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SCIENTIFIC ARTICLES

Searching for Situational Patterns in Cannabis Dealing, Possession and Use in a Scandinavian Context

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Abstract
Although cannabis is the most frequent illicit drug consumed in Sweden, little is known about the situations in which cannabis trade, possession and use occur. Following a recent strand of international research on the effect of recreational drugs on crime, this study uses a unique specially tailored database, Geographical Information Systems (GIS) and regression models, to investigate the situational conditions of cannabis offenses as they are detected in Stockholm, Sweden. Cannabis coincides with the location of drug markets initially delimited by the police but also extends over to locations far from the radar of the police, such as private residences (comfort places). Modeling results indicate that several land uses (convergent public places) have significant predictive value of the geography of cannabis offenses after controlling for other neighborhood characteristics. The article finishes by stating new research questions and making recommendations for practice.

Keywords Marijuana · Recreational drugs · Narcotics · Hashish · Moran's I · Spatial autoregressive models · GIS

Introduction

A recent strand of international research calls for knowledge about the potential criminogenic impact of illicit recreational drugs on neighborhoods following the liberalization of marijuana in the United States (Contreras, 2017; Hughes et al., 2020; Lu et al., 2021). This lack of evidence is not exclusive to the United States. In Sweden, where the use and possession of cannabis are criminal offenses with the possibility of incarceration (SFS 1968:64), there is limited knowledge about the situational conditions in which these illicit drugs are detected by residents, place managers or by the police.

Internationally, the lack of knowledge about cannabis dealing, possession and use is related to the fact that police official crime statistics are often considered poor indicators of illicit drug activities. This is because traditionally police records are said to vary by police practices (when, where and how they work on the streets) and the deployment of criminal justice resources. This bias follows situational factors in the representation of incidents in police accounts that can lead to biased analysis and outputs (van Ooyen-Houben & Kleemans, 2015). However, recent evidence shows that more than a third of police records of the cannabis trade in Sweden are captured thanks to calls of residents to the police (The Swedish Police Authority, 2019), and not solely through police action. Another issue is that police recorded statistics rarely specify the types of illegal substances detected, which reduces the value of these records for the understanding of potential links between illicit drugs and other crimes. As suggested by Felson and Clarke (1998, p. 25) drug-related offenses may lead to other crimes, since those who sell illegal drugs may use some themselves, or they get involved in violence as they cannot resolve disputes via the criminal justice system. In Sweden, although drug markets have been associated with violence (Gerell et al., 2021; Magnusson, 2020; Sandberg, 2012), it is unclear if this also applies specifically to cannabis. All this presents a motivation to explore the potential of police statistics to investigate the situational conditions in which cannabis is recorded by the police.

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Therefore, in this article, we make a contribution to this knowledge base by mapping the location of cannabis activities as reported to the police using a new and specially tailored fine-grained database—which is unique—over Stockholm, the capital of Sweden. This study fills an important gap in the scant literature on situational conditions of cannabis dealing, possession or use by integrating perspectives from environmental criminology to investigate the situational conditions in which this drug (dealing, possession or use) take place. Then we compare these places with the locations of open drug markets (ODM) previously identified by the police. We assess the nature of these places in relation to different land uses and the neighborhood context in which they are embedded using GIS, spatial techniques and regression models. Finally, we finalize the article with recommendations for future research and implications of the results for practice.

This article is novel as it attempts to contribute to a better understanding of the situational conditions of drug related offenses. Firstly, evidence from the Nordic context is missing in the international literature, especially in countries such as Sweden where drug policies are stricter (they are criminal offenses with the possibility of incarceration) than ones found in the United States or other European countries. Sweden is a welfare state country, with more prosocial institutions and different societal values than the market-oriented economies (Rafiqui, 2010) which may explain why more than a third of police records of the cannabis trade in Sweden are not captured solely through police action but thanks to calls of residents to the police (The Swedish Police Authority, 2019). Additionally, police data reflect also people's lower levels of tolerance towards disorder, including drugs as was shown in the US (Sampson et al., 1999). Secondly, certain micro-settings are 'better suited' for drugs and 'misbehavior' than others regardless of their overall societal acceptance or police presence, so the question is, which are these settings? Which types of land uses and routine activities lead to the formation of crime generators and crime attractors (Brantingham & Brantingham, 1995a, 1995b; Cohen & Felson, 1979) and where do cannabis consumption and trade take place? Finally, this analysis makes use of a new detailed dataset (not previously available) that breaks down cannabis offenses by type allowing comparisons within trade, possession and consumption as well as with other types of narcotics and other crimes.

In the remainder of this article, we first give an overview of the international literature on mostly drug-related crimes and their situational conditions. We then later turn to our empirical study and discuss our research design and research questions before presenting our empirical findings.

The Situational Conditions of Illicit Drugs: Theory and Research Questions

International research on illicit drugs (Barnum et al., 2016; Bernasco & Jacques, 2015; Eck, 1995; McCord & Ratcliffe, 2007; Rengert, 1996; Sandberg, 2012) show that drug use and/or dealing are influenced by the demographic and socioeconomic conditions of the resident population. Economically vulnerable areas are often associated with weak social control, which also leads to criminality according to the theory of social disorganization (Kornhauser, 1978; Rengert, 1996; Robinson & Rengert, 2006; Shaw & McKay, 1942). In Sweden, for example, the interlinkages between open drug markets (ODM, also called ODS, Open Drug scenes) and violent crimes have been identified by the police (Gerell et al., 2021; Magnusson, 2020) as one crime seems to produce opportunities for another (Felson & Clarke, 1998). These ODM constitutes of "a geographic area, sustained in space and time, where use and dealing of drugs takes place in the public and is perceived as problematic by authorities and/or the public" (Magnusson, 2020, p. 306), with visible negative impacts on neighbourhoods (Wilhelmsson et al., 2021).

A more recent research strand focused on the effect of marijuana dispensaries on levels of crimes in neighbourhoods in the United States has shown mixed findings. Hughes et al. (2020) showed cannabis dispensaries were associated with increases in rates of neighbourhood crime and disorder but not murder and auto theft. Contreras (2017) also suggested that they were associated with changes in violent crime rates, in particular for homicides and robberies. Lu et al. (2021) indicated that marijuana legalization and sales have had minimal to no effect on major crimes in Colorado or Washington. Similarly, Zakrzewski et al. (2020) found that the exception of one location, crime decreased or remained constant in geographical areas following the opening of a dispensary.

The environmental criminology literature has long suggested that the distribution of crimes in time and space is strongly related to aggregated elements of the perceived physical environment: nodes, paths, edges and an environmental backcloth (Brantingham & Brantingham, 1993). These elements create different criminogenic environments, some are crime attractors, namely places affording many criminal opportunities that are well known to offenders, while others are examples of generators of crime, including transportation hubs. The large number of crime or disorder events that occur in these convergent settings is mostly due to the large number of place users and targets (Brantingham & Brantingham, 1995a, 1995b). As suggested by Felson and Clarke (1998, p. 23) "if a drug market serves local people, it serves to generate crime that might not have occurred". As outsiders hear about it and decide to go there, it becomes a crime attractor. Drug dealing in particular is associated with "convergent settings", such as transportation nodes, bars or neighborhood centres, "where expected earnings relative to invested time and effort are high and where the risk of apprehension is low" (Bernasco & Jacques, 2015).van Ooyen-Houben and Kleemans (2015) examined predictors of cannabis use and detection among young adults in Amsterdam, the Netherlands and found that the likelihood of being detected by police is higher when cannabis is consumed in public places than in private places. They also found that Police are more likely to stop and search in places close to crime hot spots (mostly close to bars, restaurants, and transit places than residential areas) and detect such offenses. In the Swedish literature, drug problems are described vaguely to be mostly concentrated in specific locations such as particular streets, squares, and courtyards (The Swedish Police Authority, 2019). Less known is the role of public places that are off the police radar and are important for criminal networks' activities but do not belong to a hotspot. Hammer (2011) suggests the existence of "comfort places," often private environments, with a clear link to particular members of a criminal network, used to carry out different types of criminal activity. Herold and Herold (2017) have shown examples that comfort places may be houses lookout spots for criminals with little risk of apprehension. Such places can be a location to temporarily store stolen goods or illicit supplies or to repackage drugs; they are discrete meeting places, for planning activities and socialization of criminals.

