RESEARCH REPORT

Spatial clustering of mental disorders and associated characteristics of the neighbourhood context in Malmö, Sweden, in 2001

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Study objective: Previous research provides preliminary evidence of spatial variations of mental disorders and associations between neighbourhood social context and mental health. This study expands past literature by (1) using spatial techniques, rather than multilevel models, to compare the spatial distributions of two groups of mental disorders (that is, disorders due to psychoactive substance use, and neurotic, stress related, and somatoform disorders); and (2) investigating the independent impact of contextual deprivation and neighbourhood social disorganisation on mental health, while assessing both the magnitude and the spatial scale of these effects.
Design: Using different spatial techniques, the study investigated mental disorders due to psychoactive substance use, and neurotic disorders.
Participants: All 89 285 persons aged 40–69 years residing in Malmö, Sweden, in 2001, geolocated to their place of residence.
Main results: The spatial scan statistic identified a large cluster of increased prevalence in a similar location for the two mental disorders in the northern part of Malmö. However, hierarchical geostatistical models showed that the two groups of disorders exhibited a different spatial distribution, in terms of both magnitude and spatial scale. Mental disorders due to substance consumption showed larger neighbourhood variations, and varied in space on a larger scale, than neurotic disorders. After adjustment for individual factors, the risk of substance related disorders increased with neighbourhood deprivation and neighbourhood social disorganisation. The risk of neurotic disorders only increased with contextual deprivation. Measuring contextual factors across continuous space, it was found that these associations operated on a local scale.
Conclusions: Taking space into account in the analyses permitted deeper insight into the contextual determinants of mental disorders.

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During the past decade, there has been growing research interest in the impact the neighbourhood of residence may have on mental health.[1–3] Authors have suggested that the identification of places with a higher risk of disease may be useful to better target potential intervention programmes, and that assessment of relations between specific neighbourhood characteristics and mental health may provide interesting clues in the understanding of the mechanisms contributing to social disparities.[3] In this study, following previous work of ours, we argue that modelling spatial variations of diseases is useful to assess whether healthcare resources can be uniformly distributed over space, or whether they should primarily be made available in specific areas.[4–7]

Many studies have explored neighbourhood variations in mental disorders.[1 2 8–21] Those studies that used multilevel models generally found weak, although statistically significant, neighbourhood variations in psychiatric morbidity or psychological problems. Differences in neighbourhood socioeconomic composition accounted for this geographical variation in some studies,[8 10 17] but not in others, where independent contextual effects were found.[1 12 13] Many authors have only considered a neighbourhood's socioeconomic level, and have generally found a weak socioeconomic contextual effect on the risk of disorders.[2 9 12 15 16] Only a few authors, attempting to better understand contextual influences, have examined whether mental disorders are more prevalent in neighbourhoods with high levels of social disorganisation.[19–22] The latter refers to the inability of a community to maintain effective social control for the civil regulation of public behaviour,[23–25] and may result in a range of signs of social or physical disorder, such as crime or incivilities, vandalism, unsanitary conditions, squalor, and physical decay.[19 26] However, studies of the impact of social disorganisation upon mental health may have been deficient in the measurement of social disorganisation, which they performed either using very indirect proxies,[20] or through subjective assessment (raising the problem of reverse causality, if mental health tends to influence assessment of the residential environment).[18 19 22 26]

As detailed below, our study, conducted in Malmö, Sweden, expands the research in this field into various directions: (1) we compared the spatial distribution of two different groups of mental disorders (disorders due to psychoactive substance use, and neurotic, stress related, and somatoform disorders), using recently developed spatial statistical techniques, rather than the multilevel approach,[6] and (2) we investigated the independent effect of objective indicators of contextual deprivation and social disorganisation (measured across continuous space on different scales, rather than within administrative areas) on mental disorders.

Regarding the first objective, we compared spatial distributions of the different disorders with respect to not only the magnitude but also, the scale of variations.[6 7] It is

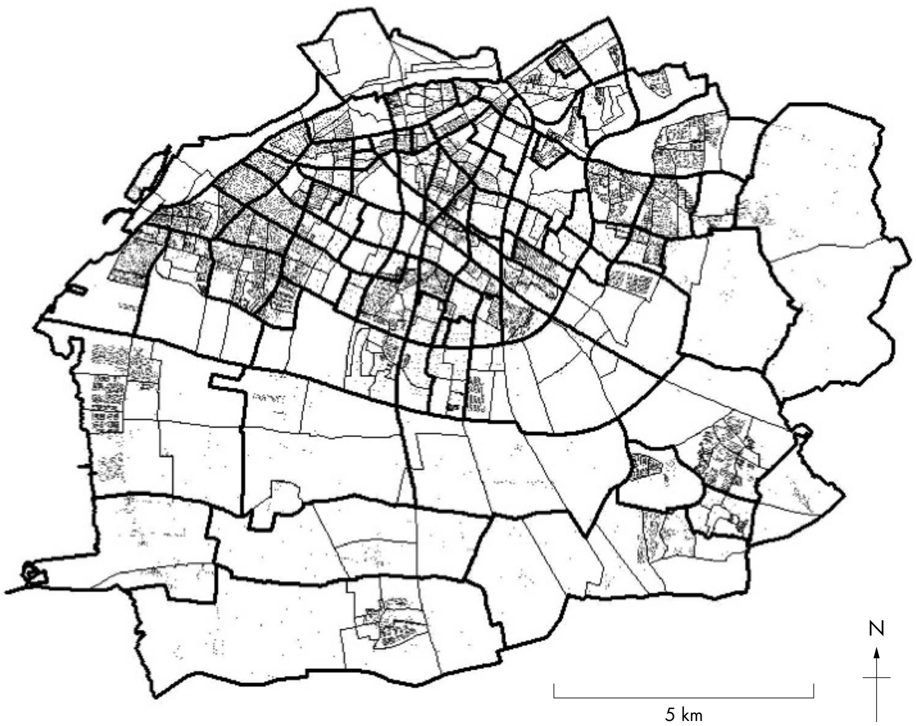


Figure 1 Spatial distribution of all 89 285 people aged 40–69 years in Malmö, Sweden, in 2001, residing in 17 010 different locations within the city. Each point shows the exact place of residence of these persons. Subneighbourhood boundaries are represented as normal lines, and neighbourhood boundaries are shown in bold.

