Final Report
No.: REPS-HU-25-02

Building AI and Machine Learning Technologies for Enhancing Transportation Station Area Safety in San Jose, CA

Bo Yang
Principal Investigator
Assistant Professor
Environmental Studies Department
University of California at Santa Cruz

Authors
Xiangyu Ren, Ph.D.
Bo Yang, Ph.D.
Ahoura Zandiatashbar, Ph.D.

2025

Sponsored By
The Research and Education for Promoting Safety (REPS) Tier 1 University Transportation Center

The Research and Education for Promoting Safety (REPS) Tier 1 University Transportation Center is a collaborative initiative aimed at enhancing transportation safety through multidisciplinary research. This center integrates cutting-edge research from civil engineering and computer science to tackle challenges related to infrastructure, traffic operations, and cybersecurity. The center is led by Howard University in partnership with the University of Maryland, San Jose State University, and the University of Nevada, Las Vegas.

U.S. Department of Transportation (US DOT) Disclaimer

The contents of this report reflect the views of the authors, who are responsible for the facts and the accuracy of the information presented herein. This document is disseminated in the interest of information exchange. The report is funded, partially or entirely, under 69A3552348323 from the U.S. Department of Transportation's University Transportation Centers Program. The U.S. Government assumes no liability for the contents or use thereof.

Acknowledgments

Funding for this research is provided by the Research and Education for Promoting Safety (REPS) Tier 1 University Transportation Center at Howard University under grant 69A3552348323 from the U.S. Department of Transportation's University Transportation Centers Program. We also extend our appreciation to the research collaborators and institutional partners whose contributions and expertise have been invaluable in shaping the direction of this study. Additionally, we would like to thank our student assistants, Henri Brillon and Boyao Huang, for their efforts and valuable contributions to this project. Their assistance in data analysis, modeling, and research implementation has been instrumental in achieving our objectives.

Building AI and Machine Learning Technologies for Enhancing Transportation Station Area Safety in San Jose, CA

Final Report
August 2025

Principal Investigators

Bo Yang
University of California, Santa Cruz

Co-PI

Ahoura Zandiatashbar
San José State University

Authors

Xiangyu Ren
Bo Yang
Ahoura Zandiatashbar

Sponsored By
The Research and Education for Promoting Safety (REPS) Tier 1 University Transportation Center

Technical Report Documentation Page

1. Report No. REPS-HU-25-02	**2. Government Accession No.** N/A	**3. Recipient's Catalog No.** N/A
4. Title and Subtitle Building AI and Machine Learning Technologies for Enhancing Transportation Station Area Safety in San Jose, CA		**5. Report Date** January 2025 **6. Performing Organization Code** N/A
7. Author(s) Xiangyu Ren, Ph.D. https://orcid.org/0009-0003-6760-7202 Bo Yang, Ph.D. https://orcid.org/0000-0001-7439-192X Ahoura Zandiatashbar, Ph.D. https://orcid.org/0000-0001-8198-4619		**8. Performing Organization Report No.** Project #2425.
9. Performing Organization Name and Address San Jose State University 1 Washington Sq San Jose, California United States 95192		**10. Work Unit No.** N/A **11. Contract or Grant No.** 69A3552348323
12. Sponsoring Agency Name and Address Office of the Assistant Secretary for Research and Technology University Transportation Centers Program Department of Transportation Washington, DC, United States 20590		**13. Type of Report and Period Covered** Final Report (January 2024 - August 2025) **14. Sponsoring Agency Code** USDOT OST-R
15. Supplementary Notes https://rip.trb.org/View/2431333		

16. Abstract

Accurate crime prediction is crucial for allocating police resources to reduce and prevent crime, particularly in large cities. Previous research has explored the relationship between social and built environments and street crime, but few studies have combined multi-source data using geo-statistical modeling. In this research, we applied a Spatial-Temporal Cokriging algorithm to predict street crime risk in San Jose, California, by integrating historical street crime data with sociological and built environmental variables. We used time-series data from 2,479 police call records in 2019, including assaults and robberies, as the primary variable. Secondary variables included transit density and walkability data from the Environmental Protection Agency (EPA)'s National Walkability Index. We analyzed crime risks across quad-week periods, predicting separately for weekdays and weekends. Our multi-variable crime prediction model compares outcomes using historical data, socio-economic data, and environmental data. The results reveal distinct crime patterns for weekdays and weekends, aiding in crime prediction for rapidly growing metropolitan areas. The study found that the spatial-temporal geostatistical prediction model performed better for weekday crimes, achieving over 70% accuracy, compared to around 60% for weekend crimes. Including transportation density and socio-economic variables significantly improved prediction accuracy, with socioeconomic variables outperforming environmental ones. Interestingly, the impact of these secondary variables varied by day of the week. The study underscores the importance of incorporating auxiliary data to enhance crime prediction and offers a nuanced understanding of the interplay between socio-economic and environmental factors in crime risk.

17. Key Words Crime prediction, ST-Cokriging algorithm, sociological variable, built environment, public transportation, walkability	**18. Distribution Statement** No restrictions.		
19. Security Classif. (of this report) Unclassified	**20. Security Classif. (of this page)** Unclassified	**21. No. of Pages** 19	**22. Price** N/A

Form DOT F 1700.7 (8-72) Reproduction of completed page authorized

Contents

Building AI and Machine Learning Technologies for Enhancing Transportation Station Area Safety in San Jose, CA

Abstract

Accurate crime prediction is crucial for allocating police resources to reduce and prevent crime, particularly in large cities. Previous research has explored the relationship between social and built environments and street crime, but few studies have combined multi-source data using geo-statistical modeling. In this research, we applied a Spatial-Temporal Cokriging algorithm to predict street crime risk in San Jose, California, by integrating historical street crime data with sociological and built environmental variables. We used time-series data from 2,479 police call records in 2019, including assaults and robberies, as the primary variable. Secondary variables included transit density and walkability data from the Environmental Protection Agency (EPA)'s National Walkability Index. We analyzed crime risks across quad-week periods, predicting separately for weekdays and weekends. Our multi-variable crime prediction model compares outcomes using historical data, socio-economic data, and environmental data. The results reveal distinct crime patterns for weekdays and weekends, aiding in crime prediction for rapidly growing metropolitan areas. The study found that the spatial-temporal geostatistical prediction model performed better for weekday crimes, achieving over 70% accuracy, compared to around 60% for weekend crimes. Including transportation density and socio-economic variables significantly improved prediction accuracy, with socioeconomic variables outperforming environmental ones. Interestingly, the impact of these secondary variables varied by day of the week. The study underscores the importance of incorporating auxiliary data to enhance crime prediction and offers a nuanced understanding of the interplay between socio-economic and environmental factors in crime risk.

