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ORIGINAL PAPER

Placing Perceptions of Unsafety: Examining Spatial Concentrations and Temporal Patterns of Unsafe Locations at Micro-Places

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Abstract

Objectives To explore the extent to which unsafe locations are concentrated to micro-places within the city of Malmö, Sweden, and whether there is a temporal stability in these micro-places over time.

Methods Information on unsafe locations is obtained from an open-ended item across three waves of a random sample community survey. Reported unsafe locations are geo-coded as polygon, polyline, and point features and merged with a 200 by 200-m grid-cell network using both unadjusted and weighted counts.

Results The results suggest that unsafe locations are concentrated to a small share of grid-cells using different metrics. There are also signs of spatial clustering and a temporal stability of unsafe locations over time.

Conclusions As unsafe locations are concentrated to a small share of micro-places the results have important implications for both theory and practice. However, further research exploring unsafety and fear of crime at micro-places is highly warranted.

Keywords Law of crime concentration · Unsafe locations · Fear of crime · Micro-place · Hot spot

Introduction

As stated by Farrell (2015: 233), "[c]rime has a tendency to concentrate in time, space and other dimensions along which it occurs." This proposition is supported by a great deal of research showing that a fraction of the population is responsible for a majority of crime (e.g. Falk et al. 2014), a small proportion of victims are repeatedly victimized (e.g. Lauritsen & Quinet 1995), and a small number of facilities suffer a disproportionate amount of reported crime (e.g. Bowers 2014). Having been shown to apply to offenders, victims, and facilities, this Pareto principle has also been proposed to apply to places. In a widely cited paper, Sherman and colleagues (1989) showed that crime incidents are not randomly

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distributed in space but are rather highly concentrated to micro-places, which they operationalized as addresses and street intersections. Similarly, Spelman and Eck (1989) argued that crime is in fact more concentrated to places than it is to offenders and victims. Drawing on these findings, Wilcox and Eck (2011) presented "the iron law of troublesome places", suggesting that most places suffer no crime, some suffer modest amounts of crime, but that most crime is accounted for by a very small number of places. In the same vein, Weisburd (2015) introduced the "law of crime concentration", which states that the majority of crime should be concentrated to a small proportion of micro-places[1] within a city. More specifically, the law of crime concentration suggests that about a quarter of all reported crime in major cities should occur at between 0.8 and 1.6 percent of micro-places, while half of all crime should occur at between 4.2 and 6.0 percent of places.

A growing body of research continues to provide empirical support for this posited law of crime concentration (for an overview see Lee et al. 2017), with supportive evidence now available from numerous cities across most continents, including North America (e.g. Weisburd 2015; Andresen et al. 2017), South America (e.g. Chainey et al. 2019), Europe (e.g. Favarin 2018; Stanković, 2021), Asia (e.g. Mazeika & Kumar 2017; Amemiya & Ohyama 2019), and Africa (e.g. Breetzke & Edelstein 2019; Umar et al. 2021). Besides showing that crime is concentrated to a small proportion of micro-places, the existing knowledge base has also demonstrated that the concentration is even more marked when smaller units of analysis are employed as compared to larger units (e.g. Steenbeek & Weisburd 2016; Schnell et al. 2017), and that there is a temporal stability in the concentration of crime to micro-places over time (e.g. Weisburd et al. 2004; Wheeler et al. 2016). With few exceptions, the majority of criminological research has to date focused on the concentration of crime events. However, a few studies have also focused on other, arguably important, criminologically relevant outcomes. These include, for instance, the spatial concentration of mental health calls for police service (Koziarski 2021), fatalities following opioid overdoses (Carter et al. 2019), and incidents of the police use of force (Sorg et al. 2021). However, one outcome that has received less attention in this line of research, despite being a recurrent topic in the field of environmental criminology, is the spatial dimension of *the fear of crime*.[2]

While it may seem obvious that fear of crime is dependent on the individual experiencing it—which justifies the prominent focus on inter-individual differences found in much previous fear of crime research (for a review see Hale 1996 and Collins 2016)—the mere fact that fear of crime varies with geography (e.g. nationally, regionally, locally) suggests that spatial or environmental factors may be of significance for the explanation of fear of crime (see Pain 2000; Lorenc et al. 2012). Although a number of high-quality multilevel studies have provided important knowledge on neighborhood mechanisms and the (mediating) role of neighborhood structural characteristics, collective efficacy, and disorder on individual-level dimensions of fear of crime (e.g. Brunton-Smith and Sturgis 2011; Brunton-Smith et al. 2014; see also Markowitz et al. 2001), it has been stressed that "(…) the macro-level perspective misses the impact of site-specific, situational, or proximate

[1] While micro-places have been defined differently, Weisburd (2015: 142) draws on both theoretical and practical considerations to advocate an operationalization based on street segments, "(…) including both block faces between two intersections".

[2] Fear of crime is here used as an umbrella term covering multiple dimensions, including unsafety. However, there is considerable debate regarding the conceptualization of fear of crime, and its many dimensions (see *inter alia* Ferraro and LaGrange 1987; Hale 1996; Jackson 2005; Farrall et al. 2009; Gray et al. 2011).

features" in the explanation of fear of crime (Nasar & Fisher 1993: 189). As such, there has been a growing interest in examining fear of crime as a context-specific phenomenon, and in terms of transitory mental states that are experienced as events during individuals' everyday lives (Gabriel and Greve 2003; Solymosi et al. 2015). Here, emphasis is placed on the immediate environmental settings and on how exogenous factors influence individual experiences of fear of crime (e.g. Engström and Kronkvist 2021). More specifically, places are not in themselves fear inducing (see Pain 1997: 233), but serve as settings comprised of external triggers that may in turn activate individual experiences of fear of crime. Such exogeneous triggers might, for example, be places characterized by the presence of fewer people, poor lighting and disorder/incivilities (Lorenc et al. 2013; see also Jansson et al. 2013; Sreetheran and van den Bosch 2014), or they may simply be dark or unfamiliar areas (see Brantingham and Brantingham 1995).

While fear of crime has been extensively researched within criminology, it has also received a lot of attention in the field of (human) geography. Here, a number of studies have examined the spatial dimensions of fear of crime using mental mapping techniques and sketch maps (see Doran and Burgess 2012; Curtis 2012). These methods allow researchers to gather detailed geographical information on the spatial dimension of fear of crime, for instance by asking respondents to mark locations that they avoid due to fear or unsafety on a map. These maps may subsequently be analyzed using geographic information systems that allow for the detailed study of the geographical dimension of fear of crime. Using such an approach, Doran and Lees (2005) demonstrated a spatial clustering of places within a central business district that respondents working in the area avoided due to fear of personal victimization. Using an online mapping tool, Jakobi and Pödör (2020: 6) gathered sketch maps that included almost four thousand polygons representing both safe and unsafe areas, with results showing "(…) significant spatial patterns with clearly identifiable hotspots of unsafe and safe areas". Using similar methods, a number of other studies have also been able to identify "hot spots" of fear and (un)safety (Curtis et al. 2014; Jakobi and Pödör 2020; Kohm 2009; Ogneva-Himmelberger et al. 2019; Pánek et al. 2019).

