


Characterizing Unusual Spatial Clusters of Male Mental Health Emergencies Occurring During the First National COVID-19 “Lockdown” in the East Midlands Region, UK: A Geospatial Analysis of Ambulance 999 Data

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Abstract

The widespread psychological effects of contagion mitigation measures associated with the novel coronavirus disease 2019 (COVID-19) are well known. Phases of “lockdown” have increased levels of anxiety and depression globally. Most research uses methods such as self-reporting that highlight the greater impact of the pandemic on the mental health of females. Emergency medical data from ambulance services may be a better reflection of male mental health. We use ambulance data to identify unusual clusters of high rates of male mental health emergencies occurring in the East Midlands of the United Kingdom during the first national “lockdown” and to explore factors that may explain clusters. Analysis of more than 5,000 cases of male mental health emergencies revealed 19 unusual spatial clusters. Binary logistic regression analysis ($\chi^2 = 787.22$, $df = 20$, $p \leq .001$) identified 16 factors that explained clusters, including proximity to “healthy” features of the physical landscape, urban and rural dynamics, and socioeconomic condition. Our findings suggest that the factors underlying vulnerability of males to severe mental health conditions during “lockdown” vary within and between rural and urban spaces, and that the wider “hinterland” surrounding clusters influences the social and physical access of males to services that facilitate mental health support. Limitations on social engagement to mitigate effects of the pandemic are likely to continue. Our approach could inform delivery of emergency services and the development of community-level services to support vulnerable males during periods of social isolation.

Keywords

COVID-19, male mental health, spatial analysis, ambulance data, rural health

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Introduction

Background

On March 23, 2020, the U.K. Prime Minister announced the first national “lockdown” to mitigate the impact of the novel coronavirus disease 2019 (COVID-19) on society. In the months that followed, the priority of researchers was to understand contagion and transmission pathways (Park et al., 2020), and to identify vulnerable communities

(Daras et al., 2021; Khalatbari-Soltani et al., 2020; Patel et al., 2020). In the aftermath of the most immediate threat to human life, governments and research communities recognized that understanding the impact of mitigation strategies, such as “lockdown” on the well-being of societies is of equal importance (Galea et al., 2020).

Most research about the mental health impacts of “lockdown” associated with the COVID-19 pandemic involves self-reporting social surveys (Adams-Prassel,



2020; Henssler et al., 2021; O'Connor et al., 2021; Pierce et al., 2020; Rajkumar, 2020; Wang et al., 2021), which are prone to selection bias (Bethlehem, 2010) or service use records, such as visits to mental health specialists, which only represent experiences of individuals who actively seek help using these routes (Sigmon et al., 2005). Almost unanimously, prior studies that utilize these methods emphasize the increased psychological distress experienced by females (Adams-Prassl et al., 2020; O'Connor et al., 2021; Pierce et al., 2020; Qiu et al., 2020). However, self-reporting and service use data typically underrepresent males who are less likely to engage in voluntary social surveys (Fischer et al., 2001) or seek help, particularly for psychological symptoms (Seidler et al., 2016).

Ambulance data may better capture the experience of males having mental health emergencies compared with data that rely on self-reporting or help-seeking (Lubman et al., 2019; Moore et al., 2021). In most cases, friends and family members who are present during mental health emergencies will call an ambulance on behalf of the individual experiencing a crisis. During the pandemic, males in the United Kingdom have been experiencing, and continue to be more likely to experience, severe or fatal COVID-19 (Islam et al., 2020), homelessness (Boobis & Albanese, 2020), and unemployment (Zarrilli & Luomaranta, 2021). Males also accounted for three quarters of all suicide completions under ordinary circumstances prior to the pandemic (Mental Health Foundation, 2020), and they were reported to have higher rates of suicide completion compared with females during the first national "lockdown" (Moore et al., 2021). Given that males are more likely than females to be exposed to many socioeconomic stressors known to increase mental health risk—such as unemployment (Kromydas et al., 2021)—it is not surprising that rates of male mental health emergencies have risen during "lockdown" conditions.

In contrast to studies that utilize self-reporting and help-seeking service use data, Moore et al. (2021) analyzed ambulance records of mental health emergencies

that occurred during the first national "lockdown" from the East Midlands Ambulance Service NHS Trust (EMAS) and reported that compared to the same period in 2019, males rather than females were more likely to experience mental health emergencies attended by ambulances. In a recent study appearing in this special edition (*Disparate Impact of COVID-19 on Men's Health*), Moore, Siriwardena, Gussy, et al. (2022) investigated the characteristics of males presenting with mental health emergencies to ambulance services in the East Midlands of the United Kingdom and reported that greater numbers of males were attended by ambulance for acute anxiety during "lockdown" compared to the same period in 2019, and they were more likely to live in the most deprived regions of the East Midlands compared with females. In the current study, we consider the *spatial* dynamics of males presenting with mental health emergencies attended by ambulances whereby paramedics record a preliminary diagnosis of conditions including severe anxiety and depression (see subsection "Measures" for in depth details about diagnosis). In this context, spatial dynamics include degree of rurality and urbanization, as well as geographical location, such as whether regions that occur in coastal compared with inland areas.

Understanding the *spatial* dynamics of mental health emergencies is important for the timely design and implementation of interventions to reduce acute psychological distress during the extraordinary circumstances associated with the COVID-19 pandemic. Psychological crises often occur when mild or moderate underlying conditions, such as depression, or susceptibilities such as deprivation, are exacerbated by exposure to environmental stressors, such as job (Frankham et al., 2020; Xiong et al., 2020) or home loss (Singh et al., 2019; Smith, 2005). Poor mental health outcomes and psychological distress are associated with socioeconomic factors such as income and education (Curtis et al., 2006; Koppel & McGuffin, 1999) and neighborhood-level measures of deprivation (Drukker & van Os, 2003; Gunnell et al., 1995), as well as features of the built environment (Daras et al., 2019) and rurality (Gregoire, 2002; Gregoire & Thornicroft, 1998).

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Socioeconomic deprivation is also related to poor health literacy and help-seeking behavior (Protheroe et al., 2017), as well as environmental conditions that produce poor health outcomes; lower-income communities tend to be located in regions with higher-density housing, such as council estates (Kearns et al., 2012), and at a further distance from safe outdoor green spaces for physical exercise and well-being compared with wealthier communities (Gidlow & Ellis, 2011). Thus, socioeconomic condition is related to the spatial characteristics of areas.

Importantly, social and environmental factors interact within the landscapes that societies inhabit (Curtis et al., 2006). Severe health outcomes, including physical (Moore, Hill, Siriwardena, Law, et al., 2022, Moore, Hill, Siriwardena, Tanser, & Spaight, 2022) and mental health conditions (Evans & Cassells, 2014; Repetti et al., 2002) are often the result of *cumulative* stressors occurring across these domains. Mental health emergencies, such as attempted suicide, are more likely to occur after multiple successive negative experiences; successive experiences create conditions of *underlying susceptibility*, while major life events, like extended periods of social isolation can act as *triggers* escalating a mental health condition and precipitating an emergency situation (Kegler et al., 2017; Kira et al., 2019). Most research considers the role of one or more of these domains on mental health; the social and environmental determinants of severe mental health outcomes are rarely considered together, and few studies examine the interaction between them (Eriksson et al., 2018). In this study, we consider the *cumulative* impact of both socioeconomic factors and features of built environments on male mental health emergencies occurring during “lockdown.”

Based on known associations among deprivation, built environments, and mental health outcomes, it might be expected that higher rates of male mental health emergencies occur in more deprived urban communities (Paykel et al., 2000), and further from healthy features of physical landscapes that promote well-being, such as in isolated rural localities (Commins, 2004; Gregoire, 2002; Gregoire & Thornicroft, 1998). However, the characteristics of communities associated with health-related emergencies vary according to geographic location. For example, Moore, Hill, Siriwardena, Law, et al. (2022) investigated the characteristics of regions with unusual clusters of suspected severe COVID-19 and identified that features of communities with high rates of severe cases varied depending on degree of urbanization and rurality, as well as location inland compared with coastal areas. Risk factors in urban areas were associated with deprivation whereas risk factors in rural areas were related to isolation from health services. Given that physical and mental health conditions often co-occur (Firth et al., 2019; Fond et al.,

2021), it is possible that high rates of male mental health emergencies during the COVID-19 pandemic are also geographically heterogeneous.

In this study, we utilize the analytical methodology developed by Moore, Hill, Siriwardena, Law, et al. (2022) to identify regions with unusually high clusters of male mental health emergencies during the first national “lockdown” in the United Kingdom, and to consider the socioeconomic and landscape features that explain the location of those clusters. In the case of a contagious disease such as COVID-19, clusters of severe illness reflect the intersection of individual exposure to the virus and underlying health susceptibility. Similarly, clusters of chronic non-communicable diseases such as mental health conditions can reflect shared social and environmental determinants of health outcomes (Koehly & Loscalzo, 2009). The purpose of our analysis is to identify vulnerable communities, investigate the characteristics of regions that may expose communities to risk associated with poor male mental health outcomes during the first national “lockdown” between March 23 and July 4, 2020, and to consider the implications for mitigating the mental health impacts of the pandemic on vulnerable males.

Conceptualizing the Relationship Between Mental Health and Built Environments. Theories about the association between mental health outcomes and the built environments that societies inhabit include perspectives that highlight the importance of *social* factors and networks (Cohen, 2004; Wilkinson et al., 1998), and urban landscape perspectives (Campbell & Wiesen, 2009; Cervero & Duncan, 2003; Williams, 2019) that emphasize the impact of *physical* features of environments on well-being. Social perspectives often draw on Bronfenbrenner’s bioecological theories (Eriksson et al., 2018; Rosa & Tudge, 2013) to consider the interactions between individual determinants of mental health outcomes and multilevel social interactions (Arakelyan & Ager, 2021; Dunn et al., 2014; Hoffman & Kruczek, 2011). Bioecological models divide the social world of an individual into four “systems”: the Microsystem, including the most immediate elements of the social world, such as family; the Mesosystem, including extended social networks; the Exosystem, including wider community services; and the Macrosystem including commonly shared cultural and social beliefs and values (Bronfenbrenner, 1979). From this perspective, mental health outcomes transcend the individual, reflecting complex connections between individuals and their social environments. In contrast, urban landscape perspectives suggest that characteristics of built environments, such as degree of urbanization and rurality (Gregoire, 2002; Paykel et al., 2000), access to “healthy” assets like green space (De Vries et al., 2003; Markevych et al., 2017), blue space (van den Bogerd

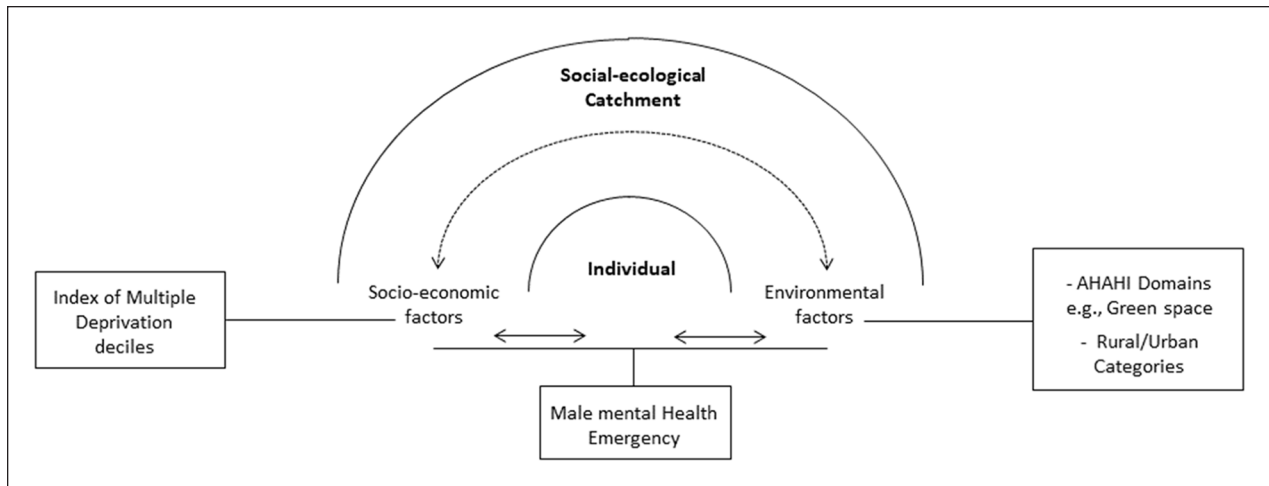


Figure 1. Schematic Showing the Social-Environmental Mesosphere Demonstrating the Multilevel Factors That May Be Associated With Acute Male Mental Health Emergencies.

