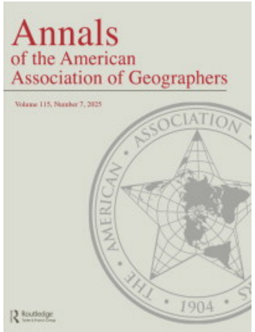

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Crime and Visually Perceived Safety of the Built Environment: A Deep Learning Approach

Jonatan Abraham,[a] Yuhao Kang,[b] Vania Ceccato,[a] Per Näsman,[a] Fábio Duarte,[c] Song Gao,[d] Lukas Ljungqvist,[a] Fan Zhang,[e] and Carlo Ratti[c,f]

[a]*Department of Urban Planning and Environment and Senseable Stockholm Lab, KTH Royal Institute of Technology, Sweden;* [b]*GISense Lab, Department of Geography and the Environment, University of Texas at Austin, USA;* [c]*Senseable City Lab, Massachusetts Institute of Technology, USA;* [d]*GeoDS Lab, Department of Geography, University of Wisconsin, Madison, USA;* [e]*Institute of Remote Sensing and Geographical Information System, Peking University, China;* [f]*Politecnico di Milano, Italy*

Although the influence of the built environment on both crime and people's safety perceptions is well documented in the international literature, less evidence is found regarding the link between urban safety perceptions and crime occurrence. In this article, we investigate the potential relationship between crime and visual perceived safety (VPS), using Stockholm, Sweden as a case. Central to the study is the VPS score, a detailed measure of VPS and situational fear, created by combining a deep learning model with a data set of local street view images and citizen impressions. We examine this measure together with traditional crime records to compare the city's distribution of safety and crime. First, geographical patterns and spatial clusters of high and low levels of crime and VPS were detected. Then, drawing from principles of environmental criminology, a spatial regression was used to examine the relationship between the VPS score and crime, controlling for sociodemographics and land-use factors. Findings show that crime rates of different types are significant predictors of poor VPS, but mismatching geographies of perceived safety and crime are common. The article discusses the findings and finishes by highlighting the impact of these results for research and practice. *Key Words: GIS, machine learning, safety perception, street view, urban environment.*

Crime and low safety perceptions are two persistent challenges for cities to address. The consequences of crime and poor perceived safety lead to substantial negative impacts on local economies and the quality of life of individuals, both in the short and long term (Hale 1996; Fajnzylber, Lederman, and Loayza 2000; Jackson and Gray 2010). Scholars have traditionally viewed perceived safety as encompassing fear of crime or treating the two as interchangeable (Hinkle 2015), causing a seemingly self-evident link with crime. There have been conflicting findings, however, of any straightforward relationship (see, e.g., Hinkle 2015; Zhao, Lawton, and Longmire 2015; Luo, Ren, and Zhao 2016), with many researchers arguing that fear of crime and perceived safety should be considered and measured as distinct constructs (Ferraro 1995; Rountree and Land 1996; Warr 2000). Additionally, scholars point to a distinction between fear dependent on individual factors (dispositional fear) and fear dependent on contextual and environmental factors (situational fear; Gabriel and Greve 2003). To that point, safety perceptions have been found to be more associated with the situational conditions and features of the built environment (e.g., level of lighting, vegetation, maintenance) rather than crime, although similar conditions influence crime occurrence (Wilson and Kelling 1982; Wood et al. 2008). Certain environments, types of land use, and conditions might increase the sense of safety but also facilitate crime events (Hipp et al. 2022). The situational nature of crime and perceived safety makes it difficult to fully grasp and disentangle how they compare and interact in the urban environment.

The most common methods of measuring people's urban safety perceptions have been through relatively time- and resource-consuming activities such as surveys or interviews, often restricting the size of

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CORRESPONDING AUTHOR Jonatan Abraham jabraham@kth.se

possible study areas or the level of spatial resolution. To overcome these limitations, recent studies capturing perceptions of the built environment have used a combination of deep learning models with street view images, allowing for larger scale assessments of perceptions of, for example, greenspace quality (Wang et al. 2021), accident risk (Kita and Kidziński 2019), but also crime and safety (Li, Zhang, and Li 2015; Zhang et al. 2021; He et al. 2022; Hipp et al. 2022; Yue, Liu, and Xiao 2023). As such, complementing traditional methodology with deep learning applications might offer greater insights into the understanding of urban phenomena.

In this study, we investigate the relationship between safety perceptions of the built environment as depicted by Google Street View images (referred to as *visually perceived safety*[VPS]) and crime rates from police-recorded statistics. We quantify a measure of VPS using a deep learning model based on a local survey of Stockholm street view images, resulting in a *VPS score*. Police-recorded crimes of different categories from Stockholm, Sweden, are then used as a comparative "ground truth" measure of safety and security. Getis–Ord Gi* spatial autocorrelation is used to compare the spatial clustering of VPS scores and crime rates. This is followed by regression analysis to explore the association between VPS and crime, controlling for socioeconomic factors and land-use indicators. Through the study we aim to better understand how people's situational safety perceptions of the environment relate to the criminogenic nature of areas.

The contribution of this study consists of several points. In contrast to existing studies combining machine learning and street view images, our constructed training data set is based on local street view images and resident perceptions of Stockholm. This provides opportunities to more accurately represent how a city is perceived by the actual city users, taking into account that fear and perceived safety are also determined by factors such as personal familiarity, attachment, and "identifiability" of places (Kaplan and Kaplan 1982; Herzog 1984; Low and Altman 1992; Day, Stump, and Carreon 2003; Lorenc et al. 2013). Second, there are, to our knowledge, few to no studies of this kind that have been conducted in a Nordic context, even less so in a Swedish or Stockholm-based one. Also, although spatial crime analyses of Stockholm have been conducted previously, there are few conducted in the pandemic to postpandemic era.

The article is structured as follows. After the introduction, we present the current knowledge on crime, fear, safety, and the urban environment, as well as previous applications of machine learning with urban analyses. We then introduce the research design, including the study area, data and methods. The overall results of the study follow and are analyzed and discussed in detail. The article closes with conclusions drawn from the results, as well as implications and recommendations for future research and practice.

Theoretical Background

Fear, Crime, and Perceived Safety

Crime and fear are complex, multifaceted phenomena, and although they are interlinked, researchers have rarely found a straightforward relationship (Hale 1996). Much of this lies in the conceptualization of fear, which, especially in the context of crime, has been ever-changing and contested by scholars. Warr (2000) defined *fear* as "an emotion, a feeling of alarm or dread caused by awareness of expectation of danger" (453). *Fear of crime* in particular has been defined as "an emotional reaction of dread or anxiety to crime or symbols that a person associates with crime" (Ferraro 1995, 23). Yet early studies have pointed to crime not being among the main predictors of fear of crime (Salem and Lewis 1986) and that public perceptions of risk do not always reflect actual crime levels (Skogan 1986; Roberts and Stalans 2000). People's fears are deeply individual and affected by a range of other aspects of urban life (Skogan 1977). The broader term *perceived safety* is as a result often used to encompass both fear of crime and other emotions, on both individual and meso- and macrolevel factors, such as social change and instability (Ceccato 2015). Researchers suggest, however, that the relationship between crime and fear depends on how fear is operationalized, emphasizing the need to treat fear of crime and perceived safety as two distinct constructs with different underlying mechanisms (Ferraro 1995; Warr 2000; Hinkle 2015; Camacho Doyle, Gerell, and Andershed 2022). In this study, we acknowledge this distinction while also recognizing the difficulty in fully disentangling the two from each other. As such, we adopt a broader definition of perceived safety to include fear of crime, perceived risk, and other general anxieties, examining the extent of its possible association with crime in an urban context.

The Role of Situational Context for Crime and Safety

Although crime and perceived safety might not always reflect each other, what makes us feel unsafe and what causes crime are often driven by similar conditions and processes. There has long been a dispositional bias in both crime and fear research, focusing more on the role of individual characteristics rather than viewing the issues as context-dependent (Solymosi et al. 2021). The theory of *social disorganization* is part of the first school of knowledge considering the effect of neighborhood conditions on crime and fear, pointing to how poverty, residential instability, and ethnic heterogeneity are associated with poorer social control, collective efficacy, and urban decay (Shaw and McKay 1942; Bursik 1988; Camacho Doyle, Gerell, and Andershed 2022). Although foundational in explaining neighborhood-level crime differences, the theory has been criticized for being unable to explain microplaces of crime and fear, and failing to consider individual behavior and movement patterns throughout cities (Ceccato and Nalla 2020). In response, criminologists have increasingly emphasized the role of environmental factors of crime and its situational nature (see *environmental criminology*; Clarke 1980; Fisher and Nasar 1992; Hale 1996). A similar development has followed studies of fear and safety perceptions, with scholars making a distinction between the *dispositional* elements of fear—driven by individual and internal factors—and *situational* and more transitory feelings of fear that are better explained by the immediate environment (Gabriel and Greve 2003; Jackson 2004). Although separate conceptualizations, the two elements are dependent on each other; as dispositional fear increases so does the probability that certain situations evoke fear, and personal characteristics might affect how individuals cope with states of situational fear (Gabriel and Greve 2003).

