Geospatial Health 2022; volume 17:1123

Spatial access to public hospitals during COVID-19 in Nottinghamshire, UK

Jishuo Zhang,[1] Meifang Li[2]

[1]School of Geography, University of Nottingham, Nottingham, United Kingdom; [2]Department of Geography, Dartmouth College, Hanover, USA

Abstract

We intend to tackle two under-addressed issues in access to healthcare services during the COVID-19 pandemic: first, the spatiotemporal dynamic of access during the pandemic of acute communicable disease; second, the demographic and socioeconomic access disparities. We used the two-step floating catchment area (2SFCA) method to measure the spatial access to public hospitals during the second COVID-19 wave (September 28th-February 28th, 2021) in Nottinghamshire, UK. To investigate the temporal variation in access along with the development of the pandemic, we divided our study period into 11 sections and applied the 2SFCA to each of them. The results indicate that western Nottinghamshire is better than the eastern part from a spatial perspective and the north-western urban area represents the highest spatial access; temporally, the accessibility of the public hospitals generally decreased when the number of cases increased. Particular low accessibility was observed at the beginning of the pandemic when the outbreak hit the university region and its vicinities during the back-to-school season. Our disparity analysis found that i) the access of the senior population to public hospitals deviated from that of the general population, ii) the access was positively associated with socioeconomic status, and iii) all disparities were related to the urban-rural discrepancy. These findings can help to plan temporary clinics or hospitals during epidemic emergencies. More generally, they provide scientific support to pandemic-related healthcare resource allocation and policy-making, particularly for people in vulnerable areas.

Correspondence: Meifang Li, Department of Geography, Dartmouth College, Hanover, NH 03755, USA.
Tel.: (603)277-8099
E-mail: meifang.li@dartmouth.edu

Key words: COVID-19; spatial access; public hospitals; 2SFCA; spatiotemporal pattern; UK.

Acknowledgments: The authors would like to thank Dr. Xun Shi at Dartmouth College for his guidance and feedback on this study. The authors would also like to thank anonymous reviewers for their constructive suggestions and comments, as well as the editor, Dr. Robert Bergquist, for his excellent comments, suggestions and language polishing.

Funding source: This research was funded by the National Natural Science Foundation of China (Grant No.: 42001342).

Conflict of interest: The Authors declare no conflict of interest.

Received for publication: 20 June 2022.
Revision received: 21 October 2022.
Accepted for publication: 23 October 2022.

Geospatial Health 2022; 17:1123
doi:10.4081/gh.2022.1123

Introduction

The World Health Organization (WHO) reported more than 613.4 million confirmed COVID-19 cases and 6.5 million deaths globally as of September 28th, 2022 (WHO, 2022). Although vaccines for COVID-19 have been developed and are generally considered successful, the impact of this pandemic is still on. Besides its direct threat and damage to human health and lives, its vast impact on society and the economy, including all sectors, can be seen worldwide (Mbunge *et al.,* 2021). According to the House of Commons Library of the United Kingdom (2021), COVID-19 had a huge influence on society and the economy of the country. By the end of 2020, the GDP had decreased by 9.7%, particularly during the first lockdown period, when the GDP decreased by 25% and the unemployment rate increased from 4% to 5.2%.

The pandemic's impact on healthcare services is particularly worth evaluation. This kind of study is essential to understanding the local supply-demand situation of public health services during the pandemic, optimising the resource allocation in terms of improving the efficiency, quality, and equity in the utilisation of public resources, and supporting related policymaking. We recognise two types of such studies: assessing the burden caused by the pandemic on the healthcare infrastructure and assessing the disparity in access to healthcare facilities. There have been many studies of the former kind due to the urgent demand for such studies in the early stage of the pandemic when effective vaccines were not yet available, and the primary goal was to *flatten the curve*, so that the healthcare infrastructure would not break down due to the surge of cases. Therefore, an evaluation of the capacity of the local healthcare system became critical. Studies on the disparity in access to healthcare facilities during the pandemic, however, have been limited, both in terms of the number of studies and geographic regions they cover, although researchers have called for such topics ever since the beginning of the pandemic (Lopez and Neely, 2021). For example, Mollalo *et al.* (2021) reviewed 36 studies on the spatial analysis of COVID-19 vaccination and found that most studies employed preliminary and non-robust spatial analysis techniques and rarely addressed data quality issues. Raeesi *et al.* (2022) reviewed the studies estimating the spatial accessibility to COVID-19 services, such as vaccination centres, intensive care units, hospitals, and test sites. They found that most studies were conducted in the USA and argued that more attention should be paid to measuring the accessibility for different populations. Another insufficiency, not only in the study of COVID-19, but also in the general literature on access to healthcare services is the temporal variation of access. For an acute communicable disease like COVID-19, it would be highly unrealistic to assume that access to healthcare services in an area remains static under continuous changes in patients and their demands. However, we are unaware of studies that explicitly and empirically have investigated this kind of dynamic during a particular epidemic. In this study, we tackled those gaps and chose Nottinghamshire, UK as our study area.

According to the UK government website (2021), there were more than 6 million confirmed cases and 154 thousand deaths in the UK up to August 16th, 2021, when this study began. The official records indicate that the first two COVID-19 cases in the UK were discovered at a hotel in York on January 29th, 2020 (British Foreign Policy Group, 2020). Since the first two cases were reported, the pandemic has been spreading continuously throughout the country. Figure 1 illustrates the temporal distribution of COVID-19 case counts for the UK as of August 16th, 2021. Three evident epidemic waves can be identified during this period, which are March-June 2020, September 2020-March 2021, and June-August 2021, respectively. The term *epidemic wave* refers to the situation in which the number of disease cases reaches a peak and then declines sustainably (Iyengar *et al.,* 2021). For this study, we chose the second epidemic wave, which occurred from September 28th, 2020, through February 28th, 2021, as our study period, since the number of cases in this wave was significantly greater than the first wave and lasted much longer, suggesting a significant demand for healthcare services; on the other hand, compared to the third wave, the second wave was a completed wave.