Source. Adapted from Moore, Siriwardena, et al. (2022).

Note. The dotted arrow indicates the interaction between socioeconomic factors and physical landscape factors within the Mesosphere.

Peripheral boxes indicate the specific measures of social and environmental factors included in the research. AHAHI = Access of Healthy Assets and Hazardous Index.

et al., 2021), and health services (Gulliford et al., 2002) influence mental health outcomes, whereby closer proximity to healthy assets is associated with better health outcomes (Daras et al., 2018).

In a recent publication (*Anonymised Authors*), we used ambulance data to identify clusters of unusually high rates of suspected severe COVID-19, and to consider the social, economic, and physical characteristics of regions with clusters that might explain vulnerability. Our analysis demonstrated that social *and* physical features of built environments are associated with vulnerability to severe illness from infectious disease. Thus, we proposed that, “physical landscape factors rightly belong in a theoretical space akin to Bronfenbrenner’s Mesosystem” (Moore, Hill, Siriwardena, Law, et al., 2022). Similar to infectious disease, mental health outcomes are associated with social factors, such as deprivation (Drukker & van Os, 2003; Gunnell et al., 1995), and physical environmental factors, such as access to services that facilitate help-seeking (Gulliford et al., 2002), and green and blue spaces that promote well-being (Daras et al., 2019). Mental health outcomes and the determinants of mental health also vary in urban compared with rural spaces (Paykel et al., 2000). In the current study, we draw on the social-environmental model of the Mesosystem presented by Moore, Hill, Siriwardena, Law, et al. (2022) to explore associations between unusual clusters of severe male mental health emergencies attended by ambulances, and factors that are known to influence mental health outcomes, including both the *socioeconomic* and *physical* characteristics

of regions. Figure 1 is adapted from Moore, Hill, Siriwardena, Law, et al. (2022) and visualizes the variables included in the current research.

Prior research considers the relationship between male mental health outcomes and either social determinants, such as deprivation (Robertson & Baker, 2017), or landscape characteristics, such as rurality (Ahmadu et al., 2021; Robertson et al., 2018). Few studies consider factors related specifically to male mental health in the context of the COVID-19 pandemic and “lockdown.” To our knowledge, no prior research has examined the interaction between social and physical features of landscapes, and mental health during the pandemic or otherwise. We consider the *cumulative* impact on male mental health of factors associated with socioeconomic condition *and* the characteristics of physical landscapes. Our analysis identifies regions with unusual spatial clusters of male mental health emergencies occurring during “lockdown,” and draws on Bronfenbrenner’s socioecological landscape, including the adapted “socio-environmental Mesosphere” (Moore, Hill, Siriwardena, Law, et al., 2022) to investigate the characteristics of regions which may explain the vulnerability of males to acute psychological distress.

Method

Site and Location

Located in the Central Eastern part of England, the East Midlands spans an area of 15,627 km² (Figure 2). The regional population includes the urban areas of Derby,

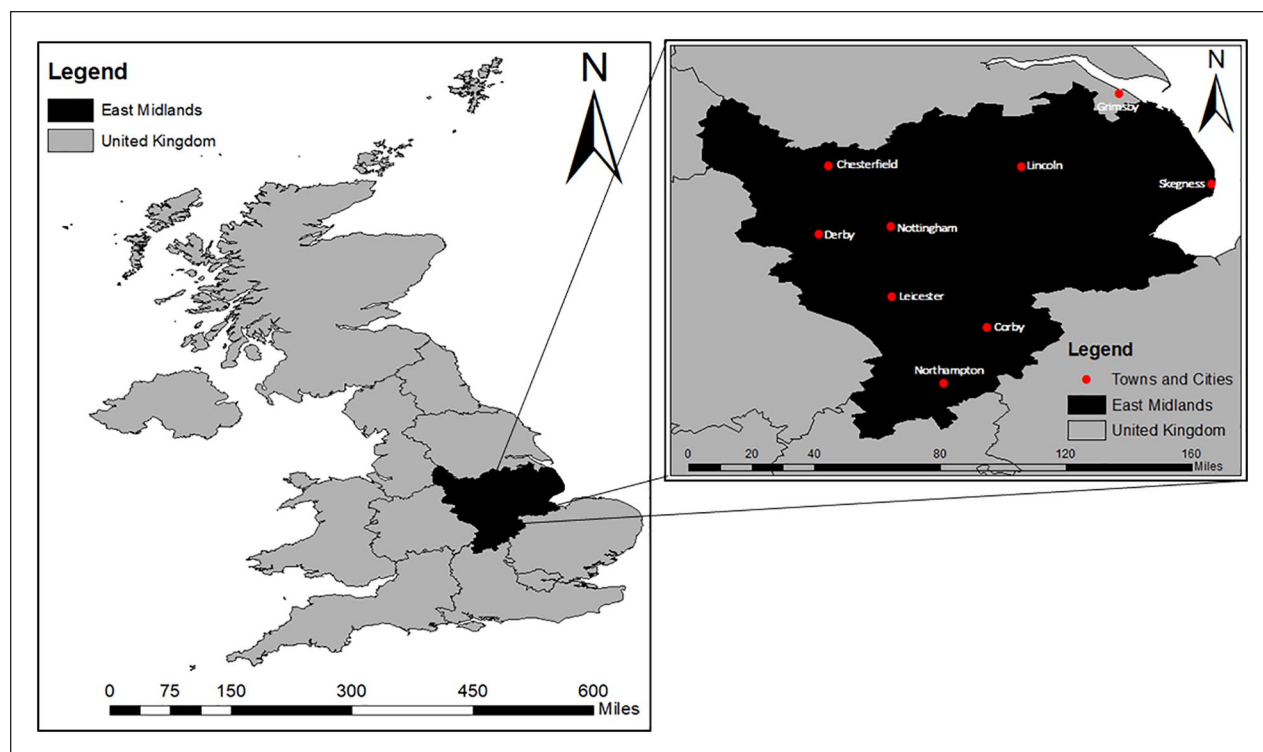


Figure 2. Map of the United Kingdom Highlighting the East Midlands Region, Including the Locations of Prominent Towns and Cities.

Leicester, Lincoln, Northampton, and Nottingham, and it has a total estimated population of 4.8 million (Office for National Statistics [ONS], 2020a). Ethnic diversity in this region is low, with 14.6% of the population identifying as other than “White UK,” compared with a national average of 20.2% (ONS, 2020b). The East Midlands is the third most rural region in England (European Commission, 2020), and in 2016, 18.5% of people lived in the most deprived quintile (Public Health England, 2018).

Research Aims

The first aim of the research was to identify unusual clusters of male mental health emergencies occurring in the East Midlands of the United Kingdom. We used more than 5,000 records of severe mental health events experienced by males attended by ambulances, recorded, and collated by EMAS during the first national lockdown between March 23 and July 4, 2020. Cluster analysis was achieved using the geospatial software SatScan™ to perform a Kulldorff spatial scan statistic which compares the actual distribution of cases with the predicted distribution based on population density, testing the null hypothesis that cases are randomly distributed rather than occurring in unusual clusters. The second aim of the research was to explore factors that predict cluster membership, which involved computing a binary logistic

regression with variables related to mental health outcomes, including measures of deprivation, degree of rurality and urbanization, as well as distance from “healthy” features of landscapes (subsection “Data Handling and Cleaning”). The third aim was to elucidate the individual characteristics of each unusual cluster of male mental health emergencies, using statistical, geospatial analysis, and mapping to determine the strongest predictors of cluster membership.

Measures

Table 1 summarizes the data sets and measures included in the research. Data collated by and obtained from EMAS include records of male mental health emergencies identified by medically trained ambulance clinicians, and the age of male ambulance users. Reliable data about ethnicity were unavailable in real-time during the first national “lockdown.” Male mental health emergencies were determined based on the clinical impression of ambulance clinicians—which includes the professional judgment of the clinician—and the mental health history reported by the patient or other individuals who are known to the patient and were present at the time of ambulance attendance, such as carers and family members. The symptoms observed by ambulance clinicians and recorded in EMAS databases include depression,

Table 1. Data Sets, Measures, and Sources.

Data set ^a	Measure		Source
Mental health emergencies	Male mental health emergencies occurring during first national lockdown (March 23–July 4), age		East Midlands Ambulance NHS Trust
IMD 2019	IMD Decile		https://hub.arcgis.com/datasets/communities::lower-super-output-area-isoa-imd-2019-osgb1936
RUC 2011	Categorical scale 1 (<i>most urban</i>) to 10 (<i>most rural</i>) ^b		https://hub.arcgis.com/datasets/ons::rural-urban-classification-2011-of-lower-layer-super-output-areas-in-england-and-wales
AHAHI 2019	Health services (distance in km)	GPs, A&E, pharmacies	https://data.cdrc.ac.uk/dataset/access-healthy-assets-hazards-ahah
	Physical environment (distance in km) ^c	Green space (passive), green space (active), blue space	

Note. IMD = index of multiple deprivation; RUC = rural urban classification; AHAHI = Access of Healthy Assets and Hazardous Index; GPs = general practitioners; A&E = accident and emergency.

^aAll data scales at lower super output area. ^bOnly eight categories were present in the East Midlands data set; male mental health emergencies requiring ambulance attendance in the East Midlands were not recorded in urban-major conurbations, villages, hamlets, and isolated dwellings of any variety. ^cPassive green space includes parks, gardens, golf courses, and allotments and active green space includes sporting areas such as playing fields and tennis courts.

anxiety, suicidality, and acute behavioral disturbance. The specific characteristics of male mental health emergencies occurring during “lockdown” are considered in a companion piece published in this special edition (Moore, Siriwardena, et al., 2022). The analysis presented in the current study is purely spatial.