While these studies provide support for a spatial clustering of areas and locations that are perceived as unsafe by respondents, a number of limitations are worth highlighting. First, with few exceptions (e.g. Kohm 2009), most previous studies have not been based on random samples of respondents, which thus limits the external validity and generalizability of the findings. Second, these studies have generally not had an explicit focus on the concentration of unsafe locations, but have rather examined other research questions, for instance the spatial relationship between fear of crime, perceived safety, and reported crime rates (e.g. Ogneva-Himmelberger et al. 2019; Pánek et al. 2019). Consequently, less focus has been directed at the detailed examination of *the extent to which* fear of crime and perceived unsafety are concentrated to micro-places. Third and last, most previous studies have used cross-sectional research designs that do not allow for an examination of the concentration of unsafe locations over time. Given these limitations, the current study will be able to supplement the current state of knowledge by providing important insights into the concentration of unsafe locations.

Aim and Research Questions

The main aim of the current study is to examine the concentration of unsafe locations to micro-places within the city of Malmö, Sweden. This aim is concretized in two research questions:

1. To what extent are unsafe locations concentrated to micro-places?
2. To what extent is there temporal stability in unsafe locations over time?

These research questions are examined using a dataset on perceived unsafe locations that has been geocoded from open-ended answers reported by a random sample of respondents in three waves of a city-wide community survey.

The current study has two important implications. First, if unsafe locations are concentrated to a small proportion of micro-places, this has important theoretical implications since it would suggest that there is at least some intersubjectivity regarding why certain places are considered unsafe. This would also imply that there are some potential elements of the social, physical, or built environment that increase the probability that individuals will perceive a given location as unsafe. Secondly, if unsafe locations are concentrated to a small proportion of micro-places, this knowledge may be important for policy makers and practitioners as it may provide an insight into *where* resources should be directed in order to potentially decrease the number of unsafe locations. Moreover, if the concentration of unsafe locations is also stable over time, this could provide an even more powerful indication of where resources should be directed in order to increase perceptions of safety.

Data and Methods

Data on Unsafe Locations

Data on unsafe locations has been gathered from three waves of the Malmö Community Survey (MCS) conducted in 2012, 2015 and 2018. The MCS is a collaboration between the Malmö city offices, the local police agency, and the department of criminology at Malmö University, and could be seen as a local version of the Swedish Crime Survey (see Viberg 2021). The MCS has an explicit focus on public safety by asking inhabitants about perceptions and experiences of crime, fear of crime and safety in relation to their own residential neighborhoods (for details see Ivert et al. 2013). Each wave of the MCS is based on a stratified random sample of respondents aged 18 to 85 who reside in a neighborhood with at least 100 residents. Of the original 136 neighborhoods in Malmö—which together had between approximately 240,000 and 260,000 inhabitants aged 18 to 85 over the course of the years examined—residents from between 104 and 107 neighborhoods were included in each wave.[3] About three and four percent of the population (i.e. 7733 to 9713 individuals) were sampled for each wave, although only about half of the sample returned the survey in the first wave and about 40 percent in the latter two. Compared to the population, the final sample contains an overrepresentation of women and of slightly older individuals (see Table 1).

The survey item of interest in this study is an open-ended question which participants have answered in their own words (hereafter referred to as Q18): "*Is there any particular place in your neighborhood that you experience as uncomfortable or unsafe to visit/pass through? Please state which place you are referring to as carefully/close as possible*."[4]

[3] Three additional neighborhoods have been included over time as their populations have increased from below to above one hundred.

[4] Despite the wording of Q18 includes both *uncomfortable* and *unsafe*, the outcome of this item will throughout this paper be referred to as simply *unsafe locations*. There is no reason to believe that reported locations would differ significantly if "uncomfortable" were to be excluded from the wording.

Table 1 Participant characteristics and differences between the full sample, participants answering Q18, and participants with geocoded answers, using independent sample *t*-tests

	Population 18–85[a]	Full sample	Participants answering Q18	Participants with geocoded answers
2012 (*n*)	240,334	4195	1808	805
Age (mean)	44.6	49.7	48.1**	45.4**
Gender (female)	50.9%	54.2%	57.5%**	63.1%**
Unsafe late at night	–	16.3%	22.2%**	30.7%**
2015 (*n*)	249,692	3,107	1609	696
Age (mean)	44.8	51.3	49.3**	45.5**
Gender (female)	50.7%	53.9%	58.7%**	66.2%**
Unsafe late at night	–	14.6%	19.6%**	29.9%**
2018 (*n*)	260,731	3845	2102	958
Age (mean)	45.0	52.2	51.7*	48.8**
Gender (female)	50.5%	53.8%	57.3%**	60.9%**
Unsafe late at night	–	18.7%	24.0%**	32.7%**
Total (*n*)		11,147	5,519	2459
Age (mean)		51.0	49.8**	46.8**
Gender (female)		54.0%	57.8%**	63.1%**
Unsafe late at night		16.7%	22.1%**	31.2%**

Unsafe late at night is a dichotomous variable showing whether participants reported feeling unsafe when walking alone late at night in the own neighborhood

*$p < .05$ **$p < .01$

[a]Data from Statistics Sweden (www.scb.se)

Q18 is located as the final item in a battery of approximately fifteen questions relating to different dimensions of fear of crime (e.g., worry of criminal victimization, risk perceptions, feelings of safety, avoidance behaviors). Since the survey is by and large concerned with respondents' perceptions of their residential neighborhood, they are throughout the survey instructed to think of "their neighborhood" as the area within a short walking distance (a couple of minutes) from their home.

As shown in Table 1, about half of the participants (n = 5519) provided some form of written response to this question, while the remainder left it blank. One possible explanation for this rather large internal attrition is, of course, that participants were unable to think of any particular place in their neighborhood that felt unsafe and consequently left the question unanswered. An independent sample *t*-test comparing the participants who answered Q18 with the full sample supports this notion, since participants who felt unsafe walking alone late at night in their own neighborhood were more likely to provide an answer to Q18.

In a first step, all answers were screened out that did not relate to unsafety (e.g. "no", "not that I know of", etc.), and answers relating to unsafety but not to a specific location (e.g. reasons for unsafety in general such as darkness or youths, or non-specific locations such as parks or squares in general) were excluded. Following this procedure, a total of

4598 unsafe locations provided by 3121 participants remained.[5] In a second step, all eligible unsafe locations were assessed regarding whether they included enough information to be reliably identified, and 919 (i.e. 20%) did not. These include, for instance, cases in which respondents had written *my* basement or *the* street. Since the only available information on participants' residence is the neighborhood from which they are sampled, such locations could not be identified. Further, 51 additional "locations" were excluded as they referred to very large geographical units (*all* or *large parts* of the city). In the final step, all locations were categorized based on their functional (e.g. park, street, square) and geographical location (e.g. park X, street Y, square Z).

Geocoding Unsafe Locations as Geographical Features

The screening of the open-ended answers resulted in 3628 unsafe locations (1305 *unique* unsafe locations) that were eligible for geocoding, reported by 2459 participants. Compared to the full sample, these participants were slightly younger, more likely to be female, and more likely to have reported feeling unsafe when walking alone late at night in their own neighborhood (see Table 1). In order to analyze the geographical dimension of the reported locations, they were categorized on the basis of their size and characteristics as either polygon, polyline, or point features (see Table 2). A total of 1126 reported locations distributed across 205 unique locations were considered larger spatial units and consequently geocoded as polygons. These include four broad categories of functional locations including parks/green areas, neighborhoods/blocks, cemeteries, and industrial areas/construction sites/harbors. Furthermore, respondents reported 1037 streets/street segments and foot/bicycle paths as unsafe, corresponding to 495 unique locations, which were intuitively considered polylines. Finally, a total of 1465 reported locations, corresponding to 605 unique locations, were geocoded as point features due to their relatively small areal extent. These locations were classified in 16 different categories, of which the majority were categorized as squares, stores/shopping malls, and preschools/schools.