The situational elements of both crime patterns and individual perceived safety are addressed in the *broken windows theory* (Wilson and Kelling 1982), which posits that poor conditions and visual cues of disorder and petty crime in the built environment might attract more serious crime and elicit fear. Essentially, we are left with a positive feedback loop where the increase in crime and fear reinforces disorder, emboldening criminals further and causing a downward spiral of decay (Skogan 1992). Environments that are perceived as dark, empty, uncared for, and deserted, for example (i.e., the *physical nature* of an area), can both be perceived as unsafe and exploited by criminals (Snyders and Landman 2018). Additionally, both *social disorder* (e.g., visible substance abuse, altercations) and *physical disorder* (e.g., graffiti, broken street lights) signal that the area's capability for controlling crime and other antisocial behavior is low (Gerber, Hirtenlehner, and Jackson 2010; Snyders and Landman 2018). People's perceived notion of disorder and crime in a neighborhood is as such often as important as the actual level of criminal activity, with evidence pointing to the idea that features of neighborhood disorders are stronger determinants of residents' troubles and fears than crime events (Wilson and Kelling 1982; Skogan 1986; Wood et al. 2008). More recent studies though, have scrutinized the applicability of the broken windows theory, questioning the link between crime and disorder overall, if the two can even be distinguished, and whether physical and social disorder cause the same mechanisms (Gau and Pratt 2008; Ren, Zhao, and Luo 2024; Weisburd et al. 2024).

Yet other visual cues in the urban environment can also influence crime and safety perceptions. According to the *theory of prospect and refuge*, specific urban design decisions can make people feel more secure, particularly when the design balances ability to observe in an environment (prospect) with available escape routes and protective spaces (refuge; Appleton 1975; Fisher and Nasar 1992; Blöbaum and Hunecke 2005). Paradoxically, these characteristics could also be exploited by offenders, as refuge might serve as hiding places and prospects can provide a way to be aware of others. Fisher and Nasar (1992) noted in their study that locations with limited prospects for an individual but a high level of refuge for potential offenders were perceived as the most unsafe.

Urban design also influences activities and mobility patterns of people (Hillier et al. 1993), and by extension creates opportunities for both crime and informal surveillance. For instance, Jacobs (1962) argued for the importance of street layouts and diverse land use to increase "eyes on the street"; that is, ensuring peer-to-peer surveillance through promoting social activity, theorized as deterring crime and improving sense of safety. The term *defensible space*, formulated by Newman (1972), addresses the influence of housing design (e.g., building height, window positioning) on residential control, territoriality, and neighborhood surveillance—building the framework of Crime Prevention Through Environmental Design (CPTED; Jeffrey 1971; Cozens, Saville, and Hillier 2005). Cozens and Sun (2019) observed in their study that locations perceived as unsafe were often lacking components of CPTED, including surveillance opportunities, as well as low and high levels of prospect and refuge, respectively. Study participants explicitly perceived opportunities for crime in the environment, contributing to their categorization of the location as unsafe. A range of theories on crime opportunity such as the *routine activity approach* (Cohen and Felson 1979, 2010) and *crime pattern theory* (Brantingham and Brantingham 1984) argue that crime occurs in the shared activity spaces of victims and offenders. For instance, locations with certain land uses can generate crime through acting as nodes for potential victims and offenders (e.g., commercial areas, bars, transport hubs) or attract crime by drawing criminals with the presence of attractive targets or low guardianship (e.g., parks, open drug markets; Kinney et al. 2008; Hipp 2010). Hipp et al. (2022) noted that several features of the environment could have a nonlinear relationship with crime and safety. Increased human activity in a location might increase crime opportunities, whereas at a certain level, the increased guardianship deters crime. Parks and greenspaces can increase social cohesion, guardianship, and sense of safety while also providing refuge for offenders. This could generate locations that are perceived as safe, for example, due to a sense of social control although crime levels remain high (and inverse cases).

Spatial Patterns of Crime and Fear

The spatial patterns of crime have in the past few decades become increasingly important in crime studies, with tools such as geographic information systems (GIS) and spatial statistics being common inclusions in methodologies. For instance, measures of spatial autocorrelation (e.g., the Getis–Ord G_i statistics [Getis and Ord 1992] and local indicators of spatial association [LISA; Anselin 1995]) have often been used to identify neighboring locations with similar crime rates; that is, spatial clusters of crime. These can help identify *crime hot spots*, especially criminogenic locations that could be targeted in particular by, for example, police efforts (Ratcliffe and McCullagh 1999; Eck et al. 2005).

Among studies within Stockholm contexts, Wikström (1991) investigated the spatial distribution of crimes such as burglaries, theft of and from cars, and vandalism; and included the proposition of a model for the geographical distribution of crime based on the composition of land use and population. Ceccato, Haining, and Signoretta (2002) used this model further, using GIS and Getis–Ord-based spatial autocorrelation to identify especially high instances of crime and changes in patterns since 1980. Uittenbogaard and Ceccato (2012) considered the temporal dimension of crime variation using space–time cluster analysis, finding that property crime concentrates in the Stockholm outskirts during the afternoon, whereas violent crime likely happens in the city center during the night.

The fact that most crimes can be tied to a specific geographic point facilitates sociospatial crime analyses compared to analyses of fear and safety perceptions. People's fears are difficult to quantify and can be associated with anything from specific objects or individuals in the environment to entire neighborhoods (or even global processes). Therefore, the spatial resolution of traditional fear studies (e.g., based on surveys or interviews) has remained relatively low or been limited to smaller geographical scopes (Dubey et al. 2016; Zhang et al. 2021).

Deep Learning, Street View Imagery and Perceptions of the Urban Environment

Breakthroughs in development of machine learning, deep learning, and computer vision have facilitated the processing of large-scale unstructured and complex geographic data, including geotagged images such as street view images (SVIs; Gao et al. 2021). SVI databases used together with deep learning approaches (e.g., deep convolutional neural networks [DCNNs]) have been used to assess and predict human perceptions of city streetscapes (Salesses, Schechtner, and Hidalgo 2013; Dubey et al. 2016). There have already been several studies adopting such approaches to assess the effect of street environments on both crime patterns and safety perceptions (see, e.g., Harvey et al. 2015;

Zhang et al. 2018; Moreno-Vera, Lavi, and Poco 2021; Zhang et al. 2021; Zhou et al. 2021; He et al. 2022; Hipp et al. 2022). Deep learning approaches have had great success in detailed and large-scale analyses of the effect on crime of common urban features such as street lights, fences, green space, and more (He et al. 2022; Hipp et al. 2022). Studies specifically quantifying SVI-based perceived safety generally point to a significant negative relationship with crime occurrence (Zhang et al. 2021; Zhou et al. 2021; Zhou et al. 2024). Zhang et al. (2021), however, also identified what they referred to as a "perception bias," where, for example, areas with high daytime traffic and low crime rates often had low "safety scores," whereas high nighttime traffic areas with high crime rates were perceived as safer. Studies have also found that the direction and strength of the association between SVI-based perceived safety and occurrence of certain crime types vary at different levels of spatial division (e.g., street segments, census block; Zhou et al. 2024).

A majority of previous studies that measure urban perceptions with SVIs rely on a global data set, for example, the MIT Place Pulse data set (Dubey et al. 2016), which contains human perceptions of SVIs of a range of different cities all over the world. Researchers have also suggested, though, that a localized data set (based on local residents and city images) might better capture citizens' perceptions of the built environments (Yao et al. 2019), presenting a current research gap. Connecting with theory, a local data set may better reflect the effects of dispositional factors on situational elements of perceived safety. Unlike the comparably foreign cities in a global data set, the local data set could capture the impact of people's relationships, familiarity, and personal attachments to places in the city where they live (even if they do not fully recognize the depicted locations), which have also been found to determine fear (Kaplan and Kaplan 1982; Herzog 1984; Low and Altman 1992; Day, Stump, and Carreon 2003; Lorenc et al. 2013). This is vital for fully understanding the relationship between perceived safety and crime.

Based on the theoretical background and previous research, this study attempts to answer the following research questions:

- Which locations and types of environments are visually perceived as (un)safe in Stockholm by the population, and how do the patterns compare to the spatial distribution of crime?
- To what degree can people's perceived safety of the built environment be associated with objective safety measures such as local crime rates, while controlling for land use and sociodemographic characteristics of the areas? Does this relationship vary by crime type?