The socioeconomic characteristics of communities were measured using the Index of Multiple Deprivation (IMD) which is an aggregate measure of degree of affluence and deprivation which takes into account factors including education, employment, and income. Low IMD scores indicate greater deprivation whereas higher scores reflect greater affluence. Decile values of IMD were used for both spatial and statistical analysis. Measures of two aspects of physical landscapes were also included in the research to investigate factors that may explain unusual clusters. First, the U.K. Rural and Urban Categories (RUC) index was used to explore the relationship between degree of urbanization, rurality, and the locality of male mental health emergencies. Second, measures extracted from the U.K. Access of Healthy Assets and Hazardous Index (AHAHI) were included, such as distance (km) of localities where ambulances have attended male mental health emergencies from “healthy” features of built environments. Access to healthy features of landscapes is associated with more positive physical and mental health outcomes (Daras et al., 2019). Physical access to health services facilitates service use, whereas proximity to green (De Vries et al., 2003; Markevych et al., 2017) and blue space (van den Bogerd et al., 2021; White et al., 2020) promotes well-being.

Distance from general practitioners (GPs), pharmacists, and hospitals with accident and emergency (A&E) wards were included in the research. GPs are often the

first point of contact for mental health service referral. During the first national “lockdown,” the number of new referrals to psychological services decreased markedly which corresponds with a decrease in GP appointments (Davies, 2020). Similarly, over the course of the pandemic, the role of pharmacies (Royal Pharmaceutical Society, 2021) has evolved to include supporting people with mental health needs, while presentations of acute mental health conditions to A&E were increasingly supported by mental health liaison units (Mukadam et al., 2021). Overall, statistical analysis to explain the location of clusters included measures of distance (km) from health services such as GPs, pharmacies, and A&E, as well as distance from passive green space, such as commons and arboretums, active green space, such as cricket pitches, and blue space, such as ponds and beaches.

Data Handling and Cleaning

The database of male mental health cases was obtained from EMAS, including the date 999 calls were received, partial postcodes (rather than full addresses) of ambulance attendance locations, sex, and age. In total, 5,779 records were received. All records were successfully linked to IMD, AHAHI, and RUC values. Only ambulance call outs for male mental health related emergencies were included in the data set.

Statistical and Spatial Data Analysis

Identifying Unusually High Clusters of Male Mental Health Emergencies. We applied a Kulldorff spatial scan statistics (Discrete Poisson model) implemented in SatScanTM software Version 9.6.1 to perform the spatial analysis

scanning to detect unusual clusters of male mental health emergency cases across the surveillance area. As spatial statistics is a cluster detection test, it detects the location of clusters and evaluates their statistical significance (Kulldorff, 1997; Kulldorff et al., 2005). The cluster detection method gradually scans a window across the study area, noting the number of observed and expected cases, based on male population (ONS, 2011), inside the window at each location using a Discrete Poisson model. For any given position of the center, the radius of the circle changes continuously and can take any value. For each circle, the spatial scan statistic calculates the likelihood of the observed number of cases occurring inside and outside of the circle. The circle with the maximum likelihood is identified as the most likely cluster, and thus the least likely to have occurred by chance. The Kulldorff spatial scan statistic tests the null hypothesis that cases are distributed randomly. Statistical significance indicates that unusual spatial clustering is unlikely to have occurred by chance. The isotopic circular scan method employed by SatScanTM has previously been validated for identifying clusters of infectious disease such as HIV (Namosha et al., 2013; Tanser et al., 2018) and COVID-19 (Moore, Hill, Siriwardena, Law, et al., 2022). To our knowledge, the only use of this method for assessing clustering of noncommunicable disease has been for cancer incidences and mortality (Amin & Rivera, 2020; Sherman et al., 2014; Wheeler, 2007). The current research is the first use of the Kulldorff spatial scan statistic to identify unusual clusters of acute mental health events, or to consider the geographical and socio-economic determinants of severe mental health conditions.

Data Conversion to LSOA and Database Compilation. A merged LSOA data set of IMD, RUC, and AHAHI scores (Moore, Hill, Siriwardena, Law, et al., 2022, Supplemental Material) was used to join each individual case of male mental health emergency to Lower Super Output Area codes (LSOA11CD). The data conversion process is outlined in detail in Moore, Hill, Siriwardena, Law, et al. (2022). The software package ArcGIS Pro 2.6.0. was used to geospatially analyze output from SatScanTM to identify intersections of where individual cases fall into unusual clusters compared with cases that were randomly distributed. In one case, three significant clusters were found to overlap considerably. Each individual case can only be assigned to one cluster. Therefore, the cluster with greatest overlap was removed. For the remaining two clusters with overlap, cases ($N = 23$) were allocated to a single cluster by splitting the overlap from the central axis. The output was a novel database with each case of male mental health emergency linked to a score for IMD, RUC, AHAHI factors (e.g., passive green space), and

either assigned to a cluster or to the category “randomly distributed cases.” This database was used for regression analysis to identify factors that predict cluster membership (subsection “Factors That Predict Male Mental Health Emergencies Occurring in Unusual Clusters”) and for geospatial analysis to produce maps and inform a predictive layer (subsection “Characteristics of individual clusters”).

Statistical Analysis and Spatial Representation of Factors That Predict Clusters. Binary logistic regression analysis was used to identify factors that predict whether individual cases of male mental health emergencies occur in usual clusters or are randomly distributed outside of clusters. All measures reported in Table 1 that were found to be significant predictors of cluster membership were included in the regression model. Regression output and cluster output from SatScanTM was used to display the relationship between determinants of clusters visually. The cluster output from SatScanTM was converted to a layer (“cluster shapefile”) within ArcGIS Pro 2.6.0.

Of 43 clusters identified, 19 were statistically significant ($p < .05$). All nonsignificant clusters were removed from the data set. A polygon representing the East Midlands was extracted from the UK Counties 2017 shapefile (“UK shapefile”) to create a shapefile to outline the area in local scene. Relative risk values extracted from SatScanTM output were assigned to each cluster within the cluster shapefile. This value for the cluster shapefile was displayed in local scene as an extrapolated elevation above ground level to display relative risk as both height and graduated color in three-dimension. Displaying clusters involved using a scale of graduated colors from green to red that were manually selected based on the spread of the data.

A predictive layer was also created using the outputs of the binary logistic regression analysis. Categorical variables such as RUC or IMD could not be included in the layer; only continuous values for AHAHI measures could be used as it is continuous data. Passive green space, blue space, GPs, and pharmacies were the four layers included in the predictive layer as they were found to be statistically significant from the results of the binary logistic regression conducted to predict cluster membership (Table 5). These layers were extracted from the IMD, RUC, and AHAHI shapefile and converted to raster’s to perform raster math to combine and weigh these layers. The layers were individually multiplied by their $\text{Exp}(B)$ values as determined by regression analysis, and then added to create a weighted predictive layer. This is a novel approach to utilizing the AHAHI variable scores to create a predictive layer and has not, to our knowledge, been performed previously.

Table 2. Descriptive Statistics for Measures of IMD, and “Healthy” Features of Landscapes for Cases of Male Mental Health Emergencies Occurring in Unusual Clusters (Mean_IN, Standard Deviation_IN) Compared With Cases Randomly Distributed Outside of Clusters (Mean_OUT, Standard Deviation_OUT).

Domain	Factor	M_In	SD_IN	M_Out	SD_Out
Health services	GPs	1.32	1.31	1.45	1.42
	A&E hospitals	11.70	13.04	12.96	11.04
	Pharmacies	0.97	1.05	1.22	1.53
Physical environment	Green space (passive)	0.33	0.32	0.40	0.48
	Green space (active)	0.52	0.51	0.55	0.46
	Blue space	1.96	1.75	2.50	2.04
	IMDDecil	3.52	2.69	4.75	2.84

Note. Measures of IMD are decile values. Measures of “healthy” features of landscapes include distance (km) from two AHAHI domains: health services (GPs, hospitals with A&E, and pharmacies) and physical environmental assets (passive green space, active green space, and blue space). IMD = index of multiple deprivation; GPs = general practitioners; A&E = accident and emergency; AHAHI = Access of Healthy Assets and Hazardous Index.

Table 3. Proportion of Cases in Unusual Clusters (In [%]) Compared With Randomly Distributed Cases Outside Clusters (Out [%]) by RUC Categories.

Rural urban classification (RUC)	In (%)	Out (%)
Urban minor conurbation	33.5	13.7
Urban city or town	54.0	69.7
Urban city and town in a sparse setting	1.3	<1
Rural town and fringe	6.6	10.1
Rural village and dispersed	4.2	5.9
Rural village and dispersed in sparse setting	<1	<1

Results

Descriptive Statistics

In total, 5,779 cases of male mental health emergencies with sufficient information to include in analysis were recorded by EMAS between March 23 and July 4, 2020. Of all cases, 1,566 (27%) fell into unusual clusters, while the remaining 4,213 (73%) cases were distributed randomly. The average age of males experiencing mental health emergencies that occur in clusters ($M = 43$) was similar to the age of male cases that were randomly distributed ($M = 44$). The mean (M) and standard deviation (SD) for measures of IMD, and distance from “healthy” features of landscapes extracted from the AHAHI included in our analysis are presented in Table 2. The proportion of cases in unusual clusters compared with the proportion of randomly distributed cases by RUC categories is presented in Table 3.

Identifying Unusually High Clusters of Male Mental Health Emergencies

SatScan™ Poisson Modeling identified 19 statistically significant ($p < .05$) unusually high clusters of male

mental health cases, displayed in Figure 3. Per 100,000 populations, the number of observed cases range from 3,260 in the Mansfield cluster to 18,367 in the cluster South of Rugby. Figure 4 demonstrates the relative risk of each cluster, meaning the likelihood of having a mental health-related case in an area compared with regions where cases are randomly distributed. The spatial characteristics of each cluster, including approximate location, radius, expected and observed number of cases, p values, specific relative risk ratios, and the number of cases in each cluster per 100,000 population are reported in Table 4.

