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Disparities in Geographical Accessibility of Permanent COVID-19 Vaccination clinics in the State of Ohio

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Abstract

Rapid and widespread distribution of the COVID-19 vaccine is crucial for containing the spread of this infectious disease. Health departments and planners must ensure that access to the COVID-19 vaccination is adequate and equitable. This study measured the spatial accessibility to permanent vaccination clinics at the census tract level using the 2-step floating catchment area method. Accessibility scores were heterogeneous across geographic regions and among different groups of people. In particular, many urban areas enjoy better access to vaccination clinics compared to rural areas. Minorities and people under poverty are concentrated in neighborhoods with above-average accessibility, while white and elderly concentrate in census tracts with below-average accessibility. The relationship between accessibility and the Social Vulnerability Index (SVI) was explored using the Spatial lag model and Bivariate Local Moran's I analysis. Patterns of high accessibility scores and high social vulnerability index could be observed in urban areas, while suburban areas enjoy high accessibility and low social vulnerability. Patterns of high accessibility census tracts adjacent to tracts with high minority rates and low adjacent to low are salient, indicating the strong relationship between race and accessibility. The Spatial Lag model also confirms this finding.

1. Introduction

COVID-19 is a contagious disease caused by severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2). Since it was first identified in December 2019, it has spread worldwide, leading to an ongoing pandemic (Zimmer, 2021). Up until August 2021, more than 36 million cases were confirmed in the U.S., causing about 6 million deaths (CDC, 2021a). With the months-long distribution of COVID-19 vaccines since the beginning of 2021, infections and deaths gradually decrease. Just when people started to feel safe, however, the emergence of the highly contagious Delta variant drove the number of infections to about a hundred thousand a day (CDC, 2021a). The currently authorized mRNA COVID-19 vaccines (Pfizer-BioNTech and Moderna) proved to be less effective against the infection caused by the variants compared with the ancestral strain. However, COVID-19 vaccinations still provide protection and are the best means to fight the pandemic (CDC, 2021d).

As of August 2021, more than 35 million vaccine doses were administered, and 167 million people were fully vaccinated in the United States. 50.3% of the total population in the U.S. is fully vaccinated, 61.3% of adults are fully vaccinated, and the percentage of fully vaccinated elderly (65 and older) is 80.5% (CDC, 2021a). Compared to the whole country, the study area-Ohio is a little behind: 46.65% of total Ohioans are fully vaccinated, and only 57.8% of adults are fully vaccinated (Ohio Dpartment of Health, 2021). Even though more and more people are getting vaccinated against COVID-19, there is still a long way to go before the whole country reaches herd immunity. The state government is promoting the process of COIVD-19 vaccination to make sure it is free and available for individuals ages 12 and over, as it is critical to help end the COVID-19 pandemic.

COVID-19 has brought health disparities and inequalities to the spotlight of public health. Health disparities refer to the situation where a segment of the population disproportionally suffers from a certain health concern or health outcome (Kilbourne, Switzer, Hyman, Crowley-Matoka, & Fine, 2006). A variety of factors drive the disparities in health, such as discrimination, health care access, occupation, education, and income gaps (CDC, 2021c). For example, discrimination leads to long-term and toxic stress and further shapes socioeconomic factors that put people from racial and ethnic minority groups at risk of catching COVID-19 (Paradies, 2006; Simons et al., 2018). Another example is that underprivileged people face various barriers to access healthcare due to the lack of health insurance, transportation access, or ability to take time off work (Berchick, Barnett, & Upton). A study shows that medical care only accounts for around 20% of the variation in health outcomes, while 80% can be traced back to health behaviors and socioeconomic factors- often referred to as social determinants of health (SDOH) (Hood, Gennuso, Swain, & Catlin, 2016). Geographic location, race and ethnicity, and socioeconomic status influence an individual's environmental exposure and health behavior and subsequent risk of adverse health outcomes (Clark, Millet, & Marshall, 2014; Williams & Collins, 2016). Evidence shows that disparities of COVID-19 and COVID-19 vaccination among racial groups exist. For example, in Ohio, African-Americans comprise 14% of the population while they comprise18.7% of hospitalization caused by COVID (Ohio Department of Health, 2021). Furthermore, only 9% percent of the COVID-19 vaccinated people in Ohio are African American (Ohio Dpartment of Health, 2021).

