Social Psychiatry and Psychiatric Epidemiology (2019) 54:1189–1198
https://doi.org/10.1007/s00127-019-01712-y

ORIGINAL PAPER

Development of the Australian neighborhood social fragmentation index and its association with spatial variation in depression across communities

Nasser Bagheri[1,5] · Philip J. Batterham[1] · Luis Salvador-Carulla[1] · Yingxi Chen[2] · Andrew Page[3] · Alison L. Calear[1] · Peter Congdon[4]

Received: 28 November 2018 / Accepted: 9 April 2019 / Published online: 15 April 2019

Abstract

Purpose We know little about how community structures influence the risk of common mental illnesses. This study presents a new way to establish links between depression and social fragmentation, thereby identifying pathways to better target mental health services and prevention programs to the right people in the right place.

Method A principal components analysis (PCA) was conducted to develop the proposed Australian neighborhood social fragmentation index (ANSFI). General practice clinical data were used to identify cases of diagnosed depression. The association between ANSFI and depression was explored using multilevel logistic regression. Spatial hot spots (clusters) of depression prevalence and social fragmentation at the statistical area level 1 (SA1) were examined.

Results Two components of social fragmentation emerged, reflecting fragmentation related to family structure and mobility. Individuals treated for depression in primary care were more likely to live in neighborhoods with lower socioeconomic status and with higher social fragmentation related to family structure. A 1-SD increase in social fragmentation was associated with a 16% higher depression prevalence (95% CI 11%, 20%). However, the association attenuated with adjustment for neighborhood socio-economic status. Considerable spatial variation in social fragmentation and depression patterns across communities was observed.

Conclusions Developing a social fragmentation index for the first time in Australia at a small area level generates a new line of knowledge on the impact of community structures on health risks. Findings may extend our understanding of the mechanisms that drive geographical variation in the incidence of common mental disorders and mental health care.

Keywords Social fragmentation index · Depression · Mental disorders · Geographic information systems (GIS) · Primary care

Introduction

Mental disorders pose a significant public health challenge for Australia and the world [1, 2]. The most common mental disorders are anxiety disorders and depression [3]. Research consistently confirms the high prevalence of mental illness in our community and its impact on the lives of people with mental illness, their families and carers [4]. Mental disorders are now the third leading cause of disability burden in Australia, accounting for an estimated 24% of the total years lost due to disability [5]. Australia spends at least $26.9 billion per year supporting people with mental disorders for health care, lost productivity and welfare benefit [6].

There is a large body of theoretical and empirical research exploring the processes by which a lack of social cohesion

✉ Nasser Bagheri
Nasser.bagheri@anu.edu.au

1 Centre for Mental Health Research, The Australian National University, Canberra, Australia

2 Research School of Population Health, The Australian National University, Canberra, Australia

3 Translational Health Research Institute, Western Sydney University, Sydney, Australia

4 School of Geography, Queen Mary University of London, London, UK

5 Visual and Decision Analytics (VIDEA) Lab, Centre for Mental Health Research, Research School of Population Health, Australian National University, Canberra, Australia

and social capital in communities may be associated with poorer mental health among residents in these communities [7–10]. In particular, social fragmentation or poor community connectedness has been highlighted as an important property of the social environment [8, 11, 12].

A number of studies have found that protective social processes within communities or neighborhoods, such as social capital, social cohesion and collective efficacy, are important contextual influences on population health, including mental health [13–16]. Such protective processes are more common in areas that are less socially fragmented, such as those with less residential mobility, low levels of non-family households and with more adults in marital or other partnerships. In fragmented areas, by contrast, resident interactions tend to be fewer and of lower quality [17]; aspects of social capital, including trust, social norms and reciprocity, are harder to maintain [18], and more people are socially isolated. Fragmentation of social environments is of ongoing interest to health and social science researchers for its potential relationship with a range of health outcomes including mental ill health [7, 19].

'Social fragmentation' is a term defined as a lack of opportunity for social integration and inclusion originating in Emile Durkheim's early research [2, 10]. Durkheim highlighted that a community which is highly fragmented would be less able to provide 'healthy' levels of support [11, 12]. In spatial epidemiology research, this construct was investigated based on the development of a social fragmentation index (SFI) to explore variation in rates of suicide deaths and suicide attempts across geographical areas in Greater London [20]. Congdon found that SFI differences explained area variations in suicide rates independent of deprivation [12, 20]. The index was created using area proportions of four variables: single-person households, unmarried adults, privately rented housing (excluding social renting), and residential turnover.

An additional New Zealand (NZ) study by Ivory et al. used 13 variables (four variables from the Congdon Index and nine additional variables) from the NZ census to construct an index of neighborhood level social fragmentation, capturing three dimensions of fragmentation: less attachment, less sharing of norms and fewer social resources [2]. The important feature of the NZ index was to capture the compositional factors thought to fragment social connections within a neighborhood.

The current study describes the development of an Australian index of social fragmentation to capture social fragmentation across neighborhoods and demonstrates how the index may be useful for understanding patterns in health outcomes by investigating the prevalence of common mental disorders across communities.

The value of spatial analysis is a well-recognized approach for assessing variations in mental health across communities [21, 22], and as a useful approach to highlight clusters or "hotspots" of chronic disease [23, 24]. However, evidence for geographic variation in mental disorders and social fragmentation at the small area level remains limited, including in Australia. Most studies have focussed on suicide [25–29] and psychosis [10, 11, 30].

The use of routinely collected data from general practice has been shown to be effective for estimating the incidence and prevalence of common chronic conditions [31]. Studies in the UK [32], US [33] and Australia [34–36] have combined general practice data and spatial analysis at the small area level to calculate diabetes risk prediction. However, few studies have applied this approach to mental health outcomes. In Australia, general practice data offer a rich source of routinely collected data that are currently underutilized for risk prediction and geospatial analysis of chronic illness.