This article builds on a data set and model originally developed by the research team, which in this study tests the relationship between VPS and crime records. Through this we aim to contribute to the literature on the situational nature of both crime and fear and potentially aid in disentangling their relationship. Previous studies have made similar examinations of this link, but we go beyond these contributions by expanding the methodology to use a data set of local citizen impressions and SVIs in a European capital.

Research Design

Study Area

The study area is the municipality of Stockholm, which is the capital and largest city of Sweden. Although the municipality rates relatively high in most measures of well-being, it suffers from socioeconomic and spatial segregation (Bremberg, Slättman, and Alarcon 2015; Segregationsbarometern 2020). To the east lies the relatively affluent inner city of Stockholm (Figure 1), whereas the southwestern and northeastern periphery of the municipality are characterized by substantially higher shares of foreign-born, low-income residents and unemployed. Total crime has generally seen a decrease in the Stockholm region, whereas vandalism and deadly violent crime have instead increased since 2015 (Brå [The Swedish National Council for Crime Prevention] 2022). According to the 2020 Stockholm Safety Survey, a fifth of the population declared feeling unsafe when out alone at night and 31 percent avoid certain places due to worry of victimization. The municipality has expressed its dsire to reduce perceived unsafety by half between 2020 and 2025 (Stockholm Stad [Municipality of Stockholm] 2022).

The basic spatial unit employed in this study refers to base areas (Swedish: *basområde)*, which is one of the smaller administrative geographical units in Sweden (Figure 1). In total, there are 419 base areas in Stockholm. All data sources used in this article are aggregated to base area level.

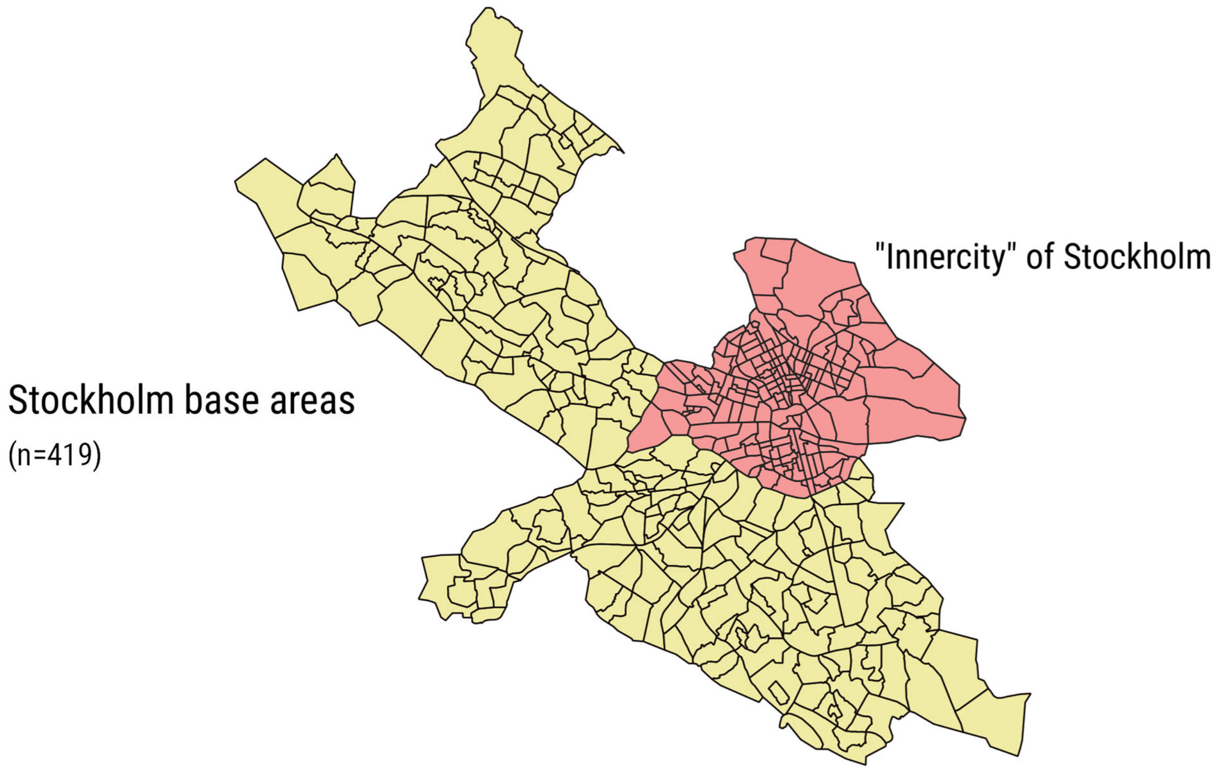

Figure 1. Base areas of Stockholm and location of Stockholm inner city.

Data

This study includes five data sets: street view imagery, crime, land use, socioeconomic data, and mobility.

Street View Images. SVIs provide eye-level panoramas of urban settings. Approximately 1 million SVIs of Stockholm were downloaded from Google. Each panoramic image contains a "panoid" as its unique identifier and consists of four SVIs to represent the different views of a location.

Crime Data. We used crime rates per 1,000 inhabitants, specifically for street violence (murder, assault, sexual assault), vandalism (damaging or defacing of public or private property), street theft (robberies or muggings and pickpocketing), and total crime. As per the Swedish Penal Code, robberies are grouped with crimes of theft and separate from violent crimes such as assault. We selected only outdoor crime as this is the realm of our SVIs; that is, crimes such as domestic violence were not included.

One limitation of base areas as units of analysis is that the population can vary greatly between zones. As such, a total of twenty-five areas (6 percent) were excluded due to low residential population (fewer than thirty inhabitants), as crime rates would potentially misrepresent the level of criminal activity in these areas. Note that the excluded areas are all environments dominated by industrial spaces, interstitial spaces, and in one case, an airport. An exception was made for seven base areas located in the city center, where the day population was used to calculate the crime rates instead. The reasoning behind this decision is that the city center is one of the more criminogenic areas in the city and would be too important to exclude. As a result, the total number of base areas included in the analysis was 387. We note that other units of analysis such as DeSO (Statistics Sweden n.d.) have constant population in the zones but instead might cover disconnected neighborhoods and environments, making base areas more suitable for this study.

Socioeconomic and Land-Use Data. Socioeconomic factors, including population by gender, age, country of birth, employment rate, and average annual income, were obtained from Sweco, a consultancy company responsible for Stockholm City's information service. These were included to measure the potential effects of, for example, social disorganization. Land-use variables and urban facilities were retrieved from Stockholm City's open data bank, Dataportalen, and OpenStreetMaps (OSM). The land-use variables include commercial, residential, recreational, industrial, forest, nature reserve, and parks. These were chosen to indicate different types of urban environments and specific features (e.g., greenery, type of activities). Urban facilities and points of interest (POIs) such as bars, restaurants, bus stops, transport stations, and gas stations were also considered for the analysis. These variables indicate features that can be considered crime generators or attractors, but also indicating activity spaces that might be perceived as safe or unsafe (e.g., due to increased or decreased natural surveillance).

Mobility Data. The cell phone data from a cellular company were generated based on millions of anonymous cellphone user activities during November 2019. The number of visitors in each hour during the weekdays and weekends was calculated.

All data sets have been aggregated to base area level. Apart from the base area division, the city has also been divided into six different urban planning regions, based on the fourteen characteristics of the built environment described in the Stockholm building code (*byggnadsordningen*; Stockholm Stad [Municipality of Stockholm] 2020; Figure 2). These serve as the basis for the sampling of survey respondents and provide information on how different urban planning styles might interact with safety and crime. See the Appendix for definitions of each region.

The Citizens Panel Survey. We adopt a data set originally collected by the research group, based on an online survey designed to assess people's safety perceptions of the built environment. Participants were recruited through a citizens' panel of Stockholm (*medborgarpanelen*). The members are age fifteen and older and were either self-registered or recruited via telephone. The participants were sampled to be statistically representative of the population of each of the six urban planning regions (Figure 2). A total of 2,371 members participated. Approximately 5,000 SVIs were randomly sampled from the data set. In the survey, each participant was presented with random pairs of SVIs and asked to assess them in terms of safety. More