Equal and adequate access to the COVID-19 vaccination is a precondition for ending the pandemic and achieving health equity within such a context. Accessibility can be understood as the relative ease by which the locations of activities can be reached from a given location (Hansen, 1959). It can also be interpreted as spatial and aspatial. Spatial access concerns distance as the barrier, whereas aspatial access emphasizes nongeographic barriers, such as social status, income, race, age, sex, etc.(Joseph & Phillips, 1984). Since the COVID-19 vaccines are free for everyone 12 and older, this greatly lowers (but does not eliminate) aspatial concerns. However, geographical accessibility remains a major problem.

Uneven distributions of COVID-19 vaccination clinics and population result in a geographical disparity in access. Studies have shown that inner-city areas tend to have more healthcare providers, shorter distances to facilities, more transportation choices, and higher healthcare quality compared to rural areas (Ghorbanzadeh, Kim, Ozguven, & Horner, 2021; Meilleur et al., 2013; Xu, Fu, Onega, Shi, & Wang, 2017). Furthermore, a higher proportion of racial and ethnic minorities suffer from poor access to healthcare facilities (CDC, 2021b). For example, African-Americans suffer from poor access to pharmacies in Baton Rouge, Louisiana (Ikram, Hu, & Wang, 2015); in Florida, seniors faced disadvantaged access to the COVID-19 vaccination sites (Tao, Downs, Beckie, Chen, & McNelley, 2020); and vulnerable populations in Chicago resided in areas where access to the COVID-19 health resources are low (Kang et al., 2020). Disparities in healthcare accessibility among different socioeconomic and race and ethnic groups correspond to differences in health outcomes (Esnaola & Ford, 2012). Research has also shown that geographically and racial and ethnic disparities are interrelated, and both could result in disparities in health outcomes (McLafferty, Wang, Luo, & Butler, 2011; Wang, McLafferty, Escamilla, & Luo, 2008).

Inspired by the aforementioned studies, this study focuses on three questions:

RQ1: Does access to permanent COVID-19 vaccination sites vary according to different urban-rural classifications?

RQ2: Does access to permanent COVID-19 vaccination sites differ by demographic groups?

RQ3: What is the relationship between the social vulnerability themes and accessibility to permanent COVID-19 vaccination sites?

2. Study Area And Data

2.1 Study Area

The study area for this research is the state of Ohio. It is the 34th largest state (U. C. Bureau, Economics, & Administration, 2012) in the United States by area, located in the Midwestern region of the country. With a population of nearly 11.8 million, it is the 7th most populous and 10th most densely populated state in the country (U. S. C. Bureau, 2021). Columbus, Cincinnati, and Cleveland are the largest metropolitan areas in the state. According to the National Center for Health Statistics (NCHS) Urban-Rural classification scheme released by the CDC (CDC, 2017), these three areas are classified as class 1-large central metro. The outskirts of these three areas are classified as class 2- large fringe metro. The next three largest metropolitan areas are Dayton, Akron, Toledo, and Youngstown, which belong to class 3-medium metro.

2.2 Data collection

All the datasets which are used in this study are listed in Table 1. Three variables are needed to calculate the geographical accessibility: supply, demand, and the geographical relationship between them. Permanent COVID-19 vaccination clinics and their capacities (the largest number of doses each clinic could administer) are considered as supply in this study. The population of each census tract is our measure of demand, and the travel time is the geographical relationship between them.