All polygons and polylines were primarily geocoded using reference data from either Malmö City Offices or The Swedish Mapping, Cadastral and Land Registration Authority. For instance, a specific park/green area reported as being unsafe was geocoded as the corresponding polygon feature provided in the reference data. Similarly, since the majority of streets and paths were named by the respondents, this allowed for quite simple matching. However, in some cases the reference data did not include a corresponding geographical feature, for which reason some were drawn manually using Open Street Map as the reference. Unlike the geocoding procedure for polygons and polylines, locations categorized as point features were geocoded manually by retrieving their geographical coordinates from an online mapping service.

Finally, each geographical feature received a count value corresponding to the number of times that the specific location had been reported as unsafe by participants. Table 2 provides an overview of the unsafe geographical features included in the subsequent analyses.

[5] The number of locations exceeds the number of answers since a single participant may report several locations.

Table 2 Descriptives for unsafe geographical features

Functional location	Reported locations n (%)[a]	Unique locations n (%)[a]	Shape size km/km^2		
			Mean (sd)	Median	Range
Polygons (total)	1126 (100)	205 (100)	0.22 (0.40)	0.05	0.00–2.31
Park/green area	849 (75.4)	115 (56.1)	0.11 (0.27)	0.02	0.00–1.86
Neighborhood/block	227 (20.2)	78 (38.0)	0.39 (0.51)	0.24	0.00–2.31
Cemetery	38 (3.4)	7 (3.4)	0.15 (0.14)	0.08	0.02–0.39
Industrial area/ construction site/harbor	12 (1.1)	5 (2.4)	0.14 (0.12)	0.07	0.03–0.32
Polylines (total)	1037 (100)	495 (100)	0.88 (1.43)	0.45	0.03–13.51
Street/street segment	702 (67.7)	331 (66.9)	0.99 (1.62)	0.48	0.03–13.51
Foot/bicycle path	335 (32.3)	164 (33.1)	0.66 (0.86)	0.43	0.04–6.20
Points (total)	1465 (100)	605 (100)	–	–	–
Square	451 (30.8)	42 (6.9)	–	–	–
Store/shopping mall	171 (11.7)	60 (9.9)	–	–	–
Preschool/school	129 (8.8)	64 (10.6)	–	–	–
Pedestrian overpass/underpass	107 (7.3)	53 (8.8)	–	–	–
Intersection/cul-de-sac	103 (7.0)	68 (11.2)	–	–	–
Bus stop/train station	87 (5.9)	39 (6.4)	–	–	–
Parking lot/garage	79 (5.4)	55 (9.1)	–	–	–
Playground	77 (5.3)	53 (8.8)	–	–	–
Health care/other public service office	57 (3.9)	23 (3.8)	–	–	–
Sports and leisure facility/ground	53 (3.6)	34 (5.6)	–	–	–
Restaurant/fast food/café	40 (2.7)	29 (4.8)	–	–	–
Address/residence	33 (2.3)	32 (5.3)	–	–	–
Other	31 (2.1)	22 (3.6)	–	–	–
Religious/cultural institution	23 (1.6)	12 (2.0)	–	–	–
Park/green area	17 (1.2)	12 (2.0)	–	–	–
Industrial area/ construction site/harbor	7 (0.5)	7 (1.2)	–	–	–
Total	3628	1305			

Reported locations represent the number of times a specific location has been reported by participants, while *unique locations* represent the number of unique geographical features these locations correspond to (i.e. taking into account that several participants may report the same location). The reason that the labels "Park/green area" and "Industrial area/construction site/harbor" are applied to both polygons and points is that, in these cases, points refer to a specific location within, for instance, a park

[a]Percentages may not total 100 due to rounding

Units of Analysis: Grid-Cells as Micro-Places

In order to merge the various and overlapping unsafe geographical features into a joint unit of analysis, a 200 by 200-m grid-cell network with cell centroids within Malmö's administrative city limits was applied to the city.[6] A grid-cell size of 200-m have been employed

[6] While much previous research has operationalized micro-places as street segments (e.g. Andresen et al. 2017; Chainey et al. 2019; see also Weisburd 2015), a number of European studies of crime concentration have used grid-cells (e.g. Hardyns et al. 2019; Stanković 2021). One argument is that the gridiron street-network pattern found in many American cities is not as common in European cities, and that the use of street segments would therefore lead to considerable differences in the size of the units of analysis (see Hardyns et al. 2019).

in similar previous research in a European context (e.g., Hardyns et al. 2019; Stanković, 2021), and corresponds to roughly twice the median (172 m) and mean (228 m) length of inner-city blocks in Malmö, similar to the operationalization of "behavioral settings" by Caplan et al. (2011). The grid includes a total of 4031 cells, which also represent the operationalization of micro-places in the current study. However, to minimize the risk for overestimating the concentration of unsafe locations to micro-places due to the inclusion of grid-cells that were not relevant to the purposes of the study, a significant proportion of the cells have been excluded. These include all cells within the Malmö industrial harbor area, cells that were more than 400 m from the administrative border of a neighborhood included in the most recent wave of the MCS, and cells located in an agricultural fields or expanses of water.[7] The exclusion of these cells resulted in a final sample of 2921 grid-cells. To test the robustness of the results in the current study, all analyses have also been conducted using smaller (100 by 100-m) and larger (400 by 400-m) grid-cells.

Main Outcome: Unsafe Count Value

In the next step, all polygons, polylines and points were merged with the grid-cell network allowing for a calculation of a summative count value of the number of times a specific geographical feature was reported by respondents for each grid-cell. As such, each grid-cell received a count value for all geographical features that the specific grid-cell intersected. These count values constitute the study's main outcome measure and have been calculated using two different methods.

In the first approach, each cell intersecting a given geographical feature received an *unadjusted count value* corresponding to the number of times that the specific location (i.e. geographical feature) was reported by respondents. As such, the total sum of unadjusted counts in the grid-cell network is 23,291 which is several times the original sum of counts (i.e. 3628). This is because the count for a given geographical feature is provided to multiple grid-cells. However, this approach may exaggerate the impact of large geographical features and potentially bias the dataset. Therefore, the second approach utilized a *weighted count value* where the unadjusted count was divided by the number of grid-cells that are intersected by the specific geographical feature (as such the weighted count value is not a count in the formal sense). Using this approach thus reduced the impact of larger (or longer) geographical features that intersected several grid-cells. Consequently, the total sum of weighted counts in the grid-cell network sums to the original sum of counts (i.e. 3628). Although the two different approaches do not affect the prevalence of unsafe locations, they do of course impact estimates of the concentration of unsafe locations to micro-places. Results for both unadjusted and weighted count values are therefore consistently reported throughout the results section. (A further elaboration and visualization of the two different methods is provided in Appendix A.)

[7] The harbour area has almost no registered residents and is by and large inaccessible to most inhabitants of Malmö. Only including cells within a 400-m radius of a neighborhood included in the MCS was deemed appropriate since participants were instructed to think of locations within a couple of minutes walking distance of their home (for gait-speed references see Bohannon and Andrews 2011).

