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Defecation, littering and other acts of public disturbance in pandemic times – A study of a Scandinavian city

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ABSTRACT

The spatiotemporal patterns of public disturbance acts are investigated in Stockholm, the capital of Sweden. Using crowdsourced data, the number of records is compared 15 months before and after the stay-at-home measures of the COVID-19 pandemic, controlling for seasonal trends. Poisson-Gamma-CAR regression models are implemented to assess the potential impact of land use on the spatial distribution of public disturbance acts, accounting for the effect of pandemic restrictions and differences in neighborhood context. Findings show that, with the exception of abandoned vehicles, there was a significant increase in records of public disturbance after the 2020 stay-at-home pandemic restrictions. Parks, transport hubs and less importantly, schools were significantly associated with public disturbances, controlling for neighborhood characteristics and reporting practices. Recommendations are made for research and practice.

1. Introduction

"A man might urinate in a graffiti-covered alleyway, but would not dream of doing so in the manicured mews outside an old folk's home." (Montgomery, 2013, p. 160).

Urban life is a series of performances in which individuals continually manage impressions of themselves in which public spaces function as a stage for such performances (Goffman, 1959). There are particular behaviors that are likely to cause 'nuisance or annoyance' and 'distress' both to the public and police and may be indicative of more serious problems (Halford et al., 2022). Wilson and Kelling (1982) suggested that physical deterioration and acts of public disorder (e.g., vandalism, abandoned cars) function as symbols of the extent to which a place is in decline. It is a sign of poor social control of the community which, in turn, attracts more nuisance and crime (Skogan, 1990). However, perceptions of 'disorder' are not the same as 'actual disorder' and reporting practices of these acts vary from place to place and may reflect and perpetuate patterns of social segregation (Taylor, 2001; Taylor, 2006). Despite the fact that there is a vast body of research showing the effect of neighborhood characteristics on crime and acts of public disturbance (e.g. Jeffery, 1971; Kornhauser, 1978; Newman, 1972; Shaw & McKay, 1942; Wilson & Kelling, 1982), the role of particular land uses in shaping such performances as acts of public disturbances is more limited (but see e.g. Inlow, 2019; Stucky, 2017).

The pandemic of 2020 presented an opportunity to examine how different types of land use may have affected people's behavior after controlling for socio-economic characteristics and the reporting of crime to the police. With the restrictions imposed by the COVID-19 pandemic, changes in the amount of time spent in public spaces because of the pandemic would have been expected to affect social interactions in different parts of the city which, in turn, could have impacted public disturbances and people's capacity to exercise social control. In England and Wales, anti-social behavior increased during the early months of the pandemic with the majority of the increase related to breaches of stay-at-home orders (Halford et al., 2022). However, Sweden did not implement an all-encompassing lockdown or curfew such as in China for example, but only restrictions and recommendations on how to use certain spaces. People were advised to stay at home with limited movements and to avoid social interactions.

The aim of this study is to investigate the level and the distribution of public disturbances acts in Stockholm before and after the recommended stay-at-home measures of the COVID-19 pandemic. Using crowdsourced data captured via websites and mobile phones, temporal and spatial patterns are examined for a number of public nuisance behaviors and the extent to which land use variables were associated with these behaviors. In order to check potential differences in reporting

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practices during the period of analysis, a visual inspection of the levels of disturbance from crowdsourced data and those recorded by the police was carried out. Then, the number of crowdsourced records was compared before and after the stay-at-home measures, controlling for seasonal trends. Finally, Poisson-Gamma-CAR regression models were implemented to assess the potential impact of land use on the spatial distribution of public disturbance acts, controlling for the effect of pandemic restrictions and differences in neighborhood context.

Stockholm constitutes an interesting case study because the city as the rest of the country had mild stay-at-home orders with businesses and primary schools open but most secondary schools and universities closed. Even though Sweden adopted different policies from those of other European countries, evaluations with mobile phone data suggested that Swedes stayed home at rates similar to their European neighbors. This may have affected people's routine activities, including patterns of littering and other public disturbances (Vogel, 2020). Using Twitter data and an online map survey, one study showed that COVID-19 restrictions impacted the use of different locations, services and amenities in Stockholm (Legeby et al. (2022).

Since police data were unreliable at the beginning of the pandemic (see e.g. Zhang et al., 2020), crowdsourced data constitute an alternative way of capturing acts of public disturbance during the pandemic. First, they are recorded by individuals. Second, these records are heterogeneous in nature and might reflect changes in population by area during the pandemic (see e.g. Chancellor et al., 2021). Third, because people spent more time at home, more reports could be filed of minor events that rarely are reported to the police, such as litter, abandoned cars or animal feces regardless if these behaviors were actually increasing or not. Previous studies based on police statistics did not provide a comprehensive picture of public disorder and anti-social behavior because a large share of reports were primarily due to breaches of COVID regulations (Zhang et al., 2020).

2. Theoretical background

2.1. Performances in public spaces and acts of public disturbances

All other things being equal, individuals strive to give the best possible appearance in public places (Goffman (1959). These performances are conscious responses to an individual's stage setting—a socially situated self, as Goffman defines it. Individuals are thought "to strive to give the best possible appearance to a public audience" (Gardner, 1990, p. 314). But do they succeed? The answer depends on whether and where it is acceptable for these acts to be socially performed and on when and by whom they are performed. The social acceptance of public disturbance acts vary based on who performs such acts (e.g., age, gender), where (e.g., behind a bush, open street), when (e.g., morning rush hours, nighttime, summer) and what (e.g., bikes, cars, urination, defecation).

While human excrement is hidden from view in the waste pipe as soon as it leaves the human body, dog feces is the most visible type of excrement that humans encounter in everyday life, especially in public spaces (Gross, 2015). The acceptance of urination in public varies over the day and has historically been both age and gender-dependent (Eldridge, 2010), as "a child who urinates in the middle of the day in a park is more accepted than a young man who urinates in the middle of the night in an alley" (Eldridge, 2010:p.40–41). Norms of behavior acceptance apply to particular objects but not to all. For example, abandonment or nuisance parking of a bike are more acceptable than those of a car and can be indications of spiral of decay (Langton et al., 2021; Skogan, 1990). Graffiti may be considered a piece of art on a wall in a park but can be punishable by law in a sports hall as a vandalism act (Gómez, 1992). These performances are said to be influenced by local physical and social environmental cues and norms (Wilson & Kelling, 1982). Certain settings are 'better suited' for misbehavior and criminal opportunities than others regardless of their overall societal acceptance.

Reporting practices of these public disturbance acts vary from place to place and may reflect and perpetuate patterns of social segregation. Previous research showed that as the concentration of minority populations and poverty increases, residents perceive heightened disorder, even after individual characteristics and neighborhood conditions are taken into account (Sampson, 2009). Disorder and acts of public disturbance could have harmful consequences for individual health and personal well-being, generating self-reinforcing processes that could perpetuate racial inequality (Sampson & Raudenbush, 2004).

2.2. The role of land use and reporting public disturbance

Acts of public disturbance are influenced by different land uses in the urban fabric. Brantingham and Brantingham (1995, p. 3) suggest "urban settings that create crime and fear are human constructions...homes, parks, factories, transport systems...the ways in which we assemble these large building blocks of routine activity into the urban cloth can have an enormous impact on our fear levels and on the quantities, types and timing of crimes we suffer".

Indeed, some land uses are conducive to offenders because they contain attractive targets, and are without the presence of guardians, place managers or other local controllers. They have a heightened chance for criminal activity (Cohen & Felson, 1979). Transportation hubs, parks and schools are examples of crime generators because of the large number of crime or disorder events they attract due principally to the large number users (Brantingham & Brantingham, 1995). In a recent review of research over several decades, Inlow (2019) showed a variety of land uses that affect crime in addition to other criminogenic conditions such as social control indicators and economic disadvantage. The role of social ties on social control and on neighborhood criminogenic conditions vary by types of offences but also across neighborhood types (Warner & Rountree, 1997).