There is a considerable knowledge gap in Australia regarding the convergence between social fragmentation and hotspots of diagnosed depression in local communities at small area levels, which may be an important foundation for the targeting of effective prevention measures and for efficient resourcing of mental health services.

The aims of the current study were to:

1. Develop a neighborhood level index of social fragmentation using Australian census data to identify hotspots of social fragmentation;
2. Identify hotspots of depression and how they converge with social fragmentation hotspots.

Methods

Developing the Australian neighborhood social fragmentation index (ANSFI)

We measured area-level social fragmentation at the Statistical Area level 1 (SA1) using information from the 2011 Australian census. SA1s typically have a population between 200 and 800 persons (average population approximately 400 persons), which allows the separation of areas with different geographic characteristics within suburb and locality boundaries across Australia [37]. Candidate variables for the proposed SFI that were available at this geographical resolution included the proportion of: population mobility < 1 year (people living less than a year in the neighborhood), privately rented households, single-person households, nonfamily households, unmarried persons, households with school-aged children, recent immigrants < 1 year, immigrants arrived > 15 years ago, residents living > 5 years in the neighborhood, and people who report volunteering. Due to the variability of the contextual factors across local

communities, composite/synthetic indices should be adapted and adjusted to the local context and one single indicator of the composite index relevant in one area may not be relevant in another area [38]. The Australian neighborhood social fragmentation index captures three domains: attachment to the neighborhood, sharing values and norms and transience. We selected available variables from the Australian Bureau of Statistics that covered each of these domains. Our index included more candidate subdomains and indicators compared to the UK and NZ indices, to ensure sufficient coverage of relevant metrics of social fragmentation [19, 20, 39].

We conducted principal components analysis (PCA) to explore relationships between these area-level characteristics and to select the most parsimonious set of variables. Data from across Australia representing 53,137 SA1s and a population of 21,004,542 (after excluding outliers reflecting very low population SA1s) were included in the PCA. Scores based on the principal components were then used to create a composite index of social fragmentation within each SA1 area, labeled the ANSFI score.

Mental health data source

We used general practice clinical data from west Adelaide in South Australia to identify cases of depression. Adelaide (population approximately 1.2 million) is the largest city in Australia's fifth most populous state. The study region of west Adelaide incorporates a population of 207,837 people, and covers suburbs with a broad range of socioeconomic status, including wealthy beachside suburbs and historically working class suburbs that are adjacent to industrial areas. In this study, we have focused on the prevalence of GP-treated depression, as this is the best available data at the small geospatial level. GPs conduct clinical interviews and classify medically defined mental disorders based on Diagnostic and Management Guidelines for Mental Disorders in Primary Care: ICD 10 Chapter V Primary Care Version. Recorded diagnosed depression data were extracted from 16 practices from 2010 to the end of 2015 using the Pen CS tool for active patients who had three visits to the GPs over the past 2 years. Data were geocoded to the SA1 area of the patient's residence address using the G-tag method which has been described previously [40]. There were 489 SA1s in the study area, covering 16 general practices. Overall, 212,708 patient records were extracted from the practices. Of these data, 84,638 cases were identified as active patients (patients who visited the general practices at least three times during the past 2 years). Patients were linked to the SA1 for spatial analysis and the adjusted rate of depression for each SA1 was calculated.

Multilevel analysis

To explore the association between social fragmentation and depression, we performed multilevel logistic regression analyses (with depression defined as a binary outcome variable, case or non-case of depression) to account for the hierarchical nature of the data (patients within neighborhoods), as data on patient characteristics and community-level characteristics were included in the models. The regression coefficients when exponentiated are the odds ratios for the increase in depression prevalence for each 1-SD change in the exposure variable. We report these results as ratios in Table 2 (e.g., the regression coefficient exponentiated), but refer to the percentage changes in the text (e.g., a ratio of 1.18 is equivalent to an 18% increase in the odds ratio of the outcome for a 1-SD change in the exposure). All comparisons of exposure and outcome were assessed with two models: model 1 included ANSFI score with adjustment for age, sex, and smoking status (individual-level factors), and model 2 additionally adjusted for neighborhood socioeconomic status. We used the index of relative socio-economic advantage and disadvantage (IRSAD) as a measure of socioeconomic index for area (SEIFA), developed by the Australian Bureau of Statistics. Scores on this index range from 664 to 1126, with higher scores indicating less socioeconomic disadvantage.

Spatial analysis

Individual depression cases were aggregated at the SA1 level to calculate area-level depression prevalence and examine spatial variation of depression across the study area. Depression prevalence adjusted for age for the spatial analyses, with the Australian population used as the reference population. Spatial hotspots (clusters) of depression at the SA1 level were examined using the Getis-Ord Gi* technique [41]. This tool compares the local sum of depression (the sum of the depression risk of the targeted SA1 area and its neighboring SA1s) to the sum of depression risk of all SA1s within the study area.

A statistically significant large, positive *Z* score signifies a local high-rate cluster hotspot. Hotspots are detected when SA1s with high rates are surrounded by other SA1s with high rates; the observed local sum of depression is higher than the expected local sum, and the difference is too large to be the result of chance alone. Similarly, a statistically significant large, negative *Z* score signifies a local low-rate cluster (cold spot), where SA1s with low rates are surrounded by other SA1s with low rates [41]. Statistically significant hot and cold spot clusters were visualized in the region of west Adelaide to highlight communities with high or low depression risk. We overlaid depression and social fragmentation hotspots and cold spots to examine the spatial convergence

of depression and social fragmentation hotspots and cold spots.