important to assess whether the magnitude of geographical variations justifies including a contextual dimension into public health programmes.[4 5 27] Moreover, we found it of relevance to determine whether health phenomena vary on a local scale or one larger, to appraise the spatial level at which public health interventions should be coordinated.

We used a cluster recognition method and a spatial regression technique, which offer complementary visualisation modes of the spatial distribution of disorders. In an exploratory step, we used the spatial scan statistic to identify clusters with a high or low prevalence of disorders.[28–33] Secondly, we used hierarchical geostatistical regression models[34 35] that capture variations of prevalence across the city with a similar but more extended random effect approach than multilevel analysis. We emphasised previously[6 7] that common multilevel models[36 37] do not incorporate any notion of space, ignoring the spatial connections of proximity existing between neighbourhoods. Accordingly, multilevel models provide information on the magnitude of correlation within neighbourhoods, but not on the range of correlation in space. Conversely, the hierarchical geostatistical model, complementing the random effect functionalities offered by the multilevel model, showed not only whether the two disorders depended on the neighbourhood context to a different extent, but also whether they varied in space on a different scale.[7 38 39]

Regarding the second objective, our investigation of contextual factors contributing to clustering of mental disorders considered not only the socioeconomic environment, but also neighbourhood social disorganisation.[19] We captured the latter dimension by means of data on criminality. On the one hand, crimes are factors that may contribute to a sense of insecurity and fear,[40 41] powerlessness,[26] isolation,[25] and chronic stress,[18 42] and eventually result in psychopathological outcomes.[1 19 21 22 43 44] On the other hand, as social disorganisation is known to result in higher crime rates,[23 24 45 46] we used crime as the marker of a wider context of social disorganisation that may be detrimental to mental health, because of other stressors such as incivilities, vandalism, and other signs of disorder[19 26 40 43] and the absence of strong social ties or cohesion.[1 23 26 41 42]

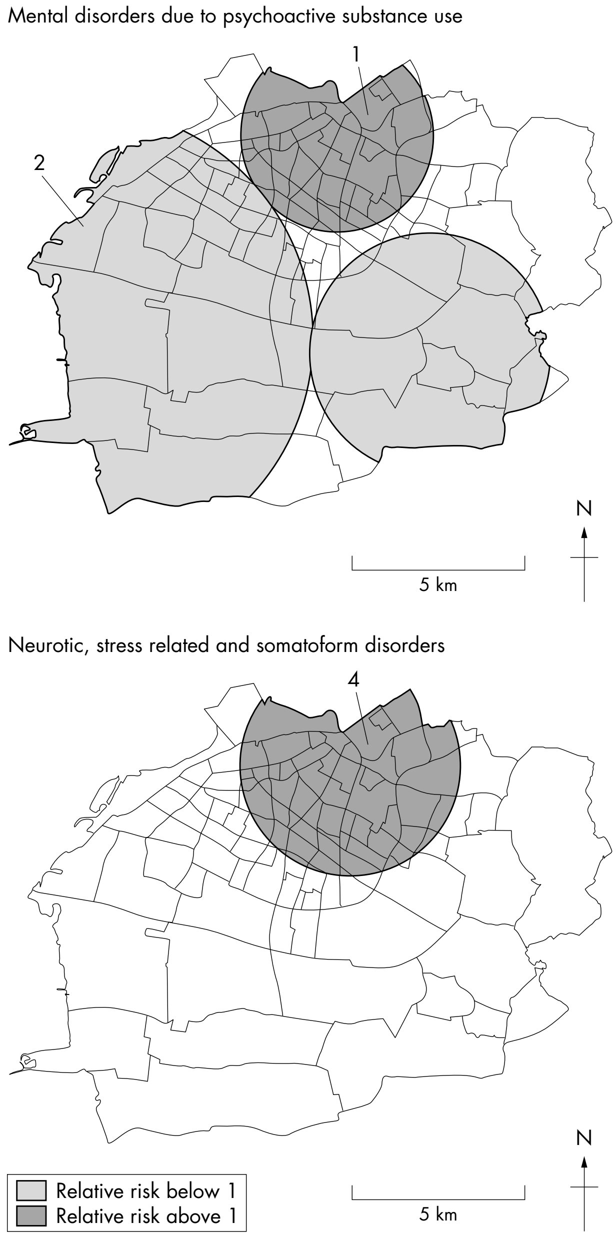
Importantly, it may not be appropriate to rely on administrative boundaries to capture these contextual influences.[6 47 48] Firstly, administrative boundaries may be arbitrary with respect to mental health.[49] Secondly, measurements within administrative areas may be particularly inadequate for people residing on the margins of those areas. Finally, contextual effects may operate on a more local scale than those bounded by administrative neighbourhoods, as commonly considered. To address these issues, we measured contextual factors in circular areas centred on the exact place of residence of individuals. Considering various radius sizes for these areas, we were able to examine whether contextual effects operated on a small or larger scale.[7 14]

In summary, our study expands past research by (1) using different spatial techniques to analyse and compare the spatial distribution of two categories of mental disorders, and (2) investigating associations between distinct characteristics of the context measured across continuous space (rather than within administrative areas) and mental health, while assessing both the magnitude and spatial scale of these effects.