Underreporting of minor offences to the police reflect looser local social ties but as Taylor argues, perceptions of disorder are not the same thing as actual disorder (Taylor, 2001, 2006). For example, the degree that people report incidents of public disturbance appears to be associated with their capacity "to see" minorities (Wickes et al., 2013). In other words, residents in socially cohesive neighborhoods not only report less disorder, but also, perceive fewer minorities when compared with residents living in less socially cohesive neighborhoods. Thus, as previously mentioned, this may generate self-reinforcing processes that could perpetuate urban racial inequality (Sampson & Raudenbush, 2004).

2.3. The pandemic and changes in routine activity

Despite the mild stay at home restrictions, habits and patterns of activities changed in Stockholm during COVID-19. Legeby et al. (2022) showed that activities in parks and green areas increased and also around basic services, interstitial spaces (small local squares and other less-specifically programmed areas) and close to outdoor serving locations. However, it is not known how the intensification of activities in these spaces translated into an increase in acts of public disturbance, despite evidence that the pandemic affected crime levels (Ceccato et al., 2022; Gerell et al., 2020).

There is a large amount of research into changes in crime levels and geography during the COVID-19 pandemic. Recent studies of North American and European cities showed that the pandemic altered the volume and distribution of crime, in particular, violence (e.g. Gerell et al., 2020; Mohler et al., 2020; Rosenfeld & Lopez, 2020). However, there have been few studies on how the pandemic affected acts of public disturbance. For example, in the UK, contrary to expectations that there would be a decrease in the occurrence of litter, rowdiness in public places, property damage, and abandoned cars, there were significant increases (Halford et al., 2022). In some North American cities, vandalism, acts of social disorder, and reported violence increased in some large cities (e.g., Rosenfeld & Lopez, 2020; Zhang et al., 2020).

In Sweden, for instance, even under weaker pandemic restrictions, the number of reported crimes decreased compared with previous years, especially for property crimes at the beginning of the pandemic (see Gerell et al., 2020; Ceccato et al., 2022). In particular, there was evidence of a reshuffle of a few crime concentrations and a few hotspots shrunk in some of inner-city districts in Stockholm while new ones popped up elsewhere. However, this evidence relied on police recorded crime and disregarded people's capacity to report minor events of public disturbance such as littering, physical damage, abandoned cars, urination or defecation by humans and animals.

2.4. Crowdsourced data as alternative records of public disturbance

Recent research identified several advantages in using crowdsourced data to not only capture nature of fear of crime but also to associate people's feelings with elements of the environmental backcloth such as incivilities, crime, and disorder (Solymosi et al., 2015, p. 198). There are also problems in using crowdsourced data. Such data tends to be affected by participation inequality (self-selection bias and repeated participation by motivated individuals), sample attrition, and under-representation of certain areas and times (see a review in Solymosi et al. (2020)). Studies in the UK and in Sweden demonstrated the potential 'over-influence' of super-contributors, people that are responsible for a large share of complaints (Ceccato, 2019; Engström & Kronkvist, 2021; Hoeben et al., 2018). Moreover, it is important to recognize "subjective bias" in individual reports in what gets reported and what is not (Solymosi et al., 2017). Despite these limitations, crowdsourced data can be a valid information together with other data sources in urban planning.

3. Research questions

Empirical studies have typically examined changes of crime in levels and geography from pre- to post-pandemic, rather than changes in public disturbances. To date, no studies have examined the relationship of neighborhood characteristics to reports of public disturbances. To address some of this gap, we turn to our empirical study in a Scandinavian context using a crowdsourced database to answer the following questions:

RQ1 - *Were there significant differences in the number of recorded acts of public disturbance before and after the stay-at-home orders?"*

RQ2 – *Controlling for seasonal trends, which acts of public disturbance changed the most because of the pandemic?*

RQ3 – *Was there a shift in the geography of public disturbance acts during the pandemic?*

RQ4 – *Were there particular land uses (transportation hubs, schools, bars) that affect the geography of public disturbances after controlling for other neighborhood characteristics?*

4. The study area

Stockholm is the capital of Sweden and the most populous city in Scandinavia. The study area is limited to the municipality of Stockholm, which had approximately 980,000 persons in 2021. 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. Stockholm has more than 1000 parks and green spaces and nearly 300 schools spread all over the municipality. On average, the percentage of residents who are foreign born is 34 % but in some suburban neighborhoods the proportion exceeds 90 %. In these neighborhoods, general unemployment rates are three times higher and average income lower in comparison to the rest of the city (Stockholms stad, 2023).

5. Data and methods

5.1. Data

The study combines several types of data: crowdsourced data, police recorded statistics, land-use data, demographic and socioeconomic data, and geographical data over Stockholm municipality (Appendix A1). For acts of public disturbance, we used crowdsourced data from *TyckaTill* which is a platform that helps people in Stockholm municipality to inform the local authority of problems needing attention, such as littering, inappropriate parking or abandoned vehicles, urination and defecation in public places, graffiti or damage of all types (https://trafik.stockholm/tyck-till/ and App, https://trafik.stockholm/tyck-till/tyck-till-med-mobilen/). Citizens can also make *suggestions* or also *praise* a service. Records are crowd feed and are associated with geographical coordinates. For this study, we used only records of disturbance *complaints* from 2019 to 2021. Physical damage to a sign, broken lamps, dog feces, littering, abandoned cars and poorly parked bikes were typical examples of these complaints. We focused on complaints involving public disturbances. Overall, we found 86,767 records that met this criteria. We removed duplicate records or records reported multiple times within a short time frame since they were likely to be the same incident. The analytical code is made available over Github: (https://github.com/parishwadomkar/Incivilities-analysis-for-Stockholm.git). Additionally, the website is administered to discourage users from false or multiple reporting.

Although the App started to be used in 2017, we selected data from 2019 because it was when the App became widely used by the population. The choice of time window was also limited by the availability of police-recorded data. We acknowledge that a longer time series could potentially provide more reliable forecasting of counterfactuals but we considered the selected period as sufficient to capture the changes in reports (e.g., Hodgkinson et al. (2018), Langton et al. (2021), Gerell et al. (2020)).

Land-use data was gathered using Open Street maps and the Open Data Portal of Stockholm City and included location of stations/bus stations, green areas/parks, bars, schools and a measure of centrality. The selection of these variables reflects the importance of each land use as crime attractors and/or generators (Brantingham & Brantingham, 1995; Inlow, 2019). We selected several socio-demographic variables and created several criminogenic indicators from them including proportion of young male population, unemployment rate, household composition, foreign population and average income per *Basområde*.

Vandalism cases reported to the Stockholm Police Authority from 2019 to 2021 were used as an indicator of the prevalence of vandalism in each area. While this measure is not a direct independent indicator of social reporting practices, it can provide some insight into the level of crime and disorder in each area. Police recorded vandalism is an independent measure of social disturbance but also indicates how accessible police services were in each area during the study period. The unit of analysis is *Basområde* which is the smallest geographical unit of analysis in Stockholm ($N = 416$). It is commonly used to designate neighborhoods since they encapsulate the size, area and population of existing neighborhoods.

5.2. Methods

5.2.1. Preparation of the data

The incidents data covered a total period of about 30 months, split into 442 days before and after the stay-at-home orders (18th March 2020). The period Before Pandemic (BP) contains 42,110 incidents for 442 days from 1 January 2019 to 18 March 2020, while the Post Pandemic (PP) contains 53,152 incidents covering 442 days from 19 March 2020 to 4 June 2021. This selection would allow a temporal comparison between the incidents categories BP and PP. Note that to reduce measurement error, we implemented data cleaning measures such as filtering out reports that did not meet our criteria, removing duplicates, and correcting inaccuracies.