Stata version 14.2 (Stata Corp, LP) was used to calculate depression prevalence and conduct descriptive analyses of our sample population, and ArcGIS version 10.4 to conduct spatial analyses and mapping. The study obtained ethics approval from the Australian National University Human Ethics Committee (protocol 2014/174).

Results

The PCA identified that 7 of the 10 candidate variables formed two distinct components accounting for 64.8% of variance. A scree plot of eigenvalues also indicated evidence for multi-dimensional construct of social fragmentation. Therefore, the first two components were retained and labeled as the ANSFI family component ($ANSFI_{fam}$) and the ANSFI mobility component ($ANSFI_{mob}$). Variables forming the $ANSFI_{fam}$ component were lone person household, non-family household with renting and married people. Variables forming the $ANSFI_{mob}$ were people living < 1 year in the neighborhood, families with school children and people lived more than 5 years in the neighborhood. Scores on the $ANSFI_{fam}$ and $ANSFI_{mob}$ ranged from −4.4 to 11.6 and −2.8 to 15.4 across the 52,162 SA1s across Australia, with higher scores indicating greater social fragmentation. A negative association was found between socioeconomic status and social fragmentation index across Australian communities, although the correlation between $ANSFI_{fam}$ and SES ($r = -0.43$, $p < 0.001$) was greater than between $ANSFI_{mob}$ and SES ($r = -0.08$, $p < 0.001$). Table 1 provides a national summary of the Australian neighborhood social fragmentation index and socioeconomic status.

The demographic, lifestyle socioeconomic status and social fragmentation characteristics of active patients' residential neighborhood within the west Adelaide region are described in Table 2. The prevalence of depression increased with age. Women comprised 65.3% of the sample, and had a higher prevalence (7.7%) of depression compared to men (4.6%). The prevalence of depression was nearly three times higher among patients who were divorced or separated (19.2%) compared to patients who identified as "never married". The prevalence of depression was approximately two times higher among current tobacco smokers (13.8%) than those who reported never smoking (7.2%), although smoking status was not recorded for 45.2% of patients. Patients who had depression were more likely to live in neighborhoods with lower socioeconomic status (mean = 946.9, SD = 79.6) compared to the non-depressed group (mean = 956.6, SD = 80.1) and had greater family related social fragmentation (mean = 0.46, SD = 0.80) compared to the non-depressed group (0.37, SD = 0.79).

Table 1 Summary of SES and ANSFI scores

	Obs.	Mean	SD	Min	Max
SES	52,162	1000.2	98.9	298	1246
$ANSFI_{mob}$	52,162	0.04	0.9	−2.8	15.4
$ANSFI_{fam}$	52,162	−0.01	0.9	−4.4	11.6

Table 3 shows odd ratios (ORs) for diagnosed depression cases in 16 general practices in the west Adelaide region. In model 1 (adjusted for demographics and lifestyle), a 1-SD increase in social fragmentation was associated with a 16% higher depression prevalence (95% CI 11%, 20%) The strength of association of ANSFI score and depression attenuated with adjustment for neighborhood socio-economic status in model 2, with only an 8% higher depression prevalence for a 1-SD change in $ANSFI_{fam}$. Marital status is one of the components of the ANSFI, while sex, age and smoking status are not. Therefore, including marital status as a separate predictor in the multi-level modeling analysis of ANSFI would be circular.

Figure 1 shows geographical variations in the social fragmentation index and age-adjusted depression prevalence in the western area of the city of Adelaide. The ANSFI ranged from −1.41 to 3.19 within west Adelaide, with greater social fragmentation (darker shades) identified among neighborhoods in the south-eastern suburbs. Depression prevalence varied from 1 to 19% across communities, with neighborhoods located in the central and south areas of west Adelaide having higher prevalence (darker shades).

Figure 2 shows significant hot spots (red) and cold spots (blue) in the patterns of social fragmentation (left map) and depression (right map). Hotspots of social fragmentation were concentrated in the eastern and northern suburbs, while cold spots were mainly located in the central part of the study area. There were no significant hotspots of social fragmentation in the western neighborhoods which comprise high socioeconomic-status suburbs. The hotspots of diagnosed depression were located mainly in the southern and central parts of the study area. Social fragmentation hotspots were most prominent in neighborhoods located in the southern east and north Adelaide near port Adelaide (Fig. 2).

Figure 3 demonstrates convergence of hot spots and cold spots of social fragmentation and diagnosed depression in west Adelaide. Interestingly, cold spots (less fragmented and low age-adjusted depression prevalence) for social fragmentation and depression prevalence were located in the western suburbs near the ocean, which tend to be high SES neighborhoods. However, converging hot spots (highly fragmented and high prevalence of depression) were found in the south-eastern suburbs, which typically have a lower SES.

Table 2 Sociodemographic, lifestyle characteristics, neighborhood socioeconomic status and fragmentation index by depression status in 16 general practice records

	Not depressed		Depressed		χ^2	*p*
	n	%	*N*	%		
Age					2700	< 0.001
0–19	27,181	99.4	148	0.5		
20–29	18,092	95.6	830	4.3		
30–39	19,150	94.1	1187	5.8		
40–49	17,917	91.7	1618	8.2		
50–59	15,505	90.6	1.602	9.3		
60–69	11,496	90.1	1257	9.8		
> = 70	15,102	90.0	1668	9.9		
Sex						
Male	58,385	95.3	2833	4.6	560.7	< 0.001
Female	65,364	92.2	5466	7.7		
Not stated	694	98.4	11	1.5		
Marital status						
Never married	22,801	93.5	1568	6.4	1400	< 0.001
Married	12,755	89.8	1439	10.1		
Divorce/separated	2373	80.7	566	19.2		
Not stated	63,375	95.1	3264	4.9		
Missing	23,139	94.0	1473	5.9		
Smoking status						
Current smoker	11,760	86.1	1887	13.8	3800	< 0.001
Ex-smoker	11,970	87.8	1655	12.1		
Never smoked	44,448	92.7	3456	7.2		
Not stated	56,265	97.7	1312	2.2		
	Mean	SD	Mean	SD	*t*	*p*
SES	956.6	80.1	946.9	79.6	11.5	0.00
$ANSFI_{fam}$	0.37	0.79	0.46	0.80	−9.10	0.00
$ANSFI_{mob}$	−0.26	0.67	−0.26	0.65	0.23	0.59