METHODS

Data and measures

After giving approval, the Regional Office of Scania (the southernmost region of Sweden) provided us with data on all of the 89 285 people aged 40–69 years living in Malmö in 2001. Our database includes sociodemographic data on individuals, and information on all inpatient and outpatient contacts they had had with public and private healthcare providers during 2001. Using the first three diagnosis codes provided at each contact (defined according to the *International Classification of Diseases*, 10th version, ICD-10), the regional office created binary variables indicating whether people had received diagnoses in different categories of health problems. The two binary outcomes investigated indicated presence or absence of the following disorders: (1)



Characteristics of the different clusters

Cluster ID	Observed cases	Expected cases	Relative risk	p Value
1	689	458	1.51	0.001
2	250	398	0.63	0.001
3	27	74	0.37	0.001
4	243	189	1.29	0.008

Figure 2 Clusters of raised or lowered prevalence of substance related disorders and neurotic disorders, as identified with the spatial scan statistic technique for all individuals aged 40–69 years in Malmö, Sweden, in 2001. Relative risks quantify the increase in risk in each cluster, as compared with the overall risk in Malmö.

mental or behavioural disorders due to psychoactive substance use (ICD-10 codes F10–F19); and (2) neurotic, stress related, and somatoform disorders (F40–F48). We used information from a separate database that could not be linked to the main dataset to describe the distribution of subdiagnoses within the main diagnostic groups.

At the individual level, we took the age, gender, marital status, education, and income into account. Age was divided into three categories (40–49, 50–59, and 60–69 years). Marital status was coded as ''married or cohabiting'', and ''other'' (that is, single, divorced, and widowed). Educational attainment was coded into two groups ($\leqslant$9 years and >9 years of education). Household income was not available; instead, we used individual income. Whereas household income may correspond to the amount of money available to the entire household, personal earnings may more directly express the position of the person within the social group. Individual income was dichotomised, using the median value as the cut off point.

We used different administrative geographical subdivisions in our study. Firstly, we divided Malmö into 100 administrative neighbourhoods. Next, we considered a subdivision of Malmö into 386 subneighbourhoods defined by municipal authorities for statistical purposes. Furthermore, we used the exact spatial coordinates of the buildings in which individuals resided. Figure 1 shows the spatial distribution of the 89 285 people aged 40–69 years over 17 010 different buildings. It also shows neighbourhood and subneighbourhood boundaries.

Two types of contextual factors were considered. Firstly, we computed mean income of individuals aged $\geqslant$25 years as a proxy for the socioeconomic environment.[50] Secondly, using police department data, we determined incidence of violent crimes around places of residence as a proxy for neighbourhood social disorganisation.[19 22] We aggregated crime data from 1999, 2000, and 2001, to obtain more reliable information on crime variations. All contextual variables were divided into quartiles.

To investigate the spatial scale on which the contextual income and crime effects operated, we measured the corresponding factors in circular areas of different radii centred on the exact places of residence.[7] However, the distinct nature of the raw data (individual locations for income and area based data for crimes) constrained us to use different strategies to define the two contextual factors within circular areas.

Using the exact spatial coordinates of individuals, we computed mean income in circular areas of different radii centred on the exact place of residence of individuals. However, because of the uneven distribution of people in space (fig 1), we would have obtained unreliable measurements for people residing in sparsely populated places had we computed mean income in areas of small radii. Therefore, with the aim of investigating socioeconomic contextual effects on a much more local scale than heretofore, we computed mean income in circular areas of constant population size (comprising a fixed number of inhabitants aged $\geqslant$25 years), rather than constant geographical size. This approach avoids the problem of unreliable measurements in low population density places by relying on spatially adaptive areas (having an adaptive window width), which are of greater size in sparsely populated areas.[7 51–53] For each of the 17 010 individual locations, we computed mean income for the 250, 500, 1000, and 1500 closest inhabitants aged $\geqslant$25 years by aggregating contextual information from surrounding locations until the required number of inhabitants was attained. Besides permitting the investigation of contextual effects on a very local scale, areas of constant population size may be more accurate to measure the characteristics of surrounding population. In fact, it may not be appropriate to compute mean income in areas of very different population size, as more extreme values may be expected where there is a low population.

In contrast with income data, crime information pinpointed to specific locations was not available, but only data

Table 1 Results of the empty hierarchical geostatistical models for mental disorders due to psychoactive substance use and neurotic disorders for all people aged 40–69 years in Malmö, Sweden, in 2001

	Substance related disorders		Neurotic disorders	
	Index	**95% CI**	**Index**	**95% CI**
Random effects				
σ_s^2 (neighbourhood variance)	0.65	(0.39 to 1.36)	0.25	(0.12 to 0.48)
ϕ (rate of correlation decay)	0.0010	(0.0004 to 0.0025)	0.0054	(0.0017 to 0.0088)
$3/\phi$ (range of spatial correlation in m)	2976	(1200 to 7827)	555	(341 to 1734)
DIC*	8162		3765	

*The deviance information criterion (DIC) can be used to compare different models estimated for a similar mental health outcome, but not to compare models for different outcomes. The lower the DIC, the better the fit of the model.