Table 1
Datasets that were used in this study

Name of the data	Description	Source
COVID-19 Vaccine Provider Locations	List of providers' names, address, country, phone number, and website	State of Ohio COVID-19 dashboard
The COVID-19 Vaccination Distribution	Distributed vaccines for each county daily	State of Ohio COVID-19 dashboard
Social Vulnerability Index (SVI)	Theme1: Socioeconomic Status Theme2: Household Composition and Disability Theme3: Minority Status and Language Theme4: House Type and Mobility	CDC
NCHS Urban-Rural Classification Scheme	1-Large central metro, 2-Large fringe metro, 3-Medium metro, 4-Small metro, 5-Micropolitan, and 6-Noncore	National Center for Health Statistics
Demographic Data	Population The percentage of people who are Minority Percentage of people who are 65 and older Percentage of people who live in poverty Percentage of people who have no vehicle.	CDC

COVID-19 vaccination provider location data were collected from the State of Ohio COVID-19 dashboard (https://coronavirus.ohio.gov/wps/portal/gov/covid-19/dashboards). The dashboard is an effort of the Ohio Department of Health to make COVID-19 data available to the public. An address list for 1,332 vaccination sites' (sites open on March 17, 2021) was obtained, and by using *geolocator*, all the sites were created as points feature in *ArcMap*.

The capacity of each vaccination clinic is estimated using vaccination administration data, which is also obtained from the State of Ohio COVID-19 dashboard and provides the number of people who started and completed vaccination daily for each county. We picked out the maximum number of administered vaccines from the starting day of the vaccination till June 19, 2021 (the day this data was collected) for each county and considered them as the vaccine distribution capacity for each county. The capacity of each vaccination site was obtained by dividing each county's capacity by the number of sites within that county. This process made two assumptions: the day that a certain county distributed the maximum number of vaccines is that county's distribution capacity, and every site in the same county has the same vaccination capacity. The assumptions are rational because the peak of inoculation was in March and

April of 2o21. Also, at that time, vaccinations were hard to obtain and could take many days (even weeks) to schedule, indicating that a great demand relative to supply.

Demographic data is obtained from CDC/ATSDR (Agency for Toxic Substance and Disease Registry) Social Vulnerability Index (SVI) (https://www.atsdr.cdc.gov/placeandhealth/svi/index.html). Social vulnerability is “the potential negative effects on communities caused by external stresses on human health” (ATSDR, 2021). The data included 15 vulnerability variables and were categorized into four themes. The first theme was socioeconomic status and comprised four variables: below poverty, unemployed, income, and no high school diploma. The second theme is household composition and disability. It also comprised four factors: aged 65 or older, aged 17 or younger, civilian with a disability, and single-parent household. Minority status and language is the third theme. This theme comprises two factors: minority and speaks English “Less than Well”. The fourth theme is housing type and transportation. Five variables comprise this theme: multi-unit structures, mobile homes, crowding, no vehicle, and group quarters. Basic information for each census tract, like total population, household, and housing unit, is also provided in the dataset. The estimated number and percent of people that fall into each variable are given, as well as the percentile for all 15 variables. Percentile rankings for each theme are also shown in the data. The latest SVI data available is 2018, and it provides data for all the states in the U.S at county and census tract levels. The Ohio census tracts level data are adopted because the accessibility based on this level is more close-to-real-life than the county level. SVI data is used to explore disparities in spatial accessibility and the relationship between themes and accessibility.

NCHS Urban-Rural Classification Scheme for Counties is used to define urbanicity at the county level. There are six urban-rural categories: 1-Large central metro, 2-Large fringe metro, 3-Medium metro, 4-Small metro, 5-Micropolitan, and 6-Noncore. Figure 1 shows the distribution of COVID-19 vaccination clinics and urban-rural classifications. These data are used to explore the accessibility difference for each category. The distribution of the COVID-19 vaccination clinics and urbanicity are also shown in Fig. 1.