Discussion

The overall aim of current study was to investigate the relationship between social fragmentation and depression at small area level to provide a new knowledge for prioritization of policy planning and intervention. We found a statistically significant relationship between family-related ANSFI scores and diagnosed depression after controlling for individual demographic and lifestyle factors. However, the main effect for neighborhood social fragmentation decreased once the model was adjusted for neighborhood SES. This finding suggests that the association between social fragmentation and depression is partially explained by neighborhood SES. Neighborhood level SES was significantly associated with diagnosed depression prevalence in primary health care. This finding is also important, as it suggests that a range of community-level factors may influence whether an individual will experience a common mental disorder, independently of individual demographic characteristics.

Developing a neighborhood-level social fragmentation index using publicly available data from the Australian Bureau of Statistics was at the core of this research. We developed the social fragmentation index by updating the Congdon Index for the Australian context. We named the index 'the Australian Neighborhood Social Fragmentation Index (ANSFI)', constructed at the small area level to capture social fragmentation across neighborhoods. The relationship between mental health outcomes with social and economic factors may be driven by a number of potential mechanisms. Neighborhoods with greater social fragmentation [42] or lower SES [43, 44] may create additional stressors on individuals and communities through factors such as limited opportunities for recreation, poorer quality housing, greater density with less green space, and increased isolation from transport, services or community amenities. Moreover,

Table 3 ORs (95% CIs) in fully adjusted model for diagnosed depression vs. not diagnosed in general practices

	Model 1	Model 2
Intercept	0.08 (0.07, 0.09)	0.26 (0.16, 0.44)
$ANSFI_{fam}$	1.16 (1.11, 1.20)	1.08 (1.02, 1.13)
$ANSFI_{mob}$	1.05 (1.00, 1.10)	1.03 (0.98, 1.08)
Age		
0–19	0.07 (0.06, 0.08)	0.07 (0.06, 0.08)
20–29	0.45 (0.41, 0.49)	0.44 (0.40, 0.49)
30–39	0.59 (0.54, 0.64)	0.59 (0.54, 0.64)
40–49	0.82 (0.76, 0.88)	0.82 (0.76, 0.88)
50–59	0.88 (0.81, 0.95)	0.88 (0.81, 0.95)
60–69	0.98 (0.90, 1.06)	0.98 (0.90, 1.06)
≥ 70	Ref.	Ref.
Sex		
Male	Ref.	Ref.
Female	1.72 (1.64, 1.81)	1.72 (1.64, 1.81)
Not stated	0.62 (0.34, 1.14)	0.63 (0.34, 1.15)
Smoking status		
Current smoker	1.81 (1.70, 1.93)	1.80 (1.69, 1.92)
Ex-smoker	1.37 (1.28, 1.46)	1.36 (1.27, 1.45)
Never smoked	Ref.	Ref.
Not stated	0.34 (0.32, 0.36)	0.34 (0.32, 0.36)
SES		0.99 (0.99, 0.99)

individuals living in such neighborhoods may have less income and education, with reduced means to engage with appropriate health services [45]. Location and resourcing of health services may also be deficient in these neighborhoods, creating further barriers to service use. Further research on the standard description and mapping of the provision system at local level [46] should examine how the resourcing of health services may magnify inequities in mental health.

The benefits of context analysis at area level for developing locally meaningful indices and understanding local variation for tailored policy planning and resource allocations are threefold. First, it enables identification, representation and analysis of small area variation within the local system. Second, it enables linkage of local clusters of fragmentation to other relevant social structure factors such as health services accessibility and availability, and built environment characteristics. Third, it enables aggregation of this information to an ecological level that is meaningful for guiding evidence-informed policy. In this context, cities have been identified as a key system level for global health planning [47], particularly in mental health.

We have previously analysed the relationship of hot and cold spots of mental disorders in urban areas with service availability and a key single socio-demographics indicators such as education, employment, income. This spatial analysis was used for policy and planning in Barcelona, Spain [48]. This study goes a step further as it provides, for the first time, a spatial analysis of key synthetic indicators and hotspots of mental disorders in urban areas.

Australian Bureau of Statistics data has some advantages over other data sources: first, census data are available at national level, providing a comprehensive measure that can be applied across the country and within different localities