5.2.2. Controlling for seasonal trends – SARIMAX Models

We forecast the PP records using seasonal autoregressive integrated moving average (SARIMAX) models and tested the temporal regularity between the two periods (BP-PP) controlling for seasonal trends. First, a general temporal trend was identified followed by a seasonality trend for the public disturbance counts and by type of disturbances. Incident counts were aggregated to weekly counts to enhance the trends. Since the predictions are based on seasonality and autoregressive trends only from the before pandemic (BP) period, the predictions indicate a variation from the norm for the after pandemic (PP) period. The accuracy to these forecasts was calculated as the 'Mean Absolute Percent Error (MAPE)'. For each predicted data point, the absolute difference from the corresponding test point was calculated, and then divided by the test point. The symmetric MAPE (sMAPE) was also calculated as the average across all forecasts made for a given time horizon. Unlike MAPE which has no limits, sMAPE fluctuates between 0 % and 100 %. See Appendix A2 for more details of the steps applied to an example (graffiti and physical damage).

5.2.3. Mapping shifts in geography BP and PP

In order to detect potential shifts in the geography of public disturbance acts, we used GIS to identify concentrations of records using kernel density estimation (Silverman, 1986). The density is calculated partly based on the number of points in a location, but also weighted by points in nearby locations. Each raster cell value is the sum of the contributions from all sample points that lie within a specified distance from the center of the cell and is weighted by the kernel density function. A threshold distance of 20 meters was used to generate the kernel density estimate (heatmaps).

5.2.4. Modelling public disturbances

Using GIS, public disturbance incidents were allocated to each of the 419 Basområde zones in Stockholm. For each Basområde, we created two data records, one for the 'before stay-at-home' period (BP) and for the 'post stay-at-home' period (PP). Therefore, there were a total of 838 geographical zones.

The number of disturbances by type were tested for changes between the BP and PP periods, controlling for land uses and socio-economic characteristics. The formal model is a Poisson-Gamma-Conditional Autoregressive (CAR) function. Formally, the number of disturbance (by type) per Basområde is assumed to be Poisson distributed and independent, and has the form:

$$y_i|\lambda_i \sim Poisson(\lambda_i) \tag{1}$$

with the mean, λ_i, organized as:

$$\lambda_i = exp\left(X_i^T\beta + \epsilon_i + \phi_i\right) \tag{2}$$

where exp() is an exponential function, β_i is a vector of unknown coefficients for the k covariates plus an intercept, ϕ_i is a spatial random effect and is estimated using a Conditional Autoregressive (CAR) function (Besag, 1974), and ϵ_i is the model error independent of all covariates, assumed to follow a gamma distribution with mean equal to 1 and a variance equal to $\tau = \frac{1}{\omega}$ where ω is a parameter that is >0 (Lord, 2006).

This function has to be estimated by the Markov Chain Monte Carlo (MCMC) method and we used the CrimeStat IV software to test the model (Levine et al., 2013).[1] Distance decay is estimated with a negative exponential:

$$w_{ij} = e^{-\alpha d_{ij}} \tag{3}$$

where 'i' is the Basområde for which we are calculating the weight, 'j' is another Basområde, 'd_{ij}' is the distance between the two Basområdes, and α as a coefficient. Thus, every other Basområde affects the weight for Basområde "i" but with closer Basområdes having a much stronger weight.

Since the chain takes time to achieve a stable state ('equilibrium'), the initial estimates were discarded ('burn in') and the results calculated on the remaining samples. The MCMC chain was run for 25,000 samples with the initial 5000 'burn in' samples being discarded. Significance levels based on credible intervals are shown in the results. In the selection of variables for the final model, only significant variables with tolerances >0.7 were kept to avoid excess multicollinearity (Goldberger, 1991). To avoid problems of multicollinearity in the regression model, a few variables were excluded. For example, we kept unemployment and excluded proportion of foreign born, which was strongly correlated with unemployment. Another example is we kept distance to city center but excluded proportion of bars, which was highly correlated with distance.

6. Results

Table 1 shows the number of public disturbance acts by type, both before (BP) and after the stay-at-home orders (PP).

Graffiti and physical damage together with littering composed the majority (92 %) of the events of public disturbance in Stockholm. Urination or defecation by animals or humans constituted 4 % of the events followed by poorly parked motorbikes and poor bike parking (3 %) and abandoned cars (1 %).

6.1. Temporal variation of records of public disturbance

Fig. 1 shows the percentage of public disturbances by type covering 442 days before and after the stay-at-home orders were implemented in Sweden. Note that there were seasonal variations in the records for all types of incidents (less so for graffiti and physical damage) with peaks in the hotter months of the year, June, July and August. Although police official records of vandalism include a variety offence that are similar to those collected by crowdsourced data (physical damage to public and private properties, such as walls, buildings, but also graffiti and littering, abandoned cars, bikes, for a detailed description, see Appendix 1), Fig. 1 shows that the acts of vandalism reported to the police slightly differ from those reported by the population using mobile phones and the Internet. Therefore, in this analysis we use police records as a benchmark and further explore the nature of public disturbance collected by crowdsourced data.

We assessed differences in the number of records before and after the stay-at-home orders in two ways. First, the total number of records before and after were examined. Second, the variation before and after the stay-at-home orders were examined controlling for seasonal trends using the SARIMAX model. Table 2 indicates that there were significant statistical differences between the amount of public disturbance before (BP) and after (PP) the pandemic stay-at-home orders, varying by type of

Table 1
Public disturbance acts: Before (BP) & After (PP) stay-at-home orders.

Main categories	Counts BP	Counts PP	Total
Urine & defecation	1643	1938	3581
Littering	16,850	22,366	39,216
Graffiti & physical damage	21,386	26,656	48,042
Abandoned cars	750	670	1420
Poor bike parking	1481	1522	3003
Total	42,110	53,152	95,262

[1] Note that we also ran individual models for BP and PP but the significant variables were the same for both sets of data in three out of five models, and only one variable differed in PP compared with BP models in two out of five models. Model results are available on request.

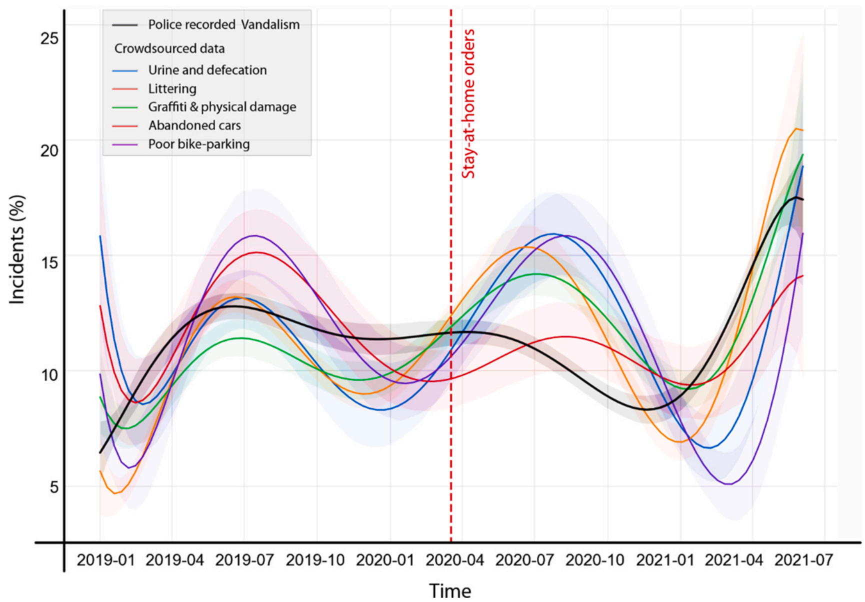


Fig. 1. Temporal variation of records of public disturbance acts reported by the population using *TyckaTill*, in Stockholm (in color) from Stockholm municipality 2019–2021 and police recorded vandalism (black line), from Stockholm Police Headquarters, 2019–2021.

Table 2
Records of public disturbance acts BP and PP.