Factors That Predict Male Mental Health Emergencies Occurring in Unusual Clusters

A binary logistic regression analysis was conducted to investigate factors that explain cases of male mental health emergencies during the first national lockdown occurring in unusual spatial clusters. The analysis examined how well features of built environments—that reflect physical access to health services—and socioeconomic characteristics of those environments that reflect social access predicted male mental health emergencies occurring in

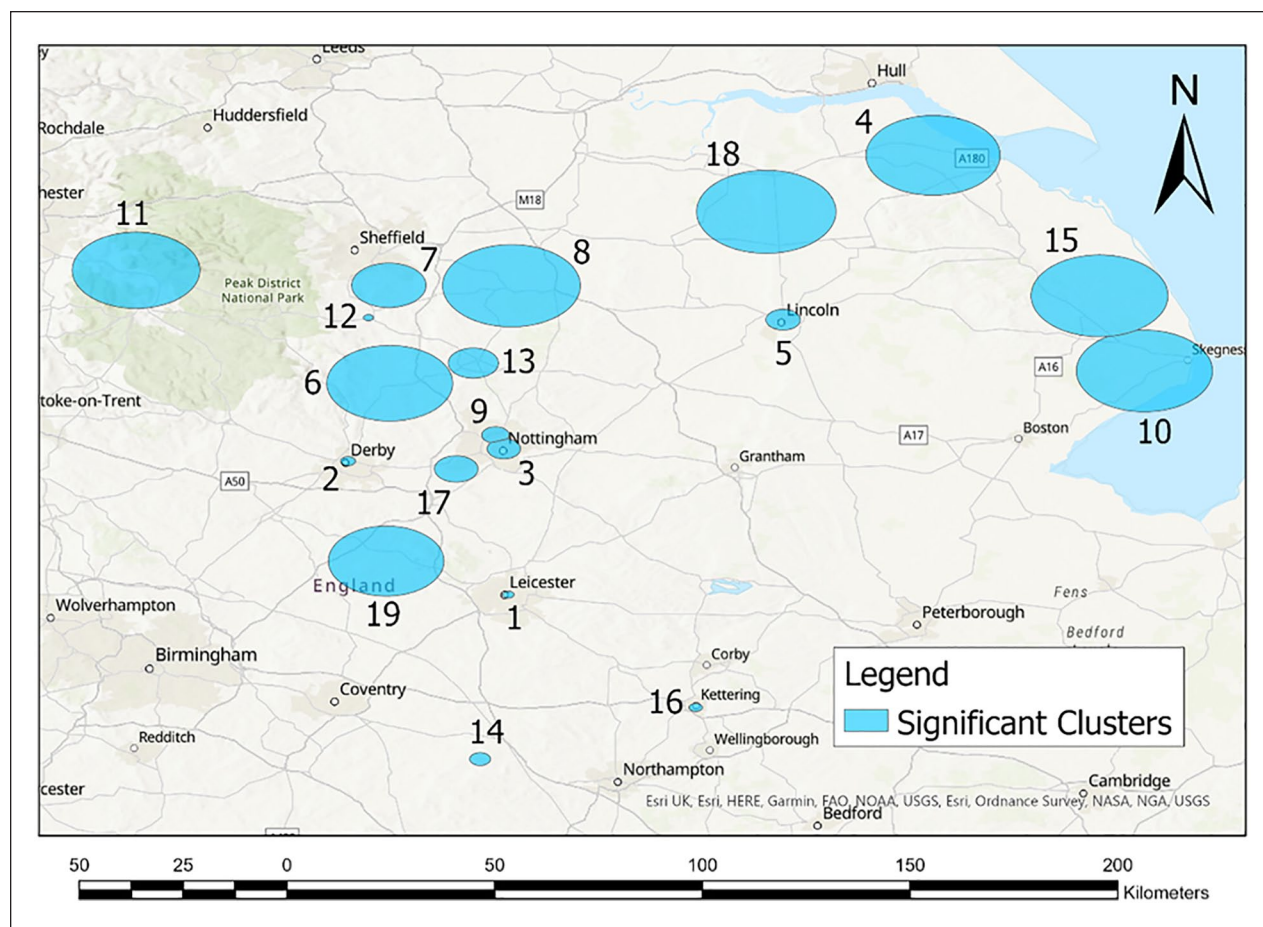


Figure 3. The Geographic Location of 19 Statistically Significant ($p < .5$) Clusters of COVID-19, Identified Using a Kulldorf Spatial Scan Statistic.

Note. Further details of clusters are given in Table 4.

clusters compared with random spatial distribution. The proportion of cases occurring in clusters compared with distributed randomly was highly asymmetrical. Therefore, the model cutoff was set to 0.3.

The results indicated that physical access to four “healthy” features of built environments, two RUC categories, and all IMD categories were significant predictors of male mental occurring in unusual clusters compared with random distribution during the first national lockdown ($\chi^2 = 787.22$, $df = 20$, $p \leq .001$). The overall predictive accuracy of the model was 72%.

Table 5 displays the binary logistic regression results for all independent variables included in the model. The reference categories for categorical variables were the most common categories as follows: “Urban city & town” for RUC and “IMD Decile 1” for IMD deciles, representing regions of greatest deprivation. Compared with randomly dispersed male mental health emergencies, cases occurring in unusual clusters were more likely to be within further distance from GPs, and closer distance to

pharmacies, passive green space, and blue space. Cases in clusters were also more likely to be located in areas classified as “Urban minor conurbation,” “Urban city and town in a scarce setting,” and “Rural village and dispersed.” Furthermore, cases in clusters were less likely to be located in areas with IMD Decile scores between 2 and 9, and therefore more likely to be located in Decile 1, reflecting areas of greatest deprivation. The strongest predictors of cluster membership were RUC categories and distance from GPs.

Characteristics of Individual Clusters

The statistical analysis presented in the subsection “Factors That Predict Male Mental Health Emergencies Occurring in Unusual Clusters” considers factors that explain whether individual cases of male mental health emergencies during “lockdown” occurred in unusual clusters in the East Midlands region. The analyses below consider the characteristics of *individual* clusters. Three

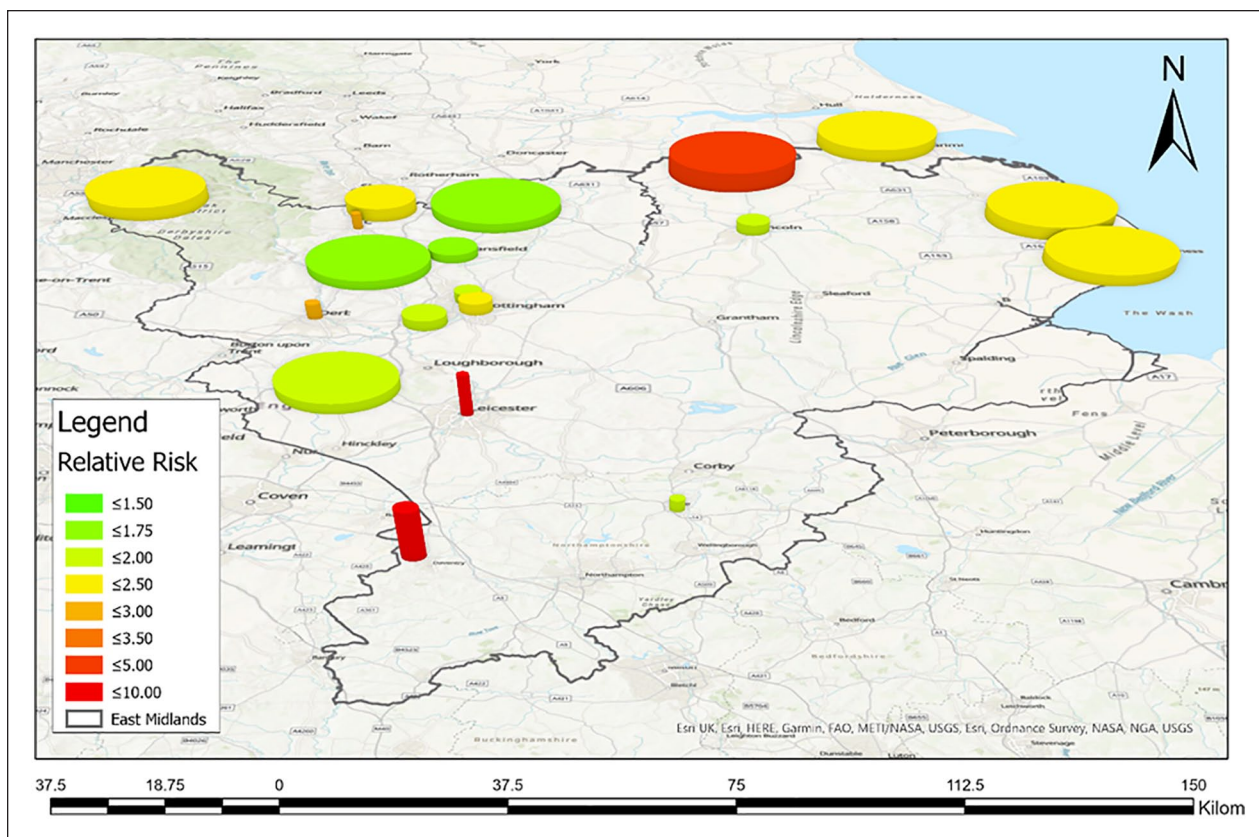


Figure 4. Spatial Representation of Relative Risk of Male Mental Health Emergencies in the East Midlands of the United Kingdom.

Note. Taller clusters and clusters closer to red on the color gradient reflect greater risk of male mental health prevalence.

maps (Figures 5–7) display the distribution of “healthy” features of landscapes, IMD, and RUC categories with cluster locations overlaid. Figure 5 synthesizes each significant landscape variable identified through regression analysis into a single predictive layer.

Following Moore, Hill, Siriwardena, Law, et al. (2022), we also compare the characteristics of individual clusters to average values for all areas with randomly distributed cases. Clusters displayed on maps show the radius within which individual cases of male mental health emergencies occur. We have not displayed the specific location of individual cases to preserve the anonymity of EMAS patients. However, Table 6 synthesizes average scores for RUC, IMD, and distance from “healthy” landscape features, and it compares these values with average scores for all areas with randomly distributed cases. In some cases, the visual characteristics of a cluster may vary from the characteristics reported in Table 6. For example, Figure 6 displays RUC scores with clusters overlaid, visualizing the rural and urban dynamics of each individual cluster. Cluster 4 is predominately rural, but most cases fall within a small urban area. Thus,

Cluster 4 is categorized as urban. Together, visual and statistical analysis represents cluster characteristics accurately while maintaining the anonymity of patient locations.

Discussion

In the short time since the COVID-19 pandemic was announced, mental health research about the psychological well-being of societies, including the effects of social isolation associated with “lockdown” measures, has been prolific. In less than 2 years, more than 50 systematic literature reviews of mental health impacts have been conducted worldwide (Chiesa et al., 2021). Overwhelmingly, these reviews synthesize social survey studies and conclude that females are experiencing greater psychological impacts than males (e.g., Kan et al., 2021; Pierce et al., 2020; Salari et al., 2020; Samji et al., 2021; Xiong et al., 2020). For example, Gibson et al. (2021) reviewed 117 studies from 28 countries and found that only seven observed worse mental health outcomes for men compared with women. Similarly, Luo et al. (2020) reviewed

Table 4. Spatial Characteristics of Unusual Clusters of Male Mental Health Cases Presented in Figure 3.

Cluster	Radius (km)	Population	Number of cases	Expected cases	Log likelihood ratio cases	p value	Relative risk	Cases per 100,000 population	Location
1	0.83	346	53	7.27	59.76	<.00	7.35	15,317	Leicester
2	1.09	2,492	141	52.33	51.78	<.00	2.74	5,658	Derby
3	2.41	5,216	219	109.51	43.36	<.00	2.04	4,198	Nottingham
4	9.57	1,832	90	38.47	25.2	<.00	2.36	4,912	Grimsby
5	2.49	2,727	109	57.17	18.75	<.00	1.92	3,997	Lincoln
6	9.09	5,358	182	112.49	18.49	<.00	1.64	3,396	West of Mansfield
7	5.35	1,277	62	26.81	16.9	<.00	2.33	4,855	North of Chesterfield
8	9.89	3,515	127	73.81	15.98	<.00	1.74	3,613	Worksop
9	1.99	2,562	99	53.79	15.36	<.00	1.86	3,864	Nottingham
10	9.81	1,669	72	35.03	15.02	<.00	2.07	4,313	Skegness
11	9.17	960	47	20.15	13.01	<.00	2.34	4,895	Peak District
12	0.75	515	31	10.82	12.49	<.00	2.88	6,019	Chesterfield
13	3.62	4,324	141	90.79	12.08	<.00	1.57	3,260	Mansfield
14	1.54	49	<10	1.02	11.63	<.00	8.84	18,367	South of Rugby
15	9.83	859	42	18.04	11.59	<.00	2.34	4,889	West of Mablethorpe
16	0.98	1,468	61	30.83	11.53	<.00	1.99	4,155	Kettering
17	3.15	2,200	82	46.2	11.36	<.00	1.79	3,727	West Nottingham
18	9.97	252	19	5.28	10.62	.01	3.61	7,539	South of Scunthorpe
19	8.34	1,799	69	37.77	10.43	<.02	1.84	3,835	Coalville

Note. Extracted from SatScan output, including population, number of cases, expected cases, log likelihood, p value, relative risk, cases per 100,000 population, and approximate location of clusters. Population has been determined at the regional postcode scale.