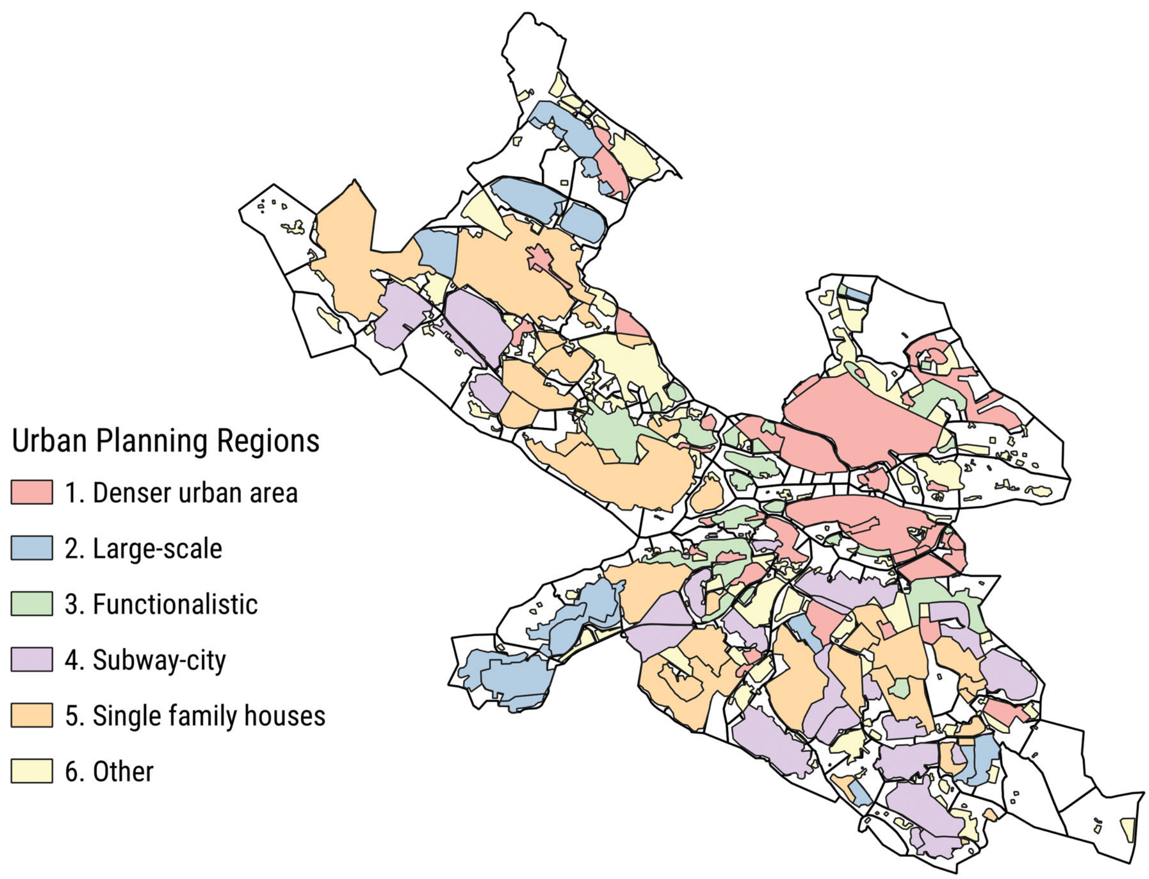

Figure 2. Distribution of the six regions based on general urban design characteristics.

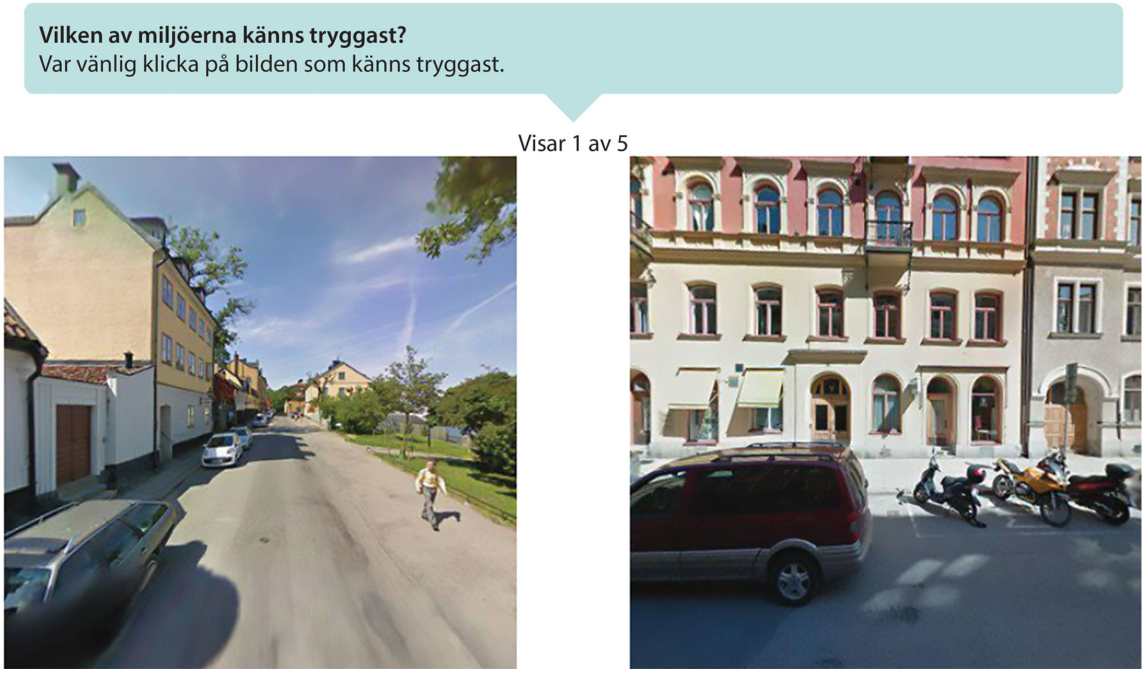

Figure 3. A screen capture of the online survey. The Swedish text reads, "Which of the environments feel safer? Please click on the picture that feels safer."

specifically, half of the participants were asked the question, "Which of these environments feel safer?" The other half of the participants were asked, "Which of these environments feel more unsafe?" (Figure 3). The purpose of this was to control for the impact of how the questions were framed. In total, the survey received 23,710 responses (ten comparisons per respondent). Each SVI was compared with other SVIs mome times on average, and images that had been compared less than five times were not included in the final data set to improve reliability.

Methods

Measuring Safety Perceptions of the Built Environment: The Visually Perceived Safety Score. We use a deep learning model originally developed by the research group, based on a widely used computational strategy that combines SVIs and computer vision approaches to learn participants' safety perceptions. First, the paired comparisons of SVIs were converted to continuous *visually perceived safety scores* (VPS scores). This was determined by the proportion of the times an image was selected as safe or unsafe, along with the frequency with which it was left unselected, corrected for the overall "safe" and "unsafe" ratios of all images it was compared against (see the strength of schedule approach; Salesses, Schechtner, and Hidalgo 2013). Then, a deep learning model was trained to learn patterns of humans' safety perceptions that can predict VPS scores of SVIs. An advanced DCNN architecture, ResNet, was employed for model training, as it has been widely applied for solving computer vision tasks. This study follows the approach of Salesses, Schechtner, and Hidalgo (2013), Dubey et al. (2016), and Zhang et al. (2018), as the strategies employed have shown high efficiency and accuracy.

After the completed training, the model gained the ability to predict safety perceptions of any SVI. Thus, we input all downloaded SVIs of Stockholm into the model, generating a VPS score for each image. The resulting data were then aggregated to area level by calculating the average VPS score of all images per base area. Figure 4 illustrates several randomly sampled SVIs with their predicted safety perception scores in Stockholm. The resulting outputs fit our common sense of how environments are most likely perceived and illustrate that our approach has "replicated" human subjective safety perceptions.

Mapping and Cluster Analysis. We used GIS to compare the spatial distribution of crime and the VPS score and employed Getis–Ord Gi* local spatial autocorrelation (Getis and Ord 1992) to identify significant spatial clusters. Getis–Ord Gi* is a local spatial statistic that considers each spatial unit and identifies clusters

Figure 4. Several random selected street view images that are predicted as (A) high safety perceptions and (B) low safety perceptions.

of similar values (in this case, VSP scores and crime rates). This is determined through the Gi* statistic (z score), p values, and confidence level of the spatial unit. Significant positive z scores indicate higher density of high values (hot spots), whereas significant negative z scores indicate higher intensity of low values (cold spots; Matijosaitiene et al. 2018).

Although other measures of spatial autocorrelation (e.g., LISA [Anselin 1995]) have been widely used in crime studies, the Gi* statistics have the capability to compare local and global averages and are better suited to identify hot spots (Ratcliffe and McCullagh 1999). Due to the nonuniform size of the spatial units, the spatial weight matrix was generated using first-order queen's contiguity rather than distance.