List of Key Terms

Crime prediction, ST-Cokriging algorithm, sociological variable, built environment, public transportation, walkability

Chapter 1: Introduction and Background

1.1 Project Motivation

Advancements in Artificial Intelligence (AI) and machine learning have increasingly influenced various fields, with applications in urban data science, particularly in crime prediction and spatio-temporal modeling, gaining prominence (Shen et al. 2023; Yan et al. 2023; Kitchin 2016; Ahoura, Shima, and Nicole, n.d.). Predictive crime modeling, combined with preventative strategies, is of interest not only to law enforcement agencies but also to researchers seeking empirical insights for policy debates (Rummens, Hardyns, and Pauwels 2017; Adepeju, Rosser, and Cheng 2016). Leveraging social behavior data to develop robust crime models is critical for shaping public policy, optimizing law enforcement strategies, and improving resource allocation. However, crafting accurate models remains challenging due to the diversity of crime types and the inherent randomness of social phenomena (Law, Quick, and Chan 2014; Brunsdon, Corcoran, and Higgs 2007; Bauer 2020).

1.2 Research, Objectives, and Tasks

Building a unified model to represent all crime types is difficult, as criminal activity is shaped by demographics, urban structures, temporal trends, and random events (Adepeju, Rosser, and Cheng 2016; Liu et al. 2020; Zhou et al. 2019; Wang and Zhang 2019; Liu et al. 2022). An effective crime prediction model can improve resource management and inform proactive interventions, reducing crime rates and enhancing public safety (H. Ratcliffe, J. Strang, and B. Taylor 2014; Ratcliffe 2016). However, the complexity of crime requires methodologies that account for the interconnectedness of different crime types and socio-environmental factors while adapting to their spatial and temporal variations (Patino et al. 2014). This study explores the effectiveness of multi-source crime data in predictive modeling, addressing key challenges in crime analytics.

Crime prediction models generally fall into two categories: those based on historical crime data and those incorporating socio-economic or environmental factors (Wang and Zhang 2019; Rummens, Hardyns, and Pauwels 2017; Patino et al. 2014; Gerber 2014). The first category relies on past crime records to forecast future incidents, exemplified by the reaction-diffusion model using Partial Differential Equations (PDEs), which explains crime patterns by modeling risk diffusion and offender movement (Short et al. 2010). The second category examines socio-economic and environmental influences, such as crime prediction using geo-tagged Twitter data with filtered keywords (Lan et al. 2023, 2019) or land use data, including the presence of commercial establishments and neighborhood structures (Gotham and Kennedy 2021). Recent research has fused these approaches, integrating machine learning with traditional crime data analysis to improve predictive accuracy (Yang et al. 2020; Yu et al. 2020). By combining historical crime data with socio-environmental factors, these models offer a more comprehensive understanding of criminal activity.

Criminological research has long established correlations between crime rates and urban characteristics such as population density, nighttime illumination, and land use patterns (Patino et al. 2014; Zhou et al. 2019). Public transportation stops are often associated with higher crime rates, particularly street crimes, though this relationship is complex and influenced by factors such as high foot traffic and insufficient surveillance (Kooi 2013). The built environment significantly affects crime patterns, with Central Business District (CBD) transit-oriented developments (TODs) featuring high activity density, mixed land use, and strong accessibility identified as safer zones (Zandiatashbar and Laurito 2023). In contrast, TODs with moderate activity density and high walkability but lower surveillance tend to experience higher crime rates. Studies suggest that walkability influences crime distribution in public transit areas, impacting individuals' willingness to use public transportation (Zandiatashbar and Laurito 2023). This research examines the role of walkability in crime prediction, given its well-documented correlation with crime rates.

1.3 Report Overview

This study applies the Spatial-Temporal Cokriging (ST-Cokriging) crime prediction algorithm (Yang et al. 2020) to analyze crime patterns in the San Jose metropolitan area. The model primarily uses historical street crime data, supplemented by socio-economic and environmental variables to enhance predictive accuracy. Key factors include transportation infrastructure, neighborhood walkability, poverty levels, and population density. By comparing predictions based on historical data alone versus models incorporating socio-environmental factors, we evaluate the influence of auxiliary data on crime forecasting. Additionally, we analyze weekday versus weekend crime patterns to identify temporal variations. This comprehensive approach seeks to improve crime prediction models, particularly in rapidly urbanizing regions.

Chapter 2: Study Site and Data

San Jose, in Santa Clara County, California (Figure 1), has become a global high-tech hub, making it California's fastest-growing economy since the 1990s (Zandiatashbar and Kayanan 2020). With a population of approximately 1.01 million, it ranks as the 10th most populous U.S. city (Berry-James, Gooden, and Johnson 2020). However, economic growth and population expansion have led to increased crime, with violent crimes per 100,000 residents rising by 33.9% from 2013 to 2019 (Yuan, McNeeley, and Melde 2022; Yuan, Sanchez, and Punla 2022, Hipp and Yates 2011). The city has implemented community policing and crime prevention measures in response (Chappell 2007). Precise crime prediction models and strategic police resource allocation are crucial for addressing these challenges.

San Jose's diverse neighborhoods and extensive crime data make it an ideal site for crime prediction. The city's neighborhoods encompass a wide range of income levels, ethnic compositions, and land use patterns, allowing for detailed spatial analysis. As a major commuter hub in Silicon Valley, San Jose exhibits pronounced differences in human activity between weekdays and weekends. The integration of these contextual variables enhances the potential accuracy and generalizability of crime risk prediction models.