We chose Nottinghamshire as the study area. Located in the East Midlands region, one of nine in the country, the county ranks among the Top-10 urban areas in the UK. In addition to the county's importance, other reasons we chose it as the study area include: i) Nottinghamshire has experienced serious pandemics following the same trends as the national epidemics - as of August 16th, 2021, there were 82,751 confirmed cases and more than 2,000 deaths in Nottinghamshire (UK government website, 2021); ii) According to previous studies, elder people are much more vulnerable to this epidemic, e.g., the death rate of older people (age >60 years) by COVID-19 is considerably greater than that of the young in the UK (UK government website, 2021) - according to the census of 2021, the Nottinghamshire population includes 21% of elderly people, which is higher than the UK average (18.6%), a trend predicted to continue - by 2034, the population (age >65 years) is estimated to have increased with over 30% (53,200 people) (Nottinghamshire County Council, 2021); and iii) last but not least, the data about healthcare services, epidemics, and the population in this area were readily available and accessible to the authors, which makes this study feasible. Therefore, we investigated access to public hospitals in Nottinghamshire by COVID-19 patients during the second epidemic wave (September 28th, 2020, through February 28th, 2021) separately for the elderly population and the total population.

In the UK, the National Health Services (NHS) is a publicly funded healthcare system, which is highly complex. Briefly, this can be simply classified into primary care (e.g., General Practices or GPs, dentists, opticians, and pharmacists), secondary care (emergency and non-emergency hospitals), and tertiary care (specialised hospitals) (The Medical Portal, 2021). For COVID-19 patients, primary care physicians provide suggestions and primary diagnoses but cannot provide any assistance, even in urgent cases since they lack the specific medical instruments needed for COVID-19 treatment. Moreover, tertiary care refers to hospitals that specialise in certain medical procedures, such as plastic surgery, which differs from COVID-19 treatment. Therefore, this study focused on secondary care, where hospitals can provide emergency treatment, intensive care unit (ICU) beds, and ventilators for COVID-19 patients. In Nottinghamshire, there are 132 GPs and 18 hospitals in total, eight of which were selected for this study (NHS, 2022). It is worth explaining the reason to exclude private hospitals. In the UK, public hospital treatment is free for the ordinarily resident, while private healthcare comes at quite a high cost, so the percentage of people choosing private healthcare is no more than around 11% (The Kings Fund, 2014). This is an average value, that in London reaches 20%, but is only 4% in northern England. Private hospitals are excluded from this paper because of the low coverage (Doyle and Bull, 2000).

In this study, we adopted the two-step floating catchment area (2SFCA) method (Luo and Wang, 2003; Wang and Luo, 2005) to evaluate spatial access to public hospitals. This method has been widely used in studies of access to healthcare services. 2SFCA is a special case of the gravity model, which measures accessibility by simultaneously considering both the supply of healthcare services and the demand for them. Essentially, the working process of 2SFCA can be summarized as follows: Step 1, for each healthcare service supply location, sum up the surrounding population demands, discounted by the distance decay function across all demand locations, and calculate the healthcare service to the population ratio. Step 2, for each location of population demand, sums up the ratios from all related healthcare supply facilities discounted by the distance decay function across all healthcare supply locations to determine the accessibility at each demand location. Shi *et al.* (2012) generated high-resolution maps using this method to

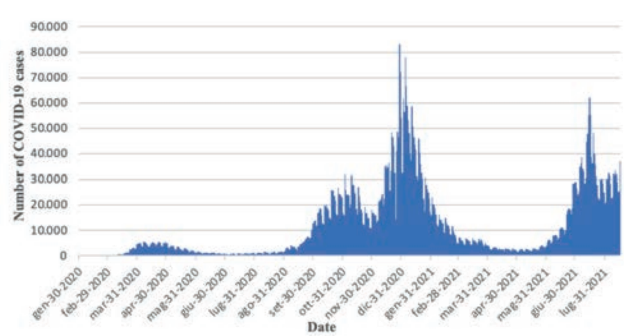

Figure 1. Number of COVID-19 cases by specimen collection date in the UK during January 29th, 2020 – August 16th, 2021.

evaluate the access and demand of cancer centres in the United States demonstrating a spatial variation of the demand at the national scale. Similarly, Yao *et al.* (2013) applied 2SFCA to study the spatial access to sexual and reproductive health (SRH) services in rural Mozambique, while Kiani *et al.* (2018) used the same approach to quantify access to haemodialysis facilities in North Khorasan Province, Iran. Donohoe *et al.* (2016) compared the traditional access measures (using population ratio and geographic boundaries) and 2SFCA measuring the spatial accessibility of the mammography centres in a four-state region of Appalachia in the US. A relative 2SFCA method was used in Donohoe *et al.*'s research, the spatial access ratio method, to minimise the differences between various 2SFCA models. Ever since the method was first proposed, a number of variants have been developed, e.g., the relative 2SFCA, which calculates the spatial access ratio (SPAR, the ratio between a block's 2SFCA score and the mean 2SFCA value of the total area), with the purpose of minimising the differences between various 2SFCA models (Donohoe *et al.,* 2016); the enhanced 2SFCA (E2SFCA), which applies the distance decay weight also to the first step of the method (Luo and Qi, 2009); the modified 2SFCA (M2SFCA), which considers both of the accessibility and the availability and make it possible to compare the spatial accessibility in subscales (Delamater, 2013); the 3-step FCA (3SFCA), which improves E2SFCA by adding the travel-time-based competition weights for facilities (Wan *et al.*, 2012); and the inverted 2SFCA (i2SFCA), which inverts the roles of patients and facilities in the model for evaluating the burden of the facilities (Wang, 2017; Wang, 2021).