Modeling Perceived Safety and Crime: Dependent and Independent Variables. The purpose of the regression analysis was to examine the relationship between VPS and crime rates, while controlling for land use, socioeconomic factors, and urban design—variables commonly considered in environmental criminology. The main model has four variations for each type of crime that is investigated. Although prior similar studies have used crime as the dependent variable (Zhang et al. 2021; Zhou et al. 2024), in this study we model the average VPS score per base area, a continuous variable. The choice of this dependent variable is mainly based on the theories of social disorganization, prospect and refuge, and neighborhood disorder (Shaw and McKay 1942; Wilson and Kelling 1982; Fisher and Nasar 1992; Skogan 1992). Overall, the VPS score is expected to be lower in places with visual signs of urban decay, social disorder, and visible features of crime opportunities (e.g., hiding places, low opportunity for guardianship and surveillance). Our selected crime types can be associated with similar types of environments, as well as criminological theories associated with these environments. Street theft is one of the more opportunistic types of crime and likely represents environments with high a chance for intersecting activity patterns (Cohen and Felson 1979; Brantingham and Brantingham 1984) and few eyes on the street (Jacobs 1962). Street vandalism tends to occur in more secluded areas with opportunities for refuge and escape (Fisher and Nasar 1992) and neglected environments characterized by visible disorder and weak informal social control, as described in broken windows theory (Wilson and Kelling 1982). Street violence likely occurs in socially disorganized neighborhoods with low social cohesion and collective efficacy (Sampson, Raudenbush, and Earls 1997), as well as low territoriality and natural surveillance, which are core principles of CPTED and defensible space theory (Newman 1972; Cozens, Saville, and Hillier 2005).

The control variables were also selected based on both theoretical relevance (Figure 5) and through a systematic statistical evaluation. A Pearson's correlation test was performed on all land-use variables, which include the proportion (of base area surface) of commercial land, recreational land, residential land, industrial land, total built-up area, parks, forests, street lights, gas stations, bars, restaurants, schools, transport hubs, libraries, ATMs, and dummy variables of the urban planning regions. Variables with high correlation were excluded, and an initial linear regression was performed using the VPS score as the dependent. Only land-use variables significant at the 0.05 level were included in the next step. Then, socioeconomic and demographic variables were added, including the proportion of men, elderly (sixty-five years and older), foreign-born, unemployed, average income per base area, and weekly daytime visitors. Finally, crime rates

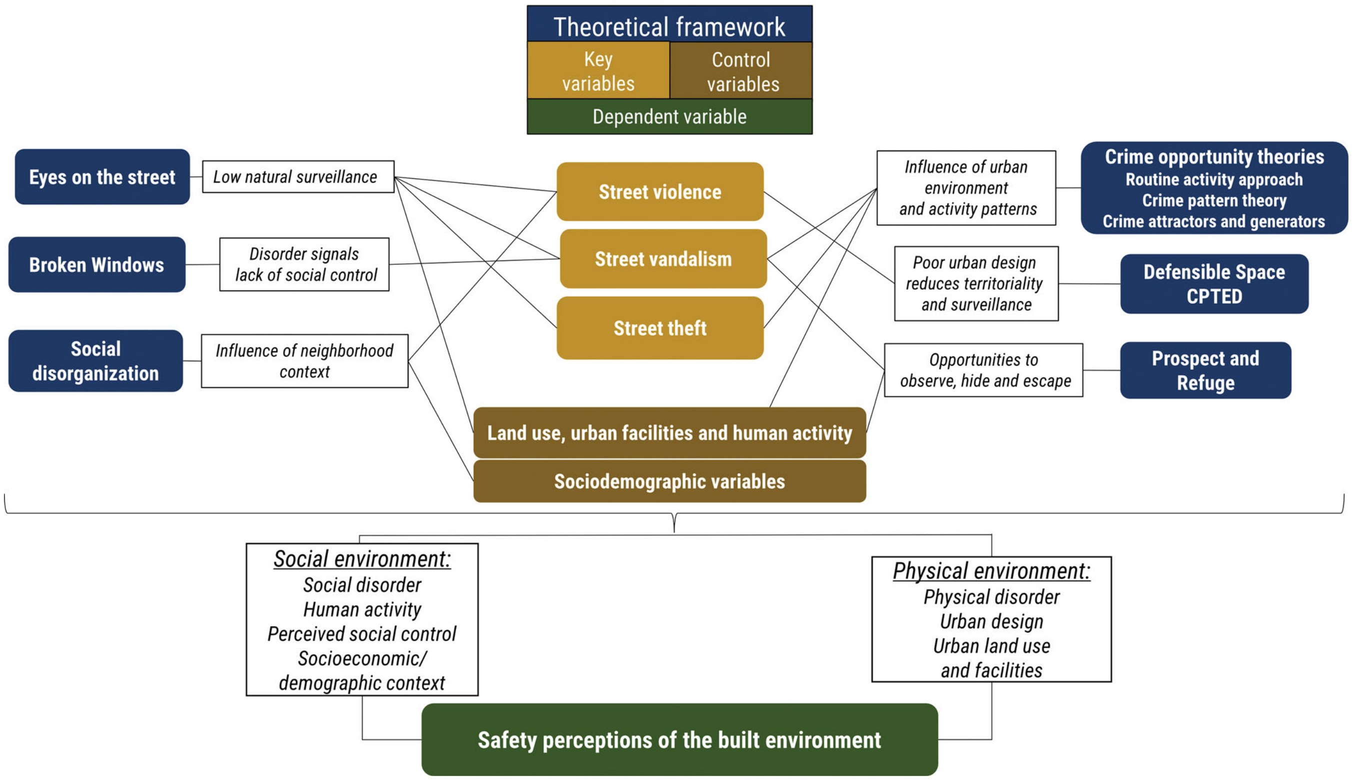

Figure 5. Research framework: Empirical and theoretical connections between visually perceived safety, crime, and the urban environment. *Note:* CPTED = Crime Prevention Through Environmental Design.

per 1,000 population for violent crimes, vandalism, street theft, and total crime were added in separate variations of the models.

Following an additional selection based on correlation and theoretical significance, the final list of independent variables included crime rates, average income of the base area, proportion of elderly, commercial land, parks, restaurants, and daytime visitors, followed by the urban planning regions. Regression diagnostics indicated spatial dependency in the dependent variable with a highly significant Moran's *I* of 0.200 and significant Lagrange multiplier tests for both spatial error and lag models. Ordinary least squares (OLS) regression, spatial lag, and spatial error regression models were then performed and compared.

Results

Mapping and Clustering Safety Perception and Crime

Figure 6 reports the geographical distribution and hot spot analysis of the VPS score. Several regions in Stockholm stand out as being perceived as particularly safe: the southwest (e.g., Herrängen, Långsjö), the central-western border (e.g., Olovslund, Nockby, Äppelviken), and the eastern inner city, all notably affluent regions. Conversely, the northern areas of the municipality (e.g., Husby, Akalla, Southern Kista), and the immediate periphery of the city center are home to significant clusters of low VPS scores. Comparing with Figure 1, these cold spots largely correspond to the second, third, and sixth urban planning regions: large-scale, functionalistic, and other, whereas hotspots correspond more to denser urban area and single-family houses. Although the city center at large is perceived as safe, the base areas containing the central train station near the city center can be observed as a cold spot for perceived safety.

In Figure 7, we can see that the distribution and high clustering of crime are relatively similar across the four types of crime, with the inner-city areas and parts of the southwest and north emerging as especially criminogenic. Some hot spots might be caused by bordering effects (e.g., Mariehäll in the north, bordering the excluded Bromma Airport), whereas the city center is known to be an area with high crime rates. The northern parts of the city, primarily characterized by socioeconomically disadvantaged neighborhoods, are not only lacking hot spots for any crime, but have cold spots for street theft and

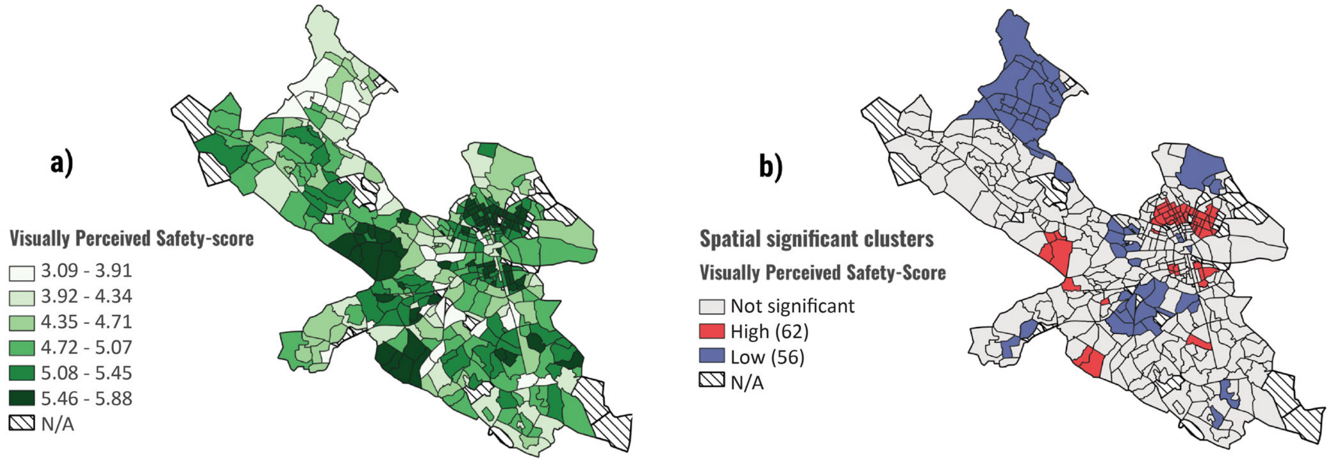

Figure 6. Artificial intelligence (AI)-based safety perceptions of the built environment in Stockholm City (visually perceived safety score): (A) geographical distribution; (B) Getis–Ord Gi* hot spot analysis of the perceived safety score.

vandalism. The southwestern edge (Skärholmen, Sätra, Vårberg) shares a similar socioeconomic disposition and likewise lacks crime hot spots and instead presents cold spots for theft. On the other hand, a persistent low cluster for all crime types can be found in the more affluent midwest (e.g., Olovslund, Ålsten).