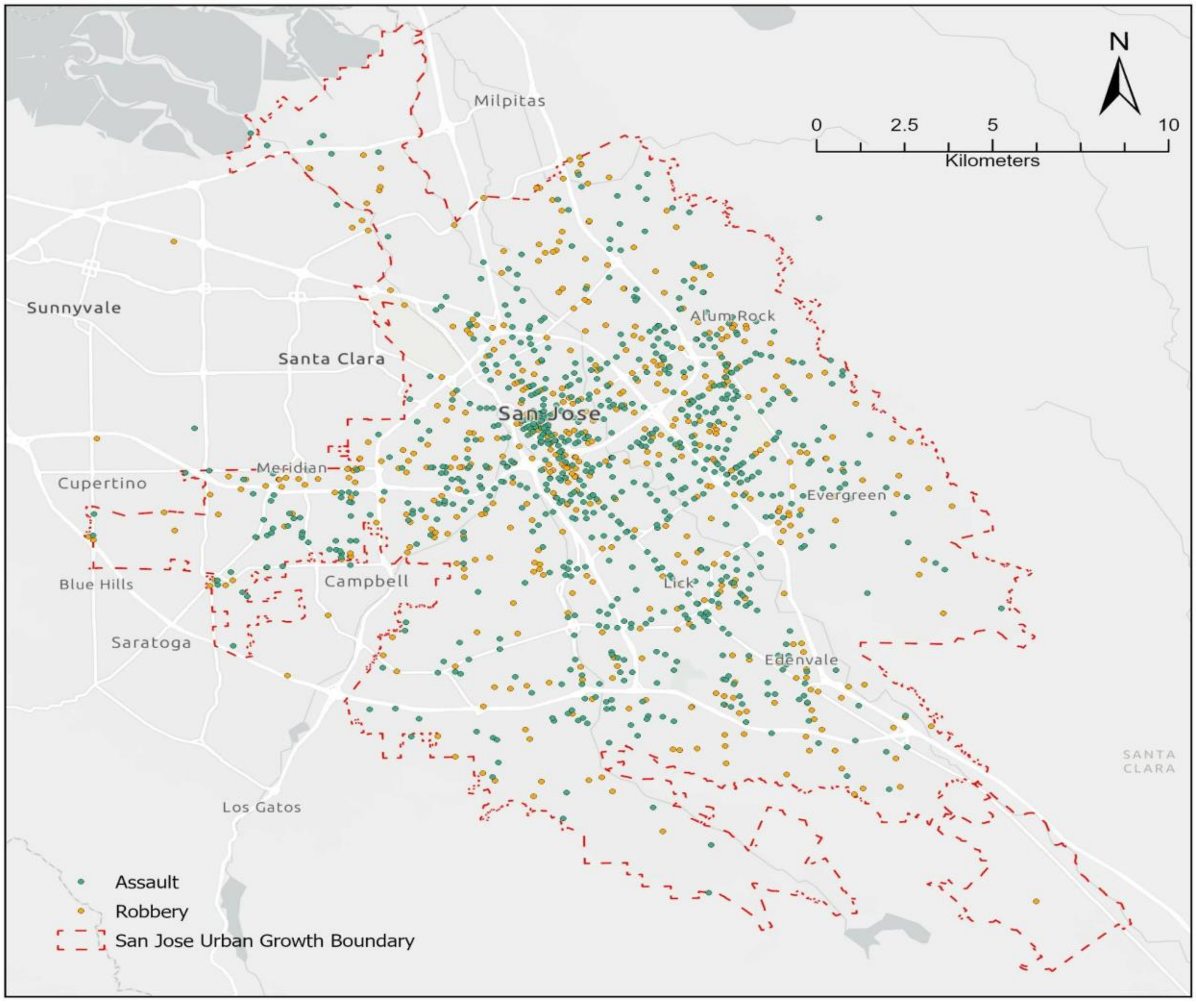

Figure 1 Robbery and assault crime records overlay with urban growth boundary and map of San Jose (2019)

This study uses various data sources to analyze crime prediction with urban dynamics and social factors in San Jose (Table 1). These sources include 2019 historical crime records, the Urban Growth Boundary, key transportation hubs, a walkability index, poverty data, and population density from the U.S. Census Bureau. The walkability index, ranging from 1 to 20, is categorized by the EPA into four groups: least walkable (below 5.75), below average walkable (5.76-10.5), above average walkable (10.51-15.25), and most walkable (15.26-20). Data was extracted at the block group level for Santa Clara County to capture population distribution accurately. These datasets provide a comprehensive overview of factors influencing urban development and quality of life in San Jose.

Table 1 Table of variables

Variable	Definition	Data Resource	Mean	Standard Deviation	Max value	Min value
Crime records	Historical valid police call in 2019	San Jose Police Department	- -	- -	- -	- -
Urban Growth Boundary	A defined perimeter is established to control urban sprawl by delineating where the city can grow and develop	The Bureau of Land Management, County of Santa Clara	- -	- -	- -	- -
Location data of Transportati on hubs	The geographical coordinates and related spatial information of key public transit points, such as bus stops, train stations, and metro stations.	Santa Clara Valley Transportation Authority (VTA)	- -	- -	- -	- -
Geospatial data of street	Geospatial data of streets is information that represents the location, length, and shape of streets on a map.	City of San Jose	- -	- -	- -	- -
Walkability Index	Block groups based on walkability by assessing factors like density, land use diversity, and proximity to transit	United States Environmental Protection Agency	13.89	2.40	5.67	19.67
Poverty	the percentage of the population for whom poverty status is determined under 2.00 in each census block	the American Community Survey (5-Year estimate) , from the U.S. Census Bureau	4.13 %	5.01%	41.67%	0
Population density	the block group level population density Unit: the number of people per square mile	U.S. Decennial Census 2020 from the U.S. Census Bureau	3137	4975	1	40452

Chapter 3: Methodology

The Spatio-temporal Cokriging (ST-Cokriging) Method (Yang et al. 2020) is applied in this study. This method expands the spatial domain into the spatial-temporal domain by generating temporally frequent predictions for the primary spatial variable (Pardo-Igúzquiza, Chica-Olmo, and Atkinson 2006). The calculations incorporate spatial, temporal, and spatio-temporal semi-variograms (Figure 2), followed by further processing to spatio-temporal covariance and correlation using actual crime training data. A key advantage of the ST-Cokriging approach is that it takes into account the rigorously derived spatio-temporal correlation between the primary target variable (Z1) and secondary co-variable(s) (Z2) (Eq 1). As a result, ST-Cokriging can provide more accurate predictions of the target variable than ordinary Co-Kriging or universal Kriging methods (Sahoo et al. 2018; Neuman and Jacobson 1984). By considering the temporal aspect of crime incidence alongside spatial data, we hope to gain a deeper understanding of crime patterns and increase the accuracy of our predictive model.

