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Measuring the built environment with Google Street View and Machine Learning: Consequences for Crime on Street Segments

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Measuring the built environment with Google Street View and Machine Learning: Consequences for Crime on Street Segments

Abstract

Objectives: Despite theoretical interest in how dimensions of the built environment can help explain the location of crime in micro-geographic units, measuring this is difficult.

Methods: This study adopts a strategy that first scrapes images from Google Street View every 20 meters in every street segment in the city of Santa Ana, CA, and then uses machine learning to detect features of the environment. We capture eleven different features across four main dimensions, and demonstrate that their relative presence across street segments considerably increases the explanatory power of models of five different Part 1 crimes.

Results: The auto-oriented measures—vehicles and pavement—were positively associated with crime rates, as was the presence of more persons in the environment. For the defensible space measures, the presence of walls has a slowing negative relationship with most crime types, whereas fences did not. And for our two greenspace measures, although terrain was positively associated with crime rates, vegetation exhibited an inverted-U relationship with two crime types.

Conclusions: The results demonstrate the efficacy of this approach for measuring the built environment.

Keywords: *Built Environment, Crime, Google Street View, Machine Learning, Semantic Segmentation*

Bios

John R. Hipp is a Professor in the departments of Criminology, Law and Society, and Sociology, at the University of California Irvine. He is the director of the Metropolitan Futures Initiative (MFI). His research interests focus on how neighborhoods change over time, how that change both affects and is affected by neighborhood crime, and the role networks and institutions play in that change. He approaches these questions using quantitative methods as well as social network analysis. He has published substantive work in such journals as *American Sociological Review, Criminology, Social Forces, Social Problems, Mobilization, City & Community, Urban Studies* and *Journal of Urban Affairs*. He has published methodological work in such journals as *Sociological Methodology*, *Psychological Methods*, and *Structural Equation Modeling*.

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Measuring the built environment with Google Street View and Machine Learning: Consequences for Crime on Street Segments

Scholars studying the ecology of crime have long focused on how social and physical dimensions of the environment can impact the amount of crime occurring in neighborhoods or smaller geographic units. Whereas measuring the social dimensions of the residents living in an area is relatively straightforward given the availability of accurate Census data in many nations, measuring the built environment is more challenging. Given the importance of the built environment posited by numerous theories such as crime pattern theory (Brantingham and Brantingham 1984), crime prevention through environmental design (CPTED) (Newman 1972), or routine activity theory (Felson 2002), this is a key challenge faced by numerous researchers in criminology, urban planning and design, and other related fields. As a consequence, researchers have turned to various strategies for measuring the built environment, including surveys of residents, field surveys, administrative, cadastral, or proprietary data. Although these strategies provide key insights, they also tend to be limited in various ways, including how large of a study area is feasible, or in the types of features of the environment they can measure.

In recent years, due to the twin development of high quality images of the built environment available on the web from sources such as Google Street View along with the recent advances in machine learning techniques that can detect characteristics in images, these limitations regarding the size of the study area that is feasible in measuring the built environment are becoming less daunting. We demonstrate in this study an approach that combines machine learning with collected images from all street segments in a large city of over 300,000 persons to explore how features of the built environment can help us understand why some street segments have more crime than others. We attempt to capture key features of the built environment and assess their relationship with crime in street segments of a large city using the semantic segmentation methodology of the Deeplabv3+ algorithm (Chen et al. 2018) on Google Street View (GSV) images to create measures of the environment.

In the next section we describe three key theories that posit features of the built environment that may be important for understanding the location of crime in micro-geographic areas. We describe four broad categories of features that we focus on, and then discuss existing strategies typically used to measure physical features. Following that, we describe our data, and our methodological approach to capturing and classifying GSV images. We present the results of the models using our built environment measures to explain the level of crime in segments of this city, including assessing nonlinearity, and conclude with a discussion of the implications.

Literature review

There are at least three theories that posit certain characteristics of the built environment can impact crime. One theory is crime pattern theory, which posits that the urban backcloth of street patterns and features on those streets impact the spatial patterns of potential offenders and targets, and therefore can impact the location of crime (Brantingham and Brantingham 2008). Research in this tradition has measured how the street network can impact travel patterns and therefore the location of crime events (Beavon, Brantingham, and Brantingham 1994; Davies and Johnson 2014; Kim and Hipp 2019). This perspective also posits that certain locations—such as retail districts—are nodes that act as crime generators that lead to more crime (Hipp 2010; Hipp and Kim 2019; Stucky and Ottensmann 2009), or that certain locations—such as bars or nightclubs—can disproportionately attract offenders given the presence of particularly attractive targets and therefore result in more crime (Groff 2011; Ratcliffe 2012; Feng et al. 2018). This perspective dovetails with a second theory—routine activity theory—which argues that it is the convergence in time and space of offenders, targets, and a lack of guardians that increases the likelihood of a crime event occurring (Felson 2002). Furthermore, a third theory is crime prevention through environmental design (CPTED), in which key features of the built environment are expected to enhance or inhibit crime opportunities through various mechanisms, including impacting guardianship capability due to limited visibility (Newman 1972). We utilize these theories in focusing on physical features within four broad categories: 1) vibrancy, 2) auto-oriented, 3) defensible space created by fences and walls, 4) greenspace. We describe these in the next section.

Key features of the environment

One important consequence of physical attributes of an area is that they might either promote or dampen the vibrancy of an area. Such vibrancy was posited by Jane Jacobs (Jacobs 1961) as important for providing the potential guardianship that can make a location safer based on routine activity theory. Thus, prior research has sometimes used administrative measures of businesses in a location as a way to measure possible vibrancy. For example, one study measured the presence of businesses in parcels and found a nonlinear relationship between them and crime levels, which they concluded as consistent with the ideas of Jacobs that in high density business environments there will be more guardians and hence less crime (Browning et al. 2010). Other research has used administrative data to create measures of the number of businesses or employees in an area and how they are related to the level of crime (Bernasco and Block 2011; Hipp, Wo, and Kim 2017; Hipp and Kim 2019). Another strategy uses detailed land use data on the presence of certain types of businesses that crime pattern theory posits are attractive to potential offenders and therefore related to crime (Bowers 2014; Deryol et al. 2016; Stucky and Ottensmann 2009). Studies using administrative data have measured the presence of multiple types of businesses that act as crime generators under the presumption that they will create a larger ambient population, which can lead to more crime at micro locations (Hipp, Kim, and Wo 2020; Boessen and Hipp 2015).

Although administrative data capturing the locations of businesses is certainly useful, it lacks the more fine grained information about the actual spatial layout of businesses. For example, there is a distinct difference between a downtown location in which the buildings front onto the street, allowing for a walkable environment with many people on the sidewalks, versus a mall or strip mall in which parking fronts the street, and patrons are typically only there if they have arrived in a vehicle. Using GSV data allows us to make this distinction. More specifically, we are interested in the degree to which buildings are located in an environment, along with humans. Furthermore, an advantage of GSV is that it can extract the neighborhood environment from the pedestrian perspective. Due to this advantage, it is reported that the neighborhood environment extracted through GSV is more closely related to individual behaviors than more traditional neighborhood environment extraction methods (Li et al., 2015; Lu, 2015; Ye et al., 2018). Using GSV, an image of a downtown location with a building fronting the street would show a higher proportion of “building” in the image, whereas the proportion of “building” in an image of a mall set back from the street would be much smaller. Buildings in environments, particularly if they are high rise buildings, may also indicate work areas in which there is a large presence of employees. Whereas Jacobs (1961) posited that such vibrant locations will have less crime given the greater presence of guardians, the routine activity theory implies that another possibility is that such locations will provide more targets and offenders, and this confluence will create more crime opportunities and therefore more crime. This uncertainty has been discussed in prior literature (Hipp and Kim 2019). Nonetheless, we test here which of these might be the case, along with whether the direct assessment of more humans in the environment matters.

Whereas the presence of buildings might imply a more vibrant environment, a second key broad category that we focus on is the presence of certain characteristics that might imply an auto-oriented environment. Specifically, we focus on the presence of vehicles or pavement, which may indicate the presence of shopping malls or strip malls. An image of a mall from the street will largely capture the impervious surface of the parking area and the presence of vehicles, which would contrast with a downtown view in which the building has a larger presence in the image. These locations imply a very different built environment, and may have consequences for crime. In particular, the existence of such impervious surfaces arguably creates a less inviting environment for people to linger in, which would imply that there are fewer guardians in the location (Jacobs 1961). If this is the case, we would expect higher crime risk in such locations. Although criminologists have rarely attempted to measure the presence of an auto-oriented environment, its potential impact on crime comes directly from the insights of crime pattern theory and routine activity theory.

A third broad category is based on the CPTED literature and the notion of defensible space (Newman 1972). The CPTED literature posits that certain features of the environment can enhance or inhibit crime events, and a particularly important feature is the presence of fences and walls. Fences or walls can make it more difficult to access a location, as they require an offender to scale the fence to gain entry, as well as possibly when exiting after committing the crime. Although fences are presumably quite important for impacting crime events, particularly property crimes, the difficulty of measuring them has limited tests of this important CPTED feature. Furthermore, given that CPTED also focuses on the visibility of the environment, we make a distinction between fences and walls. Specifically, we measure fences as those you can see through, such as picket, chain link, or wrought iron fences. And we measure walls as those that you cannot see through. Thus, whereas both fences and walls make entry more difficult to a location, walls also minimize visibility, which in the CPTED literature would imply that they might be less effective in reducing crime compared to fences. This is because once scaling the wall, the offender would be out of sight of nearby residents who could otherwise act as guardians. We test this possibility here.