Table 5. Binary Logistic Regression for Predicting Whether Male Mental Health Emergencies During the First National Lockdown in the United Kingdom Occurred in Usual Spatial Clusters Compared With Random Spatial Distribution.

		B	SE	Wald	df	Exp(B)	95% CI
Physical landscape features	Accessibility to GP practices	0.13	.04	12.40	1	1.14*	[1.06, 1.22]
	Accessibility to A&E hospitals	-0.00	.00	1.15	1	0.99	[0.99, 1.00]
	Accessibility to pharmacies	-0.15	.05	10.35	1	0.86*	[0.78, 0.94]
	Accessibility to blue space	-0.18	.02	73.15	1	0.84*	[0.81, 0.87]
	Accessibility to passive green space	-1.05	.1	111.13	1	0.35*	[0.29, 0.43]
	Accessibility to active green space	-0.03	.1	0.06	1	1.00	[0.79, 1.20]
Rural/urban categories	Urban minor conurbation	1.43	.08	312.04	1	4.16*	[3.55, 4.87]
	Urban city and town in a sparse	1.17	.46	6.44	1	3.23**	[1.31, 7.99]
	Rural town and fringe	0.11	.14	0.58	1	1.11	[0.83, 1.46]
	Rural village and dispersed	0.54	.24	5.11	1	1.72**	[1.08, 2.75]
IMD deciles	Rural village and dispersed in sparse	1.25	.65	3.67	1	3.50	[0.97, 12.63]
	IMD Decile 2	-0.79	.11	52.48	1	0.47*	[0.38, 0.58]
	IMD Decile 3	-0.35	.12	9.08	1	0.70*	[0.56, 0.88]
	IMD Decile 4	-0.98	.11	73.10	1	0.38*	[0.30, 0.47]
	IMD Decile 5	-0.93	.12	57.99	1	0.39*	[0.31, 0.50]
	IMD Decile 6	-1.08	.14	63.98	1	0.34*	[0.26, 0.44]
	IMD Decile 7	-1.46	.18	67.35	1	0.23*	[0.16, 0.33]
IMD Decile 8	-0.98	.16	35.38	1	0.38*	[0.27, 0.52]	
IMD Decile 9	-1.69	.16	106.67	1	0.18*	[0.13, 0.25]	
IMD Decile 10	-1.14	.16	48.67	1	0.32*	[0.23, 0.44]	

Note. Predictor variables include accessibility to four physical landscape features, two rural/urban categories, and all IMD deciles. CI = confidence intervals; GP = general practitioner; A&E = accident and emergency; IMD = index of multiple deprivation.

*Statistically significant at $p < .01$. **Statistically significant at $p < .05$. Exp(B) values in bold indicate variables that are statistically significant in the model.

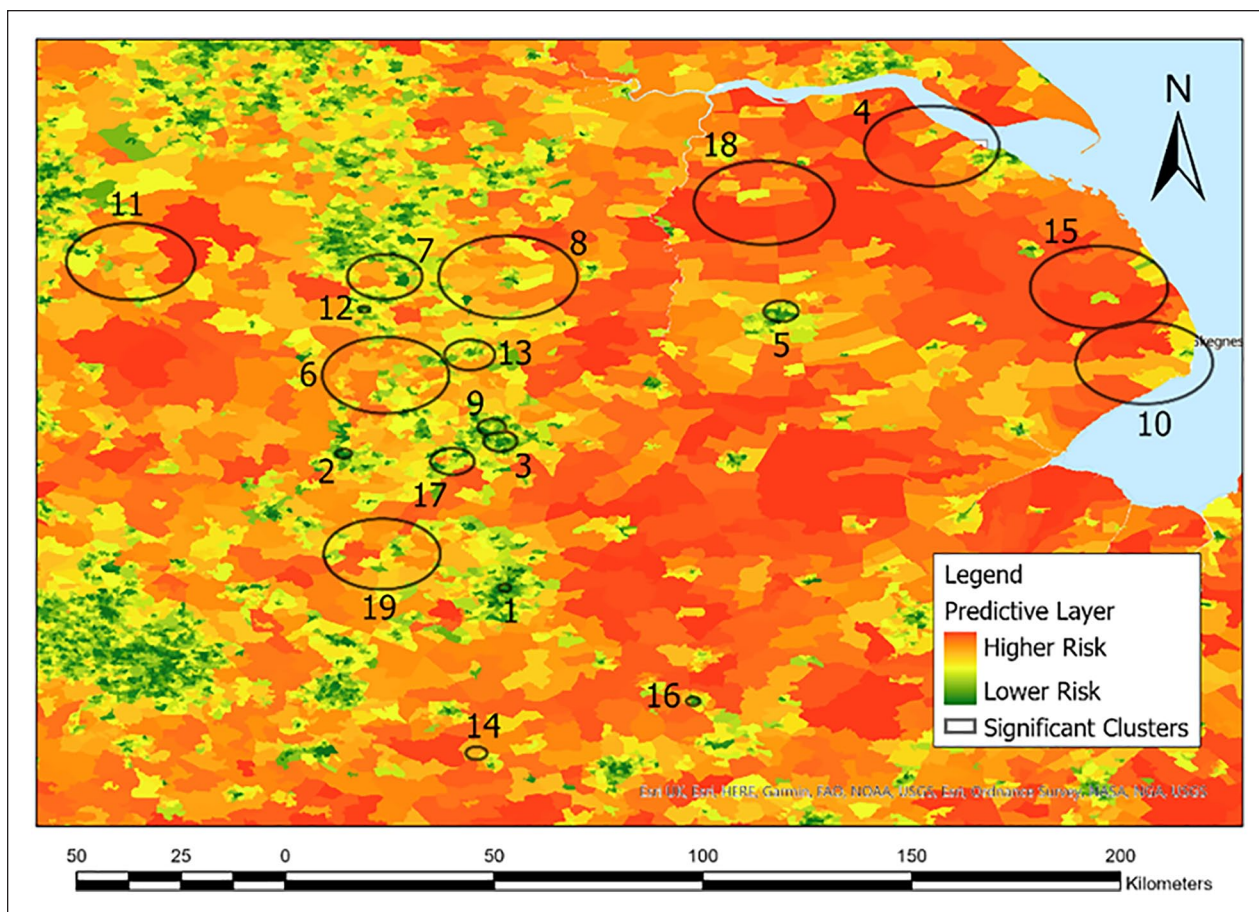


Figure 5. Map Displaying Male Mental Health Clusters Superimposed Over a Predictive Layer for Vulnerability Including Four Measures From the AHAHI: Passive Green Space, Blue Space, Pharmacies, and GPs.

Note. The graduated colors of the layer represent higher risk of unusual clustering: green represents lower areas of risk, and red represents higher risk areas. The predictive layer is made up of a combination of four individual layers: passive green space, blue space, pharmacies, and GPs. The 19 clusters of male mental health cases (identified using a Kulldorff spatial scan) are superimposed as black circles and numbered consistent with Table 6. AHAHI = Access of Healthy Assets and Hazardous Index; GPs = general practitioners.

62 studies from 17 countries and concluded that females were associated with higher risk of poor mental health outcomes. Importantly, the proportion of male compared with female participants involved in studies included in meta reviews tends to be lower (Octavius et al., 2020; Pierce et al., 2020). Thus, it is possible that common narratives about mental health reported in most COVID-19 studies more accurately reflect female compared with male mental health.

Moore, Hill, Siriwardena, Law, et al. (2022) suggested that ambulance data may be a more accurate reflection of male mental health during the COVID-19 pandemic and demonstrated that during the first national “lockdown” males were more likely than the prior year to experience acute anxiety. Male presentations of mental health emergencies were more likely to involve externalizing symptoms, such as acute behavioral disturbance, rather than internalizing symptoms, such as

depression, that are typically associated with psychological distress in females. Males are also less likely to seek help from formal health services (Seidler et al., 2016) and tend to be more receptive to community-based options (Robertson et al., 2018), such as sports settings (Robertson et al., 2010). In this study, we identify local regions with high rates of male mental health emergencies occurring during the first national “lockdown” in the East Midlands of the United Kingdom, and investigate the socioeconomic and environmental characteristics of those clusters. This analysis offers two important opportunities to improve care pathways for vulnerable males. First, identifying local clusters is a first step to improve the community services available to males experiencing psychological distress. Second, elucidating the landscape characteristics of clusters that may precipitate mental health emergencies could inform urban planning to reduce vulnerability during the