3. Methods

3.1 Workflow

The workflow utilized in this research is shown in Fig. 2. The two-step floating catchment area method (2SFCA) was used to measure the accessibility to the COVID-19 vaccination sites for all the census tracts in Ohio. Dummy variable regression was used to explore the difference in accessibility for urban-rural classification. To explore the difference in accessibility for different demographic groups, weighted ordinary least square was used. Lastly, the spatial lag model and bivariate local Moran’s I were adopted to examine the relationship between vulnerability themes and accessibility.

3.2 Measuring accessibility using 2SFCA

2SFCA is the most widely-used method (Neutens, 2015) to measure spatial accessibility (Luo & Wang, 2003). It has been used to measure the accessibility to all kinds of facilities, such as physicians (Luo & Qi, 2009), pharmacies (Ikram et al., 2015), green space (Cheng, Liu, & Li, 2011), and food (Dai & Wang, 2011; Kuai, 2015). In this study, we use this method to measure the accessibility for every census tract in Ohio. In this study, we use this method to measure the accessibility for every census tract in Ohio. As indicated in the name, the computation of the 2SFCA comprises two steps. The first step is to identify the demand population which live in the catchment area of a certain vaccination clinic j, and then calculate the vaccination-to-population ratio R_j for that clinic with Eq. (1)

$$R_j = \frac{S_j}{\sum_{k \in (d_{kj} < d_0)} P_k} \quad (1)$$

The catchment area is obtained by using the provider locations as centers and taking distance (e.g., 15 miles or 30 miles) or travel time (e.g., 15 min or 30min drive) as the search radius. In this study, 60-min drive time is chosen as the catchment area because it performs the best.

The second step is to calculate the accessibility score A_i for each census tract *i* using Eq. (2):

$$A_i = \sum_{j \in (d_{kj} < d_0)} R_j \quad (2)$$

where A_i is the accessibility of census tract *i*. This step considers the access of demand sites to the supply sites. By summing the population-to-vaccination ratio of providers that fall into the catchment area of a certain population site (census tract centroid), the accessibility score of that census tract is obtained.

3.3 Statistical analysis of accessibility disparities

A simple regression with dummy variables is used to examine the variability of COVID-19 vaccination accessibility across geographic areas of different urbanicity. This method was adopted by Xu et al. in their study of disparities in geographical accessibility of National Cancer Institute Cancer Centers (Xu et al., 2017). Accessibility value is the dependent variable. The independent variables are the dummy variables coded for the different urban-rural categories. Here, six categories are coded with five dummy variables: “large central metro” is coded as $x_1 = x_2 = x_3 = x_4 = x_5 = 0$, indicates it’s the reference category; “large fringe metro” is coded as $x_1 = 1$, $x_2 = x_3 = x_4 = x_5 = 0$; “medium metro” is coded as $x_2 = 1$, $x_1 = x_3 = x_4 = x_5 = 0$; “small metro” is coded as $x_3 = 1$, $x_1 = x_2 = x_4 = x_5 = 0$, and so on. The model is:

$$A = b_0 + b_1x_1 + b_2x_2 + b_3x_3 + b_4x_4 + b_5x_5 \quad (3)$$

where A is the accessibility score, the intercept b_0 represents the average accessibility score of the large central metro. And the coefficients b_1, b_2… or b_5 represent the difference of the average scores of the other five categories to the average score of the reference category (large central metro). For example, if the intercept b_0 is 20, and b_1 is -2, these mean that the average accessibility score of large central metro (i.e.,

reference category) is 20, the average score of the large fringe metro is 2 scores different form the reference catogory's, more specifically, 2 scores lower than the average score of large central metro.