A fourth broad category of the environment is that the vegetation and terrain of an area can provide greenspace that also has important implications for crime. Urban studies and public health scholars are interested in the presence of vegetation in an area (such as trees and shrubbery) given that it can make the environment more desirable. This greater desirability is expected to create more attachment to the neighborhood (Lee et al. 2008), higher home values (Kestens, Thériault, and Rosiers 2004) and therefore more potential informal social control. It may also encourage residents to walk more which can improve physical health in addition to creating more potential social interaction in the neighborhood (Rogers et al. 2010; Sung and Lee 2015). On the other hand, the crime prevention through environmental design (CPTED) literature posits that more shrubbery near homes may provide more crime opportunities, especially for burglaries, if it provides cover for offenders (Patino et al. 2014).

Likewise, the presence of open green areas—or what we term terrain—can indicate a more desirable environment. This terrain can be an indication of a more suburban type of environment, and may be perceived as nicer and more desirable compared to areas with more impervious surfaces. Furthermore, similar to the presence of vegetation, the presence of greenspace may encourage more outdoor activity, which would also lead to more neighborhood social interaction and potential for informal social control. It may also be the case that greenspace increases visibility, which may discourage offending as others in the area can serve as potential guardians given the ability to observe crime events.

There is limited research studying how greenspace on street segments can impact the location of crime within the street segments of an entire city. Some research has measured greenspace, but in studies with very small geographic scope, given the challenge of manually coding for its presence, or using overhead satellite images (Patino et al. 2014). Instead, some studies have assessed how parks are related to crime (Kimpton, Corcoran, and Wickes 2017; Groff and McCord 2011). Parks are different from more general greenspace given that they occur only in specific locations; furthermore, the theoretical predictions and evidence about their relationship with crime is more uncertain. On the one hand, it has been suggested that parks may act as gathering places that can increase neighborhood cohesion and guardianship capability (Hipp et al. 2014; Cohen, Inagami, and Finch 2008). On the other hand, they can also act as gathering spots for potential offenders, or provide a location in which few guardians are present. These two competing perspectives imply opposite predictions about the relationship, and indeed whereas some studies have detected a positive relationship between parks and crime (Kim and Hipp 2017), other studies suggest that this relationship depends on the characteristics of the park (Kimpton, Corcoran, and Wickes 2017; Groff and McCord 2011) or the characteristics of the surrounding environment (Boessen and Hipp 2018).

Nonlinear relationships with crime

For each of these four dimensions we have described there is the possibility of nonlinear relationships with crime rates. That is, each of these dimensions arguably does not imply an expected straightforward linear relationship with crime, but rather they often involve a more complicated combination of targets, offenders, and guardians in an environment. As a consequence, we would expect some of these measures to exhibit nonlinear relationships with crime. For example, as an environment becomes more vibrant based on buildings or humans we might expect crime to increase due to increased opportunities, but then at some point a critical mass is obtained and the potential presence of guardians in the environment indicates that at higher levels of vibrancy we would expect crime rates to begin decreasing (Browning et al. 2010). Likewise, the presence of more greenspace may indicate more desirability and therefore less crime, but there may be a saturation effect where at very high levels crime is not further reduced. Therefore, we test for possible nonlinear effects for all of our measures of these four dimensions.

Measuring these physical features

A challenge with measuring characteristics of the built environment is that it is typically not possible to measure many of these features with administrative data. Instead, researchers often rely on strategies that use surveys of residents or field experts, which are generally costly to implement and therefore are limited in the geographic scope that is possible for any one research project. For example, studies using self-reported survey data and field surveys are often limited in geographic scale of the study area due to higher survey costs (Edwards et al. 2013; Marco et al. 2017; Nesoff et al. 2018), not to mention possible biased perceptions on the part of respondents (Gracia and Herrero 2006; Clarke et al. 2010; Rundle et al. 2011).

Given the challenges of traveling to neighborhoods to physically observe them, some recent studies have utilized virtual neighborhood audits using open-source street view imagery data. These studies have used Google Street View (GSV) data instead of conventional field surveys (He, Páez, and Liu 2017; Odgers et al. 2012; Gong et al. 2018; Mooney et al. 2016). Studies have frequently used GSV data to measure physical disorder—abandoned cars, graffiti, litter, poor conditions of lawns, abandoned houses, or broken windows (Marco et al. 2017; Odgers et al. 2012)—and how it might be related to crime (Curtis and Mills 2011; He, Páez, and Liu 2017; Kang and Kang 2017; Zhang et al. 2019). However, these studies typically use manual evaluation methods to extract information from the GSV images in which trained researchers observe and rate each image, which also necessarily limits the geographic scope of the studies.

Another strategy that moves beyond manual evaluation strategies—and offers the possibility of measuring other features of the environment beyond disorder—is exemplified by recent studies applying machine learning technologies to analyze GSV data using deep neural networks such as AlexNet and Inception-v3 (Kang and Kang 2017; Zhang et al. 2019). For instance, Kang and Kang (2017) suggested a feature-level data fusion method with environmental context based on a deep neural network (DNN) of AlexNet and showed that the DNN model is more accurate in predicting crime occurrence than other prediction models. Similarly, Zhang et al. (2019) analyzed crime predictors using open source data of GSV, Twitter, and Foursquare and concluded that open-source data could achieve significantly better crime prediction accuracy. This same study also argued that person offenses and theft are most likely to be associated with a high concentration of commercial buildings and less green areas.

Thus, a few recent studies on the relationship between built environments and crime have moved from manual evaluation methods to applications of big data and a machine learning algorithm. Such an approach allows measuring features of the environment that we have described earlier as potentially important for explaining the location of crime. Furthermore, existing studies typically do not focus on the level of crime in micro-geographic units, another advance of the present study. We next turn to a description of our strategy for exploring these questions.

Data and Methods

Study area

This study focuses on the city of Santa Ana, which is located in Orange County about 53 km southeast from downtown Los Angeles (see Figure 1). The city is fully developed with an area of 70.85 km^2 and a population of 332,727 in 2018 (U.S. Census Bureau), but it contains a range of built environment settings providing a valuable opportunity to understand how variation in settings can shape the dynamics of crime. The units of analysis for the study are street segments, which are defined as both sides of a street between two street intersections. We combined crime data collected from the local police agency, socio-demographic data from the U.S. Census, business data obtained from Reference USA (Infogroup 2015), and images collected from GSV that were analyzed and aggregated to street segments.

<<<Figure 1 about here>>>

Dependent variables: counts of crime events

Our outcome variables are counts of the number of crime events that occurred on a street segment during 2018. The crime data were obtained from the police agency, and then geocoded to a street segment. The geocoding match rate was 97.6%. We aggregated the count to each street segment for five serious crimes: aggravated assaults, robberies, burglaries, motor vehicle thefts, and larcenies. This allows us to assess the relationship between built environment characteristics and these five different types of crime to gain a nuanced understanding of the relationship patterns.

Collecting GSV images

We acquired GSV images to extract the elements of the cityscape in Santa Ana. A question is how many images to take for each street segment. In Santa Ana, there are 5,343 road segments with an average distance of 135.5 m. Prior studies have used various intervals to collect images, such as 20 m (Lu 2018), 50 m (Ye et al. 2018), or 100 m (Li et al. 2015; Wang et al. 2019). For greater reliability in assessing the features of the segment, we chose to use 20m intervals. About 60.4% of road segments are between 50 and 150 m, and our study had 6.8 GSV acquisition points per segment. We did not include images from points located near intersections, given that these capture the environment of more than a single segment. At each point we pulled four images using the GSV API that were oriented based on direction (front, rear) or side of the street (right, left). The Google Street View metadata API provides the date of the image, and we determined that 94.5% of the images were taken between 2017 and 2020, and therefore we limited our extraction to images from this time period. The total number of images is 108,656 from 27,164 acquisition points on the road segments. GSV images were not available on some roads, perhaps due to limited access to some private properties such as gated communities; this was the case for 756 of 5,343 segments. In addition, there are 30 segments with no population within ½ miles so our analyses used 4,518 segments. On these criteria, there are 6.10 acquisition points and 24.4 images per road segment, respectively.