The 2SFCA method and its variants have also been employed to evaluate the access to healthcare services related to the COVID-19 pandemic. For example, with the E2SFCA model, Mohammadi *et al.* (2021) assessed the potential spatial access to COVID-19 vaccination centres in Mashhad, Iran, including i) only public hospitals, ii) only public healthcare centres and iii) both. Kang *et al.* (2020) used E2SFCA to evaluate the accessibility of confirmed COVID-19 cases in Illinois to ICU beds and ventilators in hospitals. Particularly, they implemented parallel processing to improve the efficiency of computation. They also linked access to socioeconomic status as measured by the social vulnerability index (SVI), a measure developed by the US Centers for Disease Control and Prevention (CDC) to identify communities in need of assistance. The SVI is calculated based on census information, which includes four aspects and 14 factors of socioeconomic status, household composition and disability, race/ethnicity/language, and housing or transportation status, where a higher value indicates greater vulnerability (Heath, 2021). Tao *et al.* (2020) and Ghorbanzadeh *et al.* (2020) accessed COVID-19-related access to hospitals in Florida, USA. Tao *et al.* (2020) implemented the 2SFCA and the E2SFCA and defined a new index, the Accessibility Ratio Difference (ARD), to compare the difference between the two. Ghorbanzadeh *et al.* (2020) considered two travel modes when implementing the 2SFCA, driving and walking, and assigned different parameter values for the two modes. There are several limitations to previous studies regarding access to COVID-19 facilities: i) most studies were focused on the US, ii) most studies took access as a static attribute without considering the dynamics of demand, and iii) the target demand is often from a single type of population, without comparisons among different populations.

In this study, we quantified the spatial access of COVID-19 patients, the general population and the elderly population (>60 years of age) to the local public hospitals in Nottinghamshire, UK using the 2SFCA method. When assessing the spatial access of COVID-19 patients to the hospitals, we took into account the temporal dimension, which has seldom been explored in similar studies. Specifically, we divided the period of September 28th, 2020 – February 28th, 2021, into 11 biweekly sections and applied the 2SFCA analysis to each of them. Through this analysis, we intended to identify areas in Nottinghamshire with high and low levels of access to public hospitals for different populations, and the dynamic of the access during the wave of COVID-19. Moreover, we also associated the spatiotemporal variation of the access with the age structure and pervert level of the population. The hypotheses we intended to test and verify by conducting this study included i) does spatial access remain stable for COVID-19 patients throughout the study period? ii) is spatial access equitable across different populations? and iii) is there a strong association between spatial access and socio-economic factors? We expected the findings of this study to be directly relevant to local policymaking and resource allocation, e.g., planning of the location and scale of mobile cabin hospitals or temporary hospitals, which would take into account land types (urban, suburban and rural) and periods (rising, peak and decline of the epidemic).

Materials and Methods

Study area

Our study area, Nottinghamshire is an inland county in the English East Midlands. As shown in Figure 2a, it has seven districts, namely Ashfield, Bassetlaw, Broxtowe, Gedling, Newark/Sherwood, Mansfield and Rushcliffe, plus a unitary authority, Nottingham which is the population centre. The location of its total hospitals in Nottinghamshire is listed in Figure 2b. In 2021, the population was 833,400 (Nottinghamshire County Council, 2021). Figure 2c shows the population distribution across the county, the density of which can reach 18,500 people/km^2 in urban areas in contrast to the rural area, whose population density is mostly below 2,000 people/km^2 (Figure 2c). People older than 60 years account for 23% of the total population in this county, and the density map of the elderly can be seen in Figure 2d. These people may have a death rate many times higher than that of those aged 0-59 years (UK government website, 2021).

Data

Four kinds of data were used in this study, including public hospitals' location and capacity, the COVID-19 case count, the population distribution and its demographic and socioeconomic features, as well as the road network.

Hospital data

We obtained information about the 18 local hospitals in Nottinghamshire from the National Health Service (NHS), the Nottinghamshire Council Website and Google Maps. The locations are shown in Figure 2b. Two of these 18 hospitals had already been closed before our study period, while five were tertiary care hospitals with three specializing in mental treatment, one specializing in rehabilitation and one specializing in audiology services; in addition, there are three private hospitals where COVID-19 patients generally would not visit due to the high costs. The ten (= 2 + 5 + 3) hospitals mentioned above were excluded from our study and the remaining eight (= 18 – 10) hospitals were the focus of this study. During our study period, these eight hospitals have remained open as separate secondary care hospitals without any hierarchical connections among them. As shown in Figures 2c and 2d, the locations of these eight hospitals corresponded closely to the current population distribution. In each of the sizeable population gathering areas, there is at least one major hospital, especially in Nottingham City and southwestern Nottinghamshire, indicating a spatial concentration of healthcare resources in the county.

For each of the eight targeted hospitals, we used its ground area to characterize its capacity for accepting and treating patients. We recognized it would be a rough estimate and was the most significant limitation of this paper. However, we were not able to obtain information regarding the records of COVID-19 patient visits and bed occupancy, or even the number of beds and ventilators at each hospital. The ground area of each hospital has been the most effective method of indicating their different capacities. To get the ground area of each hospital, we manually created the polygon of ground coverage of each hospital based on Google Maps and then calculated the size of that polygon with ArcGIS Pro (ESRI, Redlands, CA, USA).

Driving time

With the road network data, we investigated three different temporal distances from the closest hospital: 0-5 min, >5-10 min, >10-15 min and >15 min.

Case data

The COVID-19 case counts were collected from the UK governmental website. This kind of data is available weekly at the Middle Layer Super Output Areas (MSOAs), which are the geographic units used by the UK government to compile statistics on socioeconomics; Nottinghamshire County has a total of 138 MSOAs. We divided the period September 28th, 2020 - February 28th, 2021 (the second wave of COVID-19 in the UK shown in Figure 1) into 2-week sections (n=11), as shown in Figure 3. Thus, our COVID-19 data were about the number of new cases in each MSOA during each of the 11 biweekly sections in both temporal and spatial dimensions (Figures 3 and 4).