	Factor	Mean	Std. deviation	Counts	t-value	p-value[a]
Urine & defecation	BP	3.55	2.806	1387	−2.007	0.045
	PP	3.96	2.919	1567		
Littering	BP	33.46	13.770	14,511	−7.423	<0.001
	PP	43.17	21.961	18,599		
Graffiti & physical damage	BP	48.96	23.403	21,139	−5.945	<0.001
	PP	60.05	28.659	26,438		
Abandoned cars	BP	1.63	1.436	700	2.407	0.016
	PP	1.41	1.209	634		
Poor bike parking	BP	2.07	1.920	885	−0.233	0.816
	PP	2.10	1.931	907		
Total	BP	89.66	30.69	38,622	−7.816	<0.001

[a] Values refer to the two-sided p (equality of means).

disturbance. With the exception of abandoned cars (which decreased), there was a significant increase in records for all other types of public disturbance.

In order to control for seasonal trends, we forecast the PP records using the SARIMAX model and tested the temporal regularity between the two periods (BP-PP).

Table 3 shows the variation in the total counts post pandemic period from types of public disturbance acts. The accuracy of these forecasts is calculated derived as the 'Mean Absolute Percent Error (MAPE)' for each category of public disturbance acts. Only 26 % variation was found for graffiti and physical damage but >60 % for urination and defecation (see also a major increase in poor bike parking). Abandoned vehicles and poor bike parking showed low temporal regularity between the two periods together with records urination and defecation.

Table 3
Mean Absolute Percentage Error (MAPE) and sMAPE statistics for forecasts.

Category	MAPE	sMAPE
Urination and defecation	69.39 %	60.20 %
Littering	37.08 %	34.84 %
Grafitti and physical damage	26.09 %	25.55 %
Abandoned cars	47.83 %	45.97 %
Poor bike parking	56.50 %	51.22 %

6.2. Geography of public disturbance and BP and PP spatial shifts

Public disturbances reported by the population between 2019 and 2021 generally show a concentrated pattern around inner-city areas. But there are some exceptions. Fig. 2 illustrates differences in the geography of two types of public disturbance acts: *urination and defecation* of humans and animals (mostly dog feces but includes also human excrements) and of abandonment of vehicles. While records of urination and defecation show a large cluster where the CBD is located (reaching an area of radius of about 4.5 km from the city center), the cluster of abandoned cars is peripheral, spreading out towards the outskirts in the West and South.

The resulting BP and PP maps show that most acts of public disturbance were spatially stable and were concentrated in inner-city areas of Stockholm, even after the pandemic restrictions. Fig. 3(a) shows an example of this stable geography for urination/defecation. A similar stable pattern was found for littering (Fig. 3(d)) and graffiti and physical damage (Fig. 3(e)). On the other hand, poorly parked bikes/scooters and abandoned vehicles show a scattered pattern, especially near the underground system (Fig. 3(b) and (c)). Note that for abandoned cars, there was a significant reduction in levels between before and after the pandemic restrictions. In addition to the Northwest hotspot (Spånga-testa-Rinkeby), two areas turned into hotspots on the Northwest (Hässelby-Vällingby and) and Southwest of the city (Skärholmen). They all contain commercial and entertainment land uses and are known criminogenic areas (Ceccato et al., 2023).

Second, reported incidents of littering, graffiti and physical damage did not shift towards the peripheral areas of the city where most people live (Fig. 3(d) and (e)). For abandoned cars, new concentrations appeared both in the outskirts and in the inner-city areas of the municipality. For poor bike parking, the cluster increased in size but remained concentrated in the inner-city.

6.3. Modelling acts of public disturbances and criminogenic land use

To better understand the underlying dynamics associated with these concentrations and types of environments in Stockholm, a series of models were run to assess the value of specific land uses controlling for other characteristics of neighborhoods at the Basområde level. The land uses selected were those that have been shown to be associated with

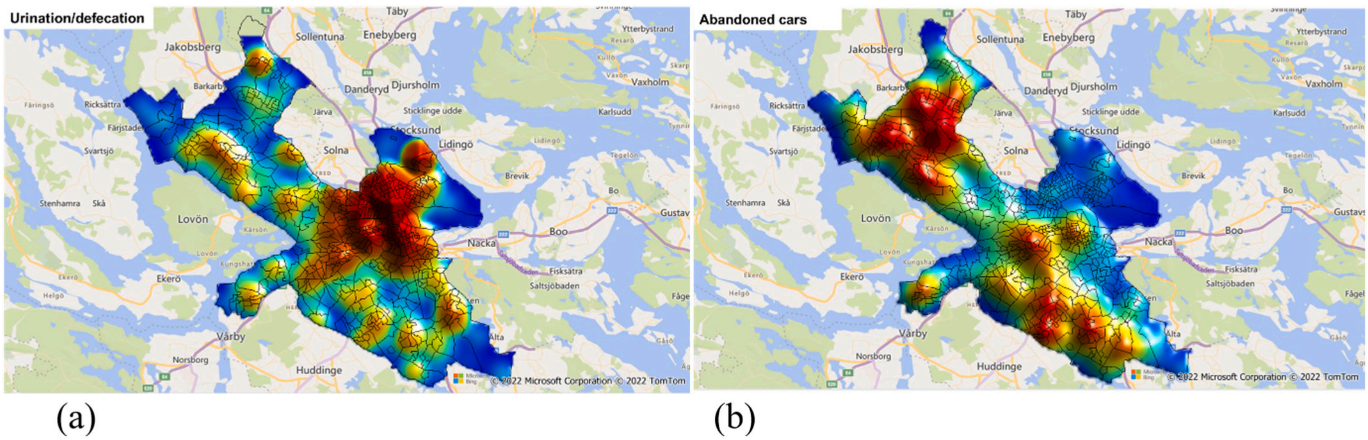


Fig. 2. Spatial concentrations of (a) urination/defecation and (b) abandoned cars in Stockholm, 2019–2021.

crime in other studies.

The results show that all of the selected land use variables were significant in explaining the spatial distribution of public disturbances, in particular green areas/parks and public transportation hubs (Table 4). The proportion of green areas/parks were significant in four out of five models (the only exception was for abandoned cars) while transportation hubs were significant in three out of five models, for abandoned cars, urination/defecation and poor bike parking. The proportion of schools was positive and significant only for littering. All these land use variables were positively associated with acts of public disturbance, the only exception was for abandoned cars in which the proportion of public transportation hubs were negatively associated with abandoned cars.

For littering, graffiti/physical damage and urination/defecation, the dummy variable for the 'post-pandemic' period was significant. In other words, independent of the socio-economic variables, the stay-at-home restrictions affected the level of littering, graffiti, and urination/defecation. The concentrated pattern of public disturbances in inner city areas was corroborated by two set of model results. First, by the negative sign of the variable 'distance to city center' in all models (except for abandoned cars) and second by the significance and negative sign of 'unemployment rate' in the models' urination/defecation and poor bike parking. The proportion of young males turned out to be positive and significant in all models.

Rates of police recorded vandalism were used as an independent indicator of crime reporting practices in the area. Findings corroborate that more police-recorded vandalism in an area was associated with more incidents of urination/defecation, poor bike parking as well as graffiti reported in the crowdsourced platform, but not for records of abandoned cars.

Littering was associated with greener areas/parks and schools. Public transportation did not affect littering after controlling for locational, demographic and socio-economical covariates. For graffiti and physical damage, the only land use that was significant was green areas/parks while for urination/defecation, a high proportions of transportation hubs and green areas/parks were associated. The only independent variable that was associated with abandoned cars was that public transportation, and that was negative (for instance, cars were abandoned away from transportation facilities).

While the overall spatial autocorrelation measure was not significant for all models, specific Basområde were positive and significant, typically for those overlapping the hotspots. In these areas, the clustering of incidents created a local area of positive spatial autocorrelation.

7. Discussion

With the exception of abandoned cars and poor bike parking, an overall increase in public disturbances was registered over a period of 15 months after the stay-at-home restrictions were imposed. Our findings confirm previous research that showed significant increases during the pandemic in visits to parks and green areas, interstitial spaces as well as around basic services (see for instance (Legeby et al., 2022). The increased visitation may have led to an increase in littering, physical damage as well as urination and defecation by animals and humans. However, these findings differ from previous research on the effect of the pandemic restrictions on crime in Stockholm, which indicated a significant drop in the first months of the pandemic followed by a fast increase a few months after the pandemic restrictions (Ceccato et al., 2022). For vandalism in particular, Gerell et al. (2020) reported that there was evidence of a possible increase but the initial trend was unclear.