Analytical Approach

To answer the first research question, three different metrics are reported to describe the concentration of unsafe locations to micro-places. First, the results presentation reports the proportion of grid-cells that account for 25 and 50 percent of the total unadjusted and weighted counts across all included grid-cells (see Weisburd 2015). Second, it reports the proportion of grid-cells that account for 25 and 50 percent of the total unadjusted and weighted counts when the analysis is restricted to non-zero grid-cells (see Levin et al. 2017). Third, since both of these first two methods rest on a counterfactual assumption of uniformity, which may risk overestimating the concentration of crime (for details see Chalfin et al. 2021)—and reasonably also of unsafe locations—an alternative metric is also included. Inspired by the *marginal crime concentration* (MCC) metric (Chalfin et al. 2021), a second simulated dataset was created for each year (2012, 2015 and 2018 respectively), and thereafter merged to form a "total" dataset, which will function as a simulated counterfactual. This includes a total of 1126 simulated polygons (i.e. random points located within the grid-cell network, with a buffer matched to correspond with the areal extent of a counterpart polygon in the observed data), 1037 simulated polylines (i.e. randomly selected streets and street-segments, excluding those shorter than the shortest street/street segment in the observed data (i.e. 30 m)), and 1465 simulated random points, for all three years combined. All features received a count value of one (1) which provides a total sum of 3628, equaling that of the observed data. The simulated unsafe geographical features were thereafter merged with the grid-cell network, with each grid-cell being assigned both an unadjusted and a weighted simulated count value following the same procedure as for the observed data. A base map illustrating the two datasets prior to merging with the grid-cells is provided in Fig. 1.

The spatial concentration of unsafe locations relative to the simulated counterfactual is calculated on the basis of the marginal crime concentration metric as proposed by Chalfin et al. (2021):

$$mcc_t^k = cc_t^k - cc_t^{k*} \tag{1}$$

Here (Eq. 1), *mcc* is the marginal crime concentration, which in this study represents the marginal concentration of unsafe locations, where k represents the proportion of grid-cells accounting for e.g. 25 and 50 percent of the sum of counts at time t. The mcc_t^k is contingent on the difference between cc_t^{k*}, which in the current case is the observed concentration of unsafe count values, and the cc_t^k, i.e. the expected concentration of unsafe count values under randomization. As different simulations might provide slightly different results, the cc_t^k is in fact the mean concentration across ten different simulations. In the results section, the mcc_t^k is reported in absolute values but also as an expected-over-observed ratio, that is cc_t^k divided by cc_t^{k*}. The absolute values denote the additional proportion of micro-places required by the simulated data to account for any given k compared to the observed data, while the latter provides a ratio of the extent to which the observed data show a concentration relative to the expected level of concentration under randomization (for elaborations see Chalfin et al. 2021).

While the analyses above consider the concentration of unadjusted and weighted counts to grid-cells, they do not answer the question of how these are spatially distributed across the study area. Therefore, choropleth maps have been produced that visualize the spatial distribution of the grid-cells that account for a quarter and half of the unadjusted and weighted counts. To provide a richer image that accounts for the full data set, i.e. not only

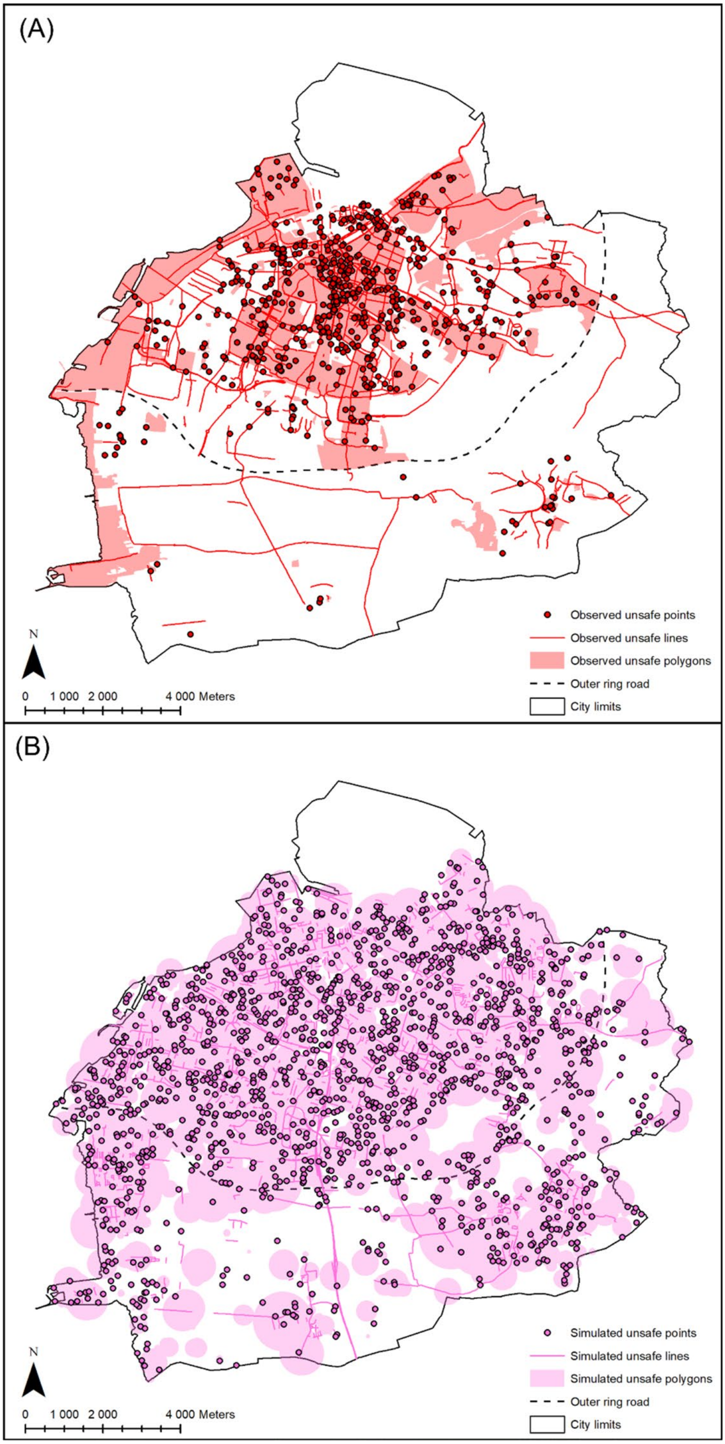


Fig. 1 Illustration of polygon, polyline and point features in the observed **A** and simulated **B** dataset for all three years combined. Outer ring road is used as a visual reference

the grid-cells that account for the top 25 and 50 percent of the counts, these two maps are complemented with density maps based on kernel density estimations (KDE).[8] In addition, a Global Moran's *I* is employed to examine spatial autocorrelation in the dataset, that is the extent to which grid-cells are surrounded by similarly high respectively low value grid-cells (Chainey 2020; see also Ratcliffe 2011). The Global Moran's *I* is produced using grid-cells as units of analysis and unadjusted and weighted count values as measure of intensity. A first order queen contiguity is employed as spatial weight, with row standardization and significance testing using 999 random permutations.[9] All maps include Malmö's outer ring road as a visual reference and have been produced using ArcGIS 10.7, and Global Moran's *I* statistics have been estimated using GeoDa 1.18.0 (see Anselin et al. 2006).

To answer the second research question, i.e. to examine the temporal stability of unsafe locations over time, a number of Spearman's rank-order correlations have been calculated. Here, grid-cells are ranked based on their unadjusted and weighted counts for each year separately. The correlation coefficients thus signify the extent to which a high (or low) ranked grid-cell in 2012 is correlated with a high (or low) rank in 2015 and 2018.

Results

Tables 3 and 4 report the cumulative proportions of grid-cells that account for 25 and 50 percent of the total sum of unadjusted and weighted counts for both the observed and simulated datasets. In addition, the tables report absolute values of the MCC and an expected-over-observed (E/O) ratio. The full relationship between the cumulative proportion of grid-cells and the sum of counts for both the observed and simulated datasets are also illustrated by Lorenz curves in Appendix B.