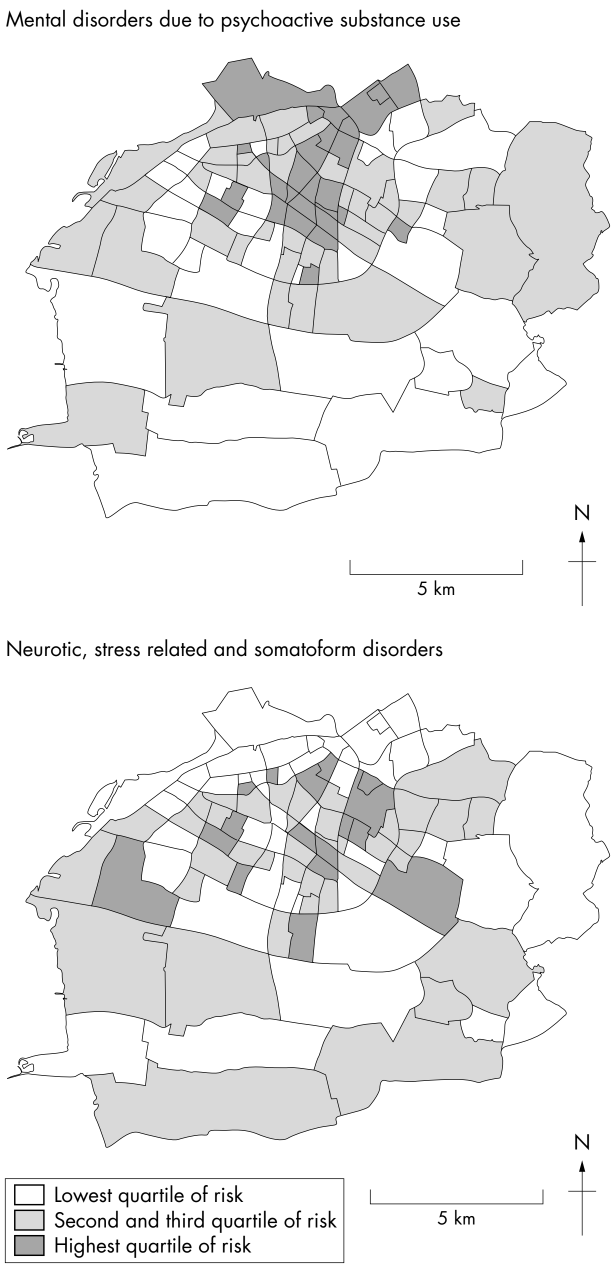


Figure 3 Crude neighbourhood prevalence of substance related disorders and neurotic disorders for all people aged 40–69 years in Malmö, Sweden, in 2001.

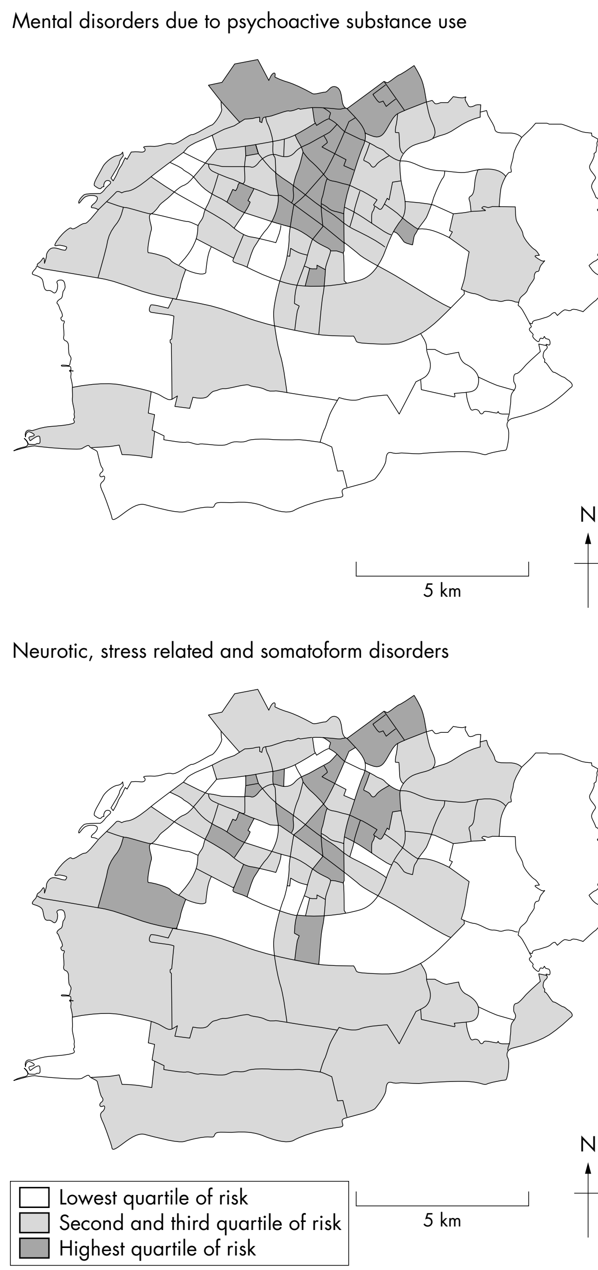


Figure 4 Neighbourhood level variations in the prevalence of substance related disorders and neurotic disorders, obtained with empty hierarchical geostatistical models for all people aged 40–69 years in Malmö, Sweden, in 2001.