Comparing this with Figure 6, there are some areas that correspond low perceived safety of the built environment with high levels of crime and vice versa, but also mismatches. It appears that the low clusters of crime, street theft in particular, in the mid- and southwest parts of the municipality match well with high perceived safety. On the other hand, we can observe cold spots of both low VPS scores and street theft (and vandalism) in the north, indicating areas of higher security but lower perceived safety. Conversely, large sections of the city center that are perceived as particularly safe are also noted as especially criminogenic.

The mapping and cluster analysis indicate that perceived safety does not match perfectly with high crime levels and vice versa, indicating that crime rates alone are perhaps not enough to explain people's safety perception of the urban environment.

Modeling Perceived Safety and Crime

As the dependent variable (i.e., the VPS score) showcased high spatial dependency, three different types of regression analyses were tested to model the safety score: OLS, spatial lag, and spatial error. The spatial lag model demonstrated the strongest performance of the three (in terms of R^2 and Akaike's information criterion [AIC]) and was selected to be the primary model of this study. The results are reported in Table 1, including the estimated coefficients and p values for each independent variable, as well as model diagnostics. The spatially lagged coefficient indicates a significant positive spatial autocorrelation. The proposed model attempts to capture the importance of crime for perceptions of the built environment, controlling for contextual parameters such as land use, socioeconomic factors, and urban planning regions. The four variations of the model differ only in the type of crime examined.

To enable a baseline comparison, we constructed a null model that produced an AIC of 680 and a log-likelihood of −337. Our suggested models showed significantly lower AIC values (494–497) and higher log-likelihood (–233 to −230). This suggests that our included independent variables (selected largely on a theoretical basis) make a substantial contribution to explaining the variance in the VPS score compared to the baseline. The four variations of the model have identical sets of significant independent variables. Notably, the level of crime appears as a significant negative contributor to perceived safety of the built environment for all crime types. As such, criminogenic locations are typically more likely to be visually perceived as unsafe. Among the potential land-use and sociodemographic explanations of the VPS score, areas with higher proportions of elderly residents, parks, restaurants, and higher average income are perceived as safer. A higher proportion of commercial land use (which could include office

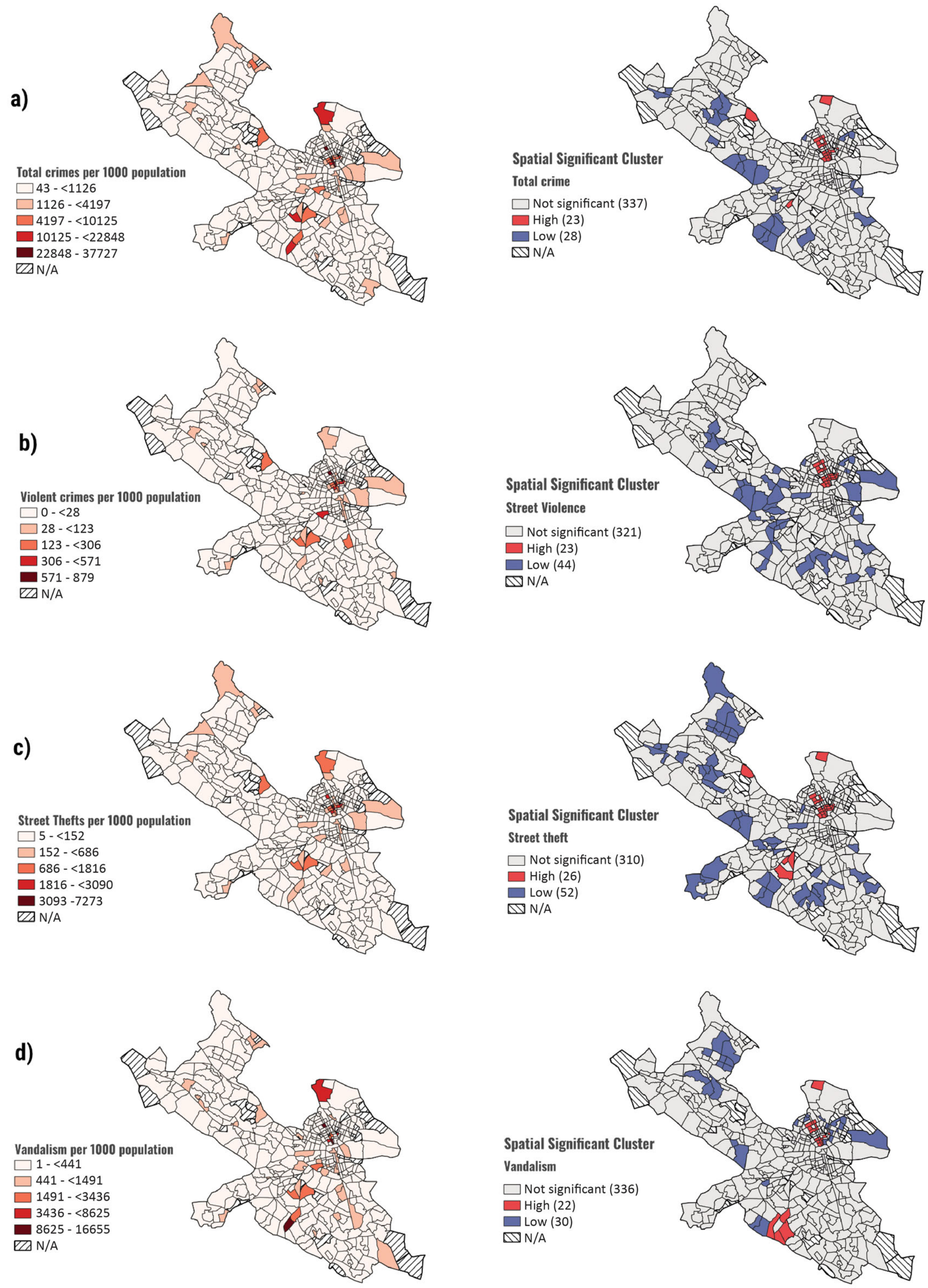

Figure 7. Geographical distribution (left) and Getis–Ord Gi* spatial clustering of crime rates per 1,000 population (right): (A) Total crime, (B) street violence, (C) street theft, and (D) vandalism.

buildings, logistic centers, malls, and parking lots) was the only land-use factor associated with lower perceived safety. Among the urban planning regions, only other (i.e., industrial land use, harbors and airports, and interstitial spaces) had a significant (negative) association with perceived safety, partly

Table 1. Spatial lag regression of the effect of crime on the VPS-score, controlling for the urban design, land use and sociodemographic factors.

	Total crime		Violent crime		Street theft		Vandalism	
Variables	Coefficient	Significance	Coefficient	Significance	Coefficient	Significance	Coefficient	Significance
Crime rate (see respective model)	**−0.560**	**0.016**	**−0.516**	**0.044**	**−0.677**	**0.048**	**−0.531**	**0.037**
Proportion of parks	**0.985**	**0.003**	**1.008**	**0.002**	**0.902**	**0.005**	**0.983**	**0.003**
Proportion of restaurants	**0.821**	**< 0.001**	**0.846**	**< 0.001**	**0.818**	**< 0.001**	**0.782**	**< 0.001**
Daytime visitors	−0.135	0.270	−0.126	0.301	−0.128	0.296	−0.137	0.262
Proportion of commercial land	**−1.611**	**0.038**	**−1.597**	**0.041**	**−1.644**	**0.035**	**−1.636**	**0.036**
Average income of base area	**0.087**	**< 0.001**	**0.087**	**< 0.001**	**0.087**	**< 0.001**	**0.086**	**< 0.001**
Proportion of elderly	**0.551**	**0.027**	**0.549**	**0.028**	**0.557**	**0.025**	**0.571**	**0.022**
Urban planning region: Large scale	−0.021	0.836	−0.013	0.893	−0.016	0.875	−0.018	0.858
Urban planning region: Functionalism	0.051	0.529	0.056	0.498	0.053	0.517	0.054	0.511
Urban planning region: Subway city	0.118	0.144	0.122	0.132	0.121	0.137	0.121	0.136
Urban planning region: Single-family houses	0.121	0.101	0.125*	0.090	0.121	0.102	0.124*	0.093
Urban planning region: Other	**−0.182**	**0.038**	**−0.192**	**0.028**	**−0.200**	**0.022**	**−0.187**	**0.033**
Constant	**1.897**	**< 0.001**	**1.876**	**< 0.001**	**1.882**	**< 0.001**	**1.864**	**< 0.001**
W_VPS score	**0.501**	**< 0.001**	**0.506**	**< 0.001**	**0.503**	**< 0.001**	**0.507**	**< 0.001**
R^2	0.494	—	0.492	—	0.492	—	0.493	—
AIC	494.7	—	496.4	—	496.5	—	496.1	—
Log-likelihood	−233.4	—	−234.2	—	−234.3	—	−234.0	—
Breusch–Pagan test	14.53	0.268	13.315	0.347	13.489	0.334	14.65	0.261
Likelihood ratio test	**65.90**	**< 0.001**	**66.54**	**< 0.001**	**66.314**	**< 0.001**	**68.09**	**< 0.001**
Moran's *I* (dependent variable)	**0.200**	**< 0.001**						