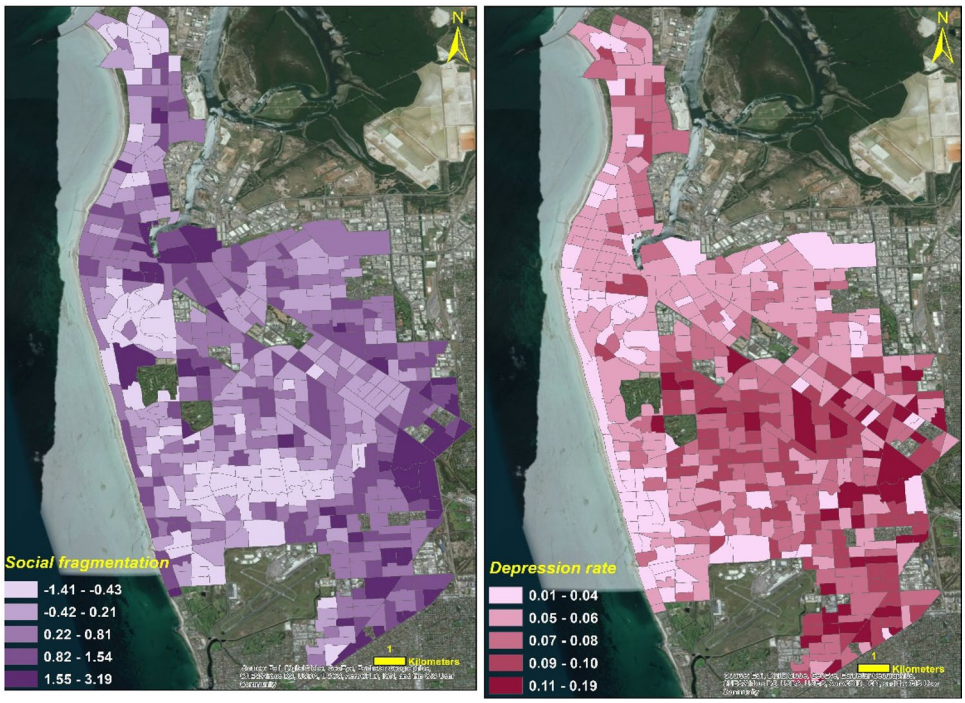

Fig. 1 Spatial variation of social fragmentation (left) and age-adjusted depression prevalence (right)

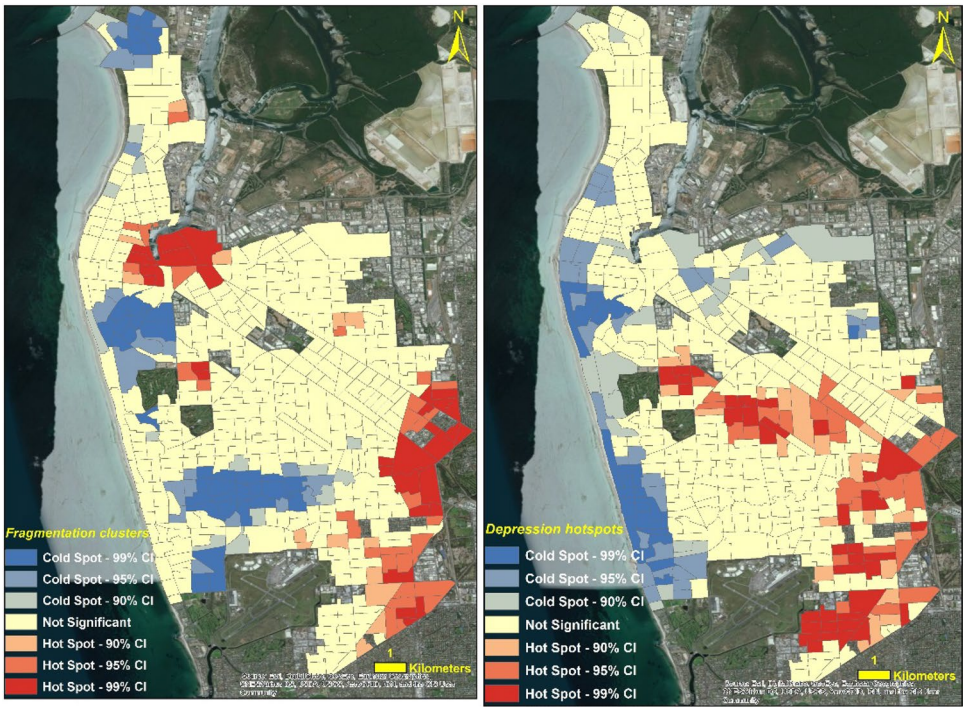

Fig. 2 Hot and cold spots in the patterns of social fragmentation (left) and common mental disorders (right) in west Adelaide

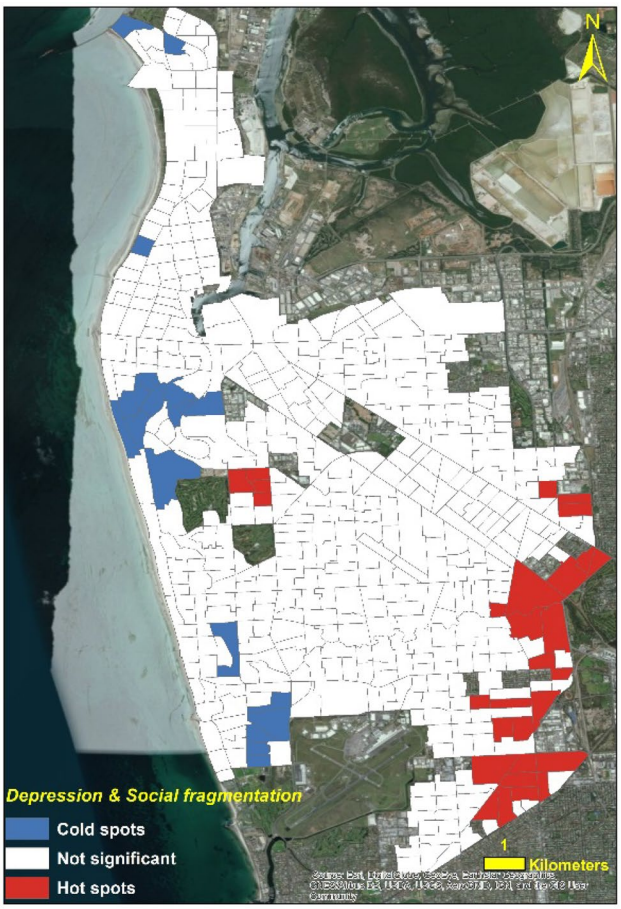

Fig. 3 Convergence of hot spots and cold spots of social fragmentation and age-adjusted depression prevalence in west Adelaide city

of the nation. Second, using similar data sources particularly census data enables researchers to increase equivalence of the composite index internationally.