Machine learning to analyze the images: semantic segmentation

To analyze the images we used semantic segmentation, a technique that uses deep learning from computer vision to classify each pixel as an image component. One alternative strategy uses a color band of an image to extract image elements (Li et al. 2015; Lu 2018). However, this method simply classifies image components based on pixel color (RGB values), which is more susceptible to falsely classifying some image elements: for example, two different components with the same color. For this reason, Lu (2018) proposed employing deep learning to classify the image components based not only on pixel color but also on the distribution and shapes of components. Therefore, the present study uses this semantic segmentation approach of deep learning to analyze the GSV images collected. Although several segmentation models exist in the literature, including FCN8s (Long, Shelhamer, and Darrell 2015), SegNet (Badrinarayanan, Kendall, and Cipolla 2017), and PSPNet (Zhao et al. 2017), we employed the Deeplabv3+ model (Chen et al., 2018), as it demonstrated excellent accuracy at the Pascal Visual Object Classification challenge as well as on the Cityscapes test dataset, and consistently yielded some of the highest accuracy in various comparisons. For example, Deeplabv3+ exhibited high accuracy (82.1% mIoU) among segmentation models for the Cityscapes test dataset[1], and 89.0% accuracy on the "PASCAL VOC 2012 datasets", and has therefore been used in several studies for image processing (e.g., Wang and Vermeulen 2020; Liu et al. 2019; Du, Ning, and Yan 2020).

To segment GSV images suitable for the research purpose, the model should be trained using a dataset similar to those to be segmented. We used the Deeplabv3+ model pre-trained with the 'Cityscapes' dataset for this purpose.[2] The dataset contains daytime urban scenes obtained from 50 cities in Germany, such as Berlin, Hamburg, and Dresden (Cordts et al. 2016)[3]. Whereas one might object that German cities have a different built environment than U.S. cities, we point out that the features we are measuring here are quite consistent across the two

[1] https://paperswithcode.com/sota/semantic-segmentation-on-cityscapes
[2] The python code for implementing this algorithm can be obtained here: https://github.com/lexfridman/mit-deep-learning.
[3] Source: Cityscapes website, https://www.cityscapes-dataset.com/dataset-overview/#labeling-policy (accessed on Jan. 28, 2020)

environments. It arguably is more difficult to measure "disorder" across various contexts, as noted in prior research (Odgers et al. 2012), but the types of features we are measuring here, such as buildings, walls, and greenspace, for example, are relatively consistent across many environments. Indeed, when we performed visual assessments of the algorithm on our study site, the classifications appeared quite accurate. Furthermore, a number of studies have used the Cityscapes dataset for training deep learning models and have applied these algorithms to various study areas (Yang et al. 2019; Wang et al. 2020; Nagata et al. 2020; Krylov, Kenny, and Dahyot 2018; Du, Ning, and Yan 2020). Thus, we believe it is reasonable to segment the GSV images from Santa Ana through the Deeplabv3+ model trained with the 'Cityscapes' dataset.

We used all of the elements extracted by the semantic segmentation algorithm that were present in the environment, although some of them we collapsed into a larger category given their conceptual similarity and rarity in the environment.[4] Our models therefore used the following eleven elements: buildings, humans, sidewalks, vehicles, pavement, fences, walls, terrain (e.g., grassy areas), vegetation (e.g., trees and shrubbery), objects (e.g. pole, traffic sign, traffic light), and sky. We then calculated the percentage of each of these elements in each image. For example, if there are 10,000 pixels classified as vegetation in the image and an image size is 640 x 640, the vegetation percentage is 2.44% (10000 / (640 * 640) * 100). In the statistical analyses, we exclude the percentage sky in an image from the models, and thus we are comparing the effect of the other elements to the percentage sky. We do not theorize the effect of objects, but simply include them in the models to achieve a cleaner reference category (sky). Note that objects include poles, traffic signs, and traffic lights; although traffic lights are typically at intersections (and we do not select images from intersections), they nonetheless can

[4] Deeplab3+ extracts 19 elements, although there were no trains in our images and therefore we had 18 elements. Further, "person" and "rider" are collapsed into the category of humans. And "car", "truck", "bus", "motorcycle", and "bicycle" are collapsed into vehicles. And "poles", "traffic signs", and "traffic lights" are collapsed into objects.

sometimes be seen in the distance in images nearer to intersections. We also note that bus benches are considered by the algorithm to be buildings, and not objects. This is a limitation of the trained algorithm, as one would need to explicitly train the algorithm to capture a specific category of bus stops if that was of interest to the study.[5]

To better understand what these elements are capturing, we present images that had relatively high values on a particular element. For example, Figure 2a shows an image in which the proportion vehicles are relatively high, as it captures vehicles parked along a curb. It also captures a fence. In Figure 2b both the proportion pavement and proportion sky are relatively high. Note that pavement captures impervious surfaces, and thus a large parking area as shown in this figure gets captured by this element. The fact that there is little vegetation is implicitly captured in the high proportion of sky. In contrast, Figure 2c has a high proportion of vegetation, which captures the large presence of trees in this environment. The proportion sky is much smaller in this image as a result. In Figure 2d we show an image with a high proportion of the buildings element, which captures high rises in the environment. The presence of more buildings in an image also occurs in the downtown area of Santa Ana, although the building presence in downtown images is not as strong as in the case of a high rise, such as this image. Finally, Figure 2e shows a fence (that you can see through) and Figure 2f shows a wall, which does not allow visibility through it. In studying how the algorithm coded our images, it does appear that the most important distinguishing feature between fences and walls is that the former allow for visibility through them, whereas the latter do not.

<<<Figures 2a-2f about here>>>

[5] GSV images acquired from wide roads can be distorted when viewing the other side of the street, as the google vehicle only travels in one direction. However, our medium-sized city has major streets that only rarely have three lanes in each direction, and thus this is a less salient problem in our case study area. Furthermore, this distortion problem is mitigated to some extent by our strategy of computing the average of images taken in four different directions when measuring the features.

We also briefly compare our approach to using data collected from the National Land Cover Database (NLCD) based on satellite images for 2016. A challenge for the NLCD is that it is coded for 30 x 30 meter grid cells, and therefore does not conform well to street segments (highlighting an advantage of our GSV approach). Nonetheless, the tree canopy cover from the NLCD 2016 was moderately correlated with our vegetation measure (.453), and the level of imperviousness was correlated .242 with our roads measure, .205 with the buildings measure, and -.544 with the vegetation measure. These modest correlations are consistent with our strategy, though the lower values highlight the limitations of using the NLCD given the limited numbers of categories it provides, and the fact that the 30 x 30 meter grid cells conform relatively poorly to street segments, which are of primary theoretical interest to criminologists.

Control variables

To minimize the possibility of obtaining spurious results, we also included several other measures of the environment that prior research has shown are important in explaining the location of crime incidents. We included several socio-demographic characteristics based on data collected from the U.S. Census. For these measures, we constructed them as an exponential decay centered on the focal segment (and including the focal segment).[6] This allows us to better capture the local environment of a segment, given that simply measuring the segment itself for demographic characteristics is arguably too small a geographic scale, whereas using pre-defined Census units such as tracts are spatially imprecise. For the variables that are available at the block level, it is straightforward for us to create our buffers based on an exponential decay around the segment. For variables that the Census only provides in larger units, such as block groups or tracts, we imputed them to blocks before then computing the buffers. In doing so, we

[6] These measures were constructed based on blocks and the exponential decay of blocks around a focal block. We then average the values for blocks adjacent to a particular segment. Of course, the buffer values in these adjacent blocks are extremely highly correlated, so this strategy does not introduce problems.

utilized the ecological inference approach that imputes them based on other characteristics of the block, an approach that Boessen and Hipp (2015) showed is typically preferred to a simple areal imputation.

We constructed measures of the racial/ethnic composition as *percent Black*, *percent Asian*, and *percent Latino* (with percent White and other as the remaining category). We constructed a measure of *racial/ethnic heterogeneity* based on the Herfindahl index combining these same five racial/ethnic categories as a sum of squared proportions, subtracted from 1. We measured *concentrated disadvantage* based on a factor score from a principle factor analysis of percent at or below 125% of the poverty level, average household income, percent with at least a bachelor's degree, and percent single parent households. We also measured *residential stability* as a factor score based on a principle factor analysis of percent owners, percent in same house 5 years ago, and average length of residence. Consideration was given to vacant units measured in terms of the *percent occupied units*, while we captured the possible presence of offenders with a measure of the *percent aged 16 to 29*.

We constructed some opportunity variables at the street segment level. To capture the presence of workers in the environment as one proxy for ambient population, we created a measure of *total employees* (we subtracted the retail/food employees, described next, from this measure). These data come from Reference USA, and provide information on the exact location of the business, which we aggregated to the street segment. We also created a measure of *retail/food employees* given that this can capture both workers and patrons of these establishments. We constructed a measure of *logged population* in the segment (after adding 1), by using Census data in blocks and apportioning it to street segments using the simple average (SA) approach described in Kim (2018). Finally, we constructed *spatial lag versions* of these three variables with an inverse distance decay capped at ½ mile around the segment (but not including the segment).

Methods

Given that our outcome variables are counts with an overdispersed distribution, we estimated negative binomial regression models. The model can be written as:

$$E(y) = exp(\alpha + B_1\boldsymbol{X} + B_2\boldsymbol{S} + B_3\boldsymbol{WS} + \nu) \qquad (2)$$

where y is the number of crime events, α is an intercept, $\boldsymbol{X}$ represents a matrix of our GSV built environment variables, $\boldsymbol{S}$ is a matrix of the structural characteristic variables, $\boldsymbol{WS}$ is a matrix of the spatially lagged variables, and ν has a gamma distribution that captures the overdispersion. We estimated initial models that included all of our control variables, but did not include our measures of the built environment, which allows us to obtain an approximate assessment of how much our novel variables help explaining the location of crime incidents based on a comparison of the pseudo R-squares.