$$\hat{Z}_1(x_0, t_0) = \sum_{i=1}^{T} \sum_{j=1}^{N_i} \alpha_{ij} Z_1(s_{ij}, t_{1i}) + \sum_{k=1}^{M} \beta_k Z_2(u_k, t_2) \tag{1}$$

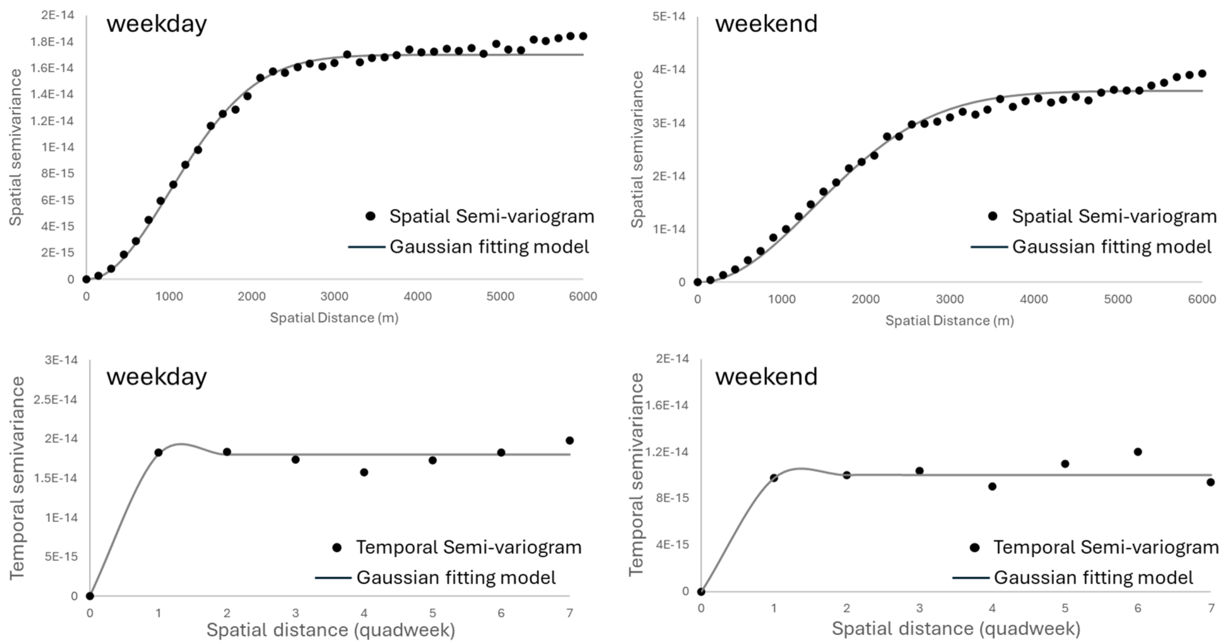

Figure 2 Spatial and temporal semi-variograms, and fitting model curves for quadweek-based period

Environmental and socio-economic co-variables were integrated into the Spatio-Temporal Cokriging (ST-Cokriging) algorithm to analyze crime patterns and improve prediction accuracy. Socio-economic variables included population density and poverty distribution, while environmental factors considered the built environment around transportation hubs. Historical crime data, segmented into 13 quad-week periods, served as the primary input. All data were converted into a 150m × 150m raster format, and spatial and temporal semi-variograms were calculated.

VTA bus stops and light rail stations were geocoded, and a kernel density analysis assessed transit stop concentrations. Hub density was incorporated as a secondary variable to improve crime predictions, alongside analyzing the built environment around transit hubs. Additional data included street intersection density, proximity to transit stops, and employment distribution. Network buffers of 0.5, 0.75, and 1.5 miles were created around each transit stop and intersected with block group walkability indices to compute summary statistics to represent a community-level walkability (Lefebvre-Ropars and Morency 2018; Adams et al. 2009). Walkability indices were assigned to respective hubs, and kernel density analysis used walkability as a population field, incorporating transportation index density and walkability index as secondary co-variables in the final prediction model (Figure 3).

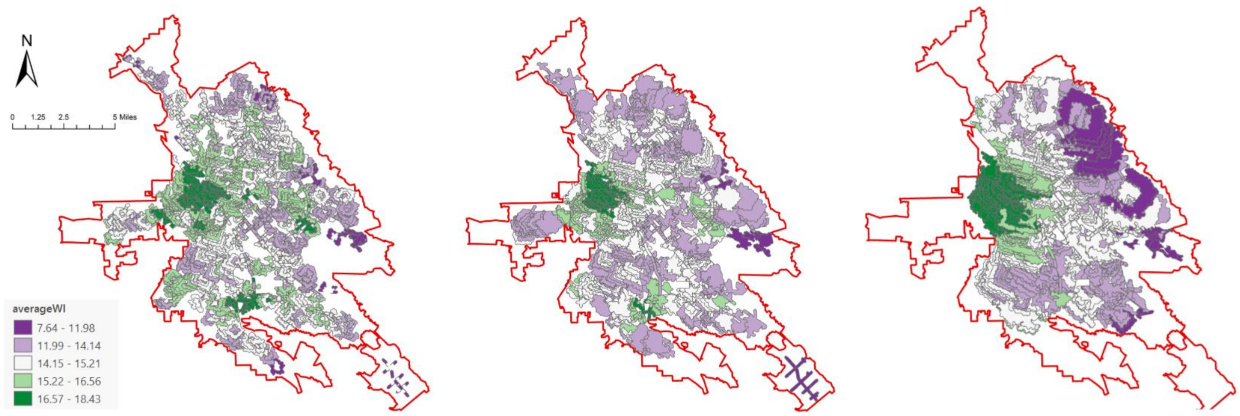

Figure 3 Network buffers of public transportation hubs with average walkability indices

This study used two socio-economic data categories as secondary variables: population density and poverty distribution, providing a detailed socio-economic landscape of San Jose. Census group/block group data were converted into a raster format with the same cell size as the primary variable data for uniform spatial analysis. The Urban Growth Boundary of San Jose was applied as a clipping mask, covering an area of 370.3 km² and encompassing 99.3% of all crime data. This ensured a consistent area for analysis and mitigated spatial bias by excluding the surrounding mountain regions. The prediction results are presented in the following chapter as crime risk maps, which visualize the predicted crime hotspots; higher values on the maps correspond to higher levels of predicted crime risk.