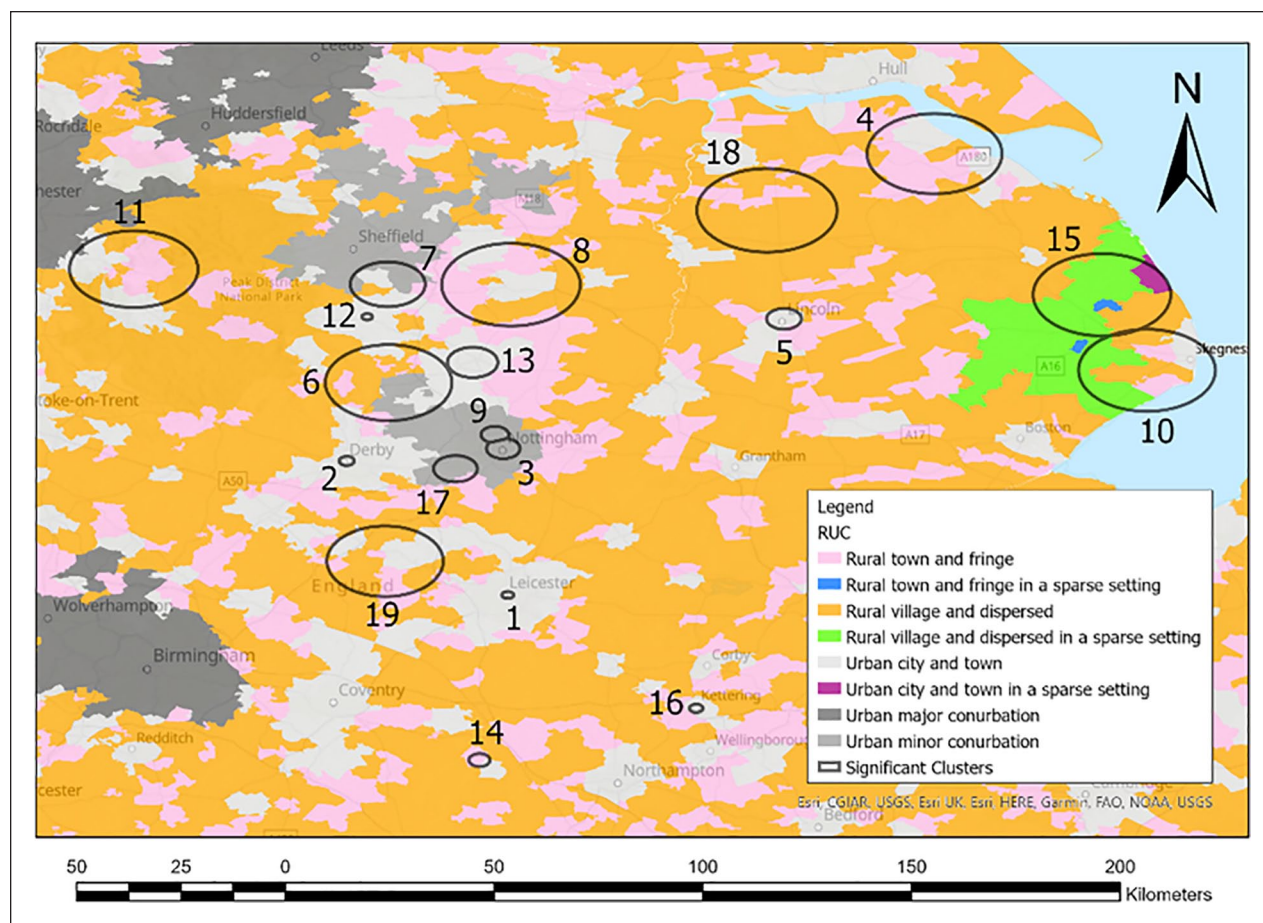


Figure 6. Map of the RUC Distribution With Unusual Clusters of Male Mental Health Emergencies Superimposed. Note. Colors in the legend reflect each rural/urban category. The 19 clusters (identified using a Kulldorff spatial scan) are represented as black circles and numbered consistent with Table 6. RUC = Rural Urban Classification.

extraordinary circumstances associated with the COVID-19 pandemic, as well as in more usual circumstances for socially isolated males.

Identifying Unusual Clusters and Predicting Cluster Membership

Spatial analysis revealed 19 statistically significant unusual clusters of male mental health emergencies (Figure 3) with rates of emergencies ranging from 3,260 to 15,317 per 100,000 population (Table 4). Regression analysis identified 16 variables that predict cluster membership. Overall, the predictive accuracy of the regression model is high and suggests good model fit.

The strongest predictor of cases occurring in unusual clusters is RUC. Compared with the reference condition (urban towns and cities), clusters of male mental health emergencies are more likely to occur in urban minor conurbations, urban cities and towns in sparse areas, and rural villages and dispersed areas. However, the very

small proportion of cases occurring in urban cities and towns in sparse areas has almost certainly inflated the odds ratio and effect size, as reflected in wide confidence intervals. Thus, this category is less representative of all cases occurring in clusters compared with other RUC that predict clusters. Clusters occur *closer* to pharmacies, blue space, and passive green space, and *further away* from GPs. Compared with the lowest IMD decile, indicating greatest deprivation, clusters are less likely to occur in areas characterized by all other IMD deciles, suggesting that clusters occur in most deprived areas.

Our observations about features of physical landscapes and male mental health vulnerability reflect patterns of public space use associated with the COVID-19 pandemic. During the first national “lockdown,” health agencies (World Health Organization [WHO], 2020) and governments (Friends of the Earth, 2021) encouraged societies to access green spaces for exercise and socially distanced social engagements to maintain well-being. Over the past 12 months, critiques have emerged of the

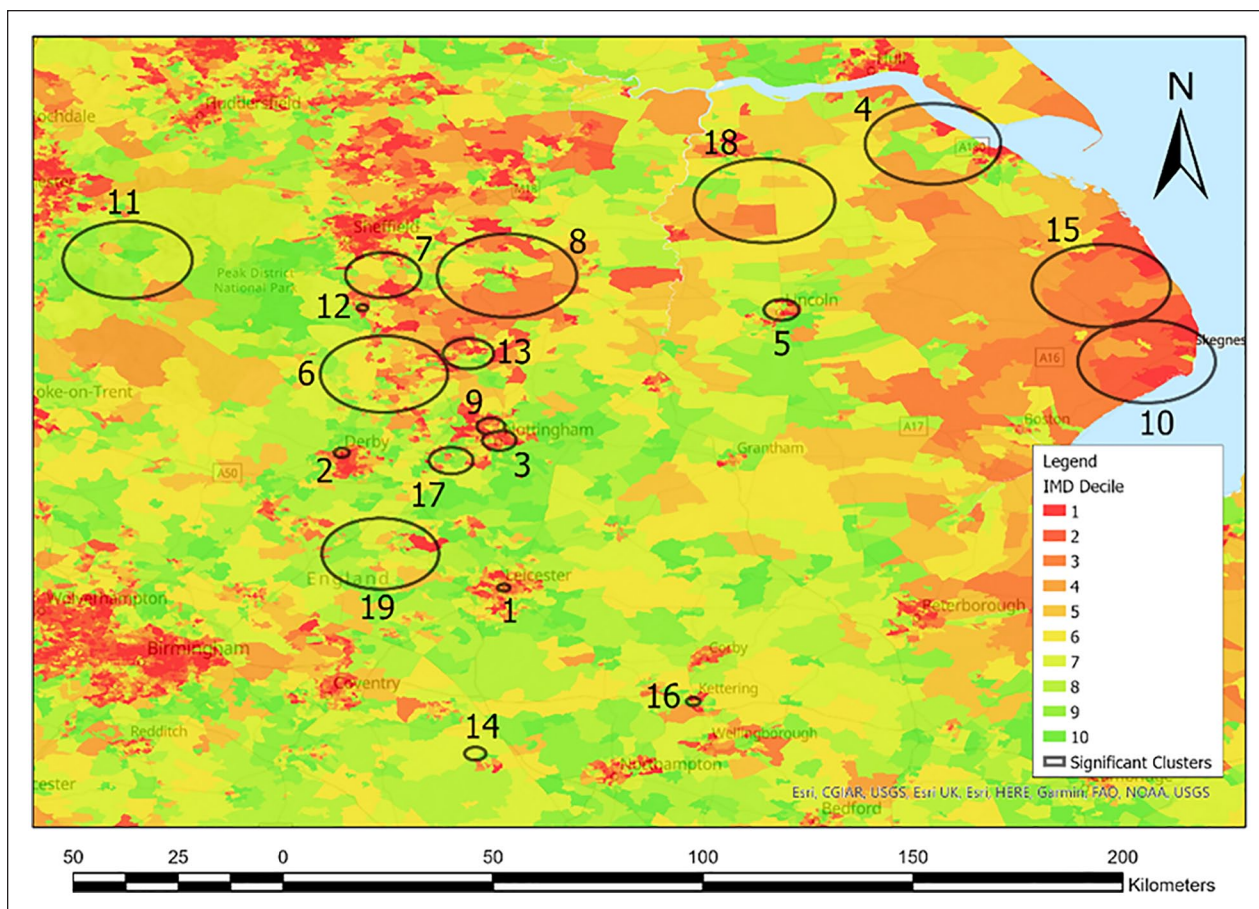


Figure 7. Map of the IMD Distribution With Unusual Clusters of Male Mental Health Emergencies Superimposed.

Note. The green spectrum indicates more affluent areas, whereas the red spectrum indicates more deprived areas. The 19 clusters (identified using a Kulldorff spatial scan) are represented as black circles and numbered consistent with Table 6. IMD = Index of Multiple Deprivation.

uniform approach taken to social distancing in the United Kingdom that failed to consider social factors, such as how people were likely to utilize green spaces during “lockdown” (Pan et al., 2021). Research suggests that passive green spaces such as parks, and blue spaces such as beaches and river frontage, particularly in urban areas that are highly connected to residential housing were associated with high risk of infection. During summer 2021, parks and beaches became renowned for large social gatherings and noncompliance with social distancing guidelines (Binding, 2020; Wright & Cole, 2020). Furthermore, hospitality venues such as pubs and bars were encouraged to adopt “al fresco” services during the summer months of “lockdown” with the introduction of temporary laws permitting alcohol sales and consumption in streets, car parks, and outdoor spaces (Braddick, 2020).

In the United Kingdom, there is a legacy of pubs and working men’s clubs providing men with opportunities for bonding and sharing (Kingerlee et al., 2014). These

spaces have long been recognized as serving important functions for promoting male mental health (Emslie et al., 2013; Tilki, 2006), particularly in rural areas where access to formal health services is typically poorer compared with urban areas (Gregoire, 2002), and mental health stigma and traditional gender norms associated with male’s supporting families financially tend to be greater (Watkins & Jacoby, 2007). Thus, it is possible that during “lockdown” males were utilizing green spaces in substitution for more traditional social environments such as pubs. However, green spaces may also have been sites of high contagion rates (Moore, Hill, Siriwardena, Tanser, & Spaight, 2022; Pan et al., 2021), and accessing green spaces could have resulted in physical illness and self-isolation, both of which are known to increase psychological distress. In this context, difficulty accessing GPs, which are usually the gateway to mental health referral (Verhaak et al., 2000), may have had a compounding effect on male mental health.

Table 6. Characteristics of Individual Clusters of Unusually High Rates of Male Mental Health Emergencies Occurring During “Lockdown” Compared With Randomly Distributed Cases, Including the Proportion of Cases in Urban (U) and Rural (R) Areas, IMD Decile, and “Healthy” Features of Landscapes Extracted From the AHAHI (Average Distance [km] From Health Services and Physical Environments).

Cluster	IMD decile	RUC (%)		Health			Landscape			X
		U	R	GP	A&E	P	BS*	P_GS*	A_GS*	
Noncluster	5	84	16	1.42	12.96	1.22	2.50	0.40	0.55	
1 Leicester	3	100	0	-	-	-	-	-	+	-
2 Derby	1	100	0	-	-	-	-	-	-	-
3 Nottingham	2	100	0	-	-	-	-	-	-	-
4 Grimsby	2	92	8	-	+	-	+	-	-	-
5 Lincoln	4	91	9	-	-	-	-	-	+	-
6 West of Mansfield	5	86	14	-	-	-	+	-	-	-
7 North of Chesterfield	5	94	6	+	-	-	+	-	-	-
8 Worksop	3	54	46	+	-	-	-	-	-	-
9 Nottingham	3	100	0	-	-	-	-	+	-	-
10 Skegness	1	77	23	+	+	+	-	-	+	+
11 Peak District	7	60	40	+	+	-	-	+	-	+/-
12 Chesterfield	3	100	0	-	-	-	-	+	-	-
13 Mansfield	3	100	0	-	-	-	-	-	-	-
14 South of Rugby	8	25	75	+	+	+	-	-	+	+
15 West of Mablethorpe	2	66	34	+	+	+	-	-	+	+
16 Kettering	3	100	0	-	-	-	-	-	-	-
17 West Nottingham	8	100	0	-	-	-	-	-	-	-
18 South of Scunthorpe	6	23	77	+	+	+	+	-	+	+
19 Coalville	6	83	17	-	+	-	-	-	-	-

Note. For cases that do not fall into clusters (noncluster), average values for each indicator are reported. For each cluster, a “+” sign indicates when the average score for each indicator is higher than the equivalent score for “noncluster” cases. A “-” sign indicates when the average score is lower than the equivalent score for “noncluster” cases. A score of “0” indicates no difference between cluster scores and indicates no difference between cluster scores and noncluster scores. Column -cluster scores. Column “X” reports the average score of aggregated indicators across the health and landscape domains. IMD = index of multiple deprivation; AHAHI = Access of Healthy Assets and Hazardous Index; RUC = rural urban classification; GP = general practitioners; A&E = accident and emergency ; BS = Blue Space; P_GS = Passive Green Space; A_GS = Active Green Space.