Our findings showed that there is a great deal of spatial variation in social fragmentation and depression patterns, and also in the association between social fragmentation and common mental disorders in the selected urban area. We found significant clusters of both hot spots and cold spots in the patterns of social fragmentation and depression in the study area. Spatial convergence of hot spots of social fragmentation and depression was observed in south-eastern neighborhoods of west Adelaide, suggesting this small area might be an important focus for social and health service interventions.

We used diagnosed cases of depression recorded in the general practice clinical data set, rather than using self-reported data and this was a major strength of the study. The ANSFI was created using a national dataset which enables this metric to be used nationally in future research. Additionally, we analysed both the outcome variable (depression) and exposure (fragmentation) at a very fine geographical level (SA1), enabling identification of local patterns of common mental disorders and social fragmentation.

Spatial analysis is a relative new approach in mental health care research, and more comparative evidence is needed for its use in policy planning. For example, we do not know whether spatial information can be transferred from urban to rural areas, or the meaning of disparities in the patterns of hot spots and cold spots of mental disorders across different areas. Similarly, further information is needed to

understand the relationship between social fragmentation and mental health outcomes, and other synthetic indexes such as social deprivation. At an international level, major differences have been identified in the urban patterns of hot and cold spots of depression in Adelaide and Barcelona [49]. While a number of hot spots and cold spots clustered together in Barcelona, a clear separation between the two zones appeared in Adelaide. In addition, spatial analysis can improve the knowledge-base on a defined health ecosystem, allowing for tailored priority setting and policy planning in small catchment areas.

We selected Adelaide to undertake the study for three reasons: (1) the availability of and completeness of primary care data including depression data, (2) existing demonstration of the usability of Adelaide GP dataset for spatial analysis of other conditions such as dementia, and (3) sufficient variability in socioeconomic status across the city. The testing of this index in relation to other key health questions should be conducted in other Australian localities. After the completion of this study, we have described social fragmentation and mental health services availability in Canberra and Perth [50], and intend to use these atlas data to address research questions around the relationship between service availability, social fragmentation and prevalence of mental health problems.

This study also has some limitations. First, we focused on a discrete and representative area of a major city where rich primary care data were available. It remains unclear whether similar relationships between social fragmentation and mental health outcomes would also be observed nationally, particularly in rural areas. While there was high variability in social fragmentation, depression prevalence and SES within the SA1s areas included in the study, there was some restriction of range, including underrepresentation of areas with very high social fragmentation. Second, there may have been threshold effects, such that only extreme levels of social fragmentation influenced mental health status. Further investigation of this relationship in highly fragmented communities such as fly-in-fly-out mining communities or highly disadvantaged rural communities may provide further insights into the role of social fragmentation.

Conclusion

Identifying highly fragmented neighborhoods and spatial convergence in hot spots of common mental disorders and social fragmentation at the small area level is likely to generate rich and novel information to allow better targeting of prevention activities across communities and more equitable allocation of health resources in the right place to the right people. In particular, these forms of data may be used to guide policymakers to identify specific geographical areas in need of additional services, ensuring that people experiencing mental health problems can access services. Further investigation of how social, economic and built environment factors might influence mental health is warranted.

Acknowledgements We would like to thank Australian Research Council's support of data collection via Dr Bagheri's DECRA (DE140101570). PJB and ALC are supported by NHMRC fellowships 1083311 and 1122544. We also thank all 16 general practices from the west Adelaide area that provided clinical data.

Compliance with ethical standards

Conflict of interest On behalf of all authors, the corresponding author states that there is no conflict of interest.

References

1. World Health Organization (2014) Mental health: strengthening our response. WHO. http://www.who.int/mediacentre/factsheets/fs220/en/. Accessed 12 Sept 2016
2. Steel Z, Marnane C, Iranpour C, Chey T, Jackson JW, Patel V, Silove D (2014) The global prevalence of common mental disorders: a systematic review and meta-analysis 1980–2013. Int J Epidemiol. https://doi.org/10.1093/ije/dyu038
3. Wittchen HU, Jacobi F, Rehm J, Gustavsson A, Svensson M, Jönsson B, Olesen J, Allgulander C, Alonso J, Faravelli C, Fratiglioni L, Jennum P, Lieb R, Maercker A, van Os J, Preisig M, Salvador-Carulla L, Simon R, Steinhausen HC (2011) The size and burden of mental disorders and other disorders of the brain in Europe 2010. Eur Neuropsychopharmacol 21(9):655–679. https://doi.org/10.1016/j.euroneuro.2011.07.018
4. RANZCP (2016) Economic cost of serious mental illness and comorbidities in Australia and New Zealand. RANZCP. https://www.ranzcp.org/Files/Publications/RANZCP-Serious-Mental-Illness.aspx. Accessed 9 Oct 2016
5. Begg SJ, Vos T, Barker B, Stanley L, Lopez AD (2008) Burden of disease and injury in Australia in the new millennium: measuring health loss from diseases, injuries and risk factors. Med J Aust 188(1):36–40
6. Lee Y-C, Chatterton ML, Magnus A, Mohebbi M, Le LK-D, Mihalopoulos C (2017) Cost of high prevalence mental disorders: findings from the 2007 Australian national survey of mental health and wellbeing. Aust N Z J Psychiatry 51(12):1198–1211. https://doi.org/10.1177/0004867417710730
7. Berkman LF, Glass T (2000) Social integration, social networks, social support, and health. In: Berkman LF, Glass T (eds) Social epidemiology. Oxford University Press, New York, pp 137–173
8. Ivory VC, Collings SC, Blakely T (1982) Dew K (2011) When does neighbourhood matter? Multilevel relationships between neighbourhood social fragmentation and mental health. Soc Sci Med 72(12):1993–2002. https://doi.org/10.1016/j.socscimed.2011.04.015
9. Pearson AL, Ivory V, Breetzke G, Lovasi GS (2014) Are feelings of peace or depression the drivers of the relationship between neighbourhood social fragmentation and mental health in Aotearoa/New Zealand? Health Place 26:1–6. https://doi.org/10.1016/j.healthplace.2013.11.002
10. Curtis S, Copeland A, Fagg J, Congdon P, Almog M, Fitzpatrick J (2006) The ecological relationship between deprivation, social isolation and rates of hospital admission for acute psychiatric