Although it is thought that public places, with mixed land use facilitates drug activity, such conditions are not expected to be homogenous across time and space. Research on environmental criminology indicates that crime, much like ordinary activities that characterize one's day (e.g., driving home from work), follows certain daily rhythms which are in turn shaped by the distribution of these criminogenic facility types across the city landscape, providing criminal opportunities for offenders as they go about their routine activities (Brantingham & Brantingham, 1993, 1995a, 1995b; Kinney et al., 2008). The necessary conditions for crime under such circumstances is that crime unfolds if and only if motivated offenders and suitable targets converge in both time and space in the absence of capable guardians (Cohen & Felson, 1979). It could also be expected that evening hours offer just the right degree of anonymity for both drug use and drug dealing, as users can still find dealers but more covertly than during daytime hours. Weekly and seasonal variations are expected to be observed following people's routine activity.

Research Questions

Using the analysis of police cannabis-related offenses, we investigate:

1. What is the nature of cannabis crimes in Stockholm? When and where are cannabis crimes most recorded?
2. Do cannabis crimes (dealing, possession and use) appear clustered in space? Are they found in ODMs previously identified by the police? Which are the types of land use more associated with such offenses? (are they e.g., public convergent places or private places?)
3. Which types of neighborhoods are most associated with these cannabis offenses? Do they differ from those patterns for narcotics in general?

Study Area

The study area is limited to the city of Stockholm, which means the inner-city area and those suburbs that administratively belong to the city of Stockholm. Stockholm, the capital of Sweden, had more than 975,551 inhabitants in 2020 and constitutes the largest municipality in Sweden. The municipality belongs to the Greater Stockholm area, which had more than 2.3 million inhabitants (Statistics Sweden, 2020) and is part of an archipelago. All underground lines pass through the Central Station, which is the main railway station of the capital, making this area a place where many travelers and workers pass daily. On average, the percentage of residents who are foreign born is 34% but in some outskirts the proportion exceeds 90%. In these suburbs, general unemployment rates are three times higher and average income lower in comparison to the rest of the city (Stockholms stad, 2023). Like many other European cities, Stockholm is thus affected by social, economic and spatial segregation. Sergels torg, a central square and one of the main meeting points of the city, is a relatively high-criminogenic area (Uittenbogaard & Ceccato, 2012), including one of the most known ODM 'plattan' (Magnusson, 2020). The punishment for possession of drugs, including cannabis, depends on the severity of the offense, classified as minor, ordinary or serious. Penalties for minor drug offenses are fines or up to 6 months' imprisonment; for ordinary drug offenses, up to 3 years' imprisonment; for serious drug offenses, 2–7 years' imprisonment; and for particularly serious drug offenses, 6–10 years' imprisonment (EMCDDA, 2017).

Data

The study is based on several datasets: offenses data, ODM, land-use data, demographic and socioeconomic data, and geographical data over Stockholm municipality (Appendix

Table 3 summarizes the characteristics of the dataset used in the study). Note that because police records on illegal drugs are not officially available split by crime code, we had to obtain approval from the Swedish Ethical Review Authority first. Given that the dataset runs from 2019 to 2020, it might be worth to mention that COVID-19 public health guidance may have affected the levels and nature of these offenses as well as police practices, which in turn may have impacted the offenses data used in the analysis.

- *Offenses data* We obtained two offenses datasets. The *first dataset* was a list of all cases related to illicit drugs, 2019–2020. To select cases of cannabis dealing, possession and use only ($N=4030$), we had to request data from the police authority and the national forensic center (NFC). The *first dataset* was extracted from the NFC's 2019–2020 ($N=981$), cannabis-related offenses containing information about age of suspects, place of residence, situational characteristics of the offense from the same period over the Stockholm region. This was later recoded into multiple crimes and then linked to the exactly geolocation in space using GIS and the crime coordinates (x, y coordinates) via the Stockholm police authority. These x and y coordinates are, respectively, the horizontal and vertical addresses of a point in any two-dimensional space and identify the exact location of a crime.
- *Open drug markets (also called Open Drug Scenes)* A total of 36 drug market locations were obtained by the police for all drugs and from those, 10 were labeled as being specialized as cannabis dealing. This definition was created by the police due to a lack of firm demarcation in time, space and in consideration to impact they have on community. The measure derives from research on open drug markets and confirmed as useful by actors involved in drug market enforcement strategies in the police. It is built with a geographic focus (a shape file in GIS), based on observed openly committed acts and their effects on people passing, living and prevention actors responsible for these locations.
- *Geographical data* Sweden's DeSOs comprise a nationwide division system that follows county and municipal boundaries. Digital boundaries are available as open spatial data. We obtained demographic and socioeconomic data from Statistics Sweden (SCB) at the DeSO level, mostly for 2018 and 2019. Malmö University provided us with the polygons of officially defined open drug markets (ODM) which were originally collected by the police authority in 2017, then used in research at Malmö University (Magnusson, 2020), including ODM that were specialized in cannabis.
- *Land-use data* Using Open street maps and the Open Data Portal of Stockholm city, we selected a number of land-use variables associated with particular criminogenic conditions and/or social control in an area. Examples are bars, location of stations/bus stations, parking lots, green areas/parks, secondary schools, presence of toilets, gas stations, presence of police stations.
- *Demographic and socioeconomic data* Data from Statistics Sweden was obtained to create variables on resident population, young male population, unemployment, household composition, foreign population and average income per DeSO.

Methods

Preparation of the Dataset

With the police cannabis dealing, possession and use ($N=4030$ such offenses from the police authority of Stockholm, x, y coordinates), we geocoded all cases except 3% that did not have either a code or a location. We worked with the x, y coordinate dataset to run the temporal and distance analysis as reported in "Temporal and Spatial Analysis" and we calculated rates by DeSO areas for each cannabis crime using resident population. Rates of the DeSO drug-related offenses were the base for assessing the geographical distribution and modeling discussed in "Modelling Cannabis Dealing, Possession And Use".

Temporal and Spatial Analysis

We split the dataset by hours of the day, days of the week and months of the year to investigate potential temporal patterns by different types of cannabis crime (dealing, possession and use) and narcotics using both the NFC database and the police data by coordinates. For the analysis of spatial patterns, we had three different strategies. First, to calculate the land uses closest to cannabis cases, we used the "near" function in ArcGis, with the option to select a pair of x, y coordinates (for each crime) for each land use and choose the facility (e.g., bar, transportation hub) closest to each crime and provide a measure in meters. Second, we tested the concentration of narcotic-related crimes by comparing the distribution of x, y coordinates of cannabis offenses to a number of selected land uses, such as bars, bus stops, transportation hubs (x, y coordinates), with the distance from random points (calculated from the centroid of each DeSO area) to the x, y coordinates of a number of urban environments (selected land uses) by distance bands. The t test was used to compare these distributions. We also tested for global spatial autocorrelation of the x, y location of cannabis (dealing, possession and use) and narcotic offenses for both years using the univariate Moran's I menu option in GeoDa, using the contiguity matrix. Finally, we also compared these locations (using our own map of density of cannabis crimes: dealing, possession and use) with the locations of existent open drug markets (ODM) previously mapped by the police to check if they matched with each other.

Modelling Cannabis Dealing, Possession and Use

Drawing from environmental criminological principles, we investigated potential covariates of rates of police cannabis-related offenses/narcotic offenses for 2019 and 2020. The covariates are composed of criminologically relevant land uses (such as transportation hubs, metro and commuting train stations, buses, bars, restaurants and nightclubs, police, secondary schools, hospitals and parks, as suggested in the international literature, often as examples of convergent settings), controlling for a series of demographic and socio-economic variables (such as income, proportion of young male population, proportion of privately owned dwellings, measure of centrality/periphery). The dataset used in the analysis is presented in Appendix, Table 3.

The analytic strategy involved here is composed of two stages: first, the testing of reliable rates for the study area, and second, the modeling. The dependent variable was composed of rates of police cannabis-related offenses (dealing, possession and use) by the smallest unit of analysis in DeSO by 1000 population. Because the rates were skewed, a natural log transformation was used to reduce or remove the skewness of the original data. The individual independent variables were pre-selected before modeling. First, an analysis of bivariate correlation between all covariates identified variables that would potentially contribute with similar information to the models. For instance, we excluded all variables with correlation greater than 0.6; e.g., unemployment rate and social allowance were both correlated with income, so the first two variables were excluded. We excluded several land-use variables, such as street illumination and ATM, which were correlated with bars/nightclubs/restaurants; all the chosen variables were kept. The regression analysis was implemented in GeoDa (Anselin, 2014), because this software has regression-modeling capabilities that are appropriate for spatial analysis. The first model was estimated using ordinary least squares (OLS). Spatial diagnostics were also tested (e.g., Moran's I). A first-order contiguity binary (queen) weight matrix was created to represent the spatial arrangement of the city and was used for the spatial diagnostics of the models. A significant Moran's I test means that the model shows problems of autocorrelation on residuals, which can, among other things, inflate the goodness of fit of the model. A common practice is to test alternative autoregressive models, such as spatial lag and spatial error models. The Akaike information criterion (AIC) measure was used as a reference to assess the performance of the models because it takes into consideration the trade-off between the number of independent variables in the equation and the number of observations. Results of the modeling section are presented for cannabis-related crimes in comparison with total narcotics. GeoDa provides several statistics measuring the fit of the model and includes diagnostic tests, such as tests for multicollinearity among independent variables and tests on model errors (normality, heteroscedasticity and spatial auto correlation).