Looking at the cumulative proportion of grid-cells (Tables 3 and 4), the results suggest that unsafe locations are indeed concentrated to micro-places within the city of Malmö. With only small variations across the survey waves, 2.3 percent of all included grid-cells account for 25 percent of the unadjusted counts of unsafe locations, while 7.5 percent account for 50 percent for all three years combined. Focusing on the roughly 60 percent of non-zero grid-cells, there is a slightly greater variation across the waves, but a total of 3.4 and 11.3 percent of the non-zero grid-cells account for a quarter and half of the total unadjusted count respectively for all three years combined. Turning to the weighted counts, the data suggest that unsafe locations are even more concentrated, with only 0.9 percent of grid-cells accounting for a quarter of the total sum of weighted counts for all three years combined, and 4.2 percent accounting for half of the weighted counts. Using non-zero grid-cells only, these proportions increase to 1.4 and 6.4 respectively. The fact that the weighted counts appear to be more concentrated than the unadjusted counts is expected, however, since smaller geographical features have a greater

[8] The density maps utilize grid-cell centroids (i.e. point features) as the input unit of analysis and unadjusted and weighted count values as the measure of intensity. The cell-size is set to 200 m, with a search bandwidth of 300 m. A five-class natural breaks (Jenks) classification is used in the final visualization (for further reading on KDE, see Chainey 2013 and Chainey 2020).

[9] As this specific analysis requires that each grid-cell has at least one neighboring grid-cell, with a recommendation on eight with a skewed distribution (Esri n.d.), this specific analysis is based on a slightly different dataset with marginally more included grid-cells (N = 2961). It should also be noted that this analysis is sensitive to zero-inflation, which is the case in the current study, why these results should be considered as a complement to the choropleth and density maps.

impact when using the weighted compared to the unadjusted counts, which inherently leads to a greater likelihood of concentration.

While these initial results suggest that unsafe locations are highly concentrated to a small proportion of grid-cells, these results are relative to an assumption of an equal distribution of counts across grid-cells (i.e. uniformity). However, Tables 3 and 4 also present the share of grid-cells that account for 25 and 50 percent of the unadjusted and weighted counts from the simulated dataset.

Using the simulated dataset as a counterfactual, the absolute MCC values suggest that the simulated dataset would require an additional 11.0 percentage points of grid-cells to explain a quarter of the unadjusted counts, and an additional 8.3 percentage points for the weighted counts, compared to the observed data for all three years combined. An

Table 3 Proportion of grid-cells accounting for 25 percent of unadjusted and weighted counts for observed and simulated datasets, and marginal crime concentration (MCC)

	Grid-cells (N = 2921)	Non-zero grid-cells (N = 1933)	Simulated grid-cells (N = 2921)	MCC^{25}	
	%	%	% (sd[a])	Diff %	E/O ratio
Unadjusted counts					
2012	2.09	4.08	9.32 (0.43)	7.23	4.46
2015	2.09	5.00	8.67 (0.44)	6.58	4.15
2018	2.23	3.97	10.48 (0.34)	8.26	4.71
Total	2.26	3.41	13.25 (0.26)	10.99	5.87
Weighted counts					
2012	0.82	1.61	5.49 (0.15)	4.67	6.68
2015	0.48	1.15	4.91 (0.16)	4.43	10.24
2018	1.20	2.14	6.06 (0.16)	4.86	5.06
Total	0.92	1.40	9.25 (0.13)	8.33	10.01

Diff difference; *sd* standard deviation

[a]Standard deviations are based on means from ten simulated trials

Table 4 Proportion of grid-cells accounting for 50 percent of unadjusted and weighted counts for observed and simulated datasets, and marginal crime concentration (MCC)

	Grid-cells (N = 2921)	Non-zero grid-cells (N = 1933)	Simulated grid-cells (N = 2921)	MCC^{50}	
	%	%	% (sd[a])	Diff %	E/O ratio
Unadjusted counts					
2012	6.88	13.45	23.14 (0.92)	16.26	3.36
2015	6.20	14.82	21.87 (0.79)	15.68	3.53
2018	7.87	14.03	26.02 (0.68)	18.14	3.30
Total	7.50	11.33	31.35 (0.43)	23.85	4.18
Weighted counts					
2012	3.25	6.36	14.21 (0.24)	10.96	4.37
2015	2.74	6.55	12.65 (0.22)	9.91	4.62
2018	4.76	8.48	16.04 (0.27)	11.28	3.37
Total	4.21	6.36	23.51 (0.20)	19.30	5.58

Diff difference; *sd* standard deviation

[a]Standard deviations are based on means from ten simulated trials

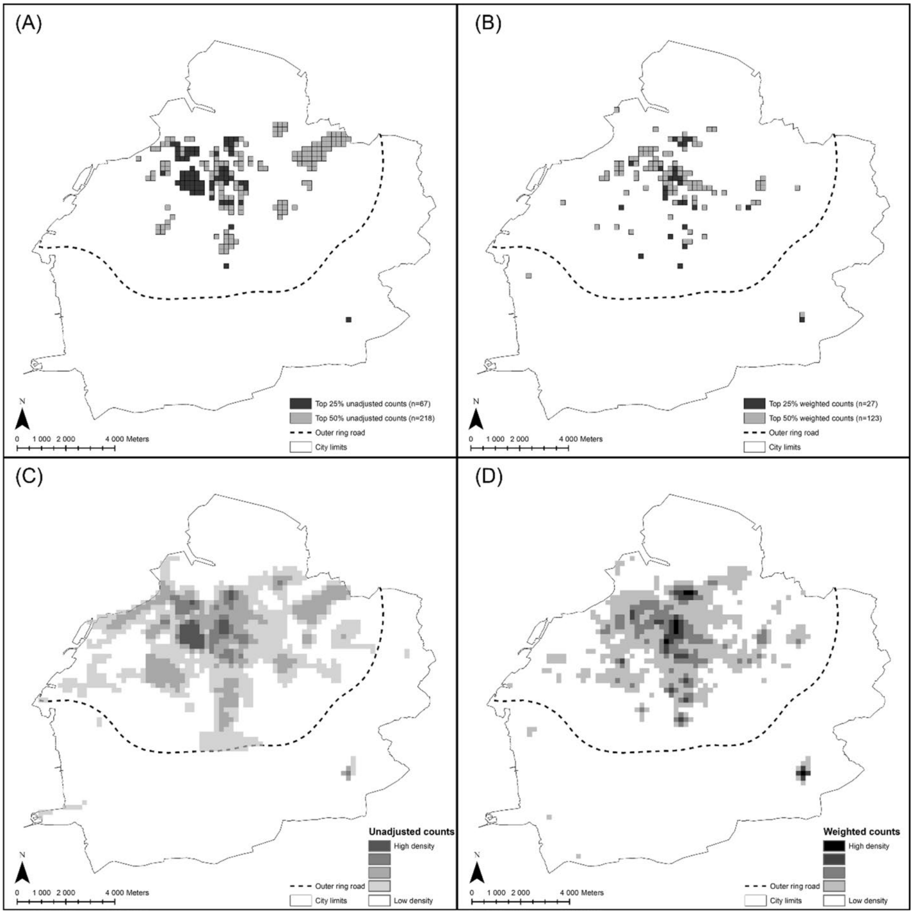


Fig. 2 Spatial distribution of grid-cells accounting for a quarter and half of unadjusted **A** and weighted counts **B**, and density maps (kernel density estimations) for unadjusted **C** and weighted counts **D**, for all three years combined. Outer ring road is used as a visual reference

alternative interpretation is that unsafe locations are between six (unadjusted MCC^{25} E/O ratio: 5.9) and ten times (weighted MCC^{25} E/O ratio: 10.0) as concentrated to grid-cells in the observed data as compared to what would be expected under simulation. Similar results are found when considering half of the counts, which are between four (unadjusted MCC^{50} E/O ratio: 4.2) and six times (weighted MCC^{50} E/O ratio: 5.6) as concentrated in the observed data compared to the simulated counterfactual. It should be noted that the standard deviations for the simulated dataset presented in Tables 3 and 4 show that there are very small variations in simulated concentrations between the ten trials.