Although bicycles and scooters continued to be used for close errands after post-pandemic restrictions, especially in the inner-city areas, the number of records of poor bike parking remained roughly the same. The overall reduction of mobility would have likely had an effect on the number of abandoned cars since fewer cars were on the streets. However, the causes for this reduction are difficult to ascertain. Abandoned cars could be associated with three distinct problems: joy riding (young people taking a vehicle without owner consent), dumping of old cars (environmental crime), and abandonment of cars after theft of the vehicle for crime commission.

We expected that certain types of public disturbance would have changed their spatial distribution after the post-pandemic restrictions. Overall, we found a fairly stable distribution of these events in inner city areas which could reflect the mild stay-at-home orders in the initial stages of the pandemic when restaurants, businesses and primary schools were kept open. We noticed some shifts in the spatial distribution of these incidents that could be associated with more local patterns of activities in public spaces. For urination/defecation, the area of concentration became larger and expanded away from the city center. Stockholm has many residential areas in the inner-city core where people reside and work. For this group, the pandemic restrictions meant fewer major changes in their daily routine activities (e.g., trips to parks, schools) than for those living elsewhere.

We found that the more central the region, the higher the counts of public disturbance reported by the population. Previous research showed that in pre-pandemic times, most crimes were reported in and around public entertainment areas such as restaurants, pubs, theaters and museums. In the case of Stockholm, these sites are concentrated in the inner-city parts (Uittenbogaard & Ceccato, 2012). The post-pandemic data show a similar geography but with enlargement towards the periphery. For instance, the geography of graffiti and physical damage as well as for littering continues to show high levels and concentrations in the inner-city areas. But the spread has shifted outward

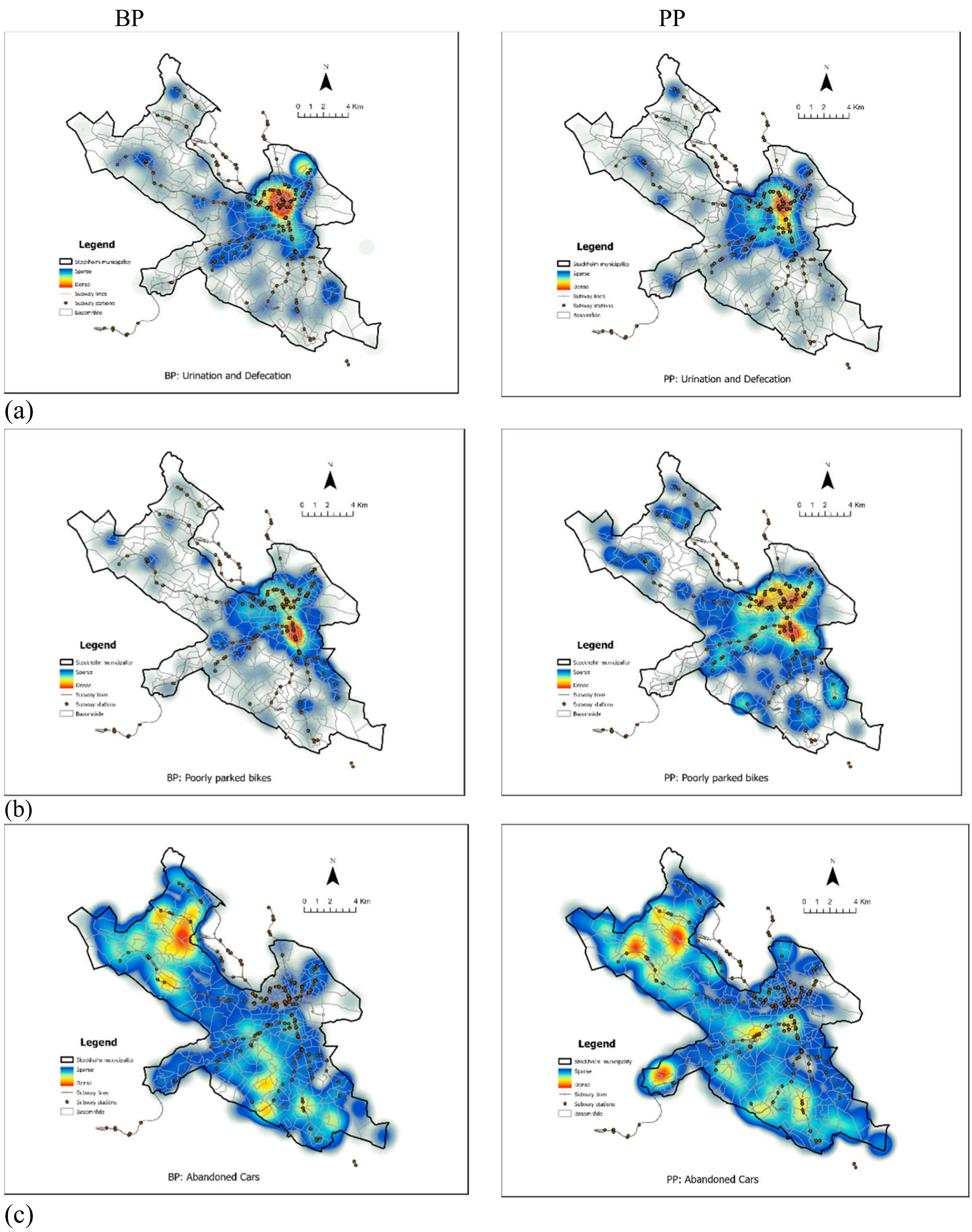
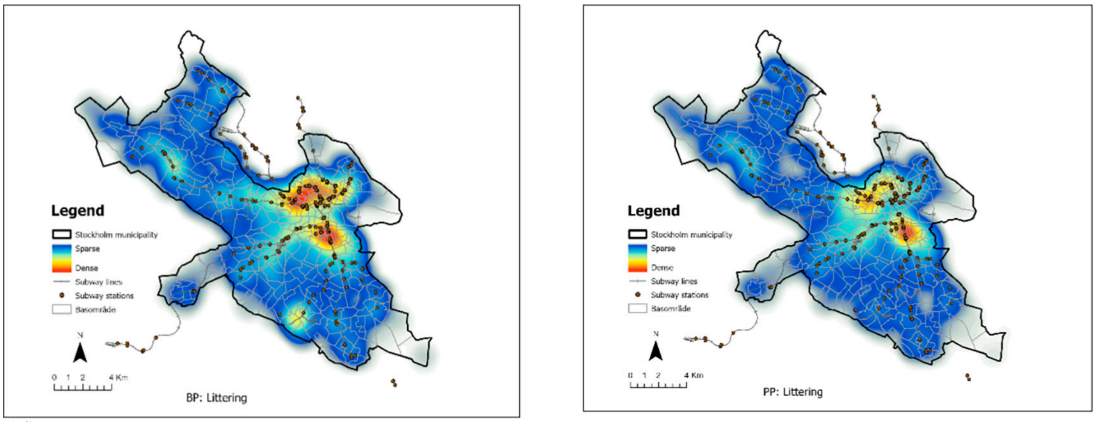


Fig. 3. Spatial concentrations of (a) urination/defecation, (b) poorly parked bikes (c) abandoned cars, (d) littering and (e) graffiti and physical damage from crowdsourced BP and PP records.