Results

The Nature of Cannabis Offenses

Around 3000 cases of cannabis offenses (dealing, possession or use) are registered each year, 55% of these in Stockholm municipality. In Stockholm municipality alone, 58% of these cannabis crimes are possession, 25% cannabis for personal use while cannabis trade composes 12% of this total, followed by 5% of others (1% production and 4% of cases were not defined). From the cases analysed in the study, 79% involved males, mostly young, 40% were under 25 years old. Note that cannabis composes about 20% of the total narcotic records that reach national forensics for Stockholm County (NFC). The large majority of individuals in the records live in the Stockholm metropolitan region, an average of 5 km from the place of their residence, if considering individuals from all of Sweden, the distance reaches 21.6 km.

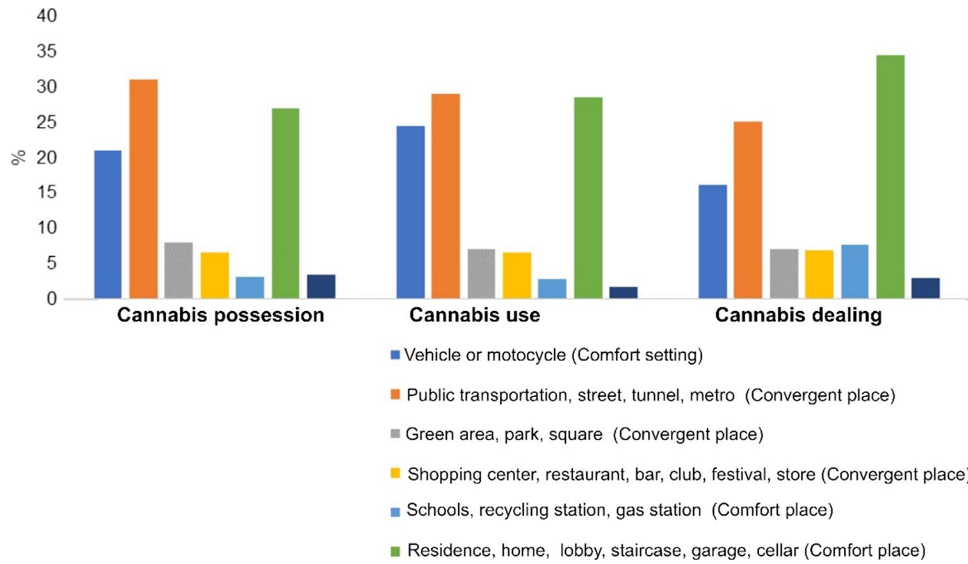
From the total cannabis offenses (dealing, possession and use), only one quarter of these crimes were recorded by the police as solely drug-related, the large majority being associated with other crimes and charges. In 35% of cases of cannabis-related offenses, drugs were associated with possession of illegal weapons, mainly knives, stolen goods, often found in house arrests. Many cases were also related to illegal driving (driving without a license or while intoxicated), theft, assault and violence, use of counterfeiting, unlawful distribution of counterfeit goods and property damage. Note that these findings do not indicate that cannabis was the 'cause' of any other crime. In many cases, the suspect was arrested for theft and cannabis was detected 'by chance' in the process. This impacts on the temporal patterns of detection of these offenses. More than half of the cases of cannabis offenses detected happened between late afternoon and evening (3–11 p.m.), roughly a quarter during the night and early hours of the morning (12 p.m.–7 a.m.) and a little less than a quarter from morning to midafternoon (7 a.m.–3 p.m.) ($N = 3343$). There are some indications of greater frequency of detection on weekdays than weekends, but no statistically significant differences were found in our dataset. Late winter and spring have almost a quarter more cases of cannabis-related offenses than late summer and autumn.

Table 1 Distances from cannabis offense locations to bars, bus stops, transport hubs, parks and high schools, Stockholm city 2019–2020, and from cannabis locations to random points ($N = 3343$)

Distance to	Park		Bar-restaurant-nightclub		Transport hub		Gas station		High school	
	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)	(i)	(j)
Ns	3277	3264	3277	3264	3277	3264	3277	3264	3277	3264
Percent at each distance (m)	From cannabis locations	From random points	From cannabis locations	From random points	From cannabis locations	From random points	From cannabis locations	From random points	From cannabis locations	From random points
0–100 m	41.07%	31.62%	42.11%	26.16%	13.37%	3.49%	31.25%	42.86%	4.42%	3.16%
101–200 m	23.53%	24.94%	20.96%	20.59%	19.13%	8.76%	37.50%	32.65%	13.18%	8.18%
201–400 m	23.25%	27.60%	20.63%	24.11%	33.81%	30.30%	25.00%	18.37%	21.73%	20.10%
401–600 m	10.01%	11.49%	9.67%	13.24%	17.85%	25.15%	2.08%	2.04%	14.40%	15.38%
601–800 m	0.98%	2.51%	2.53%	6.80%	6.04%	12.07%	2.08%	2.04%	11.29%	10.51%
800–1000 m	0.55%	0.58%	1.68%	4.29%	3.30%	7.29%	2.08%	2.04%	9.15%	8.49%
> 1000 m	0.61%	1.26%	2.41%	4.81%	6.50%	12.93%	0.00%	0.00%	25.82%	34.19%
Totals	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%
Median (m)	132.212	169.923	131.878	221.288	289.338	449.378	878.407	976.217	527.564	657.579
% within 200 m	64.60%	56.56%	63.08%	46.75%	32.50%	12.25%	68.75%	75.51%	17.61%	11.34%
% within 100 m	41.07%	31.62%	20.96%	26.16%	13.37%	3.49%	31.25%	42.86%	4.42%	3.16%
T test	57.515	60.383	48.663	55.544	56.715	68.622	96.770	99.297	61.926	67.253
C.I. at 95% Lower	261.15	304.72	302.23	425.72	501.95	720.83	961.410	1030.344	977.76	1148.63
C.I. at 95% Upper	279.59	325.18	327.61	456.88	537.90	763.24	1001.174	1071.853	1041.70	1217.61
p value	< 0.001		< 0.001		< 0.001		< 0.001		< 0.001	

Data source: Stockholm Police Authority, 2021

Fig. 1 Location of the cannabis detected by the police



Cannabis offenses (dealing, possession and use) are detected in both public places, convergent places as well as comfort settings, private homes, regardless offenses type (Fig. 1). As many as 52% of cases detected were in public places (public transportation, gas station, parks), 46% private settings (homes, entrances, stairwells, garages, basements), often after meeting suspects (followed by house inspection) on the street and in 2% of cases missing location information. Public places also include here cars, motorcycles and other vehicles (for example, in cases where drivers were stopped by police at a checkpoint in the streets). The second most important public place is on the streets, not specified or in combination with nearby public transport, such as a metro station or bus stops.

Parks (43%) was the closest land use associated with cannabis offenses detected (while for narcotics in general, parks accounted for 37%) followed by bars, restaurants and nightclubs (36%). These findings are confirmed when we also investigated whether cannabis offenses were more associated to particular environments than they would do by chance. We calculated the distances to bars, bus stops, transport hubs, parks and high schools for 3277 cannabis offenses' locations and for 3264 random points with the crime data from 2019–2020 (Table 1). With these distances, we compared distances from cannabis offenses to locations (columns (a), (c), (e), (g) and (i)) to distances from random points (columns (b), (d) and (f), (g), (j)) using six distance bands as shown in Table 1.

As much as 42% of cannabis offenses (dealing, possession and use) were recorded within 100 m of a bar, compared to just over 26% of random points. Similarly, 41% of cannabis offenses were recorded within 100 m of a park, compared to just over 31% of random points. Some 13% of cannabis offenses occur within 100 m of the nearest transport hub, compared to less than 3% of random points. The next distance ring (101–200 m to the nearest cannabis offense) also shows stark differences for transportation hubs and secondary schools but not for bars and parks. Each of the paired comparisons (cannabis offenses and random points) differs at the 0.00001 level, which means that in comparison to distances from random points, cannabis offenses occur relatively nearer to bars and other types of land use than they would by chance.