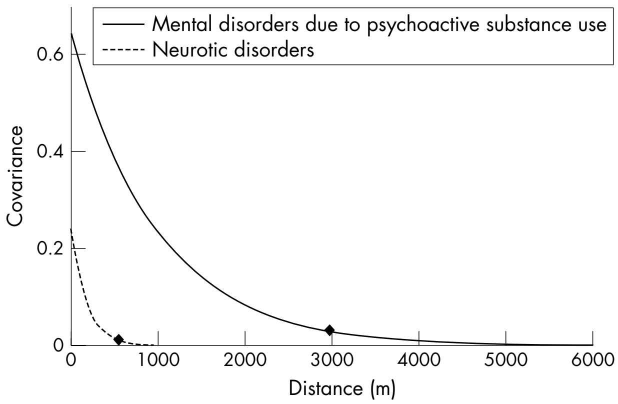


Figure 5 Covariance between neighbourhoods in terms of substance related disorders and neurotic disorders, as estimated from empty hierarchical geostatistical models for all people aged 40–69 years in Malmö, Sweden, in 2001. Functions show how similarity in prevalence level decreased as the distance between neighbourhoods increased. The value of functions at $x=0$ corresponds to the neighbourhood level variance. Diamonds show the spatial range of correlation ($3/\phi$).

at the level of the 386 subneighbourhoods. Crimes were also recorded in certain subneighbourhoods, such as public spaces, where no one resides. We were interested in estimating the approximate number of crimes committed at different distances from the place of residence of individuals. For each of the 17 010 locations, we computed the number of violent crimes in circular areas of a 500, 750, and 1000 metre radius centred on individuals (if a certain percentage of the surface of a subneighbourhood fell within the circular area considered for computation, we attributed that percentage of the crimes of the subneighbourhood to the circular area).

Because of the positive relation between population size and number of crimes in an area, a standardisation procedure may be necessary. However, definition of the standardisation is problematic. Considering that a given number of crimes is more acutely felt in sparsely populated areas, the relevant contextual factor must be defined as number of crimes per capita. Conversely, as a large proportion of crimes are committed in public spaces, it may be argued that what matters for individuals is the absolute number of crimes in their environment, regardless of population density. The true psychosocial process at play probably takes place between these two extremes. We expressed this uncertainty by defining the crime variable associated with x crimes committed in an area as $x/(pop^{\alpha})$, where *pop* is the number of residents aged $\geqslant$25 years in the circular area, and α, a parameter ranging between 0 and 1. When $\alpha=0$, the crime variable is independent of population size. Conversely, when $\alpha=1$, the crime variable is the number of crimes per capita. In this paper, we report results for an intermediate value of α ($\alpha\approx0.6$), chosen so that one crime has 1.5 times the impact when committed in an area with half the population, rather than once or twice the impact when $\alpha=0$ or $\alpha=1$. Sensitivity analyses showed that this parameter did not have an important influence on the association between crimes and mental disorders, except when α was close to 1 (and the crime factor therefore measured as a rate), in which case the association tended to be weaker.

Statistical analyses

The spatial scan statistic[28 29] was used to identify areas of raised or lowered prevalence of mental disorders (see appendix for details). This technique imposes a circular form on the clusters,[33] but allows them to be centred in any of the different individual locations and take any possible size (with a maximum size of 50% of all individuals). This approach tests the statistical significance of clusters with a likelihood ratio statistic, whose distribution under the null hypothesis is obtained through Monte Carlo simulation. This strategy allows one to derive a p value for each potential cluster (see appendix). We used the spatial scan statistic as an exploratory tool. Therefore, its implementation did not consider any individual or contextual covariates. These were included in the next analytical step.

To gain further insight into the spatial distribution of disorders, we estimated a hierarchical geostatistical model[34 35] that included a set of spatially correlated random effects, with individuals georeferenced at the centroid of their

Table 2 Effect of contextual income, measured on different scales, on mental disorders due to psychoactive substance use and neurotic disorders. Results were obtained from hierarchical geostatistical models adjusted for individual covariates* for all people aged 40–69 years in Malmö, Sweden, in 2001

	Substance related disorders		Neurotic disorders	
	Index	95% CI	Index	95% CI
Income of 250 closest inhabitants (*v* fourth quartile)†				
Third quartile	1.08	(0.83 to 1.40)	1.21	(0.84 to 1.73)
Second quartile	1.81	(1.40 to 2.34)	1.73	(1.23 to 2.45)
First quartile	2.46	(1.88 to 3.24)	2.03	(1.44 to 2.89)
DIC‡	7134		3635	
Income of 500 closest inhabitants (*v* fourth quartile)†				
Third quartile	1.01	(0.78 to 1.32)	1.33	(0.93 to 1.95)
Second quartile	1.66	(1.28 to 2.18)	1.94	(1.37 to 2.80)
First quartile	2.10	(1.61 to 2.83)	2.02	(1.42 to 2.94)
DIC‡	7150		3635	
Income of 1000 closest inhabitants (*v* fourth quartile)†				
Third quartile	1.09	(0.85 to 1.42)	1.15	(0.81 to 1.64)
Second quartile	1.91	(1.46 to 2.50)	1.55	(1.11 to 2.20)
First quartile	1.94	(1.45 to 2.62)	1.78	(1.27 to 2.54)
DIC‡	7162		3641	
Income of 1500 closest inhabitants (*v* fourth quartile)†				
Third quartile	1.09	(0.85 to 1.40)	1.26	(0.89 to 1.82)
Second quartile	1.42	(1.08 to 1.87)	1.45	(1.03 to 2.08)
First quartile	1.65	(1.25 to 2.23)	1.59	(1.12 to 2.28)
DIC‡	7179		3647	

*The models were adjusted for age, gender, marital status, education, and income. †Contextual income variables measured on different scales were introduced into separate models. ‡The deviance information criterion (DIC) can be used to compare different models estimated for a similar mental health outcome, but not to compare models for different outcomes. The lower the DIC, the better the fit of the model.