Note: The independent crime rate-variable varies with each model. Values shown in **bold** indicate significant at 0.05 level. AIC = Akiake's information criterion.
*Significant at 0.1 level.

confirmed in the spatial comparison. Although the single-family housing region was found to be significant only at the 0.1 level, the variable is noted to have a positive impact on perceived safety.

The other urban planning regions and the number of daytime visitors did not appear significant in any model variation. It should be noted that several versions of the model were tested as part of robustness checks, including adding and removing alternative control variables and controlling for interaction effects. These did not alter the main findings in any substantial way.

Discussion

The results emphasize the complex nature of people's safety perceptions. In our analysis, we focus on a specific dimension of safety related to the visual impression of the built environment and how well it corresponds to local crime rates. We attempt to identify such a relationship from two fronts: through a cluster analysis and spatial regression. Both approaches helped us reveal how VPS is influenced by location and contextual characteristics.

Spatial Patterns of Perceived Safety and Crime in Stockholm

The initial spatial analysis revealed that, like crime, the VPS score is not evenly distributed across the city but concentrates in clusters. Clusters are largely located in areas with high and low socioeconomic status for high and low perceived safety, respectively. Both social disorganization theory and broken windows theory would suggest that low-income areas are more likely to suffer from visual signs of urban decay, lack of social control, and low collective efficacy, which in turn would lead to decreased feelings of safety (Wilson and Kelling 1982; Camacho Doyle, Gerell, and Andershed 2022). Furthermore, many of these low-income areas align with the large-scale planning region (Figures 1 and 7) and are typically characterized by high-rise residential areas built during the housing program *Miljonprogrammet*. Although it has been praised for securing housing for many, the program has also been criticized for being overly utilitarian in its design, creating bland neighborhoods without identity or charm, and neglecting the outdoor environment (Hall and Vidén 2005). The theory of defensible space (Newman 1972) partly supports these findings, similarly noting the generally poor opportunities for residential sense of control and responsibility around high-rise housing complexes. Conversely, high-income areas likely have more resources to maintain and develop visually appealing and safe environments. The distribution and clustering of crime matches previous studies in Stockholm (Ceccato, Haining, and Signoretta 2002; Uittenbogaard and Ceccato 2012) to some degree, pointing to the city center as a typical hot spot of crime. Yet the cold spots of theft in the city's outskirts point to possible emergent trends (possibly connected to the COVID-19 pandemic).

The spatial distribution of our two measures matches in some cases, but there are multiple areas that are perceived as visually safe but are insecure in terms of crime, and vice versa. Zhang et al. (2021) also investigated this discrepancy and introduced the term *perception bias*. Aligning with the findings of their study, the dense and more developed built environment of Stockholm's inner city is associated with high perceived safety, yet we also identify high clusters of crime. This might not be explained by the ideas of social disorganization, but the theories of crime opportunities (Cohen and Felson 1979; Kinney et al. 2008) would suggest that areas that draw large flows of people (e.g., a city center) also attract potential offenders. As Hipp et al. (2022) also noted, there might be a nonlinear relationship between certain urban features and crime deterrence, but that relationship might be different for the sense of safety. Designing environments that are perceived as safe might not be enough to also deter crime. The mismatches could also be potentially explained by certain familiarity or emotional attachment to the depicted locations. Although specific neighborhoods are relatively difficult to identify solely through an SVI, Stockholm has quite distinct urban planning styles as denoted by the six urban planning regions. This means that, for instance, the aforementioned *Miljonprogram*-era residential housing could be recognized and, depending on the individual citizen, elicit fear or possibly a sense of belonging (Low and Altman 1992).

The spatial juxtapositions of crime and safety found along the lower income areas on the northeast periphery of the city are particularly noteworthy. Here, we not only observe a lack of high-crime clusters in areas with low perceived safety, but even significant clusters of low rates of vandalism and street theft. This suggests that the relationship between VPS and crime is highly context-specific and dependent on crime type, but also calls the overall relationship into question. The fact that vandalism, a crime often linked to defacing or damaging the built environment, had a lesser presence in a region with low VPS was somewhat unexpected. Here the nature of the crime variables becomes relevant: These are offenses reported to the police and as such are dependent on the residents' willingness to report or ability to notice them. Crimes, and vandalism in particular, might not be reported or even noticed by the average citizen, especially in low-income areas where social control and trust in police might already be weak. Vandalism could also potentially be committed in locations that would not be observable in an SVI. It is important to remember what constitutes the link between perceived safety and crime in this study; rather than identifying observable crimes that might trigger feelings of unsafety, it is recognizing locations and environments that could both cause fear and attract crime. Nonetheless, the findings of the cluster analysis initiate a questioning of this very link.

Explanatory Power of Crime and the Urban Environment on the VPS Score

Despite the mismatches of crime and safety identified in the initial spatial analysis, our regression models reveal that crime rates possess a significant explanatory power of the VPS score, even when we control for contextual factors (including land use, socioeconomic factors, and urban design). This could be interpreted to mean that typical criminogenic environments have characteristics and features that are also perceived as unsafe, at least on a visual basis. As we noted, the different crime types included in the model can be used to represent various perceivable environmental contexts and features (e.g., fewer eyes on the street, more opportunities to hide, low territoriality, or natural surveillance), affecting the VPS score. These points are supported once more by several theories covering the effect of place characteristics on safety and crime, such as the architecture and urban design (Jacobs 1962; Newman 1972; Fisher and Nasar 1992) and location-specific conditions (Wilson and Kelling 1982; Skogan 1986). The broken windows theory notably states that unaddressed minor offenses could lead to more serious offenses, which might explain why all types of crime were significant in relation to the VPS score. These results align with other SVI-based analyses of the link between perceived safety and crime (although other studies have used crime as the dependent variable; Zhang et al. 2021; Zhou et al. 2024). As this association has been found to vary at different geographical units of analysis (Zhou et al. 2024), however, future studies could incorporate street segment-level analyses in Stockholm to explore the nuances of safety and crime on a finer scale.

The regression modeling also further emphasizes the multifaceted nature of urban safety perceptions, which cannot be fully captured by the variation in crime alone. A higher proportion of elderly indicated environments perceived as safer, which could have multiple interpretations. Planners could cater to elderly residents by promoting urban design focusing on mobility and accessibility, avoiding crowded and narrow places associated with fear. Alternatively, elderly people might just be more likely to situate themselves in such neighborhoods. Similarly, high-income base areas might also be perceived as safe, as people with higher income have more opportunities to settle in neighborhoods designed with safety and pleasing aesthetics in mind. This is supported by the findings of the spatial analysis and could also point to potential issues with gentrification when attempting to improve perceived safety through urban design. The positive association of restaurants and parks with safety was expected based on theory and previous findings. Restaurants are most densely located within the inner city of Stockholm (which was perceived as particularly safe in the spatial analysis), often situated along vibrant streets providing opportunities for more social interaction and eyes on the streets (Jacobs 1962). On the other hand, these facilities could also be considered crime attractors or generators (Kinney et al. 2008), which would help explain the high crime rates in the city center. Parks and other forms of urban green areas have generally been found to have s positive influence on quality of life, including perceived safety, although there have been conflicting findings (Li, Zhang, and Li 2015; Mouratidis 2019). As the variable is defined as the proportion of parks per base area, it most likely indicates the effect of the level of greenery, whereas it informs us less about the perceived safety of parks as places in detail. This is particularly relevant because the SVIs are restricted to environments accessible by car.