Comparison Between Cannabis Reported Offenses and Police's Open Drug Markets (ODM)

The geography of cannabis offenses (dealing, possession and use) follows the subway lines. Figure 2 shows that although the police indicate that only 10 out of 36 ODM are specialized in cannabis-related crimes, we found that cannabis-related offenses spreads over a larger area than the area previously indicated by the police. All areas with a high density of cannabis trade have a drug scene/market near or on top of the police's ODM. Note that because most of the cannabis offenses were recorded together with other crimes, any type of cannabis offense might follow the pattern of the other initial offenses. One example is the open drug market (or open drug scenes) in the central area of Sergels torg, and one of the most traditional ones (Magnusson, 2020). The area has the biggest public transit junction in the city and is close to the largest hotspots of theft. Together these characteristics might generate many cannabis crimes, because body searches might reveal both drugs and knives and potentially any evidence of other crimes, such as theft. Note also that the higher rates in this central area may be explained by local police departments having specialized drug units dedicated to drug crimes. The actual cannabis market (density per sq

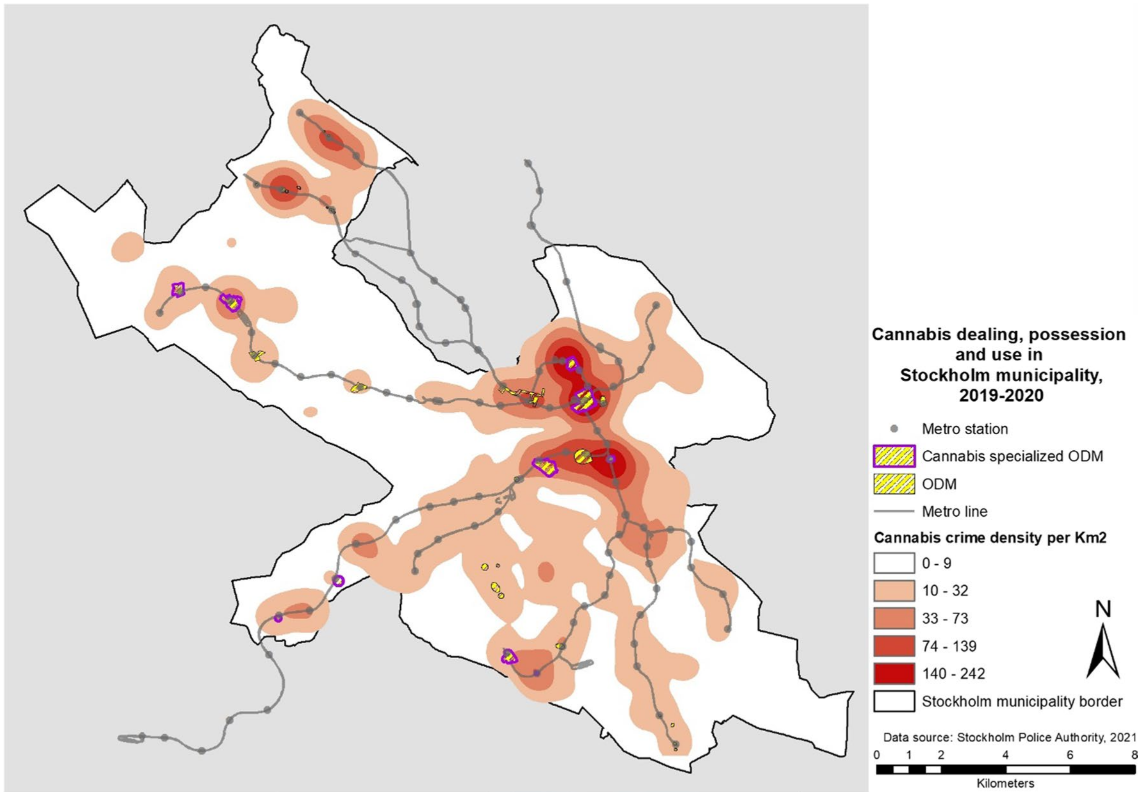


Fig. 2 Police's ODM specialized in cannabis dealing (in yellow/violet), ODM with all other drugs (in yellow) and the density of the cannabis market density per sq. Km, 2019–2020 (in beige-red)

km) covers a network of locations along subway systems with the exception of a few small stations on the green line, covering residential areas as well as places with the mixed land use.

Cannabis crimes recorded by the police tend to be clustered in space. Cannabis possession and cannabis use, as well as total cannabis (all cannabis-related offenses—dealing, use and possession) and total narcotic-related crimes—all exhibit a significant clustered pattern (total cannabis, Moran's $I = 0.041$, $p = 0.00$; also cannabis use, Moran's $I = 0.03$, $p = 0.00$; and cannabis possession, Moran's $I = 0.07$; $p = 0.00$, and total narcotics, Moran's $I = 0.04$, $p = 0.00$ while for total crime rate for Stockholm, Moran's I is $= 0.08$, $p = 0.00$). However, note that the geography of cannabis dealing shows indications towards a random pattern (Moran's $I = 0.018$, $p = 0.09$). Despite the police recorded data reflecting reporting practices of individuals other than those carrying out police(ing) activities, we recognize that the data might be influenced by the location of place managers that are actively controlling these spaces.

The cannabis-related offenses in the police records tend to be concentrated geographically in the inner-city and a few areas in the outskirts (Fig. 3). Stockholm's inner-city areas have a rate of 111.4 cannabis offenses per 1000 population, which is 33 times higher than the overall cannabis crime rate for Stockholm municipality. This is followed by neighboring DeSOs in the city center, with around 70 cannabis offenses per 1000 population. High rates of cannabis are also found in the outskirts of the city. The northwestern parts of Stockholm, has a rate of 27.2 cannabis offenses per 1000 population, which is the highest in the periphery (8.1 times greater than the overall cannabis crime rate for Stockholm), followed by areas in southeast Stockholm, with a rate of 19.4 offenses per 1000 population (5.7 times greater than overall). Figure 2 illustrates these concentrations for selected cannabis offenses and total narcotics, 2019–2020: possession (a), trade (b), all cannabis-related offenses—dealing, use and possession (c) and narcotics (d). The geography of such rates shares similarities with the geography of total narcotics rates, but there are differences based on type of cannabis offense.

Modelling Cannabis Dealing, Possession and Use

Variables indicating the proportion of particular land uses (parks, schools, etc.) explain a third of the variation of the rates (log) of total cannabis (all cannabis-related offenses—dealing, use and possession offenses) recorded by the police,