Table 3 Effects of the crime variable, measured on different scales, on mental disorders due to psychoactive substance use and neurotic disorders. Results were obtained from hierarchical geostatistical models adjusted for individual covariates* for all people aged 40–69 years in Malmö, Sweden, in 2001

	500 m radius†		750 m radius†		1000 m radius†	
	Index	95% CI	Index	95% CI	Index	95% CI
Substance related disorders						
Violent crimes (v first quartile)						
Second quartile	1.62	(1.23 to 2.15)	1.43	(1.10 to 1.89)	1.29	(0.98 to 1.70)
Third quartile	2.11	(1.59 to 2.82)	1.87	(1.43 to 2.50)	1.66	(1.25 to 2.23)
Fourth quartile	2.34	(1.73 to 3.18)	2.01	(1.51 to 2.72)	1.89	(1.40 to 2.57)
DIC‡	7166		7174		7176	
Neurotic disorders						
Violent crimes (v first quartile)						
Second quartile	1.34	(0.94 to 1.94)	1.20	(0.84 to 1.71)	1.31	(0.93 to 1.89)
Third quartile	1.53	(1.06 to 2.20)	1.43	(1.00 to 2.04)	1.33	(0.92 to 1.92)
Fourth quartile	1.65	(1.15 to 2.41)	1.42	(0.99 to 2.06)	1.26	(0.87 to 1.85)
DIC‡	3644		3647		3647	

*The models were adjusted for age, gender, marital status, education, and income. †The crime variables measured on different scales were introduced into separate models. ‡The deviance information criterion (DIC) can be used to compare different models estimated for a similar mental health outcome, but not to compare models for different outcomes. The lower the DIC, the better the fit of the model.

neighbourhoods (see appendix). The variance σ_s^2 of the spatial effect allowed us to quantify the magnitude of neighbourhood variations. The parameter ϕ indicated the rate of decrease in correlation in neighbourhood risk with increasing distance between neighbourhoods. To compare the spatial scale of variations of the different disorders, we computed the range of spatial correlation as $3/\phi$,[38 39] defined as the distance beyond which the correlation between neighbourhoods is below 5% (see appendix). Based on the model, we estimated the value of the spatial effect in each neighbourhood, which allowed us to map variations of prevalence (see appendix).

We first estimated empty models. Adjusting for individual factors (age, gender, marital status, education, and income), we then estimated separate models with contextual deprivation measured on the different scales, and used the deviance information criterion (DIC)[54] to select the most appropriate spatial scale of measurement (one model might be considered as having a better fit than another if its DIC was at least 3 points lower[54]). Similarly, we used the DIC to select the most relevant scale of measurement for the crime variable. Contextual deprivation and crime were finally entered into the same model, but only retained if they were significantly associated with the outcome. Hierarchical geostatistical models were estimated with MCMC simulation (see appendix).[55]

RESULTS

In our population, mental disorder due to psychoactive substances was diagnosed in 1.32% of individuals, and a neurotic disorder in 0.47%. Regarding substance related disorders, alcohol was involved in 79% of individuals, opioids in 11%, and sedatives or hypnotics in 10%; clinical conditions comprised a dependence syndrome for 85% and harmful use for 17% of individuals. Among individuals with neurotic disorders, non-phobic anxiety disorders were diagnosed in 48% of individuals, and stress related disorders in 36%.

The spatial scan statistic identified a cluster of increased prevalence in similar locations in the northern part of Malmö for the two mental disorders (fig 2). The p values for these clusters were 0.001 and 0.008 for substance related and neurotic disorders, respectively. These clusters of increased prevalence were of much larger size than administrative neighbourhoods, with a radius of about 2750 and 3150 metres, and a population size of 34 800 and 40 400 individuals aged 40–69 years for substance related and

Table 4 Results of the full hierarchical geostatistical models* for mental disorders due to psychoactive substance use and neurotic disorders for all people aged 40–69 years in Malmö, Sweden, in 2001

	Substance related disorders		Neurotic disorders	
	Index	95% CI	Index	95% CI
Fixed effects (odds ratios)				
Income of 250 closest inhabitants (v fourth quartile)†				
Third quartile	0.99	(0.75 to 1.29)	1.21	(0.84 to 1.73)
Second quartile	1.56	(1.18 to 2.07)	1.73	(1.23 to 2.45)
First quartile	2.08	(1.52 to 2.83)	2.03	(1.44 to 2.89)
Violent crimes, 500 m radius (v fourth quartile)†				
Second quartile	1.40	(1.04 to 1.90)	–	
Third quartile	1.45	(1.05 to 2.03)	–	
Fourth quartile	1.52	(1.07 to 2.17)	–	
Random effects				
σ_s^2 (neighbourhood variance)	0.11	(0.05 to 0.24)	0.06	(<0.01 to 0.19)
ϕ (rate of correlation decay)	0.0024	(0.0005 to 0.0083)	0.0061	(0.0023 to 0.0089)
$3/\phi$ (range of spatial correlation in metres)	1266	(360 to 5149)	488	(339 to 1308)
DIC‡	7132		3635	

*In the full models, the different contextual effects were adjusted for each other and for individual covariates (age, gender, marital status, educational level, and income). †The crime variable varied in space on a larger scale than contextual deprivation: separate ecological geostatistical models with (a) the contextual income factor, and (b) the violent crime variable as outcomes (at the administrative neighbourhood level) showed that the spatial range of correlation was 3613 metres and 6036 metres, respectively, for these two contextual factors. ‡The deviance information criterion (DIC) can be used to compare different models estimated for a similar mental health outcome, but not to compare models for different outcomes. The lower the DIC, the better the fit of the model.

neurotic disorders, respectively. Relative risks for these clusters were 1.51 and 1.29, respectively (using overall risk in Malmö as a reference).