A regression model developed by Ikram et.al (Ikram et al. 2015) is used to implement the statistical test of indicating the difference between the sample mean of demographic groups percentages in the tracts with above-average accessibility scores and the sample mean of those below-average. One may argue that the pooled t-text could do the same, but this model is simpler to implement and interpret. Weighted Ordinary Least Squares (WOLS) regression is used in this study to account for the fact that the population of a demographic group varies across the study area. More specifically, each demographic group's population is considered to weigh heavier on the error term for the census tract with more population. The formula is:

$Y = a + b * Flag$ (4)

where Y denotes as a percentage of demographic groups; the independent variable Flag is a binary dummy variable with 0 representing those census tracts with accessibility score above-average, and 1 coded as those tracts with score below-average; a is the average percentage of a demographic group in the tracts that with above-average accessibility score, and b indicates the difference in the average percentage of that group live in the below-average score tracts.

3.4 Spatial Association Analysis for accessibility and SVI

Social vulnerability themes, which may correlate with accessibility, were examined using a spatial lag model and bivariate local Moran's I analysis. In the spatial lag model, we use accessibility as the dependent variable and the four themes of SVI as dependent variables. The fields which are used are the percentile ranking of four themes: socioeconomic status, household composition and disability, minorities and language, and housing type and mobility. The Spatial lag model is needed here because accessibility is usually spatial autocorrelated, which would make the widely adopted Ordinary Least Square (OLS) model not suitable for this study. The Spatial lag model adds a variable in the model that indicates the spatial interaction between neighboring census tracts. In this study, we used the Queen contiguity method to define neighboring tracts.

Bivariant local Moran's I (Anselin, Syabri, & Smirnov, 2002) is also used to explore patterns in spatial accessibility relative to four themes of SVI by comparing the spatial distribution of SVI themes with accessibility. It is calculated with Eq. (5) :

$I_{B,i} = cx\mathrm{i} \sum_{j} w\mathrm{ij} y\mathrm{j}$ (5)

where $I._{B.,I}$ is the bivariant local Moran's I for given location *i*, the two variables *x* and *y* have been standardized to have their means of zero and variances of one, w_{ij} is the spatial weight between location *i* and *j*, *c* is a scaling factor. It essentially measures the association between variable *x* in location *i*, and variable *y* in nearby locations. For instance, it could examine whether a high accessibility census tract is surrounded by a high or low concentration of minorities.

4. Results

4.1 Spatial accessibility patterns

The distribution of COVID-19 vaccination accessibility scores for all the census tracts in Ohio is shown in Fig. 3. All the census tracts are covered in the 60-min driving service area. It shows that urban areas, like Cleveland, Columbus, Cincinnati, Dayton, and Toledo, enjoy high COVID-19 vaccination access. Interestingly, the scores of inner-city areas do not fall into the highest band of vaccination accessibility (25.62 to 41.65) but fall into the second-highest (20.89 to 25.62) band. Those with extremely high scores are distributed in the suburban areas. For example, the score of the tracts in the core of Toledo falls in the second-highest band, whereas the score of the south and west census tracts are salient; some of the tracts are two standard deviations away from the mean. This also occurs in the census tracts in Cleveland, Akron, Cincinnati, Dayton, and north of Columbus. The southeast census tracts are in rural areas but enjoy high accessibility because the capacity of a clinic in Monroe County, which is located on the eastern border of Ohio, is extremely high and drives the accessibility scores of the whole tracts around it high.

The spatial autocorrelation indicator Moran's I is 0.77 with a p-value of 0.00 when using queen contiguity as the conception of spatial relationship, which indicates a high clustered pattern. The Hot Spot analysis (Fig. 3 (b)) shows where the clusters occur. Cleveland, Akron, Toledo, Lima, Columbus, Cincinnati, and Dayton, and southeast areas are hot spots. The census tracts are located on the outer areas of hot spots, and the between hot spots areas are cold spots. The concentration of high-value accessibility scores in the urban area and low-value scores in the rural areas indicate that differences of access across urbanicity levels exist, which is examined in the following subsection.