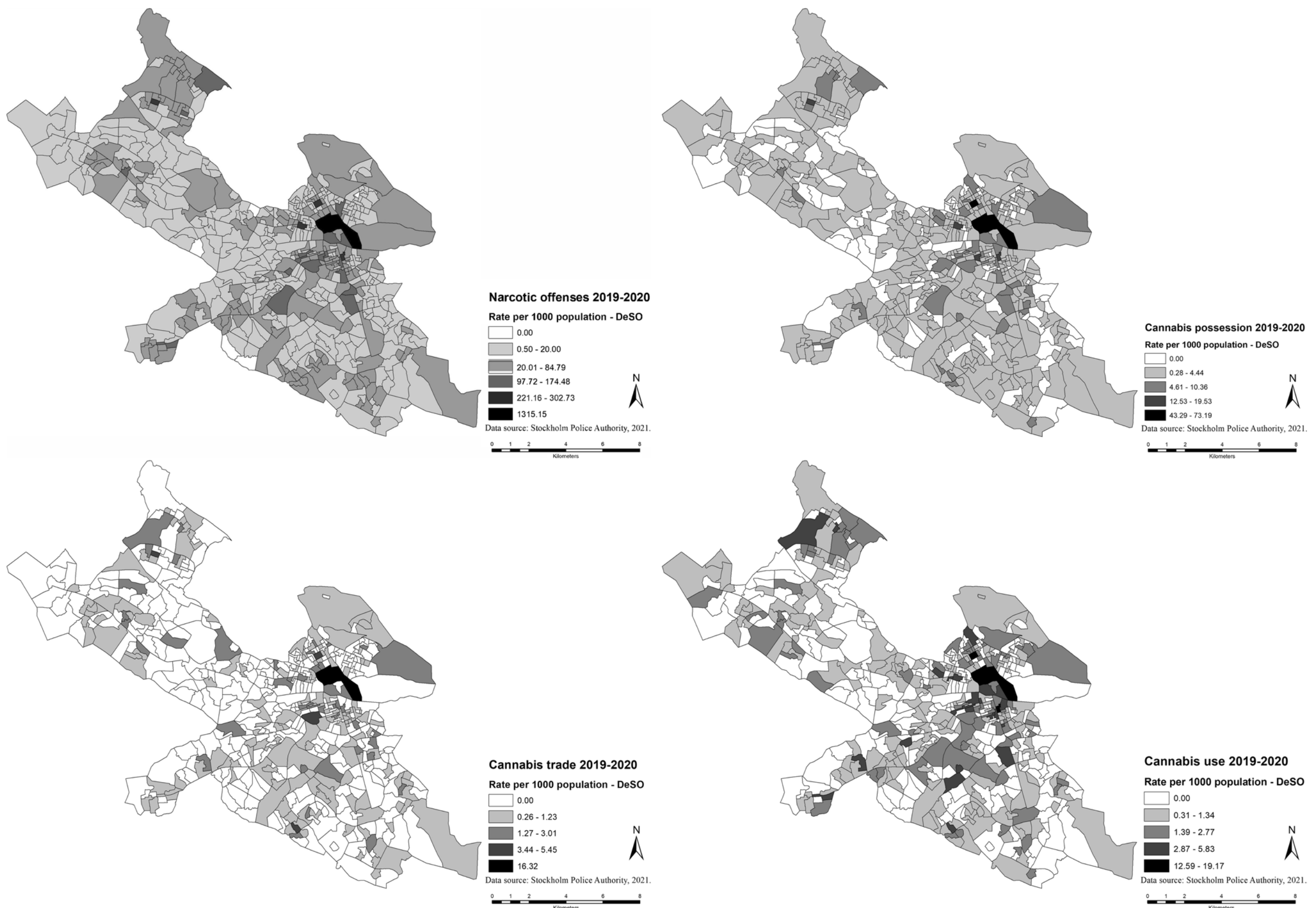


Fig. 3 Rates of cannabis offenses (dealing, possession and use) and narcotics in Stockholm, 2019–2020. $N = 3343$ cases. Data source: Stockholm Police Authority, 2021

after controlling for area differences in income, demography, housing type, the distance to the city center. Regardless of the modeling strategy employed, cannabis offenses are more likely to take place in areas containing a high proportion of transportation hubs, parks, secondary schools, hospitals, bars and restaurants, police stations, toilets and gas stations. The importance of land use variables is less pronounced for the model of cases of cannabis use (parks, transportation hubs, secondary schools are not significant) than for the other models (Table 2).

In order of magnitude, the model of all cannabis-related offenses—dealing, use and possession shows that deprived areas (income), presence of police station, a transportation hub (train, toilet), school, periphery, all affect victimization patterns. The ordinary least square model (OLS) showed that lower income areas tend to show higher records of rates of police cannabis-related offenses and narcotics offenses. Since most of the models presented problems of heteroscedasticity of the residuals (non-constant variance of the residuals), we used a categorical variable (in this case center, instead of distance decay) to deal with the problem. This solved the problem for the model (a) for all cannabis-related offenses—dealing, use and possession, but not for the other models. Because several models showed problems with autocorrelation on residuals (Moran's *I* was significant), the autoregressive models (spatial lag and error models) were implemented using GeoDa (Anselin, 2014) and are therefore reported in Table 2. Note that the spatial lag and spatial error models are used for several reasons. First, because OLS models that show problems with spatial autocorrelation on residuals go against the basic assumptions of OLS regression. As suggested in the literature, one solution is to use spatial lag and spatial error models to obtain unbiased and efficient estimates for the regression parameters in the model. Another reason has to do with the nature of the phenomenon to be modelled. For example, the spatial lag model can help indicate the concentrations of rates of cannabis offenses that go over polygon boundaries and perhaps capture a possible diffusion process over space. However, in our case, error models performed better than the spatial lag models and OLS models, possibly because the spatial error model "captures the spatial influence of unmeasured

Table 2 Modeling rates of cannabis offenses and narcotics (log) in Stockholm 2019–2020

	(a)						(b)		(c)						(d)						(e)					
	OLS Total Cannabis		LAG Total Cannabis		Error Total Cannabis		OLS Cannabis trade (5005)		OLS Cannabis possession (5010)		LAG Cannabis possession (5010)		Error Cannabis possession (5010)		OLS Cannabis use (5011)		LAG Cannabis use (5011)		Error Cannabis use (5011)		OLS Total Narcotics		LAG Total Narcotics		Error Total Narcotics	
Variable	Coeff	Sig	Coeff	Sig	Coeff	Sig	Coeff	Sig	Coeff	Sig	Coeff	Sig	Coeff	Sig	Coeff	Sig	Coeff	Sig	Coeff	Sig	Coeff	Sig	Coeff	Sig	Coeff	Sig
Park	–	–	–	–	–	–	–	–	0.390	0.031	0.347	0.047	0.338	0.062	–	–	–	–	–	–	–	–	–	–	–	–
Bar-Restaurant-Nightclub	–	–	–	–	–	–	1.306	0.000	–	–	–	–	–	–	1.463	0.000	1.29	0.000	1.342	0.000	–	–	–	–	–	–
Transport stations	1.422	0.000	1.448	0.000	1.487	0.000	0.389	0.014	1.214	0.000	1.230	0.000	1.262	0.000	–	–	–	–	–	—	2.205	0.000	2.274	0.000	2.286	0.000
Gas stations	0.819	0.011	0.792	0.011	0.802	0.008	–	–	0.661	0.014	0.653	0.011	0.668	0.007	–	–	–	–	–	–	1.442	0.000	1.368	0.000	1.405	0.000
High school	1.045	0.012	1.021	0.011	1.047	0.007	–	–	0.781	0.025	0.752	0.025	0.736	0.023	–	–	–	–	–	–	0.965	0.033	0.876	0.032	0.851	0.026
Police stations	1.908	0.000	1.954	0.000	1.955	0.000	0.941	0.000	1.851	0.000	1.865	0.000	1.804	0.000	1.087	0.003	1.188	0.000	1.264	0.000	2.603	0.000	2.563	0.000	2.334	0.000
Public toilet	1.171	0.000	1.013	0.000	1.056	0.000	–	–	1.079	0.000	0.931	0.000	0.988	0.000	0.555	0.006	0.503	0.011	0.574	0.003	1.815	0.000	1.522	0.000	1.772	0.000
Health facilities	–	–	–	–	–	–	–	–	–	–	–	–	–	–	0.855	0.016	0.874	0.011	0.871	0.01	1.351	0.016	1.242	0.014	1.162	0.016
Open drug market	–	–	–	–	–	–	0.388	0.019	0.802	0.002	0.786	0.001	0.799	0.001	–	–	–	–	–	–	1.380	0.000	1.254	0.000	1.293	0.000
Income	–2.045	0.000	–1.750	0.000	–2.013	0.000	–0.451	0.000	–1.477	0.000	–1.250	0.000	–1.45	0.000	–0.939	0.000	–0.816	0.000	–0.918	0.000	–2.836	0.000	–1.977	0.000	–2.404	0.000
Rental house	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	0.428	0.003	0.355	0.007	0.310	0.027
Centrality	0.434	0.000	0.342	0.000	0.421	0.000	–	–	0.305	0.000	0.236	0.000	0.295	0.000	0.182	0.000	0.136	0.003	0.19	0.001	0.575	0.000	0.360	0.000	0.483	0.000
Constant	1.487	0.000	1.131	0.000	1.478	0.000	0.344	0.000	1.034	0.000	0.770	0.000	1.028	0.000	0.655	0.000	0.52	0.000	0.636	0.000	3.107	0.000	1.765	0.000	2.991	0.000
R-square	0.295		0.330		0.339		0.154		0.311		0.346		0.353		0.184		0.214		0.224		0.493		0.573		0.584	
Moran's *I*	5.920	0.000	–	–	–	–	1.515	0.129	5.939	0.000	–	–	–	–	4.934	0.000	–	–	–	–	10.14	0.000	–	–	–	–
AIC	1096.73		1077.91		1071.22		389.899		890.712		870.684		865.486		681.097		668.458		662.054		1174.53		1100.38		1095.77	
Multicollinearity	7.439		–		–		6.120		7.655		–		–		6.883		–		–		11.982		–		–	
Jarque–Bera	4.750	0.093	–		–		294.44	0.000	16.819	0.000	–		–		137.36	0.000	–		–		33.865	0.000	–		–	

$N = 544$ DeSO areas

independent variables" (Baller et al., 2001, p. 567). In other words, the spatial error model can help assess the extent to which the clustering of rates of cannabis offenses are not explained by the measured independent variables and can instead be accounted for with reference to the clustering of error terms. In all cases, despite improvements in performance, problems with heteroscedasticity remained in all models.