Results

Table 1 presents the descriptive statistics of the variables. We also present a map of robberies on street segments in our study area to give a sense of the clustering of crime events (see Figure 3). Among our measures of vibrancy, buildings constitute 5% of these images, on average, 3% is sidewalks, whereas humans are just 0.1%. For the auto-oriented measures, about 4% of the image is vehicles and 27% is pavement. Fences and walls are each at less than 1%, on average. And for the measures of greenspace, 22% is vegetation and 2% is terrain. Given the relative novelty of our measured elements of the built environment, we explored their correlation with the other measures in the models and display these in Table 2. For the measures of vibrancy, the presence of more buildings is positively correlated with high job density and concentrated disadvantage in surrounding areas, and negatively correlated with residential stability, whereas the presence of humans is positively correlated with job density in the surrounding area. Pavement in the environment is negatively correlated with residential population on the segment and in the surrounding area. The element of vehicles is positively correlated with percent Latino (.26) and concentrated disadvantage (.22), but negatively correlated with racial/ethnic heterogeneity (-.28). In contrast, terrain has the opposite correlations with these variables. Fences are positively correlated with percent Latino and concentrated disadvantage, but negatively correlated with percent Black, highlighting a distinction between Black and Latino neighborhoods. Vegetation tends to capture residential areas, as it is positively correlated with residential population in the street segment.

<<<Figure 3 about here>>>

<<<Table 1 about here>>>

<<<Table 2 about here>>>

We next turn to the negative binomial regression results, presented in Table 3.[7] We present McFadden's pseudo R-square from the models *without* the built environment variables in the row second from the bottom. The row four from the bottom lists the pseudo R-square for the presented models, and the bottom row of this table shows the percentage increase in the pseudo R-square when adding these novel built environment measures. As can be seen, our new measures improve the pseudo R-square notably in these models. For example, there is a 33% increase in the pseudo R-square for the model with larceny as the outcome variable. This is the weakest improvement in model fit of the various crime types. For burglary (46%), motor vehicle theft (63%) and aggravated assault (70%) there is an even stronger improvement in model fit

[7] The logged alpha term capturing overdispersion was highly significant in all models, indicating the need to use a negative binomial regression rather than a Poisson model.

when including these measures of the built environment. The largest improvement occurs in the robbery model (84%), indicating that these measures are particularly useful in understanding the location of robberies in the environment.

<<<Table 3 about here>>>

Turning to the coefficient estimates for our measures of elements in the environment, we begin with our measures of vibrancy. In general, the measures of buildings and humans tend to exhibit positive relationships with crime, either as linear or slowing positive relationships, as does the sidewalks measure. For example, buildings exhibit weak positive relationships with aggravated assaults and a slowing positive relationship with robberies.

There are strong slowing positive relationships between the presence of our measure of humans and all five crime types. These nonlinear relationships are plotted in Figure 4, and in all figures we plot the built environment characteristic from the 5th to the 95th percentile of values. Furthermore, we generally only plot relationships with a crime type that were nonlinear and statistically significant. The strongest positive relationships are between the presence of humans and larcenies and the violent crimes of robberies and aggravated assaults. Going from no humans to 0.15% in the environment results in about a 80% to 100% increase in these three crime types, and going from 0.15% to 0.3% results in a 50 to 70% increase in these three crime types. The pattern is similar, but a bit weaker, for the two other property crimes of burglaries and motor vehicle thefts.

<<<Figure 4 about here>>>

There are also relatively robust positive relationships between sidewalk presence and crime levels. A one standard deviation increase in the presence of sidewalks in the environment is associated with about 20 to 40 % more crime for these crime types. The presence of sidewalks have a slowing positive relationship with burglaries, indicating a satiation effect in which burglaries increase more slowly in environments with a very high sidewalk concentration. A one standard deviation increase in sidewalks above or below the mean results in a 40 to 65% increase in burglaries.

Turning to our auto-oriented measures—vehicles and pavement—we find a positive relationship between these measures and crime rates. A one standard deviation increase in vehicles is associated with 30% more robberies, 45% more larcenies, 60% more burglaries, and 80% more aggravated assaults. And there is a slowing positive relationship with motor vehicle thefts such that a one standard deviation increase in vehicles from the mean is associated with 70% more motor vehicle thefts. Regarding pavement, there are linear positive relationships as a one standard deviation increase in pavement is associated with 55% and 75% more larcenies and robberies, respectively. And pavement exhibits an increasing positive relationship with the three other crime types, as shown in Figure 5. The largest increases in these crime types occur in environments with particularly large concentrations of pavement.

<<<Figure 5 about here>>>

Turning to our two defensible space measures, we see different effects for fences and walls. Fences have a more modest relationship with crime, as their presence is only significantly associated with two crime types. The presence of fences exhibits a slowing positive relationship with aggravated assaults, and an inverted-U relationship with motor vehicle thefts in which the presence of a moderate amount of fencing is the most crime-prevalent setting. In contrast, the presence of walls has a slowing negative relationship with all crime types except robbery, as shown in Figure 6. Whereas walls reduce visibility, it nonetheless is the case that they are associated with reductions in crime, in contrast to fences (which allow visibility). Walls exhibit their strongest negative relationship with burglaries.

<<<Figure 6 about here>>>

Finally, we turn to our two greenspace measures. Although the presence of vegetation was expected to have a negative effect on crime given that it would create a more pleasant environment and therefore a presumed higher level of collective efficacy, it did not have a significant relationship with three of the crime types. And for the other two—aggravated assault and motor vehicle theft—there was an inverted-U relationship between vegetation and these crime types. As shown in Figure 7, the highest amount of aggravated assault and motor vehicle thefts occur on street segments with a moderate amount of vegetation—it is only when vegetation is particularly prevalent that the level of these crime types returns to the same levels as street segments with no vegetation. Contrasting with vegetation that captures trees and bushes, terrain captures the presence of open green space. There is generally a positive relationship between the amount of terrain and crime. A one standard deviation increase in terrain is associated with 20% to 30% more of the property crimes. And the positive relationship between terrain and aggravated assault only slows and begins slightly falling at the highest concentrations of terrain. Although we did not hypothesize an effect between the density of objects in the environment and crime, these generally exhibited either inverted-U or slowing positive relationships with the crime types (not shown).

<<<Figure 7 about here>>>

We briefly note that we obtained these effects even when controlling for a host of measures commonly accounted for in ecology of crime studies. These control variables generally have the expected relationships with crime levels. Higher levels of concentrated disadvantage in the surrounding area is associated with higher levels of aggravated assault and burglary, whereas nearby residential stability is associated with less property crime. Street segments with more total employees and retail/food employees have higher crime levels.

Conclusion

This study has demonstrated the usefulness of a strategy that combines GSV images with a machine learning technique to extract various features of the built environment, and use this information assess their relationship with crime in street segments. Prior research has highlighted the importance of measuring crime patterns at the micro-level (Zhang et al. 2019; He, Páez, and Liu 2017; Weisburd, Bernasco, and Bruinsma 2009), and we have done so here. We demonstrated how GSV images and semantic segmentation can extract characteristics of the built environment at a micro level, and these methods are cost-efficient compared to methods that extract image components manually. Semantic segmentation also has the advantage of being able to identify factors affecting crime because it can extract visible cityscape elements from the perspective of a pedestrian, such as greenness, vehicles, fences, buildings, and so on. It was notable that adding these measures to the standard models resulted in a considerable improvement in model fit. We focused on how four dimensions of the environment might impact crime at street segments, and we discuss these results here.

A first key finding was that our measures of the environment that might capture vibrancy were *not* related to lower crime rates. We used measures of the presence of buildings in the environment—typically those that are close to the street—as well as the presence of more people in the environment. The strategy of using GSV is well suited for measuring buildings given that these are difficult to obtain using traditional data collection methods. Thus, it is not just the presence of businesses that this measure was capturing—indeed, we controlled for the presence of all businesses as well as retail/food businesses—but rather it captures the presence of buildings at the edge of the street, and implies a more walkable environment. The presence of buildings was generally unrelated to crime levels, except for the strong positive relationship with robberies. Note that this is not just a measure of opportunity for commercial robberies, as we controlled for the number of businesses—instead there is something about the clustering of these buildings in the environment that results in more robberies. Our measure of people in the environment is presumably a more direct measure of vibrancy, and yet it exhibited a consistent positive relationship with crime. Again, this is likely capturing opportunity. This measure did not specifically capture some of the ideas of Jane Jacobs, as it could not distinguish between the mere presence of people and the presence of potential guardians. Thus, similar to studies finding that a greater ambient population is related to higher levels of crime at micro locations (Malleson and Andresen 2015; Hipp et al. 2019), this measure of the presence of persons in the environment was also consistently related to higher levels of crime.

As we hypothesized, our auto-oriented measures generally were positively related to crime locations. The measures of the presence of vehicles and pavement in the environment both often serve to capture sprawling parking lots. Effectively, all crime types were higher with the presence of either of these features. The presence of more vehicles is contradictory to a walkable environment, and it is interesting to note that such environments experienced notably larger crime risks. Arguably the strongest relationship with crime risk occurred with more pavement in the environment. If these are large parking areas, they would limit the walkability of an area and the potential for guardians. Such locations may well provide more attractive targets, along with fewer guardians, explaining why they were particularly at risk for all types of crime.