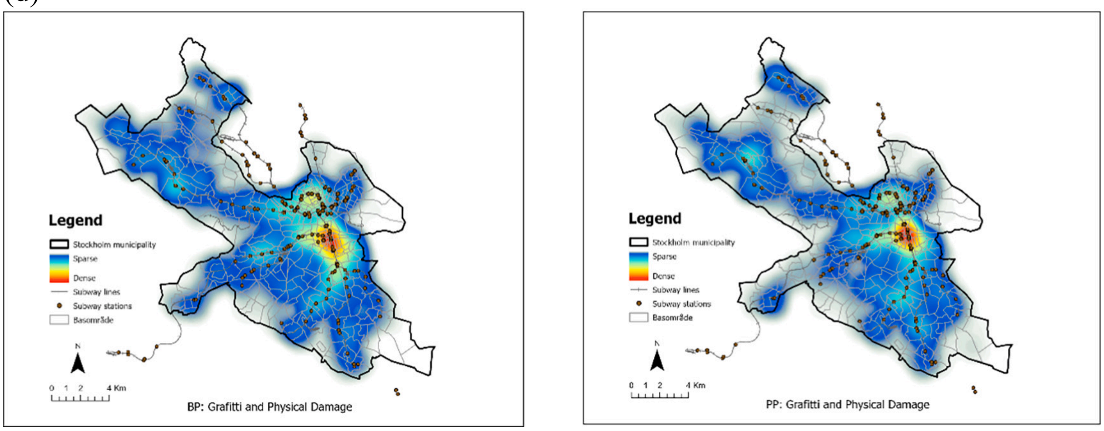
towards the suburbs.

Despite a reduction of reports of abandoned cars, new clusters of abandoned cars appeared in three parts of the outskirts of the city, especially in known criminogenic areas in the West and South of the city (see e.g. Levine & Ceccato, 2021). The association between acts of public disturbance and crime has long received support from the international criminological literature (Skogan, 1990; Wilson and Kelling (1982) and has since the 1980s been analyzed in previous studies in Stockholm (Wikström, 1991). As stated by Sampson, Morenoff and Felton (1999, p. 609), "…these visible public disorder incidents may not directly 'cause' other more serious crimes but they do share the same explanatory processes, with the difference that littering or physical damage can be observed by many in the area: residents, visitors and potential offenders". Previous research also suggests that physical damage is highly associated with fear of crime (e.g., Killias & Clerici, 2000) and that the reporting of these acts generate self-reinforcing processes that help perpetuate urban racial inequality (Sampson, 2009; Sampson & Raudenbush, 2004; Wickes et al., 2013).

Public transportation hubs, parks and schools continued to be "generators" of public disturbance acts (Brantingham & Brantingham, 1995) during the pandemic and also afterwards, reflecting an intensification of activities as well as more guardians, place managers or other



(d)



(e)

Fig. 3. (*continued*).

Table 4
Results of the Poisson-Gamma-CAR regression models using Monte Carlo (MCMC) estimation method for public disturbance acts for Stockholm, by Basomrade, N = 838.

Dependent variables	Littering	Graffiti & physical damage	Urination & defecation	Abandoned cars	Poor Bike Parking
N	838	838	838	838	838
Df	826	826	826	826	826
Log-likelihood	−3828.6055	−4140.566994	−1829.3215	−1221.9949	−1599.8099
AIC	7681.2109	8305.133987	3682.6429	2467.9898	3223.6199
BIC	7737.9831	8361.906204	3739.4152	2524.7620	3280.3922
Mean absolute deviation	25.0584	42.536447	3.2101	1.8646	1.8743
Mean squared predicted error	1416.2729	4440.866597	35.1647	25.0896	11.3843
Dispersion multiplier	0.50******	0.772589*	1.30 n.s.	1.30 n.s.	0.68 n.s.

Modelled parameters										
Independent variables	Coefficient	Tolerance	Coefficient	Tolerance	Coefficient	Tolerance	Coefficient	Tolerance	Coefficient	Tolerance
Intercept	2.5844***		2.8998***		0.9234***		−1.5877***		0.5531***	
Factor (BP = 0. PP = 1)	0.2371***	1.00000	0.1676*	1.00000	0.1944**	1.00000	−0.0286 n.s.	1.00000	0.1186 n.s.	1.00000
Public transportation hubs	0.0165 n.s.	0.8314	−0.0034 n.s.	0.8314	0.0739***	0.8314	−0.0679***	0.8314	0.0287**	0.8314
Green areas/parks	0.0355***	0.9421	0.0562***	0.9421	0.0261**	0.9421	0.0002 n.s.	0.9421	0.0240**	0.9421
Schools	0.0182***	0.9323	0.0231 n.s.	0.9323	0.0169 n.s.	0.9323	−0.0052 n.s.	0.9323	−0.0004 n.s.	0.9323
Young males	5.5994***	0.9394	4.6487**	0.9394	2.8191*	0.9394	3.2779**	0.9394	4.7054***	0.9394
Unemployment	0.0486 n.s.	0.9695	−0.4114 n.s.	0.9695	−2.7720***	0.9695	0.4413 n.s.	0.9695	−1.3868*	0.9695
Police records of vandalism	0.0031*	0.7872	0.0065***	0.7872	0.0055***	0.7872	0.0038 n.s.	0.7872	0.0030**	0.7872
Distance from City Center	−0.0000*	0.7176	0.0000 n.s.	0.7176	−0.0001***	0.7176	0.0002***	0.7176	−0.0002***	0.7175
Area	−0.0000***	0.7795	0.0000***	0.7795	0.0000***	0.7176	0.0000***	0.7795	0.0000***	0.7795
Spatial autocorrelation (Phi):	0.0051 n.s.		0.0034 n.s.		−0.0011 n.s.		0.0009 n.s.		0.0035 n.s.	

p-value = 10 %: *.
p-value = 5 %: **.
p-value = 1 %: ***.
[n.s.]: Not significant.

local controllers. These conditions may have facilitated reporting of littering, graffiti and physical damage and a few others acts of disturbance.

Therefore, the most important message from the analyses, and in direct answer to the last research question, is that land-use indicators did matter for predicting the level and geography of public disturbances, reflecting an expected intensification of human activities in and around parks and services that were close to people's homes. Future research and public policies should therefore focus on these particular places (parks, public transportation hubs) to strengthen neighborhoods and consequently improve residents' quality of life.

8. Limitations

We recognize that there are limitations associated with crowdsourced data, but we have taken steps to minimize potential measurement error. There are differences in reporting practices by socioeconomic status with higher income neighborhoods more likely to use the crowdsourced tools than in low income neighborhoods. Future research could further investigate potential differences in reporting practices within neighborhoods, micro places or by different types of routine activities. In particular, it would be interesting to explore variations in the use of the tool in the same neighborhood. In particular, an examination of whether there are 'super contributors' who could, potentially, bias the results. Moreover, we also acknowledge that there is a conceptual and empirical difference between perceptions of incivilities and the actual signs of disorder in the streets. Our study measures perceived incivilities reported by community members through a crowdsourcing platform, which may be influenced by their personal biases, stigmas, and racist perceptions of individuals and their neighborhoods. We recognize that these issues can affect the analyses but despite these limitations, we believe crowdsourced data can be a valid data source. For example, the fact that police recorded crime (vandalism) and crowdsourced data showed different patterns of reporting indicate that they could be complementary data sources for safety interventions to be used in urban planning.

9. Conclusions

This study explores the use of crowdsourced data to investigate the levels and the spatial distribution of public disturbance events (littering, graffiti and physical damage, urination and defecation, abandoned cars and nuisance parking of bikes) in Stockholm, Sweden before and after the pandemic restrictions. The study confirmed previous research that showed how city environments were differently affected by the intensification of human activities (Legeby et al., 2022). Particular land uses—specifically, parks, transport hubs and schools were associated with an increase in events of public disturbance, after controlling for neighborhood location and characteristics.

Our results add to the ongoing debate on the implications of COVID-19 for future city planning by illustrating the importance of these 'close to home'-public spaces for people's quality of life and overall city sustainability. The COVID-19 pandemic disrupted daily life in cities worldwide, and the paper's findings suggest that public spaces close to home became increasingly important for people's well-being during this time. Therefore, city planners may need to prioritize the creation and maintenance of such spaces to ensure the resilience of urban communities in the face of future disruptions.