While the results thus far confirm that unsafe locations are substantially concentrated to a small proportion of grid-cells, Fig. 2 provides an illustration of the spatial clustering of these grid-cells. The figure includes four maps that represent grid-cells that together account for a quarter and half of the unadjusted (A) and weighted counts (B) for all three years combined, and also a more detailed account of the full dataset in the form of two density maps that represent each count (C and D).

Table 5 Spearman's rank-order correlations for unadjusted and weighted counts across years

	Unadjusted counts			Weighted counts		
	2012	2015	2018	2012	2015	2018
2012	1.000	.688	.585	1.000	.558	.437
2015	.741	1.000	.629	.673	1.000	.504
2018	.717	.724	1.000	.642	.661	1.000

All correlations are significant at $p < .001$. Values below the diagonal of the matrix are based on all grid-cells (N = 2921) while values above the diagonal are based on non-zero grid-cells (N = 1933)

A visual inspection of the unadjusted counts (A) in Fig. 2 reveals that, with few exceptions, the grid-cells appear to be spatially clustered. This pattern is also evident in the density map (C), which also provides a more fine-grained visualization of the spatial concentration of the unadjusted count values across the full dataset. The test of spatial autocorrelation in the full dataset (i.e., not only top 25 and 50% of grid-cells) confirms this observation by showing that grid-cells with similar unadjusted counts are significantly clustered as compared to spatial randomness (Moran's $I = 0.65$; $z = 63.7$, pseudo $p < 0.001$). However, the spatial clustering observed is not surprising given the structure of the data. For the unadjusted counts, polygons and polylines (e.g. parks and streets) reported as unsafe by numerous participants will be prominent and thus signify a spatial clustering as a result of the original geographical feature. In other words, a park covering for instance 10 grid-cells, with an unadjusted count of e.g. 30, will inevitably signify a clustering of grid-cells. This is because each of the 10 grid-cells that intersects the original polygon feature receives a count of 30, which by default will be contingent or adjacent. Thus, when we turn to the weighted counts (B) in Fig. 2—where larger polygons and polylines have less impact—the spatial concentration is not as visually striking. However, there remains a significant spatial clustering in the data (Moran's $I = 0.30$; $z = 31.1$, pseudo $p < 0.001$), which becomes clearer in the density map (D).

To answer the study's second research question, that is whether there is temporal stability in unsafe locations over time, Table 5 presents a number of Spearman's rank-order correlations for the unadjusted and weighted counts respectively. Here, the focus is shifted from the grid-cells accounting for 25 and 50 percent of the unadjusted and weighted counts, and instead focuses on the full range of counts. However, the lower half of the matrix reports the coefficients from the case in which all grid-cells (N = 2921) are included, while the upper half reports the same coefficients when the focus is directed only at non-zero grid-cells, across all three years (N = 1933).

The results point to relatively strong correlations when all grid-cells are included, and the focus is directed at the unadjusted counts. Although the relationship becomes somewhat weaker when the focus is directed at the non-zero grid-cells, the correlations remain both significant and moderately strong. A similar pattern is also found for the weighted counts, but with generally somewhat weaker correlation coefficients. A noteworthy but perhaps not very surprising result is that the correlations are generally stronger between contiguous survey waves. In other words, the correlations between grid-cell counts for 2012 and 2015 are generally stronger across all analyses than for 2012 and 2018. This may imply that there is a transition in unsafe locations over time with some "new" unsafe locations emerging (and others potentially disappearing).

Alternative Grid-Cell Size

Given the somewhat arbitrary choice of using 200 by 200-m grid-cells as the unit of analysis, the data have been restructured and the main analyses replicated using 100 by 100-m (N = 9743) and 400 by 400-m (N = 898) grid-cells. The use of different scales represents an important sensitivity analysis given the nature of documented issues relating to the Modifiable Areal Unit Problem (MAUP), since different scales may affect the results (e.g. Gerell 2017). However, using differently sized units of analysis does not alter the general interpretation of the findings, but rather confirms a strong concentration of unsafe locations to (both larger and smaller) micro-places. However, as expected given findings from previous research (see Steenbeek & Weisburd 2016; Schnell et al. 2017), the degree of concentration increases slightly with smaller units of analysis, and diminishes somewhat with the employment of larger, although these differences are generally negligible.

Nor does the use of differently sized units of analysis affect the interpretation of whether there is temporal stability in unsafe locations over time. In fact, the results verify that there is temporal stability in unsafe locations across waves, as suggested in the main analysis, but also show that these patterns appear to be slightly stronger when using larger units of analysis. (A full account of the analyses using alternative grid-cell sizes is available in the online supplementary appendix).

Discussion

Spatial Concentration of Unsafe Locations and Future Directions

A large body of research has to date examined the spatial concentration of crime to micro-places finding support for the law of crime concentration (e.g., Breetzke and Edelstein 2019; Chainey et al. 2019; Favarin 2018; Mazeika and Kumar 2017; Weisburd 2015). A few recent studies have also examined the spatial concentration of other important and criminologically relevant outcomes including mental health calls for police service (Koziarski 2021), fatalities following opioid overdoses (Carter et al. 2019), and incidents of the police use of force (Sorg et al. 2021). The current study adds an additional criminologically relevant outcome to the current state of research. Using rather unique georeferenced survey data from a community survey on places perceived as unsafe by city inhabitants the current study set out to explore the spatial concentration of unsafe locations. Summarizing the main findings, three important conclusions may be drawn. First, there seems to be quite substantial evidence that unsafe locations are concentrated to a small proportion of micro-places, operationalized as 200 by 200-m grid-cells, in Malmö. More specifically, a narrow bandwidth of grid-cell proportions accounts for a substantial proportion of unsafe locations when either unadjusted or weighted counts are employed. But how should these results be interpreted?

Given the lack of research on the concentration of unsafe locations, the only viable point of reference is that relating to crime concentrations. As such, the resulting bandwidths from the current study are quite similar to those provided by Weisburd (2015) for crime concentrations on street segments in five larger American cities (i.e. 25% of crime within 0.8–1.6% of micro-places; 50% of crime within 4.2–6.0% of micro-places). Similarly, using the results of Chalfin et al. (2021) as a reference (i.e. all crimes at micro-places across three American cities), the expected-over-observed ratios noted in the present study lie either in the same ballpark, or within a lower range, for both a quarter (25% = 7.9–17.0) and half of the counts (50% = 4.9–9.5). Thus, although arguably focusing on a completely different outcome, the results from the current study on unsafe locations are quite similar to those reported in previous research on crime concentrations. At the same time, researchers with access to geographical data on unsafe locations should be encouraged to replicate the current study and further examine the spatial concentration of unsafe locations at micro-geographic units of analysis.