care: a comparison of London and New York City. Health Place 12(1):19–37. https://doi.org/10.1016/j.healthplace.2004.07.002
11. Allardyce J, Gilmour H, Atkinson J, Rapson T, Bishop J, McCreadie RG (2005) Social fragmentation, deprivation and urbanicity: relation to first-admission rates for psychoses. Br J Psychiatry 187:401–406. https://doi.org/10.1192/bjp.187.5.401
12. Congdon P (2013) Assessing the impact of socioeconomic variables on small area variations in suicide outcomes in England. Int J Environ Res Public Health 10(1):158–177. https://doi.org/10.3390/ijerph10010158
13. Sampson RJ, Morenoff JD, Gannon-Rowley T (2002) Assessing "Neighborhood effects": social processes and new directions in research. Ann Rev Sociol 28(1):443–478. https://doi.org/10.1146/annurev.soc.28.110601.141114
14. Sampson RJ, Raudenbush SW, Earls F (1997) Neighborhoods and violent crime: a multilevel study of collective efficacy. Science (New York, NY) 277(5328):918–924
15. Xue Y, Leventhal T, Brooks-Gunn J, Earls FJ (2005) Neighborhood residence and mental health problems of 5- to 11-year-olds. Arch Gen Psychiatry 62(5):554–563. https://doi.org/10.1001/archpsyc.62.5.554
16. Veling W, Susser E, Selten J-P, Hoek H (2015) Social disorganization of neighborhoods and incidence of psychotic disorders: a 7-year first-contact incidence study. Psychol Med 45(09):1789–1798
17. Putnam RD (2007) E Pluribus Unum: diversity and community in the twenty-first century The 2006 Johan Skytte prize lecture. Scand Political Stud 30(2):137–174. https://doi.org/10.1111/j.1467-9477.2007.00176.x
18. Fagg J, Curtis S, Stansfeld SA, Cattell V, Tupuola AM (1982) Arephin M (2008) Area social fragmentation, social support for individuals and psychosocial health in young adults: evidence from a national survey in England. Soc Sci Med 66(2):242–254. https://doi.org/10.1016/j.socscimed.2007.07.032
19. Ivory V, Witten K, Salmond C, Lin E-Y, You RQ, Blakely T (2012) The New Zealand index of neighbourhood social fragmentation: integrating theory and data. Environ Plan A 44(4):972–988
20. Congdon P (1996) Suicide and parasuicide in London: a small-area study. Urban studies 33(1):137–158
21. Amaddeo F, Salazzari D, Salinas-Perez JA (2014) Is a geographical approach worthwhile for epidemiological research in mental health? Epidemiol Psychiatr Sci 24(1):38–41. https://doi.org/10.1017/S2045796014000705
22. Diez Roux AV, Mair C (2010) Neighborhoods and health. Ann N Y Acad Sci 1186:125–145. https://doi.org/10.1111/j.1749-6632.2009.05333.x
23. Curtis AJ, Lee WA (2010) Spatial patterns of diabetes related health problems for vulnerable populations in Los Angeles. Int J Health Geogr 9:43. https://doi.org/10.1186/1476-072x-9-43
24. Qi X, Hu W, Page A, Tong S (2012) Spatial clusters of suicide in Australia. BMC Psychiatry 12:86. https://doi.org/10.1186/1471-244x-12-86
25. Chang S-S, Sterne JAC, Wheeler BW, Lu T-H, Lin J-J, Gunnell D (2011) Geography of suicide in Taiwan: spatial patterning and socioeconomic correlates. Health Place 17(2):641–650. https://doi.org/10.1016/j.healthplace.2011.01.003
26. Middleton N, Sterne JAC, Gunnell D (2006) The geography of despair among 15–44-year-old men in England and Wales: putting suicide on the map. J Epidemiol Community Health 60(12):1040–1047. https://doi.org/10.1136/jech.2005.045302
27. Middleton N, Whitley E, Frankel S, Dorling D, Sterne J, Gunnell D (2004) Suicide risk in small areas in England and Wales, 1991–1993. Soc Psychiatry Psychiatr Epidemiol 39(1):45–52. https://doi.org/10.1007/s00127-004-0707-y
28. Ngamini Ngui A, Vasiliadis H-M, Préville M (2015) Individual and area-level factors correlated with death by suicide in older adults. Prev Med 75:44–48. https://doi.org/10.1016/j.ypmed.2015.03.015
29. Collins J, Ward BM, Snow P, Kippen S, Judd F (2016) Compositional, contextual, and collective community factors in mental health and well-being in Australian rural communities. Qualitative Health Res 27(5):677–687. https://doi.org/10.1177/1049732315625195
30. O'Donoghue B, Roche E, Lane A (2016) Neighbourhood level social deprivation and the risk of psychotic disorders: a systematic review. Soc Psychiatry Psychiatr Epidemiol 51(7):941–950
31. van Baal PH, Engelfriet PM, Hoogenveen RT, Poos MJ, van den Dungen C, Boshuizen HC (2011) Estimating and comparing incidence and prevalence of chronic diseases by combining GP registry data: the role of uncertainty. BMC Public Health 11:163. https://doi.org/10.1186/1471-2458-11-163
32. Noble D, Smith D, Mathur R, Robson J, Greenhalgh T (2012) Feasibility study of geospatial mapping of chronic disease risk to inform public health commissioning. BMJ Open 2(1):e000711. https://doi.org/10.1136/bmjopen-2011-000711
33. Gabert R, Thomson B, Gakidou E, Roth G (2016) Identifying high-risk neighborhoods using electronic medical records: a population-based approach for targeting diabetes prevention and treatment interventions. PLoS One 11(7):e0159227. https://doi.org/10.1371/journal.pone.0159227
34. Bagheri N, Gilmour B, McRae I, Konings P, Dawda P, Del Fante P, van Weel C (2015) Community cardiovascular disease risk from cross-sectional general practice clinical data: a spatial analysis. Prev Chronic Dis 12:E26. https://doi.org/10.5888/pcd12.140379
35. Bagheri N, McRae I, Konings P, Butler D, Douglas K, Del Fante P, Adams R (2014) Undiagnosed diabetes from cross-sectional GP practice data: an approach to identify communities with high likelihood of undiagnosed diabetes. BMJ Open 4(7):1–10. https://doi.org/10.1136/bmjopen-2014-005305
36. Jiwa M, Gudes O, Varhol R, Mullan N (2015) Impact of geography on the control of type 2 diabetes mellitus: a review of geocoded clinical data from general practice. BMJ Open 5(12):1–8. https://doi.org/10.1136/bmjopen-2015-009504
37. Australian Bureau of Statistics Australian Statistical Geography Standard (ASGS). http://www.abs.gov.au/websitedbs/D3310114.nsf/home/Australian+Statistical+Geography+Standard+(ASGS). Accessed 24 Aug 2018
38. Garrido-Cumbrera M, Almenara-Barrios J, Lopez-Lara E, Peralta-Saez JL, Garcia-Gutierrez JC, Salvador-Carulla L (2008) Development and spatial representation of synthetic indexes of outpatient mental health care in Andalusia (Spain). Epidemiol Psichiatria Sociale 17(3):192–200
39. Congdon P (2004) Commentary: contextual effects: index construction and technique. Int J Epidemiol 33(4):741–742. https://doi.org/10.1093/ije/dyh173
40. Mazumdar S, Konings P, Hewett M, Bagheri N, McRae I, Del Fante P (2014) Protecting the privacy of individual general practice patient electronic records for geospatial epidemiology research. Aust N Z J Publ Health 38(6):548–552. https://doi.org/10.1111/1753-6405.12262
41. Ord JK, Getis A (1995) Local spatial autocorrelation statistics: distributional issues and an application. Geograph Anal 27(4):286–306
42. Takagi D, Kondo K, Kondo N, Cable N, Ki Ikeda, Kawachi I (2013) Social disorganization/social fragmentation and risk of depression among older people in Japan: multilevel investigation of indices of social distance. Soc Sci Med 83:81–89. https://doi.org/10.1016/j.socscimed.2013.01.001
43. Hudson CG (2005) Socioeconomic status and mental illness: tests of the social causation and selection hypotheses. Am J Orthopsychiatry 75(1):3–18