The models for cannabis trade/dealing and cannabis use differ somewhat from the geography of cannabis possession and for the model of all cannabis-related offenses (Table 2b, d). The presence of bars, police stations (which may reflect more active police actions in these areas), transport hubs, ODM (excluding those specialized in cannabis dealing) and presence of deprived areas help explain the variation of cannabis trade. In contrast, variables such as secondary schools, gas stations and other indicators of local neighborhood centers (such as proportion of toilets) do not. Although transportation hub and ODM areas turned out significant variables in all these models, it is the presence of police station, deprivation and presence of bars and restaurants that affect the most the geography of cannabis possession, cannabis use and all types of recorded drug-related offences (total narcotics).

High rates of police records of cannabis use are more likely to be detected in inner-city areas of Stockholm, areas that have a high proportion of public toilets (often used by drug addicts), bars, restaurants and nightclubs and also police stations. Figure 4 shows two density maps of cannabis offenses and selected land uses in the inner-city areas and in an example in the periphery of Stockholm.

The modeling results also indicate that the location of ODM do explain the variation of cannabis rates, especially for trade/dealing. This finding can be related to the presence of security guards and police at locations of drug trade but also active place managers in the area, which are also hotspots for other crimes as previously suggested in the literature (as suggested by Magnusson, 2020), or that there might be a symbiosis between the cannabis dealing and the trade of other types of drugs.

Although secondary schools are not particularly close to cannabis markets, they are an important variable in the model to explain the geography of cannabis and narcotics in general (see models a, c and e). It is in schools that pupils spend most of their waking hours studying and socializing, and if drug use or possession is evident, guardians, particularly teachers and staff, will contact the police and file a complaint. Therefore, it is expected that high rates of offenses for cannabis and other drugs would be associated with areas with a greater proportion of secondary schools. Note, however, that the variable "secondary schools" is not significant to explain the variation of rates of selling cannabis, rather to explain cannabis possession and use only.

Discussion of the Results

Cannabis offenses (dealing, possession and use) recorded to the police in 2019–2020 in Stockholm happened often in association with other types of crime such as illicit possession of weapons, theft, violence. This is not a surprise because as suggested by Sandberg (2012) in street markets and in the higher levels of the cannabis economy, a rather violent and criminal culture may dominate the area. These findings also confirm some of the recent research on the impact of effect of marijuana dispensaries on levels of crimes in neighbourhoods in the United States (e.g., Contreras, 2017; Hughes et al., 2020).

We also found that cannabis dealing in particular spreads over a larger area than the official police's ODM open drug

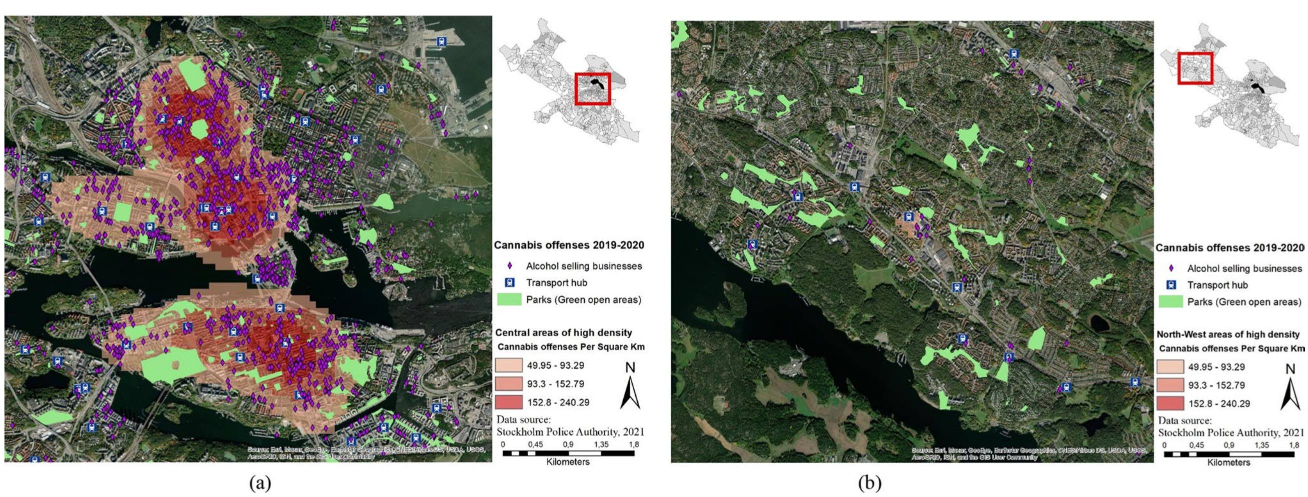


Fig. 4 **a** Inner-city areas of Stockholm and **b** Vällingby station (Northwestern Stockholm)—Density map of cannabis offenses and selected land uses, 2019–2020 ($N = 3343$)

markets. These cannabis markets might be identified by residents and place managers in places such as in schools and transportations hubs. All areas with a high density of cannabis trade contain a drug scene near or 'on top' of the police's ODM despite the fact that the police indicate that only 10 out of 36 ODM were specialized in cannabis-related crimes. This is a confirmation that there is some overlap between other types of drug dealing and the geography of cannabis. International literature shows that it is difficult to differentiate them because 'illegal drug markets are embedded in each other and buyers in one market are often sellers in another and vice versa' (Sandberg, 2012, p. 1147). It is possibly that these particular places may be associated with areas where criminal gangs share their territory (Gerell et al., 2021). Note that in 35% of the cases in this study, drugs were registered at the same time with possession of illegal weapons, mainly knives. This in interesting pattern but it is worth pointing out that this study found distinct geographies of drug markets, some with links to private homes.

We also found that particular public places, with particular land uses are more associated with cannabis offenses (dealing, possession and use) than they would be by chance. Locations where cannabis-related offenses are detected tend to be either places where people converge, such as public transit environments or in settings that Hammer (2011) calls comfort places, such as apartments, garages, but also vehicles that are poorly surveilled. As previous research indicates, drug sellers in the United States seek apartment buildings that have no building manager on the premises (Felson & Clarke, 1998). These private locations allow for social contact between individuals without the police or the community noticing, as these locations also offer a low risk of police arrest, use and/or possession of cannabis/drugs. Previous research shows that through redesign, management and patrol, drug markets have been driven out of parks and shopping malls" (Felson & Clarke, 1998, p. 19).

Although cannabis rates were 33 times greater in inner-city areas than the average for Stockholm municipality as a whole, several hotpots of mixed land use also concentrated cannabis crimes, especially in the most deprived areas in the outskirts, often around parks, outlets selling alcohol and transport nodes. Our evidence indicates the importance of specific facilities for crime, in particular, the role of managers in combating and/or promoting illicit drugs (Eck et al., 2007). These findings can also be associated with principles of routine activity and social disorganization in some of deprived areas (see significance of income and rental), in ways that go beyond the traditional interpretation (e.g., Kubrin & Weitzer, 2003), perhaps linking decision-making regarding land use and crime distribution within and across neighborhoods in a city.

On a more technical note, model results suggest two contrasting components in the cannabis geography (dealing, possession and use). High rates of cannabis and narcotic offenses appear to occur both where there are more opportunities for crime (more supply and demand and use) and where there is more formal social control (more police, secondary schools and healthcare facilities). This pattern can be associated with the supply to drugs in healthcare facilities (stolen drugs) and/or police knowledge of what happens in the area as well as their interventions (police station). The level of explanation attained by the model varies from 15 to 58%. Since problems of heteroscedasticity remained in most models, we suggest for future research inclusion of a categorical variable in the ML–Ghet model—groupwise heteroscedasticity to deal with the problem. The incorporation of new variables into these regression models is essential if their explanatory performance is to be improved. Now we turn to the final conclusions and further recommendations to research and practice.

Conclusions and Recommendations

This study sought to answer recent calls for better knowledge on the situational circumstances in which illicit recreational drugs occur by focusing on cannabis offenses (dealing, possession and use) as recorded to the police in Stockholm, Sweden. The analysis is exploratory and it challenges the current taken for granted ideas about ineffective use of police statistics. Using a specially tailored police recorded database, we learned about the nature of cannabis offenses as they are recorded to the police in a Scandinavian city using spatial analysis techniques and regression models. Our findings show that the police records provide insightful information about a significant share of drug-related activities that was until now unknown in the Swedish context. Results revealed the links between drugs and other offenses in particularly criminogenic areas, the characteristics of the settings and the situational conditions in which cannabis use, possession and/or dealing occur. This study also provides evidence of interlinkages between cannabis and other crimes, opening up for new research questions in criminology and other related disciplines that are now discussed below.