A second important insight from the current study is that the results suggest evidence that grid-cells with high (and low) count values are significantly clustered in space. While this is expected for the unadjusted counts, given the nature of the unsafe geographical features prior to aggregating the grid-cells, spatial clustering is also evident for the weighted counts. As such, and in accordance with other studies on unsafe locations (e.g. Curtis et al. 2014; Doran and Lees 2005; Jakobi and Pődör 2020; Kohm 2009; Ogneva-Himmelberger et al. 2019; Pánek et al. 2019), this indicates that there are a number of unsafe locations within the city of Malmö that are reported by numerous respondents and that might consequently be considered to constitute pockets or "hot spots" of unsafety. However, more refined spatial analyses could provide further insights into the spatial clustering of unsafe locations, which should also be encouraged in future research.

A third important finding is that there seems to be, at least to some extent, a temporal stability in (un)safe locations. In other words, there is a correlation between grid-cells having high and low-ranked count values respectively in 2012, and their having high and low-ranked count values in 2015, and similarly between 2015 and 2018. These findings corroborate previous research on crime showing a temporal stability in micro-places with high (and low) crime counts over time (e.g. Weisburd et al. 2004; Wheeler et al. 2016). With additional data covering a longer period of time than the current three waves of the MCS, it would be both feasible and interesting to study the trajectories of unsafe locations over time.

In summary, the current study has two important implications that deserve to be emphasized. First, since unsafe locations are concentrated to a small proportion of micro-places, this supports the idea that there are some features linked to particular locations that lead to them being perceived as unsafe, not only by different participants cross-sectionally, but also over time. Second, the results from the present study may also be important from a practitioner's point of view. Since the results indicate that unsafe locations are concentrated in space, this suggests that efforts to reduce levels of perceived unsafety might be focused on a small number of locations. Perhaps hot spot strategies aimed at reducing the prevalence of unsafe locations will become an important topic in the future, with a potential to create safer urban spaces.

However, knowing where people experience unsafety does not necessarily answer to why these locations are perceived as unsafe. Without such an understanding it is difficult to develop knowledge-based interventions. In a next step, a highly important task is to further examine *why* perceptions of unsafe locations cluster to certain micro-places. What is it about these places that make people perceive them as unsafe? Is it characteristics of the built environment, the ambient population at these locations, or any other social and/or physical cues? Reflecting upon the results from the present study it is reasonable to assume that there are both mutual and distinct explanations to why different types of locations are perceived as unsafe. For instance, a large share of all reported unsafe geographical features represents parks and green areas. Previous research on urban green spaces and fear of crime, or feelings of unsafety, has showed that both social and physical characteristics—including the presence (or absence) of other individuals, unmaintained vegetation and shrubs, and poor lighting and darkness—may act as fear inducing elements (see Jansson et al. 2013; Sreetheran and van den Bosch 2014). These characteristics may of course be more general exogenous triggers of fear of crime stretching beyond parks and green areas. For instance, a large share of all reported locations in the present data—not only those relating to green spaces—are in fact discussed in relation to a temporal dimension, that is only considered unsafe during "evenings", "nights", or "after dark".[10] One may also question the extent to which there is an agreement between unsafe locations and reported crime rates. While some studies have supported the notion that neighborhood crime rates affect individual-level fear of crime (e.g., Brunton-Smith and Sturgis 2011), studies focusing on unsafe locations as unit of analysis shows rather mixed findings. Jakobi and Pödör (2020) found quite inconsistent relationships between places reported as unsafe by respondents and reported crime rates with some unsafe places also having high crime rates, while others having no or only a few reported crime events (see also Ogneva-Himmelberger et al. 2019; Pánek et al. 2019).

However, since the aim of the current study has been descriptive, focusing on the *where*, there is more room for more careful examinations of *why* these locations are consistently reported as unsafe. Although the present study shows that certain functional locations (e.g. parks, streets and squares) are recurrently reported as unsafe, another important question to consider is what characterizes the particular geographical locations that are recurrently reported as unsafe (e.g. park X, street Y and square Z).

Limitations

While the MCS is based on a random sample, a response rate ranging between 40 and 50 percent across the three waves is problematic with regard to representativeness, generalizability and the external validity of the data. In addition, the analysis of the participants who answered Q18 revealed a bias with regard to which individuals' perceptions of unsafe locations are reflected in the current study, as compared to the sample as a whole. In addition, legitimate criticism could also be directed at what Q18 actually captures. For instance, the item does no mention crime, which consequently allows participants to report locations as being perceived as unsafe as a result of a range of different concerns (see Gray et al. 2011; Ferraro and LaGrange 1987), e.g. fear of traffic-related accidents (Jakobi and Pödör 2020). However, given the context of the question—i.e. its inclusion in a neighborhood survey on (fear of) crime—the significance of crime is by and large implicitly communicated to survey participants. However, future research should consider including additional items capturing information on *why* specific locations are perceived as unsafe or uncomfortable to visit/pass though. Such information may assist to sort out any irrelevant answers (e.g., unsafety not relating to crime) but also provide more detailed information on unsafe locations relating to specific crime types.

A further limitation relating to Q18 is that it asks about locations in the participants' own neighborhood, which may have limited the number of unsafe locations reported. As such, the data may miss locations *outside* of the participants' own neighborhoods that they may encounter during their everyday lives and also perceive as being unsafe to visit/pass

[10] Although participants were not asked to state any reasons for unsafety at the reported locations the open-ended character of Q18 allowed for such elaborations which consequently led to a lot of answers including reasons for unsafety at particular locations.

through. On the other hand, this may in fact strengthen the findings from the present study, since there appear to be strong concentrations of unsafe locations *despite* participants being asked to think about their own neighborhood only.

Another important limitation relates to the use of an open-ended question to chart geographical locations more generally. A considerable number of the answers to Q18 were not geocoded, since participants either gave answers that did not relate to unsafety or described general characteristics of locations that they avoided or perceived as being unsafe, e.g. “dark parks”, “crowded squares”, or “desolate streets”. Further, a substantial number of locations could not be geocoded because participants did not provide enough information about the location (although instructed do so). For instance, although “the adjacent park” or “the street outside my house” are both viable locations, these could not be geocoded given the lack of more precise information. The use of an open-ended question to geocode locations also involves two other important issues. First, screening such answers for eligibility for geocoding, and then subsequently geocoding the answers, are both time-consuming tasks. Second, and perhaps more importantly, interpreting open-ended answers presents issues with regard to geographical reliability. In the context of this approach, the researcher who codes the data functions as an intermediator between participants’ subjective conceptualizations of a given location and the operationalized geographical feature representing that specific location. For instance, participants may have a well-defined location in mind, which they refer to by name, but their subjective views need not necessarily correspond to the actual area as defined by administrative geographical boundaries (i.e. geographical reference data). Although the two are probably similar, there are also likely to be discrepancies between them.

Given these issues relating to the use of an open-ended question to survey perceptions of unsafety at locations, future research should consider other viable alternatives. These include, for instance, sketch maps on which participants may mark locations that they perceive as unsafe—either as points, polylines or polygons (e.g. Jakobi and Pödör 2020). Such an approach would be beneficial as it would nullify many of the issues presented above. However, while a sketch map could quite easily be integrated into an online version of a questionnaire (e.g. the MCS), it would be more problematic in relation to a paper-and-pen version of the same survey. Therefore, future research is encouraged to elaborate on alternative methods and instruments to continue the development of both reliable and valid information on the geography of unsafe locations.