Figure 3 shows maps of crude prevalence of disorders in each neighbourhood. However, such a representation may be unreliable, because the disease rates computed in neighbourhoods with a low population size are unstable due to random variations associated with the small population at risk. To address this problem (see appendix), we estimated empty hierarchical geostatistical models (table 1). The two mental disorders exhibited neighbourhood level variations (represented in fig 4), which were considerably larger for substance related disorders than for neurotic disorders (table 1 and fig 5). The hierarchical geostatistical model also provided information on the spatial scale of variations: the range of spatial correlation ($3/\phi$) was 555 metres for neurotic disorders, and 2976 metres for substance related disorders, showing a considerably larger range of geographical correlation for the latter outcome (fig 5). This difference in the scale of variations is also obvious from the maps in figure 4, where substance related disorders show more spatially structured variations than neurotic disorders.

Including contextual income in models adjusted for individual covariates, the individual risk of both disorders increased with contextual deprivation (table 2). Associations strengthened with decreasing size of areas considered, and the DIC showed a better fit for models measuring contextual income on the most local scale. Regarding neighbourhood social disorganisation, the individual risk of mental disorders increased with the incidence of crime around individual residences (table 3). Slightly stronger associations were found and a better fit obtained when measuring the crime variable on a more local scale; however, this pattern was more obvious for substance related disorders than for neurotic disorders.

Adjusting the two contextual effects for each other, the individual risk of substance related disorders significantly increased with both contextual deprivation and crime incidence (table 4). Conversely, only contextual income remained associated with neurotic disorders. Therefore, independent associations with crimes were found only for the group of disorders that varied in space on the largest scale, which is not surprising as the crime factor itself varied on a larger spatial scale than contextual deprivation (see footnote to table 4).

DISCUSSION

Our study compared spatial patterns of two mental disorders in Malmö, Sweden, in 2001. Using a cluster recognition approach and a spatial regression technique, we found that the two disorders exhibited a different spatial distribution, in terms of both magnitude and spatial scale of variations. Mental disorders were associated with two deleterious dimensions of the social context, namely, neighbourhood deprivation and social disorganisation. Measuring contextual factors across continuous space, such associations appeared to operate on the narrowest local scale investigated.

What is already known about this topic

- Previous studies have found weak although statistically significant neighbourhood variations in psychiatric morbidity. Some of them have reported an increased risk of mental disorders in socially deprived neighbourhoods, after adjustment for individual socioeconomic factors.
- Most of these previous studies have relied on the multilevel models in common use, and have focused on effects of the socioeconomic environment defined within administrative areas.

What this study adds

- Spatial analytical techniques showed that mental disorders attributable to the consumption of psychoactive substances showed larger neighbourhood variations, and varied in space on a larger scale, than neurotic disorders.
- After adjustment, the individual risk of substance related disorders increased independently with neighbourhood deprivation and neighbourhood social disorganisation; prevalence of neurotic disorders only increased with contextual deprivation. These associations operated on a local scale.
- Building continuous notions of space into analytical procedures may allow researchers to gain deeper insight into the spatial distribution of mental disorders.

There are limitations to our study. Firstly, we relied on diagnoses made during contacts with the healthcare system, and spatial patterns of treated morbidity may not exactly correspond to the real variations in prevalence. However, the expected underuse of services by deprived people, rather than explaining the observed contextual effects, may have led us to underestimate them. Potential problems also include incorrect diagnoses, and the fact that private physicians may not register diagnoses as systematically as public physicians; however, it was not possible to assess if this may have affected our results. Secondly, our assessment of neighbourhood social disorganisation was based on crime data from the police department rather than on victimisation survey data.[24 46] Finally, our investigation relied on cross sectional data, preventing any causal interpretation.

Describing the spatial distribution of disorders

Describing spatial distributions of mental disorders with appropriate spatial techniques provides information that may serve as a relevant factor in public health planning.[32] Beyond assessment of the magnitude of geographical variability, estimating the spatial scale of variations in mental disorders may be useful when determining the most appropriate level at which programmes should be coordinated.[6 7]

The spatial scan statistic technique[28 29 31 32] identified large clusters of increased prevalence of mental disorders. Its strength lays in its exploratory role and simple visualisation mode. However, imposing a circular form to the clusters, it may not be appropriate for detecting their exact borders.[30 33] Moreover, the spatial scan statistic tends to identify large clusters with considerable population size but low increase in risk (as these clusters have the highest statistical power), and to ignore smaller clusters with higher relative risks contained within these areas.[56]

In a second step, departing from previous studies that used multilevel models, we considered spatial regression techniques. As multilevel models do not take space into account and ignore spatial connections between neighbourhoods, they permit assessment of the magnitude of neighbourhood variation, but fail to provide information on its spatial scale. To obtain this information, we used a hierarchical geostatistical model,[34 35] with spatially correlated neighbourhood random effects (as compared with independent random effects in multilevel models). This approach extends the random effect analysis functionalities offered by multilevel analysis. A multilevel model would have detected a significant neighbourhood variance in mental disorders, but would have missed the correlation between neighbourhoods in close proximity to each other. Conversely, our spatial analyses showed that geographical variations of substance related disorders occurred on a larger scale than those of neurotic disorders. Therefore, specific interventions for the different disorders may need to be coordinated on a varying geographical scale.