Although we hypothesized that fences would reduce crime more than walls, this was not the case. Whereas both fences and walls serve as barriers, and thus to some extent can serve as defensible spaces, based on the insights of CPTED we presumed that some of this benefit would be attenuated for walls given that they obstruct views. This view obstruction is expected to increase crime opportunities since guardianship capability is reduced, but this was not the case. Instead, we found that walls were the one feature of the environment that we measured that consistently was associated with reduced crime risk. In contrast, fences were not beneficial, and were actually associated with more motor vehicle thefts. Why this might be is not clear, and calls into question some presumptions of the CPTED perspective.

Finally, our measures of greenspace—terrain and vegetation—had relatively strong relationships with crime. These are features that are difficult to measure using traditional data collection methods. Thus, the GSV approach using machine learning was particularly important for detecting these two features. Most notably, the vegetation measure had a particularly robust inverted U-shaped relationship with aggravated assaults and motor vehicle thefts. Thus, street segments with the lowest risk of these crimes were those with either very little or a very high density of vegetation. Why a moderate amount of vegetation would be particularly crime enhancing for aggravated assaults and motor vehicle thefts is not entirely clear. Nonetheless, this highlights the importance of scholars measuring these features of the environment, and future work will need to assess if these relationships we detected are observed in other settings.

We acknowledge some limitations of this study. To some extent, this was an exploratory approach introducing the technique. In part, this is because it is not precisely clear what each of the features is capturing, in terms of posited theoretical mechanisms. As one example, the robust inverted-U shaped relationship between our vegetation feature and crime was unexpected, and raises the question of what this is capturing. How this relationship operates is unclear, and will need more careful exploration. Relatedly, we did not measure mechanisms in general, so we cannot say why we observe the particular relationships we did, even for the ones we hypothesized. A limitation of GSV is that the researcher cannot control the time of day or the season that the images are extracted. All GSV images are taken in the daytime, which differs from crime that often can occur in the evening.[8] For our measures, this is likely not as important since we were measuring features many of which would be similar in the evening. Nonetheless, our more ephemeral measures of humans or vehicles could be more strongly impacted by the time of day, as could measures of disorder. Furthermore, some measures—such as vegetation—could be impacted by the season of the images: how the season might impact how deciduous trees are classified is a needed area of future work. Also, some of our images were taken in 2019 and 2020, whereas the crime data is for 2018, which introduces temporal issues. Given the relative stability of the built environment, we do not believe this introduces a serious issue, but it should be kept in mind. It should also be noted that measurement of GSV variables depends on how they are extracted. There are numerous ways to extract GSV images in terms of spacing, direction, and extension. A comprehensive sensitivity analysis would be helpful in deciding between extraction methods. Nonetheless, we believe this approach provides new insights that should spawn future research that might measure and test possible mechanisms.

In conclusion, we have demonstrated that combining GSV images with a machine learning technique provides key insights to criminologists about how characteristics of the built environment can impact levels of crime in small geographic units such as street segments. The results we found here highlighted the importance of certain features, including greenspace and

[8] For example, in our study site, about 60% of robberies occur after dark, and about 50% of aggravated assaults, 45% of burglaries and motor vehicle thefts, and 40% of larcenies occur after dark.

buildings, for understanding the location of crime. It is our belief that further studies utilizing this general technique will be a fruitful direction for the field and yield additional key insights. Generating new techniques for measuring key constructs of interest is an important general direction for criminology, and will help to further advance our knowledge.

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Tables and Figures

Table 1. Summary statistics of variables used in analyses

	Mean	S.D.
Dependent variables		
Aggravated assaults	0.17	0.58
Robberies	0.10	0.49
Burglaries	0.39	1.19
Motor vehicle thefts	0.34	0.88
Larcenies	0.47	2.04
Street view characteristics		
Percent buildings	4.9	3.7
Percent humans	0.1	0.1
Percent sidewalks	3.2	1.6
Percent vehicles	4.3	2.7
Percent pavement	27.3	3.2
Percent fences	0.9	0.96
Percent walls	0.6	0.72
Percent vegetation	22.3	10.3
Percent terrain	2.3	1.7
Percent objects	0.4	0.3
Percent sky	33.8	9.4
Demographic variables: exponential decay		
Percent Asian	10.7	12.4
Percent Black	1.0	0.7
Percent Latino	76.6	18.9
Racial/ethnic heterogeneity	0.33	0.20
Concentrated disadvantage	4.08	4.76
Percent vacant units	4.3	2.4
Residential stability	0.00	0.95
Percent aged 16 to 29	25.8	2.3
Segment variables		
Population (logged)	4.7	1.6
Number of employees	24.5	117.6
Number of retail/food employees	3.1	20.7
Surrounding 1/2 mile		
Population (logged)	9.0	0.7
Number of employees (in 1000s)	9.7	11.8
Number of retail/food employees (in 1000s)	2.0	2.0
N = 4,518 street segments in Santa Ana		

Table 2. Correlations of physical characteristics and socio-demographic variables

	Build-ings	Hu-mans	Side-walks	Vehic-les	Paveme nt	Fences	Walls	Vege-tation	Terrai n	Objec ts	Sky
Segment variables											
Total employees	0.10	0.01	0.00	-0.04	0.13	-0.05	-0.05	-0.11	-0.01	0.06	0.05
Retail employees	0.00	0.03	0.01	0.00	0.11	-0.04	-0.05	-0.11	-0.03	0.10	0.08
Population (logged)	-0.19	-0.10	-0.01	-0.01	**-0.20**	0.06	0.06	**0.20**	0.11	-0.14	-0.09
Exponential decay											
Percent Asian	-0.11	-0.12	0.09	-0.14	0.11	-0.16	0.04	-0.16	0.05	-0.10	**0.21**
Percent Black	0.06	-0.11	0.05	-0.17	0.14	**-0.20**	-0.09	-0.05	0.18	-0.08	0.02
Percent Latino	0.08	0.17	-0.09	**0.26**	-0.17	**0.30**	0.05	0.05	**-0.21**	0.14	-0.09
Racial/ethnic heterogeneity	-0.06	-0.17	0.10	**-0.28**	0.18	**-0.34**	-0.06	-0.04	**0.23**	-0.15	0.07
Concentrated disadvantage	**0.21**	**0.22**	-0.08	**0.22**	-0.07	**0.28**	0.03	-0.07	**-0.29**	**0.24**	-0.01
Percent vacant units	0.17	-0.01	0.02	-0.04	0.02	-0.07	-0.05	-0.05	0.05	0.02	-0.01
Residential stability	**-0.38**	-0.19	0.04	-0.08	-0.05	-0.07	0.06	0.09	0.19	**-0.22**	0.06
Percent aged 16 to 29	0.08	0.09	-0.03	0.19	-0.09	**0.20**	0.07	-0.07	-0.18	0.06	0.04
Surrounding 1/2 mile											
Population (logged)	0.09	0.14	0.01	0.14	**-0.20**	**0.22**	0.09	0.08	**-0.20**	0.03	-0.09
Total employees	**0.52**	**0.20**	0.04	-0.02	0.10	-0.05	-0.09	-0.13	-0.10	**0.21**	-0.07
Retail/food employees	**0.39**	0.17	0.01	0.02	0.13	-0.03	-0.09	-0.13	-0.14	0.18	-0.03
Humans	**0.22**										
Sidewalks	0.10	0.06									
Vehicles	0.08	0.07	**-0.48**								
Pavement	-0.18	0.01	-0.19	**-0.43**							
Fences	0.02	0.08	0.12	0.07	**-0.33**						
Walls	-0.01	-0.03	**0.27**	-0.08	**-0.23**	0.16					
Vegetation	**-0.22**	-0.08	-0.19	0.03	-0.20	-0.08	-0.07				
Terrain	-0.12	**-0.21**	0.06	**-0.27**	**-0.26**	**-0.20**	-0.14	**0.22**			
Objects	0.11	**0.25**	**0.23**	-0.14	0.18	0.13	0.10	**-0.45**	**-0.26**		
Sky	-0.11	-0.02	0.15	-0.07	0.19	0.07	0.07	**-0.93**	-0.18	**0.38**	

Table 3. Models predicting violent and property crime in street segments using GSV measures (using all four images)

	Aggravated assault		Robbery		Burglary		Motor vehicle theft		Larceny	
Street view characteristics										
Buildings	0.0328	†	0.1425	**	0.0223	†	0.0131		0.0065	
	(1.90)		(3.22)		(1.73)		(0.97)		(0.48)	
Buildings squared			-0.0032	*						
			-(1.98)							
Humans	4.476	**	4.804	**	3.839	**	2.601	**	5.295	**
	(3.96)		(3.42)		(3.98)		(3.03)		(5.79)	
Humans squared	-3.927	*	-2.856	†	-3.909	**	-1.343		-4.190	**
	-(2.24)		-(1.74)		-(2.58)		-(1.35)		-(3.63)	
Sidewalks	0.2204	**	0.1768	**	0.4633	**	0.1537	**	0.1020	**
	(4.56)		(2.81)		(4.73)		(4.17)		(2.61)	
Sidewalks squared					-0.0314	**				
					-(2.90)					
Vehicles	0.2102	**	0.1015	*	0.1676	**	0.2955	**	0.1308	**
	(5.44)		(1.99)		(5.58)		(5.76)		(4.37)	
Vehicles squared							-0.0085	*		
							-(2.32)			
Pavement	-0.4582	**	0.1740	**	-0.1989		-0.2021		0.1323	**
	-(2.99)		(3.88)		-(1.47)		-(1.50)		(5.10)	
Pavement squared	0.0119	**			0.0070	**	0.0065	**		
	(4.37)				(2.96)		(2.73)			