Importantly, regression analysis also revealed that some physical features of landscapes that predict cluster membership are more indicative of clustering than others. Figure 5 displays the predictive layer produced from utilizing the likelihood values identified through regression analysis for spatial modeling. We found that further distance from GPs, followed by access to pharmacies, were the strongest predictors of clustering compared with other landscape features. These services were central to facilitating mental health referrals and support for psychological distress during “lockdown” (Davies, 2020; Royal Pharmaceutical Society, 2021). Thus, despite closer access to passive green space in more rural areas, rural clusters (Clusters 15, 10, 18, and 11) appear to be more vulnerable than urban clusters because of their further distance from health services that were instrumental in facilitating help-seeking during the pandemic.

This differentiation between rural and urban clusters in relation to health care access suggests that risk factors for individual clusters vary. The observation that unusually high rates of male mental health emergencies occur

in most deprived areas is consistent with wide research which suggest that deprivation is associated with poorer male mental health outcomes (Curtis et al., 2006; Koppel & McGuffin, 1999), and suggests that, compared with physical landscape accessibility, deprivation may be a consistent characteristic of clusters in urban and rural spaces.

Characteristics of Individual Clusters of Male Mental Health Emergencies

The spatial analysis presented in Figures 5 to 7 and Table 6 indicates that the characteristics of clusters vary in two ways: first, degree of relative risk, and second in relation to important geographical distinctions. In order, clusters with the highest relative risk compared with medium value (2.07) were South of Rugby (Cluster 14), Leicester (Cluster 1), South of Scunthorpe (Cluster 18), Chesterfield (Cluster 12), Derby (Cluster 2), Grimsby (Cluster 4), West of Mablethorpe (Cluster 15), Peak District (Cluster 11), and North of Chesterfield (Cluster 7). Four of nine high risk clusters occur in areas that are more rural

compared with areas with randomly distributed cases. This analysis gives some indication of regions where males may be particularly vulnerable to acute mental health conditions during periods of physical isolation.

Geographical distinctions between clusters include degree of urbanization and rurality, and the nature of wider landscapes, or hinterlands, where clusters occur. Clusters with a higher proportion of cases occurring in urban areas compared to areas with randomly dispersed cases tend to be located closer to health services, such as GPs, and further from healthy physical features of landscapes, such as blue space. Clusters with higher proportions of cases in rural areas tend to be further from health services and closer to blue space. There are some exceptions whereby urban clusters are located further from hospitals with A&E (Clusters 19, 4). Similarly, one rural cluster (Cluster 8) is located closer to most health services.

Regardless of degree of urbanization and rurality, most clusters are located closer to passive green space than regions with randomly distributed cases. Thus, although access to health services varies considerably between rural and urban clusters, most are within less than half a kilometer of passive green space that could have been utilized during "lockdown" for social encounters. Importantly, the quality of green space is likely to vary between more affluent and more deprived areas; green spaces in poorer communities are often associated with crime and are less likely to be well maintained compared with green spaces in affluent communities (Gomez et al., 2004). Thus, proximity may not always reflect actual use. Similarly, despite proximity to health services, service utilization is likely to vary between more affluent and more deprived communities. Poor mental health literacy and help-seeking behavior (Protheroe et al., 2017) are associated with deprivation, particularly for males. Affluence could facilitate physical access to more distant services, while deprivation, and by proxy lower levels of education and health knowledge may inhibit access to services that are physically close in proximity.

Clusters also vary with regards to the characteristics of geographic hinterlands. Three of six rural clusters occur in the wider setting of rural villages, such as the Peak District (Cluster 11), South of Rugby (Cluster 14), and South of Scunthorpe (Cluster 18). By comparison, other rural clusters are located on the periphery of sparse urban areas, such as Worksop (Cluster 8), Skegness (Cluster 10), and West of Mablethorpe (Cluster 15). Cases occurring in the West of Mablethorpe cluster in particular are divided between sparse urban and sparse rural areas. Similarly, urban cluster hinterlands also vary in relation to central compared with more peripheral location. And, 10 of 13 urban clusters occur within or close distance from an urban center, including Leicester (Cluster 1),

Derby (Cluster 2), Nottingham (Cluster 3), Grimsby (Cluster 4), and Lincoln (Cluster 5). The remaining three urban clusters are located on peripheries of "urban minor conurbations." These areas represent larger urban districts with multiple central hubs and include clusters in West Nottingham (Cluster 17), North of Chesterfield (Cluster 7), and West of Mansfield (Cluster 6).

Our spatial and statistical analysis suggests that geographic hinterlands are associated with socioeconomic conditions. Rural clusters in village settings occur in more affluent areas, whereas rural clusters on the fringe of sparse urban areas occur in more deprived areas. Conversely, clusters occurring within or close to central urban hubs tend to be in more deprived areas, whereas urban clusters located on the periphery of conurbations are characterized by greater affluence. Thus, urban and rural spaces are not homogeneous. Rural affluence has been associated with intentional urban-rural migration, including "back-to-the-land" gentrification, and the counter-urbanization movement (Halfacree, 2007; Meijering et al., 2007). Rural poverty is less well understood.

Compared with urban poverty which tends to be spatially concentrated, rural poverty is typically highly dispersed, resulting in "invisibility," which presents additional challenges for addressing health inequalities (Commins, 2004). In England, rural poverty has long been obscured by the romanticized rhetoric of "village living." Furthermore, idealist cultural norms around community and rural aesthetic preclude efforts to increase the accessibility of the hidden rural poor to services, including health care services (Commins, 2004). The underutilization of mental health services in rural areas is compounded by extreme social stigma around mental illness (Gregoire, 2002; Gregoire & Thornicroft, 1998). Thus, while urban poverty may be more prolific, the rural poor are physically isolated from services, face significant cultural and social barriers to help-seeking, and are spatially difficult to identify and support.

In the context of the COVID-19 pandemic and "lockdown," it is likely that males experiencing psychological distress in deprived rural areas on sparse urban peripheries have struggled to access social and medical support. In total, male mental health emergencies occurring in deprived rural communities accounts for 15% of all cases in unusual clusters, whereas emergencies occurring in more affluent rural communities account for 5%. This may reflect the cumulative effect of physical isolation *and* deprivation reducing opportunities for mobility and access to services.

In contrast to rural peripheries, clusters located in urban peripheries are associated with greater affluence compared with clusters in or close to urban centers. The peripheral hinterlands of urban conurbations are typically

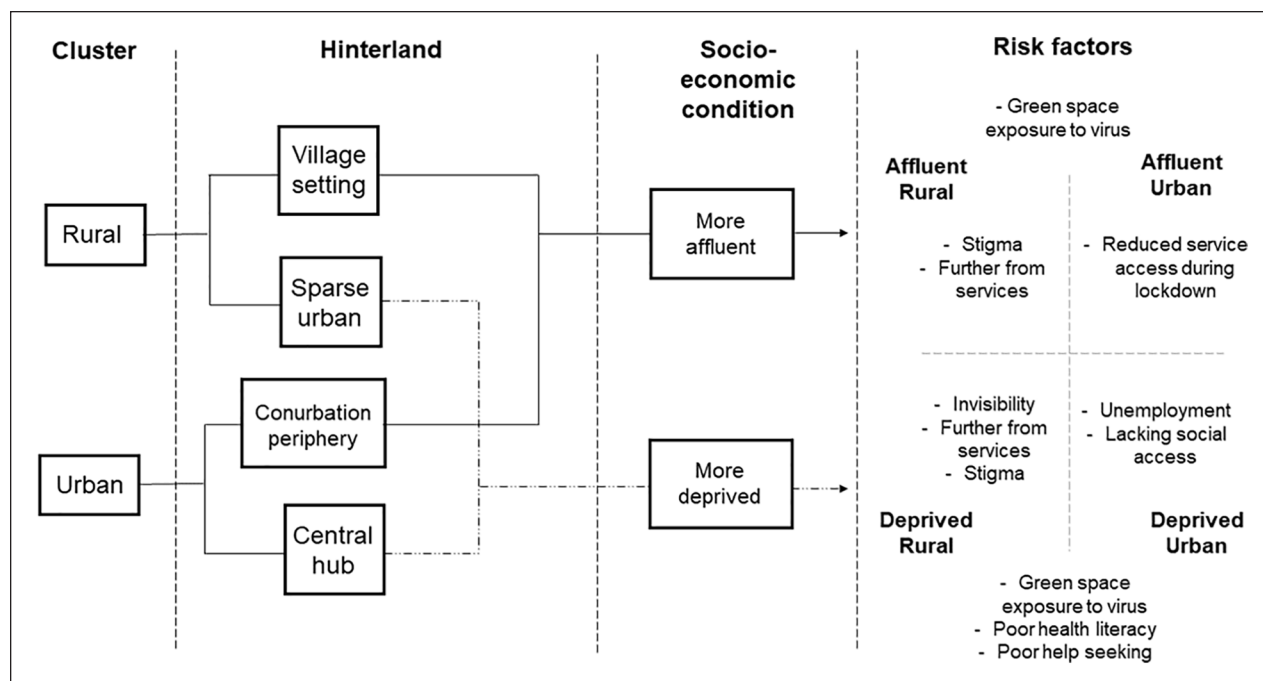


Figure 8. Schematic Representing the Distinction Between Hinterlands, Socioeconomic Condition, and Risk Factors Related to Male Mental Health Emergencies in Clusters That Are More Rural or More Urban.

Note. For risk factors, the text centered and above the quadrant indicates factors that are common to rural and urban affluent clusters. The text centered and below the quadrant indicates factors that are common to rural and urban deprived clusters.

areas of new housing development (Couch & Karecha, 2006). The expansion of suburban housing further from urban centers offers affordable alternatives for home buyers compared with the increasingly prohibitive inner city housing markets. Three clusters (Clusters 17, 7, and 6) occur in these peripheral urban spaces with hybrid urban/rural hinterlands, accounting for less than 20% of all male mental health emergencies occurring in clusters attended by ambulances during “lockdown.” While closer to services than most rural clusters, these fringe spaces may also face barriers to physical access during “lockdown” when movement was constrained, and more central urban areas may have been outside of permissible travel distances.