To validate our results, we use Pearson's Correlation Coefficient metrics to compare the true-crime risk map and our predictions. Calculations are performed using Python, NumPy, and GDAL libraries (Canty 2014). Raster-formatted images are converted into one-dimensional NumPy arrays for computational ease. Pearson's Correlation Coefficient quantifies the linear correlation between actual and predicted crime data.

Chapter 4: Results and Discussion

San Jose exhibits a diverse geographical distribution of population density and poverty rates (Figure 4). Downtown and North San Jose are characterized by higher population densities and a mix of income levels, while South San Jose tends to have lower population density and higher poverty rates.

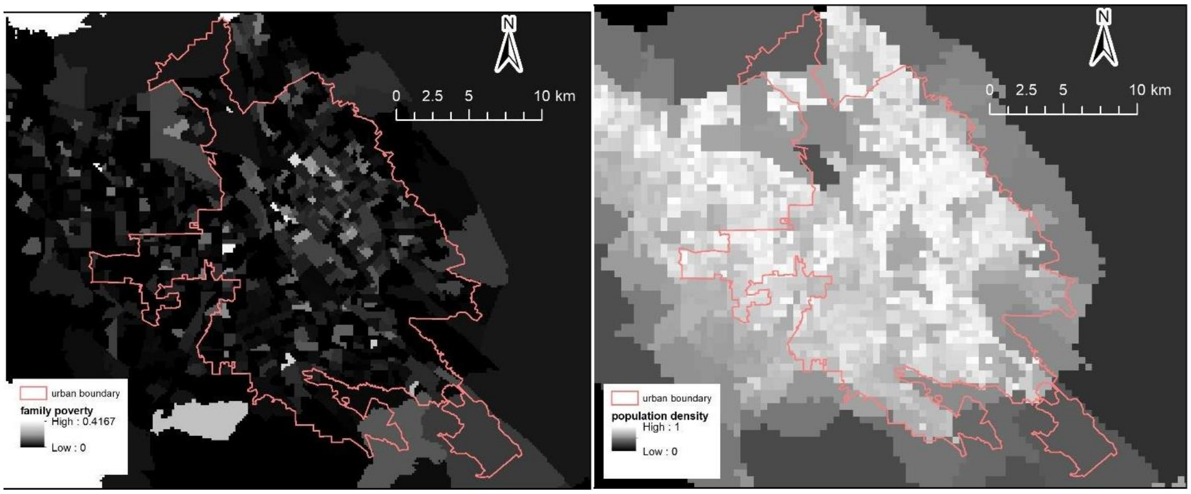

Figure 4 The social-economic secondary co-variables in this study (left: population density in 2020; right: the percentage of families with income below the poverty level by block group)

This study included built environment data of public transportation as secondary variables. The spatial density of public transit hubs in San Jose (Figure 5) showed high density in downtown and East San Jose, with smaller clusters along main roads in South San Jose. While hub density reveals geographical clusters of public transportation, the built environment is more closely related to crime rates and city safety. Figure 5 highlights transportation hub density with the walkability index. North San Jose and some areas in Southeast San Jose became less prominent compared to spatial density analysis, indicating lower relative walkability. Walkability impacts the likelihood of individuals choosing to walk for transportation and correlates with street crime distribution. The intensity of transportation hubs, considering walkability, was included in the crime prediction model.

Figure 5 Density of transit hubs using walkability as a population field

Crime reports, originally recorded as street addresses, were digitally mapped using GIS geo-coding technology (Figure 1). For our prediction model, we sorted the 2479 street crime records into 53 weekly feature classes. Each class corresponds to one week, starting at 0:00 am on Monday and ending at 11:59 pm on Sunday. This chronological organization aligns with the common perception that a year typically comprises about 53 weeks, ensuring consistency throughout the study.

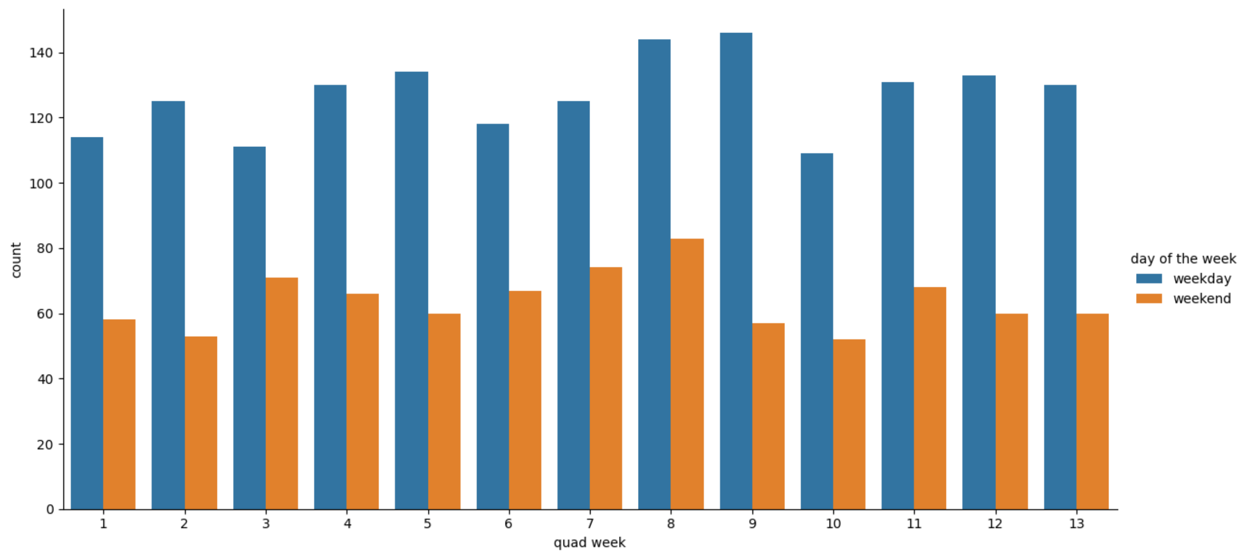

Figure 6 Crime counts by quad-week and the day of the week, 2019

Significant variations in crime amount and spatial distribution were noted between weekdays and weekends. The weekly data was divided into two classes for more granular analysis and condensed into quad-week data, combining four consecutive weeks as one quad-week. The weekday and weekend data were divided into two datasets (Figure 6). The model operates at a quad-week temporal resolution, predicting crime risk for each quad-week interval. Two distinct models were trained using separate datasets, one containing only weekday data and the other containing only weekend data.. The study used a pixelated format, dividing the area into 42,188 pixels (150m x 150m each), arranging both primary and secondary variables in this grid format to reveal nuanced patterns.