Investigating the magnitude and scale of different effects of the social context

The individual risk of substance related disorders increased both with contextual deprivation and social disorganisation. Only contextual deprivation increased the risk of neurotic disorders. As crime incidence varied in space on a larger scale than the deprivation factor did, this pattern of association is consistent with the finding that substance related disorders exhibited a larger spatial scale of variations than neurotic disorders.

We measured contextual factors across continuous space[6] to assess, beyond the magnitude of contextual effects, the spatial scale on which they operated. We computed contextual income in spatially adaptive areas—that is, areas adapting their size to the local population density[51–53]—to assess deprivation effects on a very local scale, while avoiding unreliable measurements in sparsely populated areas.[7] However, even if this approach allowed us to capture the neighbouring conditions on a very local scale, it is far from representing a person's own subjective definition of what constitutes their neighbourhood.[57]

The association between deprivation and mental health considerably increased as the size of areas used for measurements decreased, showing that this association may operate on a smaller geographical scale than that of administrative neighbourhoods. Similarly, the association between neighbourhood social disorganisation and mental health was better captured in quite local areas.

Regarding causal pathways, our cross sectional design did not allow us to rule out the possibility of reverse causality. Spatial filtering of mentally ill persons from advantaged to disadvantaged neighbourhoods may contribute to the associations reported here,[58] even if we adjusted models for individual socioeconomic factors that constitute intermediate steps in selective migration processes.[19] Longitudinal studies are needed to assess whether neighbourhood social characteristics have an independent effect on the onset of mental disorders. According to the literature, contextual deprivation may play a part in creating a sense of hopelessness and powerlessness, and may lead to increased long term life difficulties, which may contribute to mental health problems.[21] With regard to neighbourhood social disorganisation, an effect may result from the daily stress of living in a place where social order is less apparent and social incivilities occur,[1 19 21 22 43 44] and from the difficulties of sustaining supportive social contacts.[1 23 26 41 42]

In summary, spatial analytical techniques allowed us to show that the two groups of mental disorders exhibited a different pattern of clustering in terms of both magnitude and scale, and a different pattern of association with distinct harmful social characteristics of the context. Such preliminary findings may help targeting potential intervention programs in places where contextual phenomena increase the need for mental healthcare assistance.

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APPENDIX

THE SPATIAL SCAN STATISTIC

In this approach, a circular scanning window is moved across the map.[28 29] Windows are centred on each residential location. For each location, the radius of the window varies constantly in size from zero to a maximum size (the window cannot include more than 50% of the total study population). Taking into account the exact place of residence of individuals, each of these circles is a possible candidate cluster. We aimed to identify both clusters of elevated prevalence and areas of lowered prevalence. Considering the prevalence rather than solely the number of cases, the approach takes into account local variations in population density when identifying clusters of disease. For each circle, the alternative hypothesis is that there is a different prevalence within the window, as opposed to outside. The likelihood function is maximised over all windows, and the window with the maximum likelihood constitutes the most likely cluster. The maximum likelihood ratio test statistic is defined as the likelihood ratio for this window. Its distribution under the null hypothesis is obtained by generating 999 random permutations of the dataset. The p value is determined by considering the rank of the maximum likelihood from the real data among all maximum likelihoods from the random datasets. If the rank is the nth highest, then p is equal to $n/1000$. In addition to the most likely cluster, we also aimed to identify secondary clusters that do not overlap with the main cluster. We used the SaTScan, version 5.1, software to implement the spatial scan statistic technique.[29]

THE HIERARCHICAL GEOSTATISTICAL LOGISTIC MODEL

We used a logistic model including neighbourhood level random effects s_j that were spatially correlated.[34 35 38 39] For an individual i in neighbourhood j, the model is defined as follows: $\text{logit}(p_{ij}) = \beta_0 + \boldsymbol{X_{ij}\beta} + s_j$. Let $\boldsymbol{S} = (s_1, s_2, \ldots, s_{100})$ be the vector of spatial effects for the 100 neighbourhoods. $\boldsymbol{S}$ has the following distribution: $\boldsymbol{S} \sim N(0, \boldsymbol{V})$, where V_{kl} is a parametric function of the distance d_{kl} in metres between the population weighted centroids of neighbourhoods k and l (we used the exact coordinates of people aged 40–69 years to compute population weighted centroids). Assuming an isotropic spatial process (in which the strength of spatial correlation does not depend on the direction), V_{kl} was defined as $V_{kl} = \sigma_s^2 \rho_{kl}$ with an exponential correlation function $\rho_{kl} = \exp(-\phi d_{kl})$.[39] The parameter σ_s^2 refers to the variance of the spatial process and allowed us to assess the importance of variations between neighbourhoods. We computed the spatial range of correlation (or distance beyond which the correlation in risk level between neighbourhoods is below 5%) as $3/\phi$. Based on the parameters of variance and autocorrelation (σ_s^2 and ϕ), we estimated the value of the spatial effect s_j in each neighbourhood, which allowed us to map variations of prevalence in the city. With such estimates, the uncertainty in risk level in neighbourhoods with a low number of individuals is taken into account by shrinking the estimate towards the city mean. Moreover, the spatial correlation structure incorporated into the model resulted in a certain smoothing of the neighbourhood estimates.

The hierarchical geostatistical models were estimated with a MCMC approach using Winbugs 1.4.[55] We used non-informative uniform priors for all parameters. We ran a single chain, with a burn-in period of 100 000 iterations. After ensuring that the chain had converged, we retained every 10th iteration until a sample size of 10 000 was attained. For each parameter, we report the median of the posterior distribution and provide the 95% credible interval.