The proportion of commercial areas and the urban planning region designated as other were the only independent variables with a significant negative association with safety besides crime. This indicates that these predictors might capture a different aspect of perceived safety, where the potential dangers are separate from crime. Commercial areas could cover facilities that are associated with high human activity, such as malls and restaurants, but they also include connecting parking lots, office buildings, and logistic centers. In a similar sense, the region designated as other consists of environments characterized by industrial settings, airports, and interstitial space. These environments could be less designed with the average pedestrian in mind, and hence, the perception of safety could be influenced by potential dangers related to traffic safety and walkability (for a review, see Arellana et al. 2020). It should be noted that although our selected variables contribute to explaining the VPS score, we acknowledge that there is likely a range of other explanatory factors. Human perceptions and behavior are difficult to predict, which is reflected in the pseudo-R^2 of the model.

Overall, although there are several important nuances to recognize, the regression model highlights a significant relationship between crime and VPS (related to the built environment in particular). Yet we also see that despite this relationship, there are certain environments in Stockholm that are not necessarily very criminogenic but still have poor perceived safety according to our deep learning model, as well as environments that might capture other anxieties than specifically crime-related safety perceptions. The results further support research on the multifaceted and situational nature of fear and the importance of contextual area-level features for crime and safety (Jacobs 1962; Jeffrey 1971; Bursik 1988; Kinney et al. 2008). The findings could support efforts combining crime prevention and safety improvement measures using urban planning, where the relationship of the two measures can be taken for granted.

The study has several limitations that could provide opportunities for future research. Google Street View imagery is limited to daylight environments within close vicinity of car-accessible roads. Other approaches could attempt to further investigate the temporal variations of safety perceptions, as well as completely traffic-separated environments. On this note, isolating crime events only committed during daylight hours could allow for a better connection with the survey perceptions of the SVIs. In a Nordic context, however, the extreme seasonal variations in daylight can make it challenging to define day and night consistently. Additionally, complementing base area-level land-use data, future studies should incorporate data on features derived directly from the SVIs, for example, using image segmentation and providing more accurate control variables directly linked to VPS score. The aggregation of data to base areas, which are not uniform in size or population, could also cause important nuances to be lost. If crime data in point form can be acquired, analysis on a streetscape level instead could be feasible. This could instead impede the control of socioeconomic variables, however, as these are usually not available at such a detailed level due to privacy laws. Additionally, although this was intentional, the citizen panel survey captures a very broad idea of perceived safety, as no definitions or further information are presented to the responders. Future studies could possibly be more precise in their question formulation to improve the reliability of using crime as a comparative measure. Even with more precise questions, though, it remains difficult to disentangle specific fears from people's overall safety perceptions. Other ground truths than crime can be applied in future studies to capture different aspects of perceived safety: for example, safety surveys, traffic accidents, injury incidents, and more.

Conclusion and Implications for the Future

This study set out to investigate the relationship between safety perceptions of the built environment and local crime levels in the city of Stockholm. Using the combination of a local citizen panel survey, SVIs, and deep learning algorithms, a detailed measure of people's safety perception of the built environment could be created: the VPS score. The use of local images and impressions allowed for potentially more accurate representations of city dwellers' safety perceptions of where they live. The VPS score was compared with crime rates using both spatial autocorrelation analyses and regression modeling, showing that crime is significantly associated with the perceived safety of a location, after controlling for physical and social contexts of the built environment. Spatial juxtapositions of security and safety are particularly notable in the city center and in the north of the municipality, highlighting the context- and crime-type-dependent nature of the relationship, as well as indicating areas of interest for urban planners. The study has contributed to the knowledge bank on people's safety perceptions of the physical environment and research relating to crime and fear. Finally, it has showcased an application of modern methodologies such as deep learning models, SVIs, and crowdsourced data in a Scandinavian context, furthering the fields of GeoAI and urban studies.

Implications for Research and Practice

This study has contributed especially to the knowledge bank of methodologies in fear and safety research. First, it further confirms that deep learning and other artificial intelligence (AI) approaches can be a useful alternative, or at least a complement to, for example, traditional surveys. Second, it has expanded on previous studies by highlighting how considering the nature of the training data sets (local vs. global) could be useful for measurements of urban safety perceptions. With AI often being referred to as a "black box" technology, it is important to use context-specific data and conduct theory-driven research design to better understand the model outputs.

Several important findings should be noted by policymakers and practitioners. For instance, the Stockholm neighborhoods with both poor perceived safety and high crime highlight especially vulnerable target areas, where resources should be focused toward crime prevention and safety measures. Yet people's low safety perceptions are, in some contexts, shown to not necessarily be solved solely by reducing crime or crime opportunities. The areas in, the northern parts of Stockholm, for example, with comparably low rates of crime and low perceived safety provide a clear target for new interventions and long-term urban planning policies. Further research could examine the microlevel effects of addressing urban features that affect crime and perceived safety in different directions (e.g., through street-level analysis), to aid the long-term development of cities that both are and feel safe.

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Disclosure Statement

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ORCID

Jonatan Abraham http://orcid.org/0000-0003-2050-8365
Yuhao Kang http://orcid.org/0000-0003-3810-9450
Vania Ceccato http://orcid.org/0000-0001-5302-1698
Per Näsman http://orcid.org/0000-0001-7606-8771
Fábio Duarte http://orcid.org/0000-0003-0909-5379
Song Gao http://orcid.org/0000-0003-4359-6302
Lukas Ljungqvist http://orcid.org/0000-0001-6831-6878
Fan Zhang http://orcid.org/0000-0002-3643-018X

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JONATAN ABRAHAM is a Doctoral Candidate and member of the Urban and Community Safety Research Group in the Department of Urban Planning and Environment at KTH Royal Institute of Technology, SE-100 44 Stockholm, Sweden. E-mail: jabraham@kth.se. His research interests include the intersections of crime and fear in both urban and rural contexts.

YUHAO KANG is the Director of the GISense Lab and an Assistant Professor in the Department of Geography and the Environment, The University of Texas at Austin, Austin, TX 78712. E-mail: yuhao.kang@austin.utexas.edu. His research interests include human-centered geospatial data science and GeoAI.

VANIA CECCATO is Professor and Head of the Urban and Community Safety Research Group in the Department of Urban Planning and Environment, KTH Royal Institute of Technology, SE-100 44 Stockholm, Sweden. E-mail: vace@kth.se. She is interested in the relationship between the urban environment and people's safety conditions.

PER NÄSMAN is a Doctorate and Statistician at KTH Royal Institute of Technology, SE-100 44 Stockholm, Sweden. E-mail: per.nasman@abe.kth.se. An important research area for Näsman is risk and security as well as resilience regarding vital parts of society's infrastructure.

FÁBIO DUARTE is the Associate Director and Principal Research Scientist at the Senseable City Lab at the Massachusetts Institute of Technology, Cambridge, MA 02139. E-mail: fduarte@mit.edu. Duarte works at the intersection of technology, data, and urban planning.

SONG GAO is an Associate Professor of Geographic Information Science in the Department of Geography, University of Wisconsin–Madison, Madison, WI 53706. E-mail: song.gao@wisc.edu. His research interests include geospatial data science, GeoAI, social sensing, spatial networks, and human mobility.

LUKAS LJUNGQVIST is employed as an Urban Strategist in the City of Stockholm and the research lead from the city's side in the Senseable Stockholm Lab. He is also pursuing an industrial PhD in applied urban design in the School of Architecture, KTH Royal Institute of Technology, Stockholm, Sweden. His PhD is on the effects of digital transformation on urban planning and design methodologies.

FAN ZHANG is an Assistant Professor at the Institute of Remote Sensing and Geographical Information System, School of Earth and Space Sciences, Peking University, Beijing 100871, China. E-mail: fanzhanggis@pku.edu.cn. His research interests include geospatial AI and data-driven urban studies.

CARLO RATTI is the Director of the Senseable City Lab and Professor of the Practice at the Massachusetts Institute of Technology, Cambridge, MA 02139. E-mail: ratti@mit.edu. Ratti's research combines data, technology, and design.

Appendix. Definitions of Regions Denoting Urban Planning Archetypes

Urban planning region	Description
1. Dense urban area (Tätstad)	• Closed neighborhoods, strict division between public and private. • Fine-meshed street network offers variation between public and private land.
2. Large scale	• Pedestrian and vehicle traffic systems are completely separate. • Large-scale residential buildings, terraced and semidetached houses. • The walkways go through the buildings or vegetation.
3. Funkis (Functionalism)	• "House-in-park" (buildings freely located in a nature-like environment). • Houses often located far into the plot with entrances facing inward. • Less clear division between streets and neighborhood land. • Walkways along streets.
4. Subway city	• Further development of "house-in-park," some impact from older environments. • Buildings grouped around courtyards or parks. • Entrances often turn inward or away from the street. • Walkways both along streets and separate through parkland.
5. Single-family houses	• One- and two-dwelling houses in garden environments. • Streets defined by bordering buildings, hedges, and avenues. • In residential environments, wide garden/courtyard zones face the street.
6. Other	• Random areas in the city, industrial sites, harbor areas, airports and fun parks, among other things.