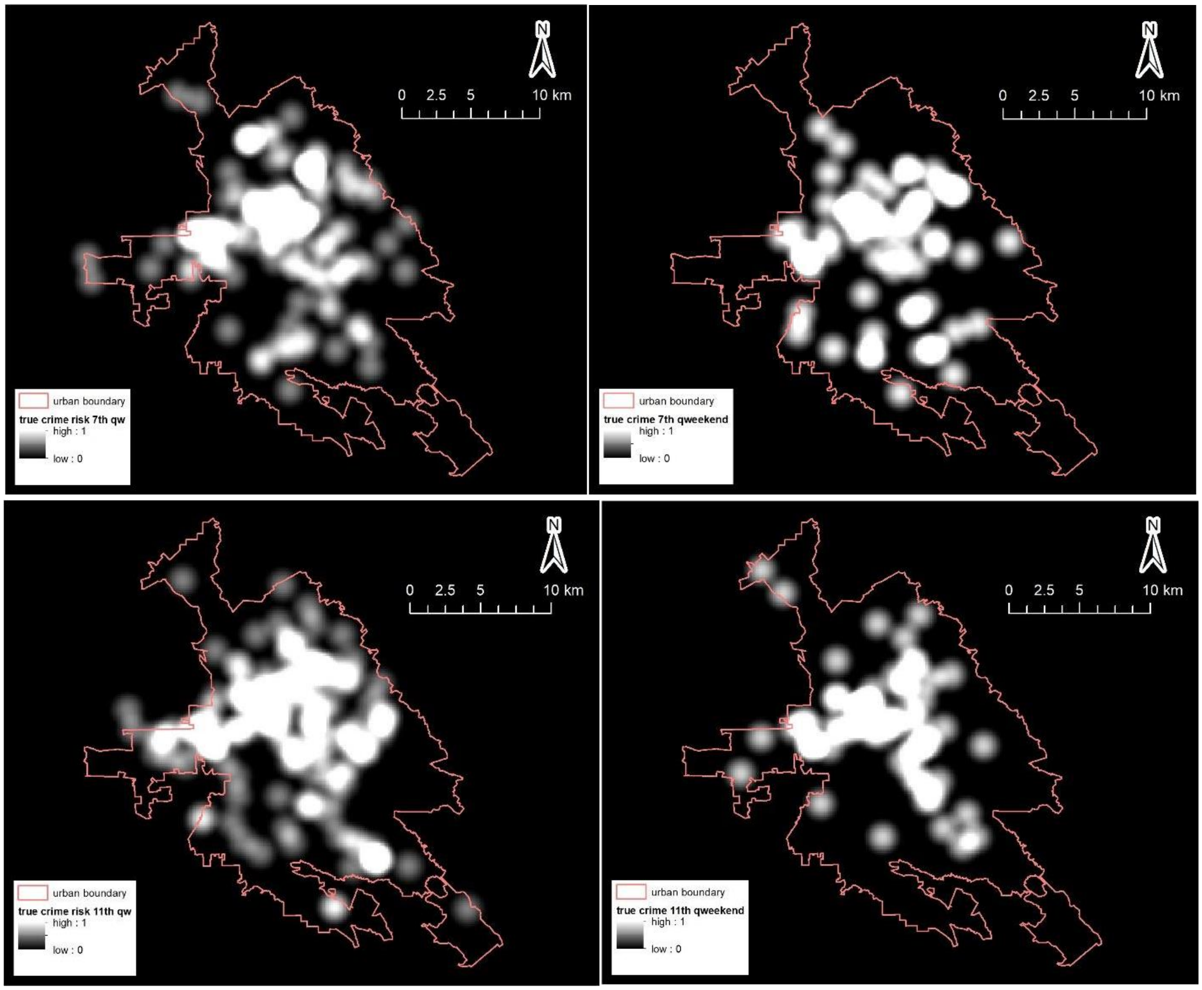

Figure 7 The crime risk map of San Jose, the 7th quad week and the 11th quad week, 2019 (left above, the weekdays of the 7th quad week; right above, the weekends of the 7th quad week; left below, the weekdays of the 11th quad week; right below, the weekends of 11th quad week)

Using geo-coded crime data points, a crime map was created by applying a kernel density estimation method with a 1500m search radius. The spatial distribution of historical crime risk in San Jose on weekdays and weekends is shown in Figure 7 for the 7th and 11th quad-week periods. The downtown area exhibits a higher crime risk compared to peripheral regions, with significant fluctuations and distinct hotspots appearing in varying locations across the city. These findings highlight the complex spatial dynamics of crime, necessitating a nuanced approach to crime prediction and prevention.

The ST-Cokriging model's performance in predicting crime risk was assessed using Pearson Correlation Coefficients (Table 2), showing consistent performance of over 70% for weekdays and variable results for weekends (0.561 to 0.721). Public transportation stops serve as robust covariates in crime prediction models. Incorporating transportation hub density as a secondary covariate led to increases of 4.3% and 6.3% in the Pearson correlation coefficients for the 11th and 9th quad-week periods, respectively. These improvements indicate that the inclusion of public transportation hub density enhances the predictive accuracy of the models for both weekday and weekend crime patterns. This enhancement was more significant than that achieved by incorporating socio-economic variables. Socio-economic co-variables led to improved prediction results compared to environmental variables. For weekends spanning the 7th to the 10th quad-week, the introduction of population density as a secondary co-variable improved the Pearson Correlation Coefficients between prediction and actual crime risk maps by 1.9% to 2.8%. This demonstrated the intertwined nature of socio-economic and environmental factors in predicting crime risk.