Fences	0.5346	**	0.0055		0.0821		0.2821	**	0.0672	
	(4.03)		(0.07)		(1.62)		(2.66)		(1.35)	
Fences squared	-0.0738	**					-0.0668	**		
	-(2.65)						-(2.64)			
Walls	-0.3135	*	-0.0165		-0.4636	**	-0.2131	*	-0.3318	**
	-(2.37)		-(0.15)		-(4.27)		-(2.16)		-(3.19)	
Walls squared	0.0503	*			0.0483	*	0.0440	**	0.0536	**
	(2.50)				(2.46)		(2.95)		(3.15)	
Vegetation	0.0471	*	-0.0013		-0.0016		0.0568	**	0.0073	
	(2.18)		-(0.14)		-(0.31)		(3.52)		(1.45)	
Vegetation squared	-0.0009	*					-0.0010	**		
	-(2.09)						-(3.14)			
Terrain	0.2925	**	0.0087		0.1486	**	0.0968	**	0.1046	**
	(2.70)		(0.13)		(4.11)		(2.70)		(2.99)	
Terrain squared	-0.0281	†								
	-(1.70)									
Objects	2.3474	**	3.8512	**	1.7726	**	1.6415	**	1.7342	**
	(3.84)		(4.59)		(4.25)		(3.80)		(4.56)	
Objects squared	-1.5777	**	-2.3259	**	-0.9875	**	-0.9494	**	-0.7485	**
	-(3.39)		-(3.80)		-(3.35)		-(2.97)		-(2.95)	
Demographic variables: exponential decay										
Percent Asian	-0.0087		0.0215		-0.0203	**	-0.0121		-0.0108	
	-(0.78)		(1.34)		-(2.78)		-(1.48)		-(1.44)	
Percent Black	-0.1516		-0.0577		-0.2459	**	-0.1816	*	-0.1690	†
	-(1.31)		-(0.36)		-(2.81)		-(2.18)		-(1.86)	
Percent Latino	0.0117		0.0272		0.0001		0.0175		0.0128	
	(0.79)		(1.26)		(0.01)		(1.62)		(1.28)	

Racial/ethnic heterogeneity	1.4626		-0.1613		2.1543	**	1.2438		2.1526	**
	(1.38)		-(0.12)		(3.18)		(1.59)		(3.12)	
Concentrated disadvantage	0.0650	**	0.0061		0.0325	*	0.0254		-0.0186	
	(2.68)		(0.18)		(2.05)		(1.52)		-(1.11)	
Percent vacant units	-0.0136		0.0504		0.0288		0.0373	†	0.0475	*
	-(0.40)		(1.29)		(1.52)		(1.86)		(2.47)	
Residential stability	0.0631		-0.1945		-0.2098	**	-0.1232	†	-0.2372	**
	(0.59)		-(1.32)		-(2.86)		-(1.67)		-(3.23)	
Percent aged 16 to 29	-0.0052		-0.0343		0.0081		0.0433		-0.0477	†
	-(0.13)		-(0.60)		(0.31)		(1.54)		-(1.74)	
Number of employees	0.0023	**	0.0013	*	0.0024	**	0.0014	**	0.0017	**
	(5.46)		(2.30)		(6.29)		(4.36)		(4.63)	
Number of retail/food employees	0.0060	**	0.0134	**	0.0091	**	0.0053	**	0.0126	**
	(3.12)		(4.92)		(4.76)		(3.63)		(6.11)	
Population (logged) in segment	0.1961	**	0.1162	*	0.0027		0.1591	**	0.1014	**
	(5.43)		(2.47)		(0.11)		(5.86)		(3.80)	
Surrounding 1/2 mile										
Number of employees	-0.0017		-0.0207	*	-0.0013		-0.0094	*	0.0025	
	-(0.29)		-(2.48)		-(0.30)		-(1.99)		(0.54)	
Number of retail/food employees	0.0639	*	0.0105		-0.0142		0.0391	†	0.0415	†
	(2.14)		(0.25)		-(0.66)		(1.79)		(1.95)	
Population (logged)	0.0328		0.1154		-0.2543	**	-0.3043	**	-0.1285	
	(0.28)		(0.70)		-(3.34)		-(4.06)		-(1.60)	

Intercept	-4.96	†		-13.54	**		-2.53			-4.73	*		-6.60	**
	-(1.77)			-(4.73)			-(1.12)			-(2.08)			-(4.66)	
N	4518			4518			4518			4518			4518	
Pseudo R-square	0.092			0.123			0.115			0.067			0.089	
BIC	4151.29			2649.54			6286.97			6510.35			7098.301	
Pseudo R-square (without GSV variables)	0.054			0.067			0.079			0.041			0.067	
Percent increase in pseudo R-square	70.4%			83.6%			45.6%			63.4%			32.8%	

*** p < .01(two-tail test), * p < .05 (two-tail test), † p < .10 (two-tail test). T-values in parentheses. N=4,518 street segments.*

Figures

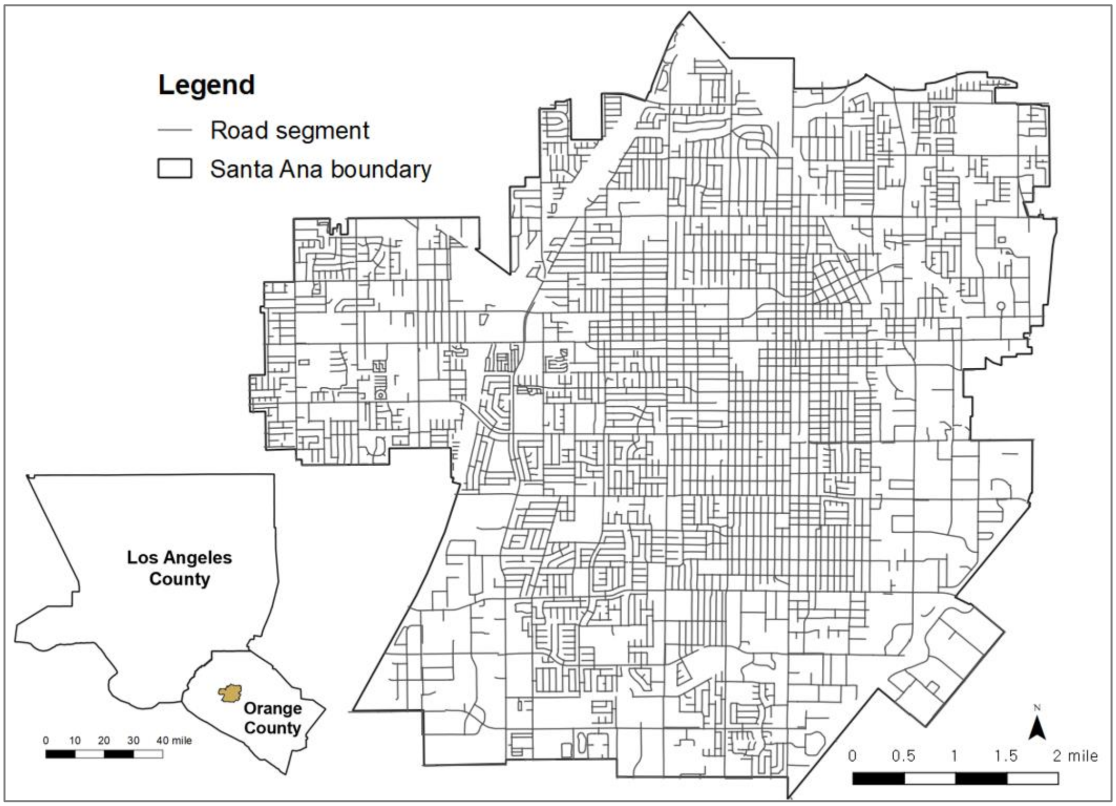
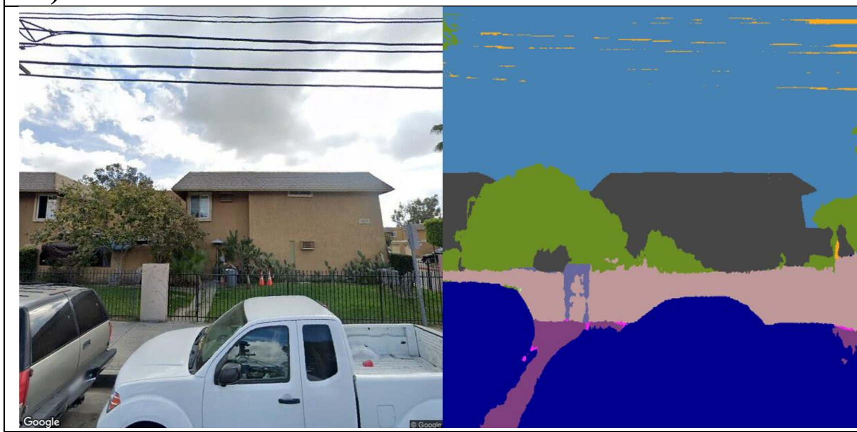