This research shows plenty of evidence of the relationship between particular land uses and crime that are crucial for both research and practice. Cannabis-related offenses (dealing, possession and use) are recorded relatively nearer to bars, restaurants, nightclubs and other particular land uses than they would be by chance. This evidence indicates the importance of specific facilities for crime (in particular, the role of managers and management styles in combating illicit drugs) and also that “something” beyond the common dynamics of routine activity or social disorganization indicators (see e.g., Inlow, 2019) may be at work at these places. That “something” may be linked to mechanisms by which decision-making indirectly influences neighborhood structure and crime levels. Mechanisms triggered by decisions taken by government agencies and private developers, but also by those responsible for local place making. Special focus in interventions should be given to inner-city areas specialized in night life economy and to some of the most crime hidden poor neighbourhoods. Note that regardless of cannabis offenses type, rates are high in inner-city areas of Stockholm but also in some of the most deprived and socially disorganized neighborhoods, often associated with presence of transportation hubs, parks, gas stations, secondary schools. This is a task not for police officers only. Urban planners and architects in particular have a key role on the planning and maintenance of these areas in cooperation with the municipality, transport operators, private stakeholders and not least civil society in general. Previous research also indicated that the layout of certain parks or design of streets invites drug dealing (Felson & Clarke, 1998). Thus, in Sweden, urban planners and architects are frequently working together with local actors, including the police and private sector, in crime prevention schemes (advising managers in apartment complexes and place managers such as stations, parks, libraries, etc.). Using participatory schemes, they may be tackling some of these places where drugs might be sold or consumed (e.g., improving natural surveillance and management in isolated parking lots, dark garages, and secluded corridors, carrying out safety audits). Some of the work carried out by these professionals might be proactive, which means at the planning stages of a residential area.

We also recommend further investigation on the nature of “comfort places” (for example, apartments, garages, basements, but also some commercial uses in residential environments), because they offer a low risk of police intervention but are important in making cannabis (and as our results show, other drugs) available to consumers. On one hand, the role of site managers (managers, landlords, house owners, security guards) in preventing drug storage/delivery in these environments should be further investigated, in particular, in-depth knowledge about the interplay between the design of mixed land use (which include both convergent settings and comfort places), the role of place managers and the approaches of other stakeholders in these areas. On the other hand, it is necessary to know more about the impact of the structure of the local housing market in generating places conducive to crime. In Sweden, rental housing markets are state regulated. However, there is an element of self-regulation by the market through second-third hand leases between non-owners. This rental system creates a lack of control over properties and makes the job of place managers difficult in criminogenic neighbourhoods.

This analysis was impaired by data limitations. First, we acknowledge that unknown share of drugs used in people’s homes or other private environments is ever going to be recorded to the police. For all types of crimes, there will always be a degree of under detection and this affects police records. Secondly, previous research indicates the problem of selection biases in the police statistics (generated by both recording inequalities and police practices) that affect the spatial analyses of the data and lead to biased outputs. However, as this study show, it is important to consider differences in country contexts, and crime types, as police records may also reflect the variability of levels of social control in neighborhoods. In Sweden, more than a third of police records of the cannabis trade in Sweden are reported to the police by residents and not as result of direct police action (The Swedish Police Authority, 2019). Thirdly, we observed that the detection of the cannabis offenses peaks in early evening, and there is some concentration in particular months of the year, but such temporal trends should be considered with caution. Finally, it would be interesting to compare 2019 data with 2020 to observe how COVID-related restrictions and social isolation affected the location of cannabis-related offenses. Crowdsourced data might be an alternative as crime reporting practices changed over the pandemic. Sweden implemented minor stay-at-home orders (still travel with public transport, walk around in parks, keep on living your life with some limitations regarding bars, restaurants and work). Previous research in Sweden showed that the number of reported crimes decreased compared with previous years, especially for property crimes at the very beginning of the pandemic (Ceccato et al., 2022; Gerell et al., 2020) but returned to previous levels by mid-June 2020. Despite these limitations, this exploratory study constitutes the first step in providing a better foundation for future analyses in investigating the situational conditions of cannabis offenses in a Scandinavian context.

Appendix

See Table 3.

Table 3 Characteristics of the dataset

Type of data		Description	Year	Source	Variables in the model	Average	Stand. Deviation
Crime statistics	Cannabis	5005—Dealing/trade of cannabis crime location (*x*, *y*)	2019–2020	Police authority	Rate of trade of cannabis per DeSO per 1000 population	0.726	1.909
		5010—Possession of cannabis crime location (*x*, *y*)			Rate of possession of cannabis per DeSO per 1000 population	3.533	8.308
		5011—Use of cannabis crime location (*x*, *y*)			Rate of use of cannabis per DeSO per 1000 population	1.498	2.814
		5004—Production of cannabis crime location (*x*, *y*)			Rate of cases of production of cannabis per DeSO per 1000 population	0.068	0.327
		Cannabis-related crime locations (*x*, *y*) meaning dealing, possession and use			Rate of cannabis-related crimes per DeSO per 1000 population	3.313	6.559
	Narcotics	Total crimes of narcotics			Rate of narcotic crimes per DeSO per 1000 population	46.761	132.897
Land use variables	ATM	Location (*x*, *y*) of ATMs	2020	Open street maps	Proportion of ATMs per DeSO population	0.189	0.835
	Bar-Restaurant-Nightclub	Location (*x*, *y*) of bars, nightclubs and restaurants	2020	Open street maps	Proportion of Bar-restaurant-nightclub per DeSO population	2.797	7.536
	Lights	Location (*x*, *y*) of lights on the street	2020	Open geo-data	Proportion of Lighting per DeSO population	204.650	295.667
	High School	Location (*x*, *y*) of high schools	2020	Open geo-data	Proportion of High schools per DeSO population	0.187	0.689
	Health facility	Location (*x*, *y*) of hospitals with emergency room	2020		Proportion of Hospital per DeSO population	0.003	0.060
	Library	Location (*x*, *y*) of libraries	2020	Open street maps	Proportion of Library per DeSO population	0.073	0.300
	Police Station	Location (*x*, *y*) of police stations	2020		Proportion of Police stations per DeSO population	0.022	0.190
	Public toilet	Location (*x*, *y*) of public toilets	2020	Open geo-data	Proportion of Toilet per DeSO population	0.181	0.475
	Gas station	Location (*x*, *y*) of gas stations in Stockholm city	2020	Open street maps	Proportion of Gas stations per DeSO population	0.084	0.343
	Parking lot	Location (*x*, *y*) of parking areas	2020	Open geo-data	Proportion of Parking areas per DeSO population	0.086	0.479
	Transport stations _	Location (*x*, *y*) of trains, subway, and bus stations	2020	Open geo-data	Proportion of Transport stations per DeSO population	0.220	0.561
	Parks	Location (*x*, *y*) of green park areas	2020	Open geo-data	Proportion of Parks per DeSO population	1.113	1.110

Table 3 (continued)

Type of data		Description	Year	Source	Variables in the model	Average	Stand. Deviation
	Open Drug Market	Location (*x*, *y*) of ODM (cannabis specialized markets excluded) but all ODM have cannabis	2020	Malmö University	Proportion of ODM (specialized cannabis markets excluded) per DeSO population	0.047	0.252
	Periphery	3 km radius around city center	2021	Own calculation	Dummy variable for distance of 3 km from city center		
Demographic and socioeconomic	Young male	The count of male pop. (ages 15–24) per DeSo	2019	SCB	Proportion of male pop. (age 15–24) per DeSO population	90.933	44.827
	Unemployment rate	Count of unemployed population per DeSO	2019	SCB	Proportion of unemployed population by DeSO workforce	229.335	122.751
	Swedish citizens	Count of population with Swedish citizenship per DeSO	2019	SCB	Proportion of population with Swedish citizenship per DeSO population	1580.275	355.842
	Non-Swedish citizens	Count of population with no Swedish citizenship DeSO	2019	SCB	Proportion of population with no Swedish citizenship per DeSO population	207.395	173.952
	Single parent families	Count of households with one parent per DeSO	2019	SCB	Proportion of single parent households per total households per DeSO	70.538	27.239
	Social allowance	The average of social allowance per DeSO	2018	SCB	The average social allowance per DeSO for population older than 20 years old	2910.845	1767.770
	Income	The average income per DeSO	2018	SCB	The average income per DeSo for population older than 20 years old	385,938 419	112,288.727
	Non-Swedish born	Count of population born abroad per DeSO	2019	SCB	Proportion of population born abroad per DeSO population	457.183	320.846
	Swedish born	Count of population born in Sweden per DeSO	2019	SCB	Proportion of population born in Sweden per DeSO population	1333.391	361.043
	Multifamily house	Count of population per multifamily houses per DeSO	2019	SCB	Proportion of multifamily houses population per DeSO population	1412.306	607.428
	Single-family house	Count of population per single family houses per DeSO	2019	SCB	Proportion of single-family houses population per DeSO population	260.805	523.962
	Rental house	Count of rental houses per DeSO	2019	SCB	Proportion of rented houses per total houses per DeSO	389.542	270.101

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Data Availability Not applicable.