Population and socioeconomic data

For population and socioeconomic data, we obtained a dataset called Index of Multiple Deprivation (IMD) 2019 released by the UK Ministry of Housing, Communities and Local Government in September 2019. The IMD 2019 is available at a finer spatial scale than the MSOAs, which are called Lower Layer Super Output Areas (LSOAs). Deprivation is considered a complex problem consisting of multi-dimensions factors, and the IMD value was proposed to quantify the deprivation and identify small poverty-stricken areas (Payne and Abel, 2012). The IMD 2019 contains information on the population and their ages as well as seven socioeconomic indices: income (22.5%), employment (22.5%), education (13.5%), health (13.5%), crime (9.3%), barriers to housing and services (9.3%) and living environment aspects (9.3%). The percentages in the parentheses were used as weights for the IMD score calculation. Therefore, IMD 2019 summarise the various deprivation factors and was used to express the deprivation conditions in this paper.

Analysis design

We first implemented the 2SFCA method to assess the spatial access to the public hospitals in Nottinghamshire for each of the 11 biweekly sections during our study period. By the use of biweekly results, we could construct a time series of the spatial hospital access situation that was aimed at identifying how the temporal variation of the spatial access corresponded to the development of

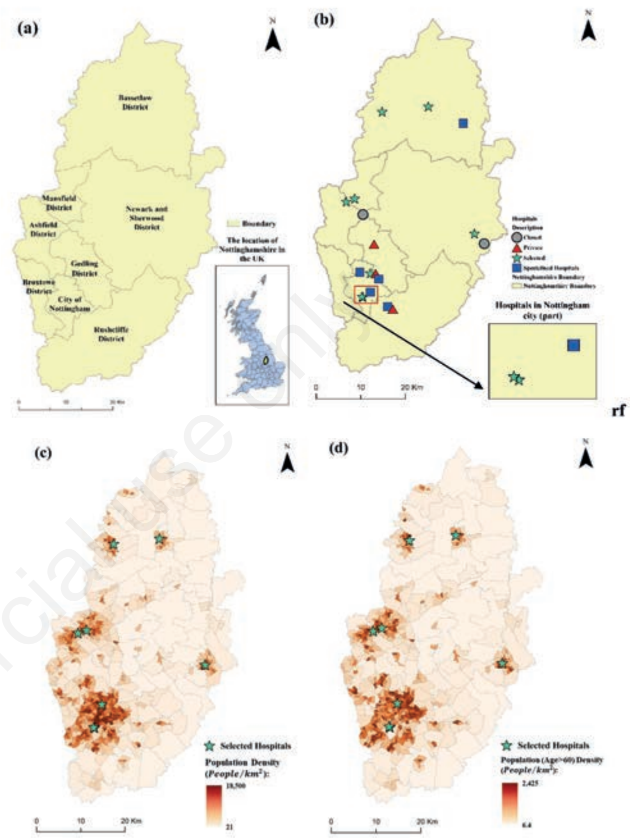

Figure 2. Distribution of population densities and selected public hospitals in Nottinghamshire. a) The study area; b) Distribution of all hospitals, and the insect map is the hospital distribution of part Nottingham city; c) Distribution of population density and selected public hospitals; d) Distribution of population density of the elderly population (age >60) and selected hospitals.

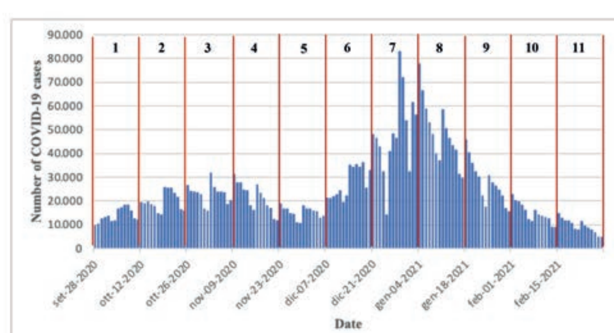

Figure 3. Number of COVID-19 cases by specimen collected date in the UK during Sep 28th, 2020-Feb 28th, 2021. Biweekly temporal scale used - 11 temporal sections in all.

the pandemic. We then detected the association between access and some socioeconomic factors. All data compilation and analysis were conducted in ArcGIS Pro 2.8.0.

The 2SFCA method

This method and its variants have been widely used in assessing spatial access to healthcare services, and methodological and technical details can easily be found in the literature (Delamater, 2013; Luo and Qi, 2009; Wan *et al.,* 2012; Wang, 2017). The first general step in this two-step method is to calculate the supply-demand ratio for each hospital, which can be represented by the equation as follows:

$$R_j = \frac{S_j}{\Sigma_{k\in\{t_{kj}<t_0\}} P_k} \quad (1)$$

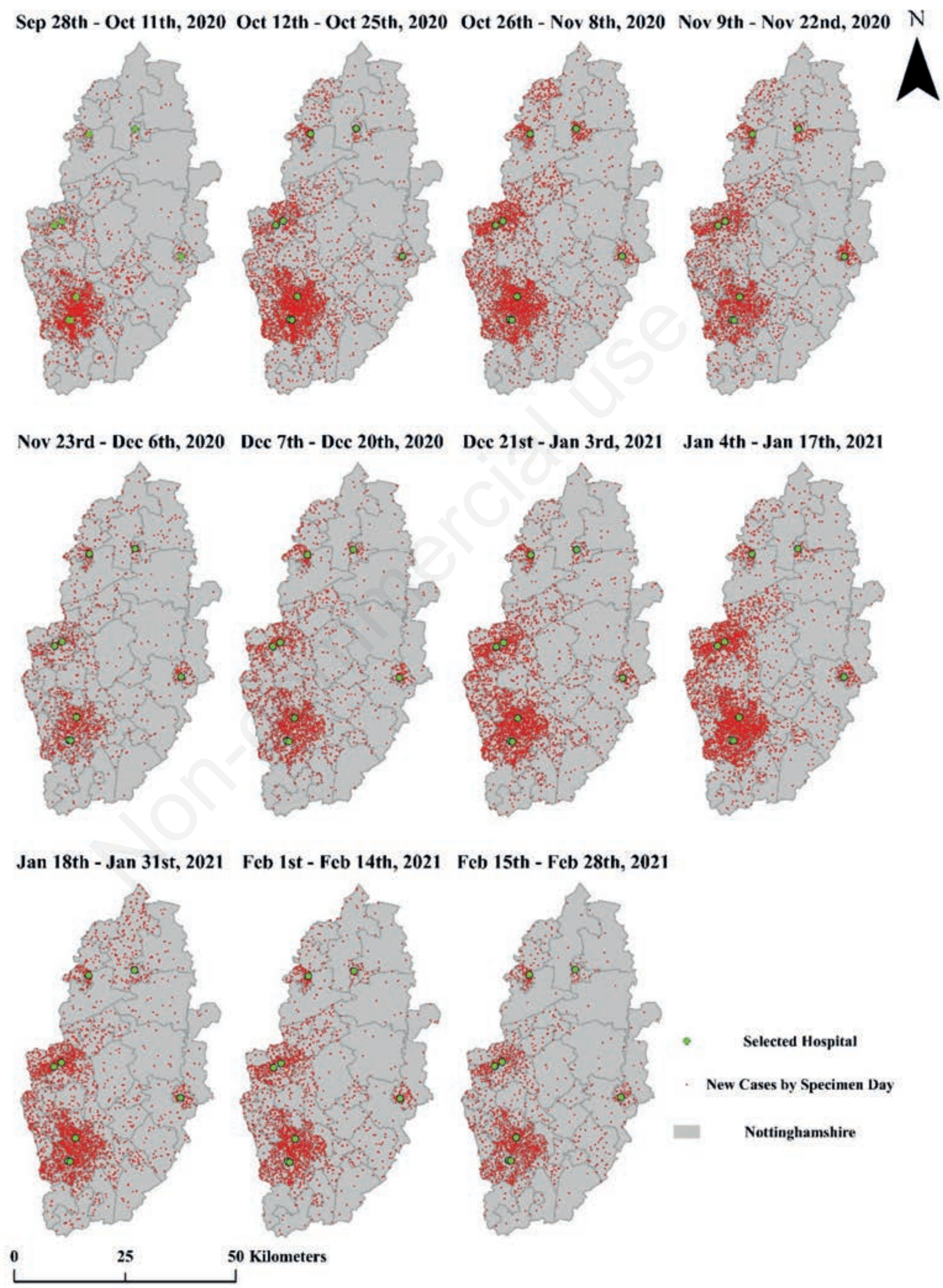

Figure 4. Density of COVID-19 cases by specimen collection date in Nottinghamshire during Sep 28th, 2020-Feb 28th, 2021. Biweekly temporal scale used - 11 temporal sections in all.

where R_j is the supply-demand ratio of hospital j; S_j is the capacity of hospital j, P_k is the demand at location k; t_{kj} is the travel time from k to j; and t_0 is the pre-specified travel time threshold, which indicates the effective spatial coverage of the hospital, i.e. the hospital's catchment area.

In this study, due to the lack of direct information about each hospital's service capacity (S_j), such as the number of doctors or number of beds, we used the ground area of a hospital as the representation of its capacity. We quantified the demand (P_k) by the number of COVID-19 patients in each MSOA. To define the catchment of each hospital, we specified 15 minutes as the travel time threshold, as we considered a 15-minute driving time to be suitable to define the effective coverage of the hospital for patients for an acute disease like COVID-19 in a condition necessitating hospitalisation. With this threshold, we delineated the hospital catchment based on road network data and speed limits at different road sections using the service area tool in ArcGIS Pro. When calculating the total number of patients in a hospital's catchment (the denominator of Eq. 1), we implemented areal interpolation, *i.e.* if an MSOA only partially falls into the catchment, we estimated the number of patients from that MSOA falling into the catchment based on the percentage of the area of that MSOA enclosed by the catchment.

The second general step of 2SFCA is to calculate the cumulative access of the patient at a specific location to all hospitals, which is represented by the equation as follows:

$$A_i = \sum_{j \in t_{ij}} R_j W_j \tag{2}$$

where A_i is the access score at demand location i; R_j is the supply-demand ratio of hospital j (calculated by Eq. 1); W_j is the weight determined by a distance decay function; and t_{ij} is the travel time from i to j.

To take into account the influence of distance on the access (*i.e.* the distance decay), we divided the catchment of a hospital into three zones based on the driving time and assigned different weights to them, *i.e.* W in Eq. 2 (Table 1). The weights were calculated using the Gaussian function (Shi *et al.,* 2012). We applied the 2-step process described above to each of the 11 biweekly sections and used both the general population and the population at high risk (age >60) to represent the demand, so a total of thirteen 2SFCA processes (eleven time-sections, the general population condition and the high-risk group condition) were considered in this study.

Table 1. Characterization of the different driving time zones used in this study.

Driving time (min)	Weight (proportion)
0 – 5	1.0
>5 – 10	0.7
>10 – 15	0.1

Socioeconomic analysis of hospital access

We chose the IMD 2019 score to represent the poverty level, as it is a widely used socioeconomic measurement and incorporates seven deprivation dimensions, including income, employment, education, health, crime, barriers to housing and services, and living environment. A detailed description and explanation of IMD can be found in Watson *et al.* (2019). To associate the IMD score with the hospital access tally calculated by 2SFCA, we employed areal interpolation to assign the hospital-access score to each LSOA, the areal unit of the IMD score. Specifically, the weight of a particular access score in an LSOA is determined by the proportion of its area (generated by 2SFCA) in that LSOA. The overall access score of an LSOA is thus a weighted average of all access scores whose areas intersect with that LSOA. Finally, using LSOA as the unit, we calculated the correlation coefficient between the two scores.