Figure 1. Case study area of Santa Ana city

Figures 2a-2f. Example images of various elements of the environment

2a)	
	**Top 5 elements** Sky 39.74 **Vehicles 26.24** Buildings 11.62 Vegetation 9.91 Fences 9.05
2b)	
	**Top 5 elements** Sky 49.30 **Pavement 34.33** Buildings 10.23 Vehicles 4.76 Vegetation 0.62
2c)	
	**Top 5 elements** **Vegetation 41.42** **Terrain 15.78** Sky 12.46 Pavement 12.20 Sidewalks 8.24

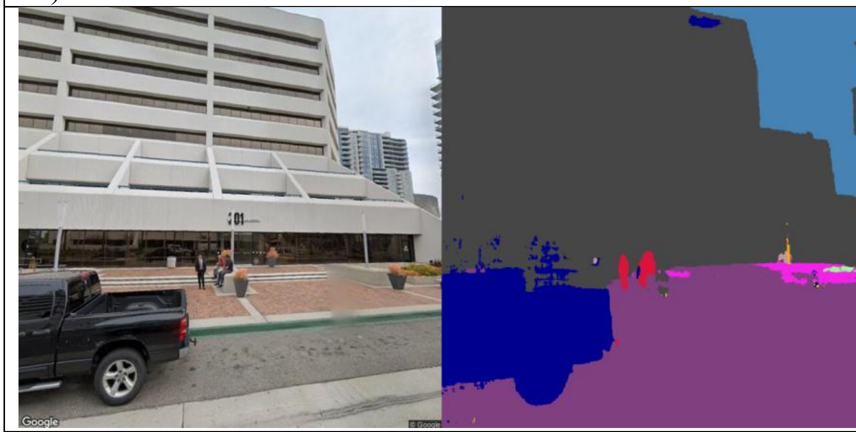
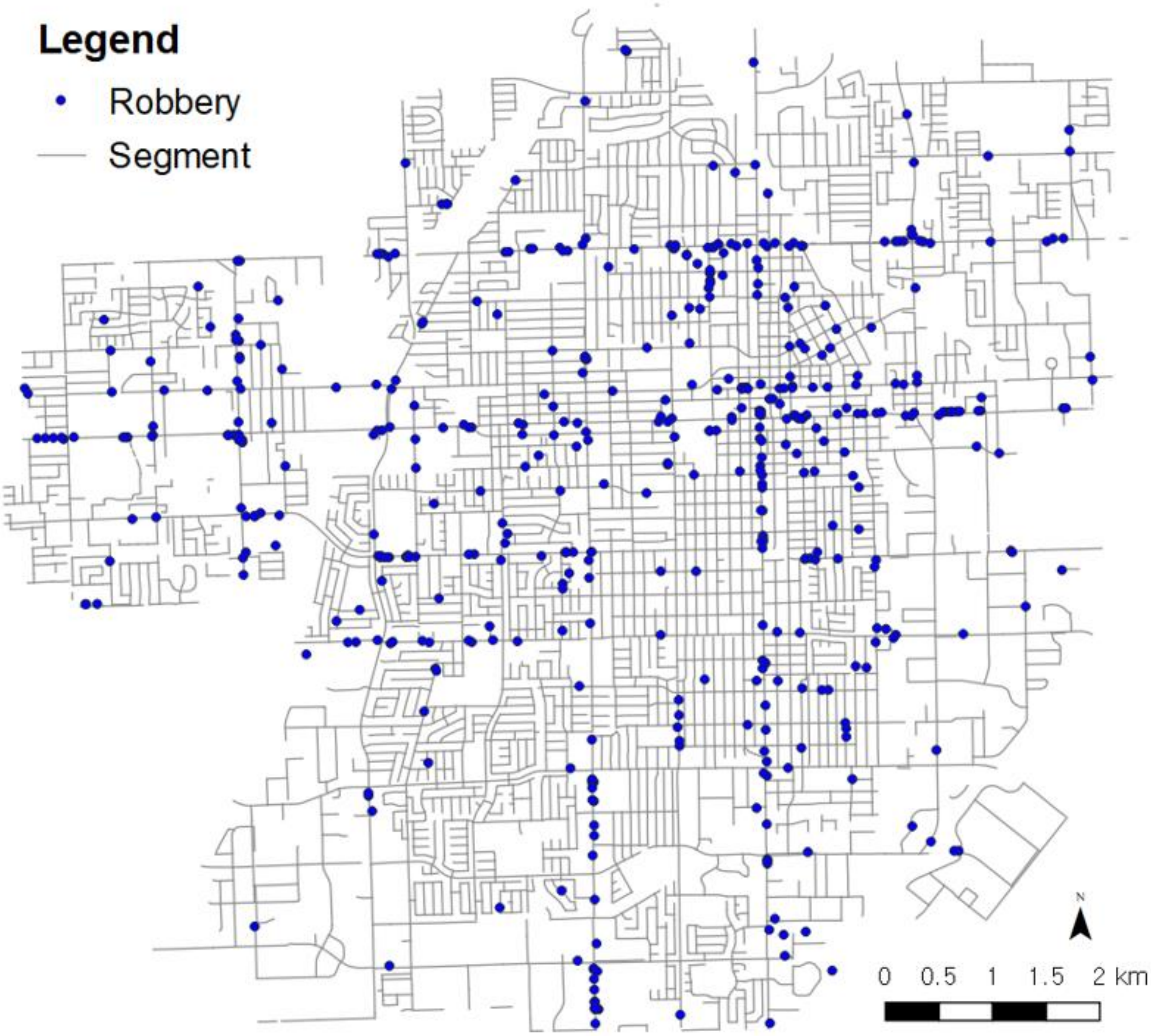
2d)	
	Top 5 elements **Buildings** **53.04** Pavement 26.36 Vehicles 10.64 Sky 8.61 Sidewalks 0.81
2e)	
	**Top 5 elements** Sky 48.47 Pavement 24.11 **Fences** **8.38** Vegetation 5.72 Buildings 5.46
2f)	
	**Top 5 elements** Sky 43.19 **Walls** **30.87** Sidewalks 15.79 Buildings 5.61 Vegetation 4.20