Declarations

Conflict of interest All authors declare that they have no conflicts of interest.

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References

Anselin, L. (2014). *GeoDa 1.6.6-1* (USA Patent No. G. C. f. G. A. a. Computation. https://geodacenter.asu.edu/

Baller, R. D., Anselin, L., Messner, S. F., Deane, G., & Hawkins, D. F. (2001). Structural covariates of U.S. county homicides rates: Incorporating spatial effects. *Criminology, 39*(3), 561–588. https://doi.org/10.1111/j.1745-9125.2001.tb00933.x

Barnum, J. D., Campbell, W. L., Trocchio, S., Caplan, J. M., & Kennedy, L. W. (2016). Examining the environmental characteristics of drug dealing locations. *Crime & Delinquency, 63*(13), 1731–1756. https://doi.org/10.1177/0011128716649735

Bernasco, W., & Jacques, S. (2015). Where do dealers solicit customers and sell them drugs? A micro-level multiple method study. *Journal of Contemporary Criminal Justice, 31*(4), 376–408.

Brantingham, P. L., & Brantingham, P. J. (1993). Nodes, paths and edges: Considerations on the complexity of crime and the physical environment. *Journal of Environmental Psychology, 13*(1), 3–28. https://doi.org/10.1016/S0272-4944(05)80212-9

Brantingham, P., & Brantingham, P. (1995a). Criminality of place—Crime generators and crime attractors [Article]. *European Journal on Criminal Policy and Research, 3*(3), 5–26. https://doi.org/10.1007/BF02242925

Brantingham, P., & Brantingham, P. (1995b). Criminality of place: Crime generators and crime attractors. *European Journal on Criminal Policy and Research, 3*, 1–26.

Ceccato, V., Kahn, T., Herrmann, C., & Östlund, A. (2022). Pandemic restrictions and spatiotemporal crime patterns in New York, São Paulo, and Stockholm. *Journal of Contemporary Criminal Justice, 38*(1), 120–149.

Cohen, L. E., & Felson, M. (1979). Social change and crime rate trends: A routine activity approach. *American Sociological Review, 44*, 588–608.

Contreras, C. (2017). A block-level analysis of medical marijuana dispensaries and crime in the city of Los Angeles. *Justice Quarterly, 34*(6), 1069–1095. https://doi.org/10.1080/07418825.2016.1270346

Eck, J. (1995). A general model of the gegraphy of illicit retail marketplaces. In J. E. Eck & D. Weisburd (Eds.), *Crime and place* (pp. 67–93). Criminal Justice.

Eck, J. E., Clarke, R., & Guerette, R. (2007). Risky facilities: crime concentration in homogeneous sets of establishments and facilities. *Crime Prevention Studies, 21*, 225–264.

EMCDDA, European Monitoring Centre for Drugs and Drug Addiction (2017). *Sweden Country Drug Report 2017*. https://www.emcdda.europa.eu/system/files/publications/4504/TD0116923ENN.pdf

Felson, M., & Clarke, R. V. (1998). *Opportunity makes the thief: practical theory for crime prevention Police research series, Issue.*

Gerell, M., Kardell, J., & Kindgren, J. (2020). Minor covid-19 association with crime in Sweden, a ten week follow up. *SocArXiv*. https://doi.org/10.31235/osf.io/w7gka

Gerell, M., Sturup, J., Magnusson, M.-M., Nilvall, K., Khoshnood, A., & Rostami, A. (2021). Open drug markets, vulnerable neighbourhoods and gun violence in two Swedish cities. *Journal of Policing, Intelligence and Counter Terrorism, 16*, 1–22.

Hammer, M. (2011). *Crime places of comfort. Unpublished Masters Demonstration Project paper*. University of Cincinnati, School of Criminal Justice.

Herold, M., & Herold, T. D. (2017). Understanding crime-place networks. In: 27thAnnual Problem-Oriented Policing Conference October 2–4, Houston, Texas. https://popcenter.asu.edu/sites/default/files/understanding_crime-place_networks_tamara_madensen_maris_herold.pdf

Hughes, L. A., Schaible, L. M., & Jimmerson, K. (2020). Marijuana dispensaries and neighborhood crime and disorder in Denver, Colorado. *Justice Quarterly, 37*(3), 461–485. https://doi.org/10.1080/07418825.2019.1567807

Inlow, A. R. (2019). Does land use matter? Understanding homicide counts beyond the effects of social disorganization. *Homicide Studies, 24*(4), 311–332. https://doi.org/10.1177/1088767919884672

Kinney, J. B., Brantingham, P. L., Wuschke, K., Kirk, M. G., & Brantingham, P. J. (2008). Crime attractors, generators and detractors: land use and urban crime opportunities. *Built Environment (1978), 34*(1), 62–74.

Kornhauser, R. (1978). *Social sources of delinquency*. University of Chicago Press.

Kubrin, C. E., & Weitzer, R. (2003). New directions in social disorganization theory. *Journal of Research in Crime and Delinquency, 40*(4), 374–402. https://doi.org/10.1177/0022427803256238

Lu, R., Willits, D., Stohr, M. K., Makin, D., Snyder, J., Lovrich, N., Meize, M., Stanton, D., Wu, G., & Hemmens, C. (2021). The cannabis effect on crime: time-series analysis of crime in Colorado and Washington State. *Justice Quarterly, 38*(4), 565–595. https://doi.org/10.1080/07418825.2019.1666903

Magnusson, M. M. (2020). Mapping open drug scenes (ODS). In M. V. Ceccato & N. Nalla (Eds.), *Crime and fear in public places: Towards safe, inclusive and sustainable cities* (pp. 305–325). Routledge.

McCord, E. S., & Ratcliffe, J. H. (2007). A micro-spatial analysis of the demographic and criminogenic environment of drug markets in Philadelphia [Review]. *Australian and New Zealand Journal of Criminology, 40*(1), 43–63. https://doi.org/10.1375/acri.40.1.43

Rafiqui, P. S. (2010). Varieties of capitalism and local outcomes: A Swedish case study. *European Urban and Regional Studies, 17*(3), 309–329. https://doi.org/10.1177/0969776409350792

Rengert, G. F. (1996). *The geography of illegal drugs*. Routledge.

Robinson, J. B., & Rengert, G. F. (2006). Illegal drug markets: The geographic perspective and crime propensity. *Western Criminology Review, 7*, 20–32.

Sampson, R. J., Morenoff, J. D., & Felton, E. (1999). Beyond social capital: Spatial dynamics of collective efficacy for children. *American Sociological Review*, *64*(5), 633–660. https://doi.org/10.2307/2657367

Sandberg, S. (2012). The importance of culture for cannabis markets: Towards an economic sociology of illegal drug markets. *The British Journal of Criminology, 52*(6), 1133–1151. https://doi.org/10.1093/bjc/azs031

Shaw, C. R., & McKay, H. D. (1942). *Juvenile delinquency and urban areas*. University of Chicago Press.

Statistics Sweden. (2020). Folkmängd efter region, civilstånd, ålder, kön och år. Statistics Sweden. Retrieved 25 February 2020.

Stockholms stad. (2023). Statistik och fakta om Stockholm. Retrieved from https://start.stockholm/om-stockholms-stad/utredningar-statistik-och-fakta/statistik/

The Swedish Police Authority. (2019). *Statisk om drograpportering*. The National Forensic Center.

Uittenbogaard, A. C., & Ceccato, V. (2012). Space-time clusters of crime in Stockholm. *Review of European Studies, 4*, 148–156.

van Ooyen-Houben, M., & Kleemans, E. (2015). Drug policy: The "Dutch model." *Crime and Justice, 44*(1), 165–226.

Wilhelmsson, M., Ceccato, V., & Gerell, M. (2021). *What effect does gun-related violence have on the attractiveness of a residential area?* The Case of Stockholm.

Zakrzewski, W. J., Wheeler, A. P., & Thompson, A. J. (2020). Cannabis in the capital: Exploring the spatial association between medical marijuana dispensaries and crime. *Journal of Crime and Justice, 43*(1), 1–15. https://doi.org/10.1080/0735648X.2019.1582351