This study only focused on disturbances in public spaces in Stockholm during the COVID-19 pandemic. The findings may not be generalizable to other cities or other time periods. Future research could explore a longer time frame to allow for more reliable forecasting of counterfactuals, including sensitivity analyses to ensure the robustness of the findings. A possible route would be to take as much data as possible from before March 2020, estimate the SARIMAX models, and then compare forecasts computed from the model estimates (the counterfactual) against observed values.

Crowdsourced data can be valuable in identifying urban problems, particularly those that are not systematically measured by government agencies such as the police. But it is important to also recognize that crowdsourced data could be biased since participation in the system is voluntary. Clearly, more research is needed.

Anonymity and poor guardianship during the pandemic created situational conditions that facilitated certain public performances less present in pre-pandemic times. The consequence was that events of urination/defecation, littering and physical damage flourished as norms of behavior and reporting changed. These findings inform research devoted to understanding of the nature of public disturbance acts in public spaces, in particular, why certain acts are more tolerated than others and the costs associated to these acts to society as a whole. Results also show that the detection of public disturbance acts in a few specific areas constitutes an important information for immediate planning actions, for instance, by improving place management practices and by raising questions about acceptable boundaries of human and animal behavior in public spaces when the goal is to promote inclusive and pleasant spaces for all.

CRediT authorship contribution statement

Vania Ceccato – conceptualisation, funding acquisition, methodology, formal analysis (modelling spatial), validation, visualisation, writing, review and editing.

Omkar Parishwad – data curation, formal analysis (modelling temporal and spatial), visualisation, editing.

Ned Levine - methodology, formal analysis (modelling spatial), validation, review and editing.

Declaration of competing interest

The authors declare no conflict of interest.

Data availability

The authors do not have permission to share data.

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Appendix A

Appendix A1

Summary of the characteristics of the dataset used in the study. N = 838, 419 in BP and 419 in PP.

Type of data		Description	Year	Source	Type of variable	Average	Standard deviation
Crowdsourced data	Public disturbance	Coordinates (x,y) of urine and defecation (human, animals)	2019–2021	Stockholm municipality - Crowdsourced data	Records of public disturbance acts per Basomrade	50.75	169.56
		Coordinates (x,y) of litter and poor maintenance				318.79	331.90
		Coordinates (x,y) of graffiti and physical damage				447.23	617.18
		Coordinates (x,y) of abandoned cars				6.24	9.97
		Coordinates (x,y) of poorly parked motorbikes				23.46	40.72
Police data	Police recorded Vandalism rate	Coordinates (x,y) of vandalism before and after the stay-at-home restrictions. Vandalism includes offences on physical targets, for example, causing damage to cars, walls, buildings, including graffiti.	2019–2020	Police authority official data	Rate for zones before and after the stay-at-home restrictions	4.33	43.18
	Factor	Dummy variable (0,1) for data before and after stay-at-home restrictions			Dummy variable for before (0) and after (1) stay-at-home	0.5	1
Land use data	Transport Hubs	Coordinates (x,y) of subway, train stations	2019	Open geodata	Proportion of transport hubs per basområde	1.19	3.57
	Parks	Coordinates (x,y) green areas/ parks			Proportion of parks per basområde	2.29	4.03
	Schools	Coordinates (x,y) schools			Proportion of schools per basområde	1.32	4.66
	Bars	Coordinates (x,y) bars			Proportion of bars per basområde	30.12	61.20
	Area	Small unit of analysis (basområde)		Own calculation	Area of basområde (sq.m)	515,760.09	609,775.32
	Center	Distance from city center			Distance of centroid of subdivision from City center (m)	5592.75	3984.02
Demographic, economic data	YoungMale	Befolkningen av. unga män (åldrarna 15–24) per basområde	2019	SCB	Proportion of young males (aged 15–24) per basområde	0.087	0.056
	Unemployed	Number of residents who are unemployed per basområde			Unemployment rate per basområde	0.039	0.153
	Foreign born	Number of residents who are foreign born per basområde			Proportion of foreign born per basområde	0.24	0.19

Appendix A2: SARIMAX model for analysis of public disturbance events

The Seasonal Autoregressive Integrated Moving Average with Exogenous Variable (SARIMAX) model was used to analyze the records of public disturbance events from 2019 to 2021. SARIMAX is a flexible linear model for time series data that can be used to model many different types of real data including seasonal terms. The multiplicative seasonal ARIMA model is represented by ARIMA(p,d,q)x(P,D,Q), where P denotes the number of seasonal autoregressive (SAR) terms, the seasonal differences is denoted by D, the number of seasonal moving average (SMA) terms is Q, and k denotes the seasonal period. In the lag operator polynomial form, the SARIMAX model (multiplicative) can be written as:

$$\varnothing_p(L)\Phi_P\left(L^k\right)(1-L)^d\left(1-L^k\right)^D Y_t=\theta_q(L)\Theta_Q\left(L^k\right)U_t$$

where ∅ and θ are the coefficients of the autoregressive and moving average components, respectively. Yt and Ut are the actual values and white noise at time t, respectively. The numbers p, d, and q determine the order of the ARIMA model, where the order of the autoregressive term is indicated by p, while d denotes the degree of differencing involved, and q is the order of the moving average. L is the backshift operator i.e. $LY_t = Y_{t-1}$ for the forecast.

To demonstrate the use of the SARIMAX model, we consider the event category of graffiti and physical damage, which showed the lowest variation in trends before and after the pandemic for forecasting. First, we decompose the time series data to check for trend and seasonality components (Fig. A1).

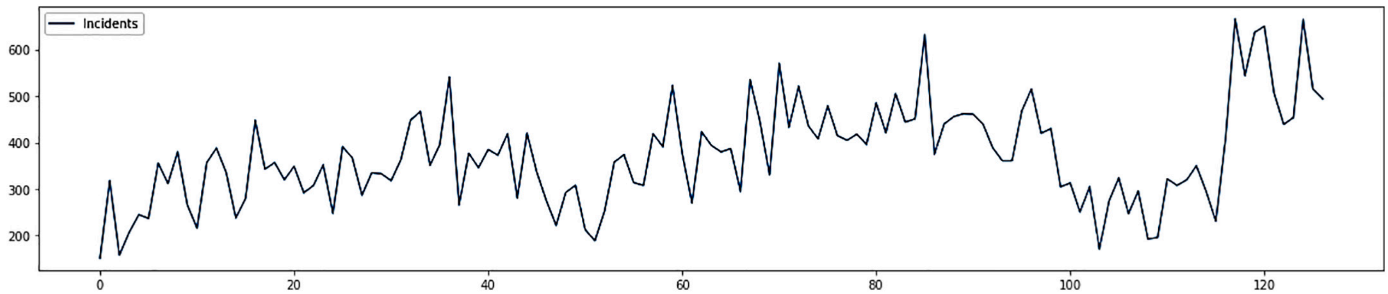

Fig. A1. Number of graffiti and physical damage events recorded in Stockholm during the considered period.

The figure shows an upward trend and a 6-month seasonality (lag = 6) in the data. We can also verify the presence of seasonality by looking at the Auto Correlation Function (ACF) plot (Fig. A3), which shows spikes at lag values of 1, 7, 13, and so on. We need to transform (scale) the data to acquire a constant mean and variance, as the considered event shows that the data is non-stationary (it has trend and seasonality) (Fig. A2).