Figure 3. Locations of robberies on street segments in Santa Ana



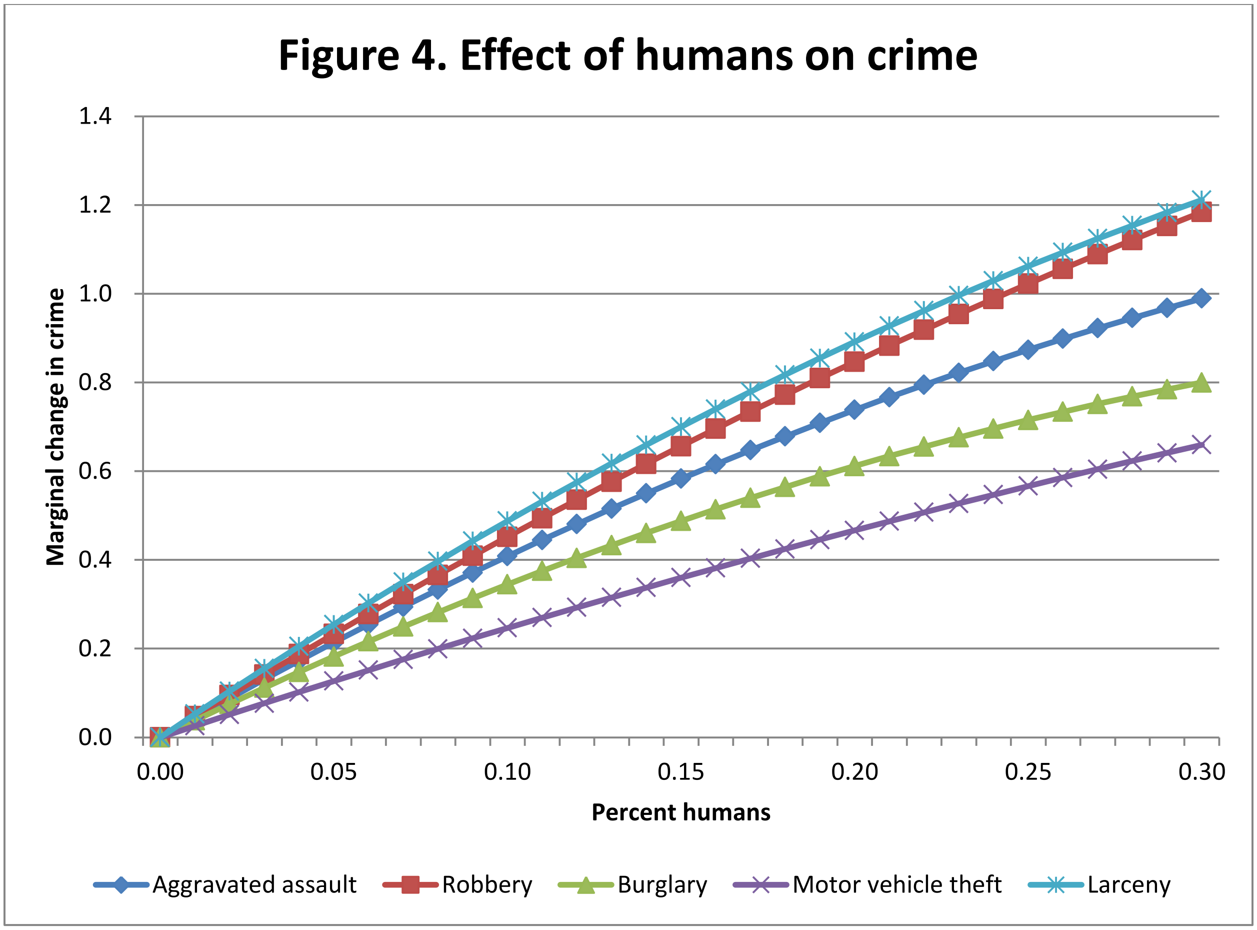


Figure 4. Effect of humans on crime
1.4
1.2
1.0
0.8
0.6
0.4
0.2
0.0
Marginal change in crime
0.00
0.05
0.10
0.15
0.20
0.25
0.30
Percent humans
Aggravated assault
Robbery
Burglary
Motor vehicle theft
Larceny

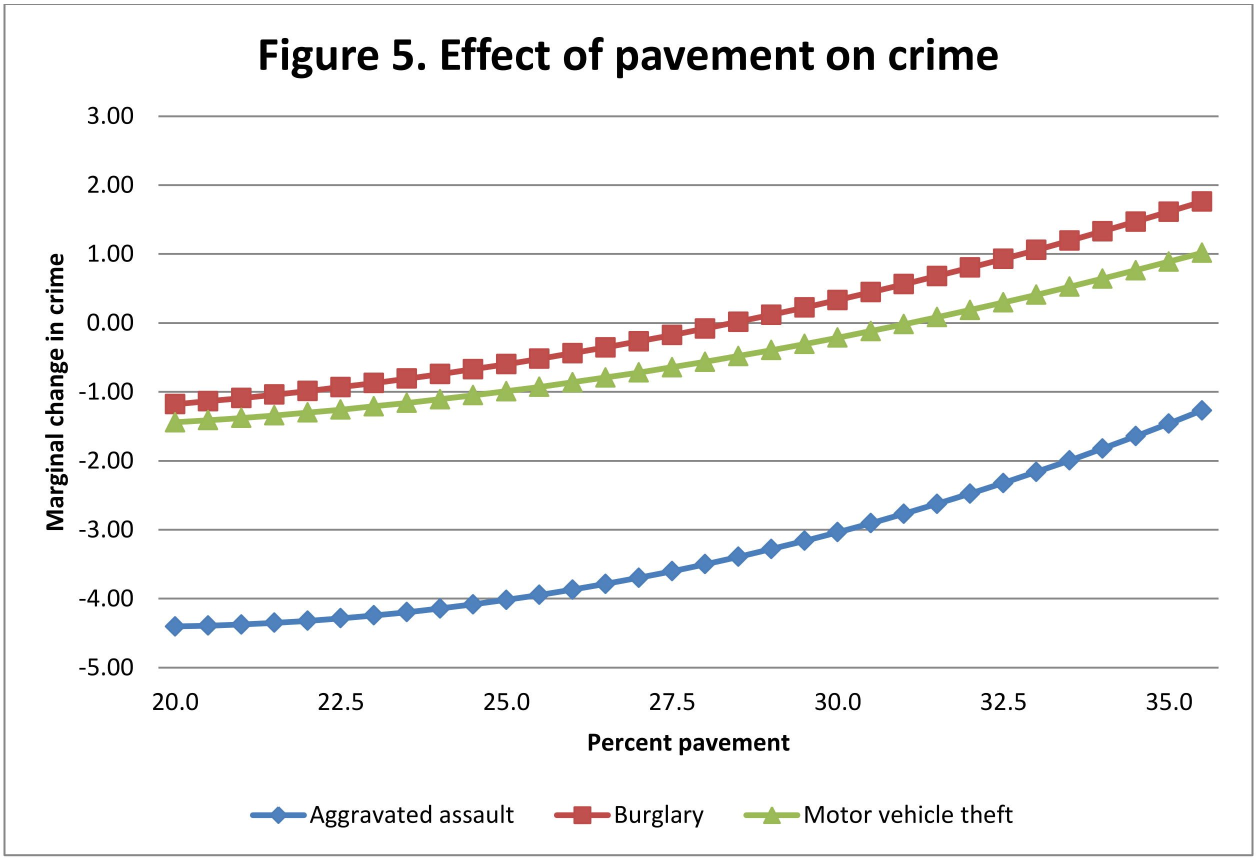


Figure 5. Effect of pavement on crime
3.00
2.00
1.00
0.00
-1.00
-2.00
-3.00
-4.00
-5.00
Marginal change in crime
20.0
22.5
25.0
27.5
30.0
32.5
35.0
Percent pavement
Aggravated assault
Burglary
Motor vehicle theft

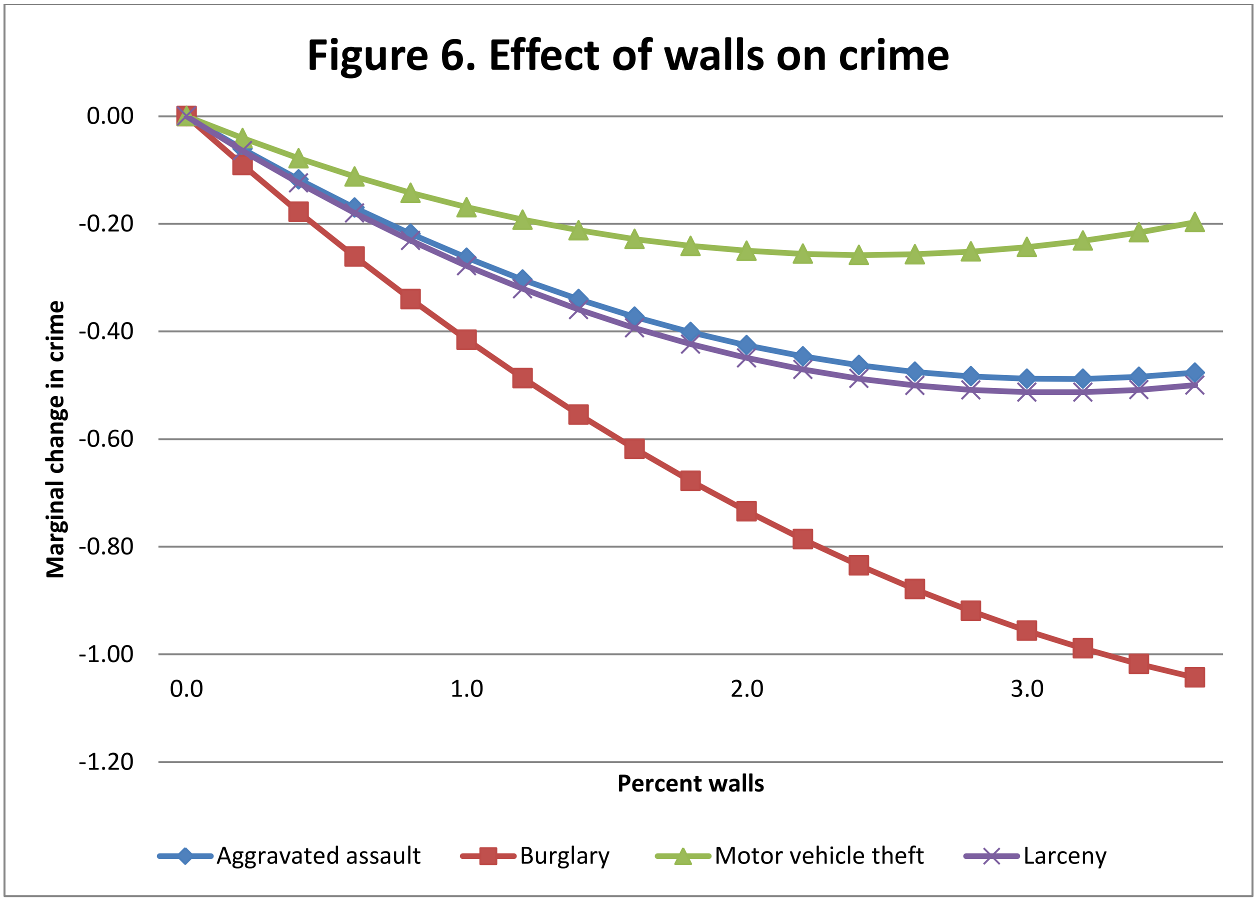


Figure 6. Effect of walls on crime
0.00
-0.20
-0.40
-0.60
-0.80
-1.00
-1.20
Marginal change in crime
0.0
1.0
2.0
3.0
Percent walls
Aggravated assault
Burglary
Motor vehicle theft
Larceny

Figure 7. Effect of vegetation on aggravated assault and motor vehicle theft