Clusters in more deprived central urban areas with predominately urban hinterlands reflect patterns of vulnerability associated with deindustrialization in the Midlands of the United Kingdom (Nixon, 2018) that have persisted after the closure of industrial sectors (High et al., 2017). For example, high rates of acute mental health conditions, such as schizophrenia, have been linked to intergenerational deprivation in postindustrial cities such as Nottingham. The poverty cycle associated with parental unemployment following the closure of coal mines, particularly unemployed fathers (Harrison et al., 2001), explains the geographic distribution of patients suffering from schizophrenia in the city of

Nottingham (Dauncey et al., 1993), with high rates of male patients located close to the city center (Giggs, 1973). Economic restructuring throughout the North of England in the postindustrial landscape favored female-dominated sectors such as manufacturing and service work while traditionally male-dominated labor markets were dramatically downsized (Forster et al., 2018). During the first national “lockdown,” males were disproportionately likely to face unemployment (Zarrilli & Luomaranta, 2021), a risk factor for declining psychological well-being. Furthermore, urban areas have consistently experienced higher rates of unemployment compared with rural areas (UK Parliament, 2021). Thus, contemporary patterns of vulnerability mirror the economic legacies of regions in the East Midlands.

The location of clusters also reflects more contemporary economic activity within the study region. Compared to the same period in 2019, unemployment rates during the study period increased across sectors such as the primary sector including agriculture, administration and support services, and transportation and storage. S-1 presents a preliminary analysis of sectors that characterize clusters and the unemployment rates associated with those sectors. Primary sectors have experienced smaller increases in unemployment rates compared with transportation and storage and administration and support. Administration and support characterize both Nottingham

clusters, whereas the Worktop and Kettering clusters are associated with transportation and storage, a sector dominated by male employees (ONS, 2021). Each of these clusters occurs in regions characterized by severe deprivation. By comparison, employment in rural clusters is typically related to the primary sector. Thus, the economic nature of clusters may reflect wider observations about unemployment and vulnerability for males; urban areas are experiencing higher unemployment rates compared with rural areas, and this may be disproportionately impacting males. Overall, our analysis suggests that the characteristics of vulnerability vary between rural and urban spaces, as well as within those spaces. These individual characteristics of clusters are synthesized in Figure 8.

Understanding Male Mental Health Emergencies in the Socioenvironmental Mesosphere

Our analysis of factors that explain the clustering of male mental health emergencies compared with randomly distributed cases highlights the importance of understanding interactions between socioeconomic and environmental characteristics of built environments. Spatial dynamics in the socioenvironmental mesosphere include degree of rurality and urbanization, degree of deprivation compared with affluence, and distance from “healthy” features of landscapes. Moore, Hill, Siriwardena, Law, et al. (2022) explored the intersectionality of socioeconomic characteristics and physical features of landscapes related to vulnerability to severe illness from COVID-19 and suggest that some dynamics of built environments are associated with *underlying susceptibility* while others pertain to *exposure*. For contagious disease, *underlying susceptibility* refers to preexisting health conditions that exacerbate illness from COVID-19, as well as socioeconomic factors such as deprivation which is commonly associated with poor help-seeking behavior and low health literacy (Protheroe et al., 2017). By contrast, factors related to *exposure* include multioccupancy housing, employment as an essential worker during the pandemic, and accessing social spaces such as parks and beaches. In the context of male mental health emergencies, similar principles apply.

Mental health emergencies occur at the intersection of *susceptibility* related to cumulative negative life experiences, and exposure to *triggers* that precipitate acute conditions (Kegler et al., 2017; Kira et al., 2019). Male mental health stigma is a constant factor associated with susceptibility, and the circumstance of “lockdown” is a consistent trigger in the lives of males experiencing mental health emergencies included in this study. However,

the classification of clusters presented above (Figure 8) suggests that the nature of susceptibility and exposure to triggers related to male mental health emergencies may vary spatially to some degree; the impact of mitigation measures is likely to differ depending on prior socioeconomic conditions and opportunities afforded by built landscapes for maintaining well-being.

The prior condition of deprivation is likely to have increased *susceptibility* to acute mental health conditions during “lockdown”; low-income and poor education and health literacy are associated with poor mental and physical outcomes and comorbidities (Protheroe et al., 2017). Furthermore, deprivation reflects negative life experiences related to regional crime, housing conditions, and financial insecurity (Gomez et al., 2004). In rural areas, financial deprivation is exacerbated by “invisibility” and the inability to access services, whereas communities in deprived urban areas are more likely to have faced unemployment during the first phase of the COVID-19 pandemic. Thus, the escalation from manageable psychological distress to mental health emergency could occur rapidly in deprived areas as “triggers” related to the pandemic accelerate preexisting vulnerabilities. In the United Kingdom, job loss in particular has been reported to affect male mental health more considerably than female mental health (Kromydas et al., 2021).

Underlying *susceptibility* also includes heightened cultural stigma in rural areas that might discourage males in both deprived and more affluent communities from help seeking prior to a major life *trigger*, such as being disconnected from social support networks, during a pandemic. Rural places more generally tend to be physically distant from health services, and many of the functions of formal health services are the domain of “third places” (Cabras & Mount, 2017), including pubs. The loss of these spaces during periods of business closure probably reduced opportunities for rural males to seek help within their own social spheres. Similarly, prior to the pandemic, more affluent communities located on urban peripheries may have relied on the ability to access central urban areas. Restrictions on physical mobility introduced during “lockdown” could have affected the ability of males in peripheral urban areas to access familiar social and service landscapes.

Few studies of male mental health during the pandemic consider risk factors beyond socioeconomic condition. Here, we demonstrate that the nature of vulnerability differs depending on multiple dimensions and how those dimensions interact. Rural discourses emphasize the dynamics of “intentional rurality,” such as the counter-urbanism movement, compared with rural poverty; we suggest that the notion of “intentional” compared with “unintentional” locality is valuable for understanding the dynamics of vulnerability in urban as well as rural

contexts. Greater affluence is indicative of intentional locality compared with greater deprivation which may imply less autonomy over locality and circumstance, such as residence and occupations in postindustrial dense urban centers, or on rural peripheries boarded by sparse urban hinterlands.

Our observations about intersectionality and the importance of hinterlands highlight the added value of considering physical components of the built environment in ecological systems frameworks. The socioenvironmental mesosphere provides a theoretical space for exploring the cumulative effects of multiple co-occurring stressors in the built environment that may explain where high rates of male mental health emergencies take place.

Strengths and Limitations

The limitations of using routine data from ambulance services as a proxy measure for individual behavior are outlined in full by Moore, Hill, Siriwardena, Law, et al. (2022). In summary, proximity to services and features of landscapes do not necessarily reflect use, and ambulance data do not capture all cases of male mental health emergencies. Health literacy, including ability to recognize symptoms of mental health conditions varies between communities; deprivation is associated with poor literacy (Niksic et al., 2015). Thus, people from more deprived communities may be less likely to call an ambulance. Qualitative research is needed to understand the findings presented here and explore factors not included in this research that may explain clustering, such as family history of mental health. Furthermore, although trained ambulance clinicians assess and record cases of mental health emergencies, these assessments are not definitive diagnoses. However, assessment takes into consideration the self-reported experience and mental health history of patients communicated by patients themselves or others attending emergencies (such as family and friends), as well as the objective observation of mental state made by ambulance clinicians. Data linkage between ambulance and hospital or primary care records would be required to determine whether males attended by ambulances during “lockdown” have current diagnoses of mental health conditions. Therefore, assessments more accurately reflect acute mental health events, rather than persistent mental health conditions.

At the time of writing in November 2021, the United Kingdom was preparing for new mitigation measures following the emergence of the Omicron COVID-19 variant. It is possible that phases of restricted social engagement will continue. The need to rapidly assess the mental health impact of mitigation measures like “lockdown” is paramount. Our novel approach using routinely collated data is a spatially accurate method for

identifying vulnerable communities rapidly, as well as understanding the socioeconomic and environmental factors that may explain vulnerability across dynamic geographical landscapes. Community-level analysis cannot predict or describe causal associations for individual ambulance users. However, spatial and statistical analysis of landscape scale trends can be used to identify vulnerable communities, such as in rural areas where populations are more dispersed and typically “invisible” (Commins, 2004). This approach triangulates convergent evidence about factors that explain the location of clusters with unusually high rates of male mental health emergencies in rural and urban spaces.

Conclusion and Implications

Writing in April 2020, Galea et al. (2020) warned, “it is time to bolster our mental health system in preparation for the inevitable challenges precipitated by the COVID-19 pandemic” (p. 818). We add to this plea the need to develop mental health support systems that are physically and socially accessible to people of all genders, including males. Severe mental health conditions occur at the nexus of underlying susceptibility and negative life experiences that trigger psychological decline, such as extended periods of social isolation. The effect of life stressors on mental health is cumulative. Thus, single determinants of psychological distress such as rural isolation or unemployment do not by themselves explain severe mental health conditions that require emergency medical attention. Our analysis draws on the social-environmental Mesosystem presented by Moore, Hill, Siriwardena, Law, et al. (2022), and it uses spatial methods rarely utilized to consider the distribution of noncommunicable disease. This novel approach offers some insights for rapid response to support vulnerable males during the extraordinary circumstances of the current pandemic, as well as more widely for urban planning and health service delivery:

- Joining ambulance data to existing data sets such as the IMD and AHAHI could help identify communities with vulnerable males in real-time for the purpose of community-based intervention and ambulance service operations;
- Considering the physical and social dynamics of male mental health vulnerability could inform preparations for future lockdowns to buffer the impact of mitigation measures on communities with vulnerable males. This might include establishing online networks for men who ordinarily rely on “third spaces” for social engagement, and identifying sectors that are likely to experience rising unemployment rates as a result of extended closures;

- The factors that may precipitate male mental health emergencies vary between and within urban and rural spaces, and therefore require multiple coordinated efforts to reduce vulnerability. Priorities in remote locations include increasing physical access to health services and reducing help-seeking stigma, whereas in urban areas greater financial support, particularly for low-income men, is needed to address the high risk of unemployment during and between successive phases of “lockdown”;
- Introducing more comprehensive guidance around green space use during lockdowns could encourage safer social interactions, allowing males to maintain social networks without increasing risk of contagion and the need to quarantine;
- Wider urban planning innovation and investment are needed to address physical and social barriers to support in peripheral spaces, including communities on rural and urban peripheries, as well as communities boarding larger urban conurbations. It is likely that vulnerability to unemployment varies between economic sectors. Thus, investment should be targeted to buffer the impacts of periods of “lockdown” on vulnerable sectors;
- To be realized, most, if not all of these recommendations require increased financial investment, either to reduce the underlying health inequalities that characterize the English landscape or to protect vulnerable males from disproportionately negative experiences during the current pandemic.

Nearly 2 years has elapsed since the first national “lockdown” in the United Kingdom. At the time of writing, the region is on the precipice of new restrictions to physical mobility that may reduce the capacity for vulnerable males to maintain their psychological well-being, amid new threats to financial stability. Now is a window of opportunity for policy makers, health service providers, and community networks to prepare males who may not be comfortable or familiar with traditional help-seeking methods with alternatives to support them through the uncertain future of the COVID-19 pandemic. In the context of national financial constraint, using ambulance data to identify hotspots of vulnerability could facilitate more effective local efforts to deliver alternative models of mental health care that meet the needs of males during future “lockdown” scenarios, as well as addressing enduring health inequalities that characterize urban and rural landscapes in the United Kingdom.

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Supplemental Material

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