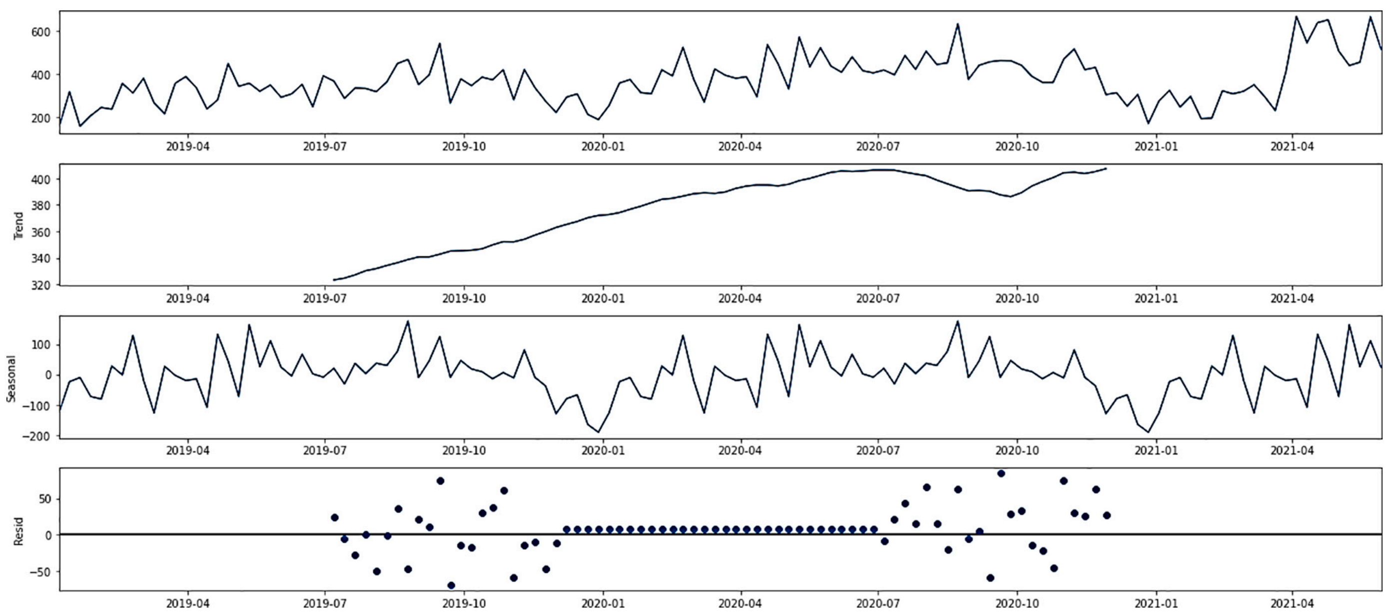

Fig. A2. Time series graffiti and physical damage data decomposed into trend, seasonality, and residuals.

We have identified three out of seven components for our SARIMAX equation: trend differencing order (d), seasonal differencing order (D), and lag = 12. To identify the other four components, i.e., p, seasonal P, q, and seasonal Q, we plot the ACF and Partial Auto Correlation Function (PACF) plots (Fig. A3).

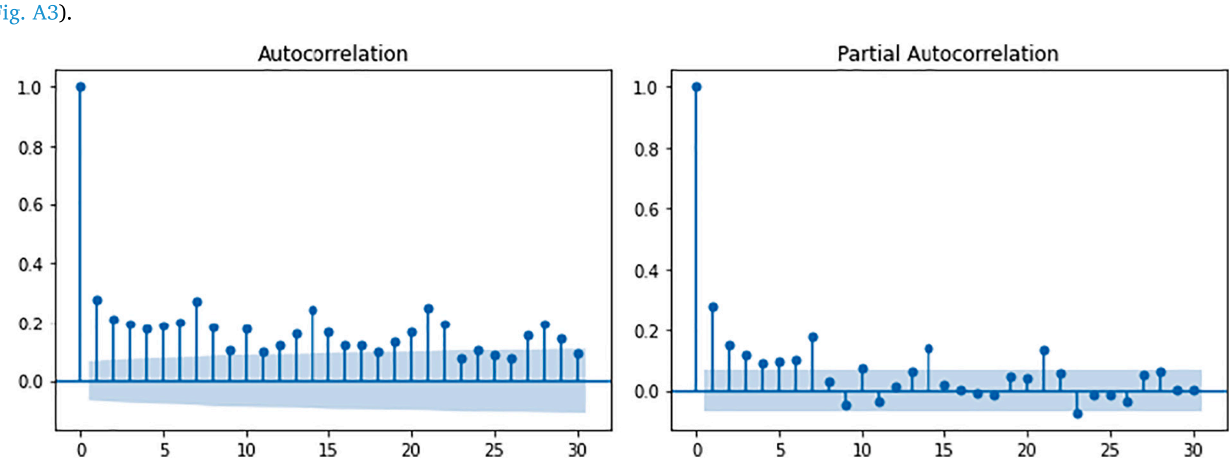

Fig. A3. ACF and PACF of complete event (graffiti and physical damage) count data.

Based on the analysis, it was found that the SARIMAX model with the exogenous variable was able to capture the trend and seasonality components of the data for the selected event category (graffiti and physical damage). The decomposition of the time series showed an upward trend and a 6-month seasonality in the data, which was verified by the ACF plot. The data was non-stationary, and thus, the SARIMAX model was used to transform the data to acquire a constant mean and variance.

The summary results of the final SARIMAX model showed the significance of derived variables and sigma variables, as well as the AIC/BIC values, signifying the validity of the model for the data. The forecasted trends for the selected event category showed that the variations in the total counts for the post-pandemic period varied only up to 26 % temporally, which was the lowest among the five event categories considered in the study.

Fig. A4 indicates a plot of the SARIMAX predictions with confidence intervals in comparison to the true counts would provide a more comprehensive understanding of the model's performance. This shows how well the model fit the observed data and how confident the model is in its predictions. Since the predictions are based on pre-pandemic period, it is another attempt to understand the variations in predicted counts through a complex but accurate approach, for the post pandemic (PP) period.

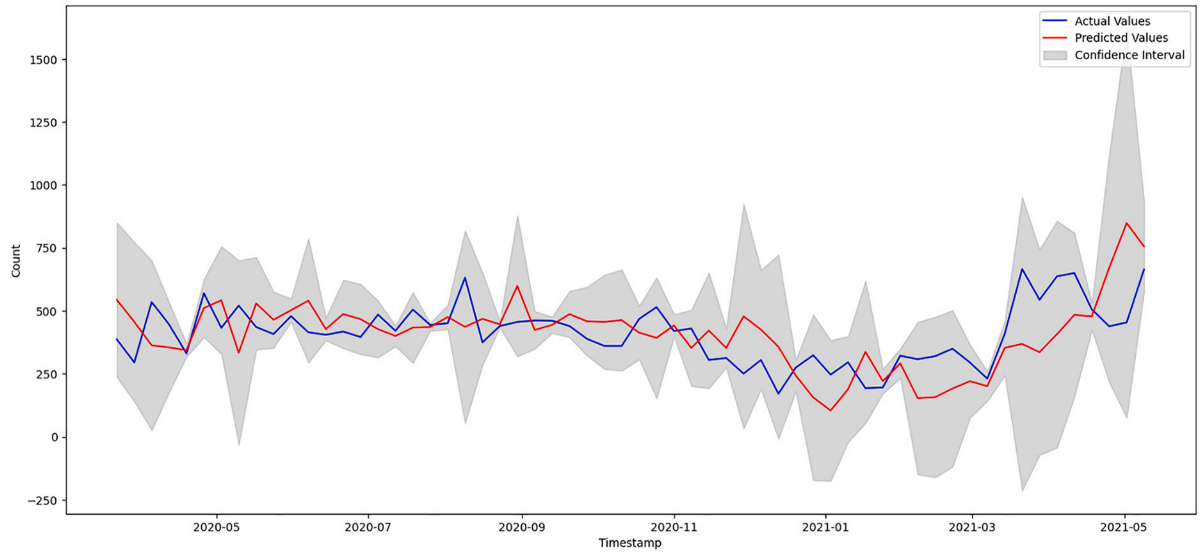

Fig. A4. SARIMAX predictions with confidence intervals for predictions post pandemic for graffiti and physical damage.

Overall, the SARIMAX model with the exogenous variable was a useful tool for analyzing the time series data on acts of public disturbance in Stockholm. The model was able to capture the trend and seasonality components of the data and make accurate forecasts for the selected event category.

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