Table 2 Pearson Correlation Coefficient between prediction results by ST-Cokriging with transit density and transit walkability co-variables and actual crime records for weekdays and weekends in the 8th to 11th quad-week

Time period		**Truth and Prediction Results**	**Weekdays**		**Weekends**	
			A	**B**	**A**	**B**
8th quad-week	A	actual crime risk	1.000		1.000	
	B	result without co-variable	0.762	1.000	0.561	1.000
	C	result with transit density	0.757	0.985	0.562	0.975
	D	result with transit walkability	0.659	0.702	0.504	0.419
	E	result with poverty	0.662	0.821	0.607	0.764
	F	result with population density	0.752	0.963	0.589	0.952
9th quad-week	A	actual crime risk	1.000		1.000	
	B	result without co-variable	0.787	1.000	0.724	1.000
	C	result with transit density	0.803	0.984	0.770	0.977
	D	result with transit walkability	0.691	0.669	0.553	0.507
	E	result with poverty	0.795	0.818	0.708	0.773
	F	result with population density	0.803	0.967	0.776	0.949
10th quad-week	A	actual crime risk	1.000		1.000	
	B	result without co-variable	0.748	1.000	0.836	1.000
	C	result with transit density	0.745	0.981	0.816	0.974
	D	result with transit walkability	0.611	0.685	0.542	0.540
	E	result with poverty	0.680	0.847	0.628	0.740
	F	result with population density	0.762	0.961	0.799	0.932
11th	A	actual crime risk	1.000		1.000	

quad-week	B	result without co-variable	0.697	1.000	0.730	1.000
	C	result with transit density	0.727	0.975	0.752	0.967
	D	result with transit walkability	0.658	0.586	0.494	0.526
	E	result with poverty	0.719	0.744	0.625	0.662
	F	result with population density	0.730	0.942	0.780	0.914

Chapter 5: Conclusions and Recommendations

This research proposed a Spatial-Temporal Cokriging algorithm for predicting crime in San Jose, using historical street crime data as the primary variable, supplemented by environmental and socio-economic co-variables. Environmental data included transportation hub density and the built environment, while socio-economic data involved neighborhood characteristics. Correlation coefficients were used to evaluate model performance. The spatial-temporal geostatistical prediction model showed over 70% accuracy for weekday crimes but dropped to around 60% for weekends. Both transportation density and socio-economic co-variables significantly improved prediction accuracy, with socio-economic factors outperforming environmental ones.

Modern machine learning-based models, though more accurate, face challenges in quantifying auxiliary variables' contributions. The debate continues on whether socio-economic or environmental variables are more crucial in crime prediction. Incorporating all potential variables is impractical due to computational constraints and the priority of historical crime data. This study forms a foundation for crime prediction in urban technology centers, offering a comparative analysis and valuable guidance for future studies. Future research should incorporate additional crime types, such as burglary and car theft, and explore the integration of geo-tagged Twitter data and hospital records. Evaluating the model's accuracy across different regions could offer valuable insights into its applicability, scalability, and the influence of contextual differences across cities and neighborhoods on model performance and the generalizability of crime prediction approaches.

References

Adepeju, Monsuru, Gabriel Rosser, and Tao Cheng. 2016. "Novel Evaluation Metrics for Sparse Spatio-Temporal Point Process Hotspot Predictions - a Crime Case Study." *International Journal of Geographical Information Science: IJGIS* 30 (11): 2133–54.

Ahoura, Z., H. Shima, and F. Nicole. n.d. "High-Tech Business Location, Transpotation Accessibility, and Implications for Sustainability: Evaluating the Differences between High-Tech Specializations …." *Sustain. Cities Soc.*

Atkinson, Peter M., Eulogio Pardo-Igúzquiza, and Mario Chica-Olmo. 2008. "Downscaling Cokriging for Super-Resolution Mapping of Continua in Remotely Sensed Images." *IEEE Transactions on*