Results

Populations in the different driving-time zones

Table 2 shows the area and population in Nottinghamshire of each driving time zone around the eight considered public hospitals. These data provide a basic and general view of the spatial variation in access to public hospitals in the county. They indicate that people in Nottinghamshire generally have good spatial access to public hospitals – nearly 95% of the population can reach a sizable general hospital within a 15-minute drive. Although lower in absolute number, the percentage of elderly people living beyond the 15-minute driving zone was slightly higher than that of the general population.

Diversity in spatial hospital access

Access is of particular importance for the elderly as they are at a higher risk of serious COVID-19 infection. Figure 5 shows the results of 2SFCA for the different population groups. Generally, people in the urban areas in western and north-western Nottinghamshire have the best spatial access to public hospitals, followed by the urban area in eastern Nottinghamshire, compared with the lower spatial access of those in the rural districts. Figure

Table 2. Areal expanse, general population, senior population in different driving time zones.

Driving time to nearest public hospital (min) (min	Area in km^2 (%)	General population (%)	Senior population* (%)
0 – 5	170 (8%)	375,834 (33.49%)	75,617 (29.19%)
>5 – 10	629 (29%)	495,610 (44.16%)	111,301 (42.96%)
>10 – 15	758 (35%)	187,966 (16.75%)	52,604 (20.31%)
> 15	605 (28%)	62,800 (5.60%)	19,536 (7.54%)

* >60 years of age.

5a shows the effect when using the general population as the demand group and Figure 5b when the senior population (age >60 years) is in that situation. Comparing the access of the general population (Figure 5a) with that of the senior population (Figure 5b), they are about the same in the central urban areas in north-western, western, and south-western Nottinghamshire, whereas in the eastern part of county, the senior population has relatively low access.

Figures 4, 6, and 7 show the dynamics of the COVID-19 pandemic in Nottinghamshire during the second wave of the pandemic in the UK and its impact on spatial access of COVID-19 patients to the public hospitals. Figures 4 and 6 present the COVID-19 case count and incidence at the level of MSOAs, while Figure 7 shows the results of 2SFCA with the COVID-19 patients in the demand category rather than the general population or elderly population as in Figure 5. Due to the space limitation, we only present the spatial access during four representative sections of the 11-section series, i.e. the beginning, turning, peak and end periods, which are shown in Figures 4 and 6. The spatial access during the other seven sections can be found in the supplementary file.

The first section, Sep 28th to 2020-Oct 11th, 2020, represents the start of the second COVID-19 wave in the UK. Figures 4, 6a and 7a, illustrate that there was a serious COVID-19 outbreak in Nottingham City and nearby, as well as in an MSOA in central Nottinghamshire, while the situation was much less severe in other regions. Noticeably, the access value in Nottingham City decreased rapidly already in the first stage (Figure 7a).

The maps of case count and incidence during the period of Nov 23rd, 2020- Dec 6th, 2020 (Figures 4 and 6b) clearly show the dynamic of the pandemic. The case number in Nottingham City decreased significantly, and the pandemic moved into the northern part. The impact of this dynamic on the spatial access to public hospitals is also obvious: during this period, the access value in Nottingham City experienced a recovery, whereas the access value in other areas of the county, especially the southern part, dropped (Figure 7b). The magnitude of dropping, however, was spatially variable: the access value in urban areas decreased more sharply than in rural areas.

Figures 4, 6c and 7c show the situation of the peak period of the second COVID-19 wave in the UK (Jan 4th, 2021- Jan 17th, 2021). The number of COVID-19 patients at the peak of the second wave was much larger than that during the first wave. Another notable feature is that the second wave covered the entire county rather than just a small portion of it. Figures 4 and 6c show that all MSOAs in Nottinghamshire were seriously affected, especially those in the western and southwestern parts of the county. As a result, access possibilities decreased across the county, although with different magnitudes (Figure 7c). The eastern part seemed to have been affected the least, while most urban, suburban, and rural areas were strongly impacted. Nottingham City suffered a considerable decrease with respect to access again, while Newark and Sherwood in the eastern part of the county maintained a reasonable

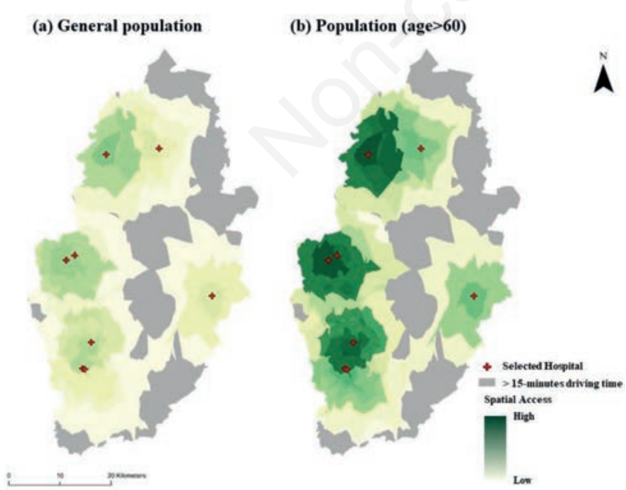

Figure 5. Spatial access to public hospitals in Nottinghamshire. a) based on the general population as demand as alternative; b) based on the elder population (>60 years old) as demand alternative. The access value shown in the maps were log-transformed values of the original values from the 2SFCA process; the colour ramps of the two maps are consistent, facilitating a visual comparison.

