clusters of high or fluctuating crime counts. The analysis results demonstrate GRF's strength in incorporating long-term temporal dependencies and spatial context.

4.3 Cross-model Comparison

To compare the effectiveness of the two modeling approaches, we evaluated STARIMA and GRF based on the same testing period and performance metrics. GRF outperformed STARIMA in both crime categories, particularly for property crimes. As mentioned in Sections 4.1 and 4.2, for crimes against persons, GRF achieved slightly better predictive accuracy (R^2 = 0.434, RMSE = 1.056) compared to STARIMA (R^2 = 0.38, RMSE = 1.13). For property crimes, GRF showed a more substantial improvement, with an R^2 of 0.545 and RMSE of 1.832, while STARIMA's performance shows room for improvement (R^2 = 0.30, RMSE = 2.21).

These differences in testing results are likely due to the inherent design of each model. STARIMA uses a fixed spatial weight matrix and is better for capturing linear spatiotemporal interactions. However, GRF can adapt spatial weighting dynamically and is better equipped to model nonlinear relationships and broader temporal trends, which may explain its better performance in both crime categories.

5. Conclusions

This study compared the spatiotemporal dynamics of two types of urban crimes (crimes against persons and property) in Austin, Texas. We tested the effectiveness of two modeling frameworks (STARIMA and GRF) when predicting different categories of crime incidents. The analysis showed that GRF outperformed STARIMA across both crime categories, particularly for property crimes, due to its capacity to integrate localized spatial dependencies with broader regional patterns.

When adopting crime prediction methods, researchers and practitioners must account for the distinct spatiotemporal characteristics of crime types. For urban policymakers, GRF's characteristics, combining global trends with neighborhood-level variations, offer a valuable tool for designing targeted policing strategies, especially where nonlinear interactions and spatial variation play important roles.

Future research can incorporate real-time environmental data, socioeconomic variables, and temporal granularity to further improve predictive accuracy. More advanced deep learning models can also be adopted to examine their performance for predicting different crime types.

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