Geoscience and Remote Sensing: A Publication of the IEEE Geoscience and Remote Sensing Society 46 (2): 573–80.
Bauer, Vanessa. 2020. *Predictive Policing in Germany. Opportunities and Challenges of Data-Analytical Forecasting Technology in Order to Prevent Crime*. GRIN Verlag.
Berry-James, Rajade M., Susan T. Gooden, and Richard Greggory Johnson III. 2020. "Civil Rights, Social Equity, and Census 2020." *Public Administration Review* 80 (6): 1100–1108.
Brunsdon, Chris, Jonathan Corcoran, and Gary Higgs. 2007. "Visualising Space and Time in Crime Patterns: A Comparison of Methods." *Computers, Environment and Urban Systems* 31 (1): 52–75.
Canty, Morton J. 2014. *Image Analysis, Classification and Change Detection in Remote Sensing: With Algorithms for ENVI/IDL and Python, Third Edition*. CRC Press.
Chappell, Allison T. 2007. "Community Policing: Is Field Training the Missing Link?" *Policing: An International Journal of Police Strategies & Management* 30 (3): 498–517.
Gerber, Matthew S. 2014. "Predicting Crime Using Twitter and Kernel Density Estimation." *Decision Support Systems* 61 (1): 115–25.
Gotham, Kevin Fox, and Daniel B. Kennedy. 2021. "Analyzing Crime Foreseeability: Premises Security Litigation and the Case of Convenience Stores and Gas Stations." *Security Journal* 34 (2): 207–30.
Hipp, John R., and Daniel K. Yates. 2011. "Ghettos, Thresholds, and Crime: Does Concentrated Poverty Really Have an Accelerating Increasing Effect on Crime?" *Criminology; an Interdisciplinary Journal* 49 (4): 955–90.
H. Ratcliffe, Jerry, Steven J. Strang, and Ralph B. Taylor. 2014. "Assessing the Success Factors of Organized Crime Groups: Intelligence Challenges for Strategic Thinking." *Policing: An International Journal of Police Strategies & Management* 37 (1): 206–27.
Kitchin, Rob. 2016. "The Ethics of Smart Cities and Urban Science." *Philosophical Transactions. Series A, Mathematical, Physical, and Engineering Sciences* 374 (2083). https://doi.org/10.1098/rsta.2016.0115.
Kooi, Brandon R. 2013. "Assessing the Correlation between Bus Stop Densities and Residential Crime Typologies." *Crime Prevention and Community Safety* 15 (2): 81–105.
Lan, Minxuan, Lin Liu, Jacob Burmeister, Weili Zhu, Hanlin Zhou, and Xin Gu. 2023. "Are Crime and Collective Emotion Interrelated? A 'Broken Emotion' Conjecture from Community Twitter Posts." *Social Science Computer Review* 41 (2): 528–53.
Lan, Minxuan, Lin Liu, Andres Hernandez, Weiyi Liu, Hanlin Zhou, and Zengli Wang. 2019. "The Spillover Effect of Geotagged Tweets as a Measure of Ambient Population for Theft Crime." *Sustainability: Science Practice and Policy* 11 (23): 6748.
Law, Jane, Matthew Quick, and Ping Chan. 2014. "Bayesian Spatio-Temporal Modeling for Analysing Local Patterns of Crime Over Time at the Small-Area Level." *Journal of Quantitative Criminology* 30 (1): 57–78.
Liu, Lin, Jiayu Chang, Dongping Long, and Heng Liu. 2022. "Analyzing the Impact of COVID-19 Lockdowns on Violent Crime." *International Journal of Environmental Research and Public Health* 19 (23). https://doi.org/10.3390/ijerph192315525.
Liu, Lin, Minxuan Lan, John E. Eck, Bo Yang, and Hanlin Zhou. 2020. "Assessing the Intraday Variation of the Spillover Effect of Tweets-Derived Ambient Population on Crime." *Social Science Computer Review*, 1–22.
Neuman, Shlomo P., and Elizabeth A. Jacobson. 1984. "Analysis of Nonintrinsic Spatial Variability by Residual Kriging with Application to Regional Groundwater Levels." *Journal of the International Association for Mathematical Geology* 16 (5): 499–521.
Pardo-Igúzquiza, Eulogio, Mario Chica-Olmo, and Peter M. Atkinson. 2006. "Downscaling Cokriging for Image Sharpening." *Remote Sensing of Environment* 102 (1-2): 86–98.
Patino, Jorge E., Juan C. Duque, Josep E. Pardo-Pascual, and Luis A. Ruiz. 2014. "Using Remote Sensing to Assess the Relationship between Crime and the Urban Layout." *Applied Geography* 55 (December):48–60.
Ratcliffe, Jerry H. 2016. *Intelligence-Led Policing*. Routledge.

Rosser, Gabriel, and Tao Cheng. 2016. “Improving the Robustness and Accuracy of Crime Prediction with the Self-Exciting Point Process Through Isotropic Triggering.” *Applied Spatial Analysis and Policy*, 1–21.

Rummens, Anneleen, Wim Hardyns, and Lieven Pauwels. 2017. “The Use of Predictive Analysis in Spatiotemporal Crime Forecasting: Building and Testing a Model in an Urban Context.” *Applied Geography* 86:255–61.

Sahoo, Madhumita, Anirban Dhar, Aman Kasot, and Amlanjyoti Kar. 2018. “Space-Time Cokriging Approach for Groundwater-Level Prediction with Multiattribute Multiresolution Satellite Data” 23 (Goovaerts 1997): 1–7.

Shen, Yongliang, Kaitao Song, Xu Tan, Dongsheng Li, Weiming Lu, and Yueting Zhuang. 2023. “HuggingGPT: Solving AI Tasks with ChatGPT and Its Friends in Hugging Face.” *arXiv [cs.CL]*. arXiv. http://arxiv.org/abs/2303.17580.

Short, M. B., P. J. Brantingham, A. L. Bertozzi, and G. E. Tita. 2010. “Dissipation and Displacement of Hotspots in Reaction-Diffusion Models of Crime.” *Proceedings of the National Academy of Sciences* 107 (9): 3961–65.

Wang, Zengli, and Hong Zhang. 2019. “Could Crime Risk Be Propagated across Crime Types?” *ISPRS International Journal of Geo-Information* 8 (5): 203.

Yang, Bo, Lin Liu, Minxuan Lan, Zengli Wang, Hanlin Zhou, and Hongjie Yu. 2020. “A Spatio-Temporal Method for Crime Prediction Using Historical Crime Data and Transitional Zones Identified from Nightlight Imagery.” *International Journal of Geographical Information Science: IJGIS* 00 (00): 1–25.

Yan, Junchi, Yukun Lai, Yi Xu, Yinqiang Zheng, Zhibin Niu, and Tao Tan. 2023. *Artificial Intelligence-Based Medical Image Automatic Diagnosis and Prognosis Prediction*. Frontiers Media SA.

Yuan, Yue, Susan McNeeley, and Chris Melde. 2022. “Understanding the Fear of Crime and Perceived Risk Across Immigrant Generations: Does the Quality of Social Ties Matter?” *Crime & Delinquency*, July, 00111287221113306.

Yuan, Yue, Claudio Vera Sanchez, and Clarissa Punla. 2022. “Procedural Justice, Neighbourhood Context, and Domestic Violence Reporting Intention among Subgroups of Immigrants.” *Policing and Society* 32 (10): 1180–92.

Yu, Hongjie, Lin Liu, Bo Yang, and Minxuan Lan. 2020. “Crime Prediction with Historical Crime and Movement Data of Potential Offenders Using a Spatio-Temporal Cokriging Method.” *ISPRS International Journal of Geo-Information* 9 (12): 732.

Zandiatashbar, Ahoura, and Carla Maria Kayanan. 2020. “Negative Consequences of Innovation-Igniting Urban Developments: Empirical Evidence from Three US Cities.” *Urban Planning* 5 (3): 378.

Zandiatashbar, Ahoura, and Agustina Laurito. 2023. “An Empirical Analysis of the Link between Built Environment and Safety in Chicago’s Transit Station Areas.” *Journal of the American Planning Association. American Planning Association* 89 (2): 225–39.

Zhou, Hanlin, Lin Liu, Minxuan Lan, Bo Yang, and Zengli Wang. 2019. “Assessing the Impact of Nightlight Gradients on Street Robbery and Burglary in Cincinnati of Ohio State, USA.” *Remote Sensing* 11 (17). https://doi.org/10.3390/rs11171958.