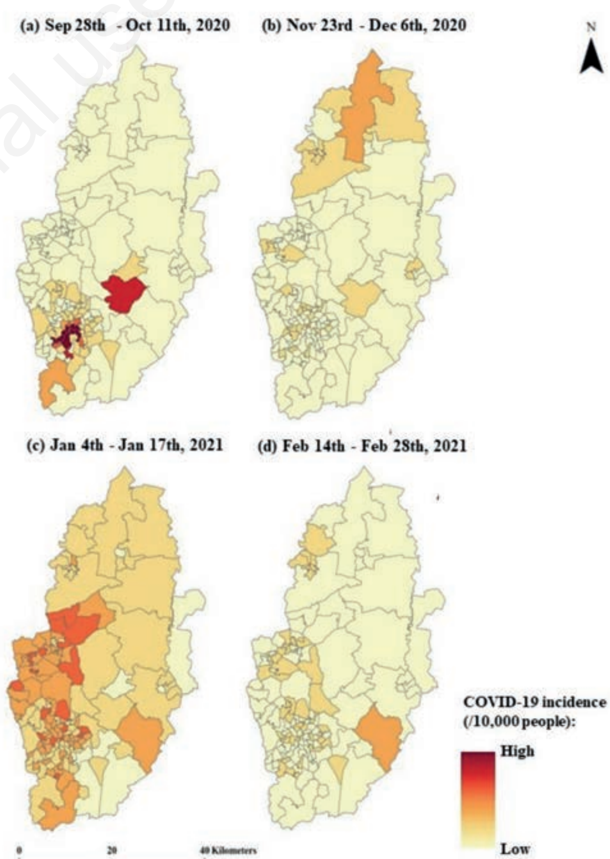

Figure 6. Spatial distribution of COVID-19 incidence in Nottinghamshire during selected periods during the second wave in the UK. The four subfigures show the situation of four periods during the wave: a) Sep 28th – Oct 11th, 2020 is about the first-time section in this research; b) Nov 23rd – Dec 6th, 2020 is about the turning period in the second wave; c) Jan 4th – Jan 17th, 2021 is about the peak period of the second wave and d) Feb 14th – Feb 28th, 2021 is about the last time section of this research.

level of spatial access. During the last section of our study period (Feb 14th, 2021- Feb 28th, 2021), the second wave declined (Figures 4, 6d, and 7d). As expected, with the number of COVID-19 cases decreasing, the spatial access of COVID-19 patients to public hospitals increased. All urban areas in the county appeared to again go back to having a high level of spatial access to public hospitals (Figure 7d).

Associations between spatial access and socioeconomic status

The correlation coefficients (*r*) between the IMD score and the spatial access of COVID-19 patients were considered. The *r* calculation, both for spatial access for the general and for the elderly populations, showed a low value during the whole second COVID-19 wave, 0.256 for the general population and 0.270 for the elderly population. Figure 8 shows the *r* between the IMD score and the spatial access of COVID-19 patients to public hospitals in Nottinghamshire in all 11 time samples. While the correlation was not strong (all values <0.5), the time series of *r* appears to roughly follow the peaks of the COVID-19 waves: during the two peak periods, the correlation was relatively strong. Notably, the smaller peak of the second wave (Oct 26th, 2020-Nov 22nd, 2020), which was much lower than the second peak of the second wave (Dec 21st, 2020-Jan 17th, 2021), corresponds to the most pronounced correlation between IMD and spatial access ($r = 0.419$).

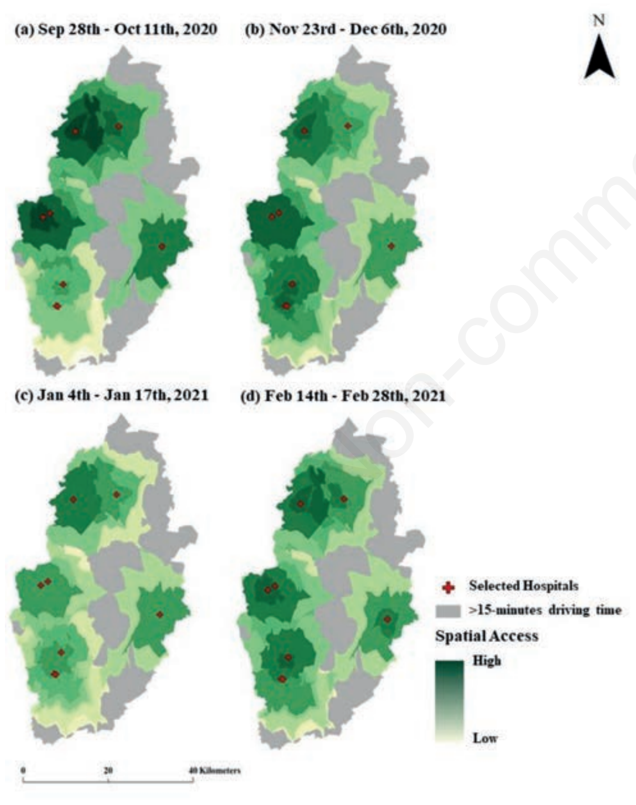

Figure 7. Spatial access of COVID-19 patients to public hospitals in Nottinghamshire during selected periods in the second wave. The four subfigures show the situation of four periods during the wave: a) Sep 28th – Oct 11th, 2020 is about the first-time section in this research; b) Nov 23rd – Dec 6th, 2020 is about the turning period in the second wave; c) Jan 4th – Jan 17th, 2021 is about the peak period of the second wave and d) Feb 14th – Feb 28th is about the last time section of this research.

Discussion

We used the 2SFCA method to measure the spatial access to public hospitals during the second COVID-19 wave in Nottinghamshire, UK and the spatial and temporal features of the access could be characterized in the study area and period. According to Figures 4 and 6a, the serious COVID-19 outbreak started in Nottingham City (Sep 28th – Oct 11th, 2020), the critical junctures were found to be the university campuses and their vicinities. This was because, at the beginning of the autumn semester (between the end of September and the beginning of October), there was an outbreak among the students who had just come back to the universities (Nottingham Trent University and the University of Nottingham). The initial outbreak of the disease in the county can be considered an emergency, which imposed a sudden and considerable impact on local access to hospitals. A demonstration of the low access caused by this impact in Nottingham city can be seen in Figure 7a, where southwest Nottingham (the university location) suffered the lowest access value during Sep 28th - Oct 11th, 2020 compared with other cities during this period and other periods within Nottingham city.