Conclusion

This study demonstrates that unsafe locations are concentrated to a small proportion of micro-places in the city of Malmö. Furthermore, these seem to be spatially clustered, suggesting that unsafe locations are not randomly distributed across urban space. In addition, the study provides empirical support for the proposition that there is temporal stability in unsafe locations, suggesting that a number of locations are consistently reported as unsafe over time. In sum, the study’s results have important implications for both theory and practice. However, since the study is subject to a number of limitations, future research should be encouraged to continue to explore the spatial dimensions of unsafe locations and, by extension, different dimensions of *the fear of crime* at places.

Appendix A

Using hypothetical outcome data, Fig. 3 exemplifies the two methods used to merge counts from polygons, polylines and points, to grid-cells. Here we have a polygon (park) that was reported as unsafe by 21 participants, and which intersects with 7 cells, a polyline (bicycle path) reported by 14 participants, which intersects with 4 cells, and a point (intersection) reported by 4 participants (points are by default located in a single cell). Using this example, the total count of unsafe locations is thus 39. In the next step, each grid-cell receives the sum of all geographical features intersecting with that specific grid-cell, reported as values in Fig. 3. For the unadjusted count value, each of the 7 cells that intersect with the polygon (park) receives a value of 21, each of the 4 cells intersecting with the polyline (bicycle path) receives a value of 14, and the cell that intersects with the point feature receives a value of 4. The total count value of the grid-cells in this example thus sums to 207.

The main difference when calculating the weighted count values is that each cell that intersects with the polygon (park) receives a value of 3, which corresponds to the number of participants reporting that location divided by the number of grid-cells intersected by the geographical feature (twenty-one divided by three). Using the same logic, each cell that intersects with the polyline (bicycle path) thus receives a weighted count value of 3.5. The count value for the point feature, however, remains the same, since points are by default located in a single grid-cell. Unlike the unadjusted counts, the total sum of the weighted counts in the grid-cell network thus sums to the original sum of counts (i.e. 39).

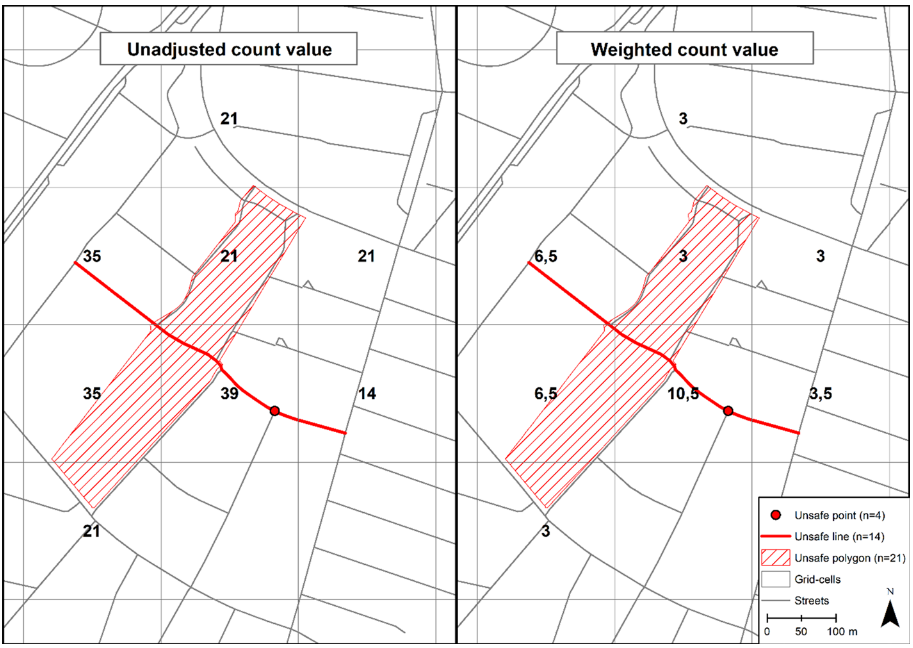
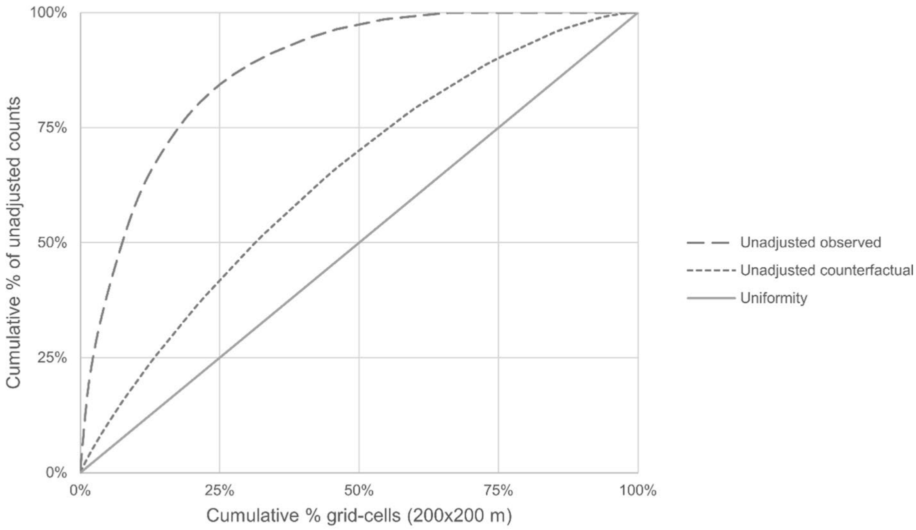


Fig. 3 Illustration of two methods of merging counts of unsafe locations from geographical features to grid-cells

Appendix B

See Fig. 4.



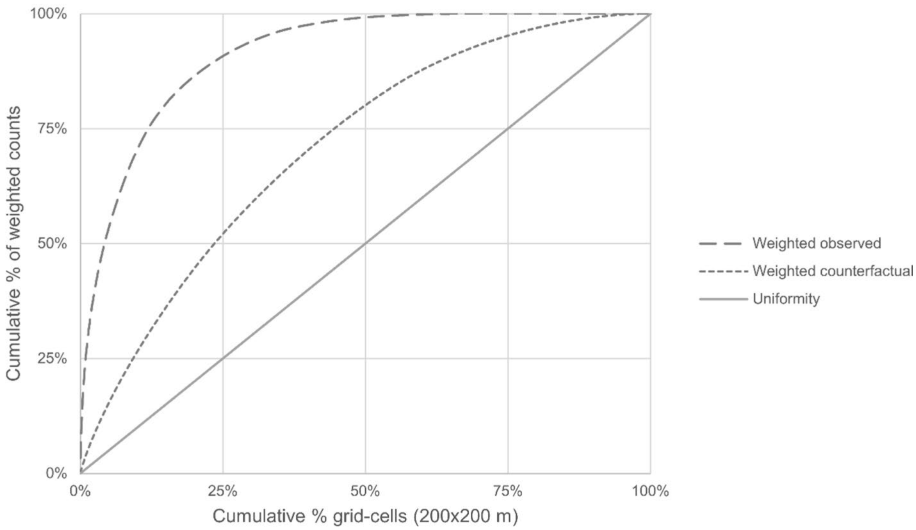


Fig. 4 Lorenz curves for the unadjusted and weighted cumulative percentages of 200 by 200-m grid-cells (N = 2921) that account for different proportions of the unadjusted and weighted counts in the observed and simulated datasets

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s10940-022-09565-6.

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Data Availability The raw data in the present study are not publicly available due to confidentiality reasons. The aggregated datasets analyzed in the current study are however available from the corresponding author on reasonable request.

Declarations

Conflict of interest The author declares no competing interests.

Ethical Approval The community survey data analyzed in the present study has been reviewed and approved by the Regional Ethics Board in Lund (Dnr. 2014/826).

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