44. Lorant V, Deliège D, Eaton W, Robert A, Philippot P, Ansseau M (2003) Socioeconomic inequalities in depression: a meta-analysis. Am J Epidemiol 157(2):98–112. https://doi.org/10.1093/aje/kwf182
45. Inaba A, Thoits PA, Ueno K, Gove WR, Evenson RJ, Sloan M (2005) Depression in the United States and Japan: gender, marital status, and SES patterns. Soc Sci Med 61(11):2280–2292. https://doi.org/10.1016/j.socscimed.2005.07.014
46. Fernandez A, Gillespie JA, Smith-Merry J, Feng X, Astell-Burt T, Maas CLS-C (2017) Integrated mental health atlas of the Western Sydney local health district: gaps and recommendations. Aust Health Rev 41(1):38–44
47. Organisation WH (2016) Shanghai declaration on promoting health in the 2030 agenda for sustainable developmen. https://www.who.int/healthpromotion/conferences/9gchp/shanghai-declaration/en/. Accessed 20 Oct 2018
48. Salinas-Pérez JA, García-Alonso CR, Molina-Parrilla C, Jordà-Sampietro E, Salvador-Carulla L (2012) Identification and location of hot and cold spots of treated prevalence of depression in Catalonia (Spain). Int J Health Geograph 11(1):36. https://doi.org/10.1186/1476-072X-11-36
49. Rodero-Cosano ML, Salinas-Pérez JA, González-Caballero JL, García-Alonso CR, Lagares-Franco C, Salvador-Carulla L (2016) A multi-level analysis of the relationship between spatial clusters of outpatient-treated depression, risk factors and mental health service planning in Catalonia (Spain). J Affect Disord 201:42–49. https://doi.org/10.1016/j.jad.2016.04.024
50. Furst M, Reynolds J, Salinas JA, Tsou C, Rock D, Hopkins J, Bell T, Woods L, McLoughlin L, Stretton A, Mendoza J, Bagheri N, Salvador-Carulla L (2018) The integrated atlas of mental health of the perth north primary health network region. Australian National University and Western Australia Primary Health Alliance (WAPHA), Perth