Figure 4 and Figure 6b show the COVID-19 epidemic and spatial access of these patients to public hospitals during the turning period of the second wave in Nottinghamshire, UK. The reason for the spatial changes can be linked to the implementation of prevention measures, such as wearing facemasks, keeping social distance, and self-isolating, which abated the outbreak in Nottingham City. Meanwhile, the pandemic started to appear in other areas of the county, especially the northern part. In addition, access changed in this period which was caused by the more drastic increase in the number of new confirmed cases in urban areas than in rural and suburban areas (Figure 7b). This study reveals that the spatial access of COVID-19 patients to public hospitals in Nottinghamshire varies spatiotemporally along with the dynamic of the COVID-19 pandemic. The spatial and/or temporal aggravation of the pandemic would lead to a corresponding increase in the

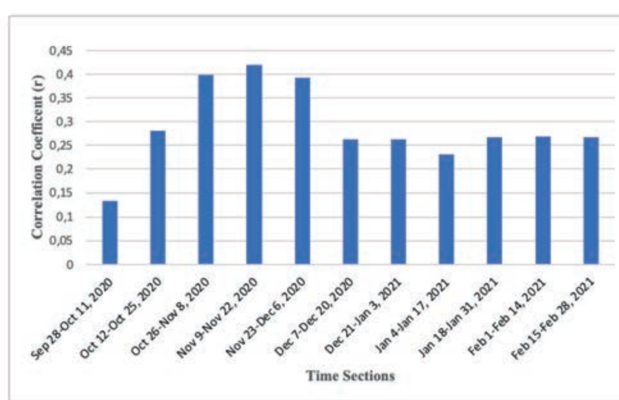

Figure 8. Time series of the correlation coefficient between spatial access of COVID-19 patients to public hospitals and Index of Multiple Deprivation (IMD) in Nottinghamshire

need for local healthcare resources, quantitatively represented in this study as the decrease in local access. Noticeably, the variation in access caused by the pandemic seemed to be more dramatic in the urban areas than in the suburban and rural regions.

This study also finds that there was a consistently positive association between spatial access and socioeconomic status in Nottinghamshire across our study period, although the association was not strong (*r* varied between 0.13 and 0.41). More interesting, this association also varied along with the dynamic of the pandemic: the socioeconomic disparity of the spatial access appeared to be stronger during the peaks of the pandemic, especially during the initial outbreak that was primarily within an urban area (Nottinghamshire City). This may indicate that during the initiation of the second wave, when the outbreak was mainly within the urban area of the city, there was a stronger disparity in spatial access of COVID-19 patients to public hospitals. Later, when the spatial coverage of the pandemic expanded, this disparity became less significant, but it still had an association with the seriousness of the pandemic.

A possible application of the findings of this study would be to support the planning of mobile cabin hospitals or other types of temporary hospitals with special reference to the size, location and duration of the provisional buildings. A temporary cabin hospital can quickly be assembled in public open spaces, such as stadiums and parks. This type of hospital was widely used in treating COVID-19 patients with mild symptoms in China during the pandemic (Zhang *et al.,* 2020). In an emergent situation, like the initial outbreak of COVID-19 occurring during the back-to-school season in Nottingham City, normal hospital burdens are likely to suddenly soar without much time of warning. In such situations, well-planned mobile cabin hospitals could play a critical role in alleviating the pressure on normal hospitals.

The limitations of this study are mainly related to the hospital data, assumptions about population distribution, the edge effect and methods application. We were not able to obtain data directly about the service capacity of a hospital, such as the number of ICU beds, ventilators and staff members. Even the numbers of buildings with medical facilities, elevators and floors of each building in each hospital were unknown to us. Here, we simply used the hospital ground area instead, which can only be considered a rough estimate of the hospital's capacity. Meanwhile, since the data limitation and the ground area we used were static, we did not consider the changes in the capacity of each hospital over the study period, such as the number of ICU beds and ventilators. In this study, we adopted the polygon model and areal interpolation to estimate the number of people at different locations. This is an improvement of the more popular point model, which assumes the population to be concentrated on the centroid of the areal unit. However, the assumption inherent in the polygon model that people are evenly distributed across the areal unit is also not realistic, especially in rural areas where the areal units tend to be large. This situation can be improved by incorporating high-resolution population products e.g., LandScan data and by using dasymetric mapping. Thirdly, in this study, we assumed that Nottinghamshire was a closed region. However, the patients in Nottinghamshire and those in the nearby counties (Leicester, Lincoln, Derby, and South Yorkshire) could always cross boundaries to seek medical services in other counties. Ignoring this medical migration would certainly cause inaccuracy in assessing the spatial access to healthcare services and its association with other factors, e.g., socioeconomic status. Last but not least, the 2SFCA method was applied in this study to estimate the "potential" access to public hospitals for COVID-19 patients, the general population, and the senior population based on proximity, which means that it assumed the targeted population to visit the nearest public hospital. Due to the lack of information regarding patient visits to each hospital, we could not verify the assumption and compare the potential access with actual patient visits.

Conclusions

Using the 15-minute driving time limit to define the effective spatial coverage of an acute human-to-human communicable disease, such as COVID-19, the eight qualified general public hospitals in Nottinghamshire can cover 72% of its spatial area, 95% of its population and 92.5% of its high-risk population (if defined as people older than 60). Generally, COVID-19 patients had better access to public hospitals in the western part of the county than in the east, and the north-western urban area provided the highest spatial accessibility; however, the accessibility of the public hospitals decreased as the number of cases increased. General and senior populations have roughly equal spatial access, and the difference between them is primarily seen in suburban areas. Additionally, we detected the association between the spatial access of COVID-19 patients to socioeconomic status measured by the IMD score at the MSOAs level. The correlations varied over time, but were generally only mildly positive, suggesting socioeconomic status may not be a significant indicator of spatial access for COVID-19 patients.

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