4.2 Disparities in the accessibility of the COVID-19 vaccination clinics

4.2.1 RQ1: Variation of accessibility in urbanicity

The outcome of this dummy variable regression is shown in Table 2. The average accessibility score to COVID-19 vaccination sites of large central metros is 21.061 and is the highest in the six levels. Hamilton, Franklin, and Cuyahoga counties are categorized as the large central metros in Cincinnati, Columbus, and Cleveland, respectively. Drug stores, grocery stores, and healthcare facilities are more concentrated in urban areas than in rural areas, and the vaccination distribution depends on these facilities, so the number of COVID-19 vaccination sites is significantly higher in these areas. For the large fringe metro areas, the average accessibility score is 19.588, lower than the large central metro by 1.473, and the difference is significant. These areas surround the large central metro areas and enjoy relatively lower access than the large central metro counties but still are the third-highest among the urbanicity categories.

One might anticipate that the access would decrease as you move down the urban hierarchy. This is not the case, however, because Toledo, Dayton, and Akron are categorized as the medium metro, and census tracts in those areas have accessibility scores close or even higher than the reference category. This is especially the case for Toledo, where some of the top 99% accessibility scores were observed, which might skew the regression outcome. Notably, the medium metro areas experience higher access to permanent COVID-19 vaccination sites than large fringe metro areas; its average score is lower than the large central metro only by 0.69 (significant at 0.01 level). The average accessibility score of the small metro areas is 19.481, which is statistically significantly lower than the large central metros and is also lower than the large fringe metros. Micropolitan and non-core areas suffer significantly lower access to permanent COVID-19 vaccination sites than large central metros; their average accessibility scores are also considerably lower than the other three categories higher than them in the urban hierarchy.

Table 2
Variation of accessibility index across urban-rural classifications in Ohio

	Coefficient	SE	t-value	Sig.
Large central metro (Reference category)	21.061	.140	149.925	.000
Large fringe metro	-1.473	.23 9	-6.158	.000
Medium metro	− .619	.210	-2.955	.003
Small metro	-1.580	.381	-4.150	.000
Micropolitan	-4.283	.246	-17.416	.000
Non-core	-5.410	.442	-12.241	.000

4.2.2 RQ2. Disparities in demographic groups

This section examines disparities in access to permanent COVID-19 vaccination sites across different demographic groups. The model used here examines the demographic group rates difference between above- and below-average census tracts. The disparities of accessibility to permanent COVID-19 vaccination sites by demographic groups are reported in Table 3. The White percentage is statistically higher in the below-average census tracts than above-average census tracts. This situation is the same for the elderly population, which means these two groups are more concentrated in the areas with below-average accessibility scores, resulting in lower access to permanent COVID-19 vaccination sites. It is understandable because White is the dominant demographic group in the micropolitan and the non-core areas, which suffer the most from the low access to permanent COVID-19 vaccination sites. The average percentage of the White population in these two areas is 92%. A hot spot analysis was conducted to examine the geographical change in the rates of elderly throughout Ohio. The results illustrate that the census tracts with low elderly percentages cluster in Cincinnati, Columbus, and Toledo, where the accessibility scores are high. The census tracts with high elderly rates cluster in Youngstown and Canton,

where the accessibility scores are low. These opposite hot and cold spot patterns in accessibility and elderly rates demonstrate that the elderly suffer from lower access to permanent COVID-19 vaccination sites. Another cold spot of elderly percentage occurs in outer Cleveland, where the accessibility scores are high, which may explain why the elderly percentage difference between above- and below-average areas are not great.

The minority rate, on the other hand, is significantly higher in the tracts with above-average accessibility, and this suggests that the minority group enjoys better access to COVID-19 vaccines. The minority tend to concentrate in the urban areas. More specifically, in the large central metro, where the places enjoy the best access to the COVID-19 vaccination, the average minority rate is 43%, whereas the average rate is only 7% in the micropolitan and the non-core areas, where accessibility is low. A higher percentage in poverty and the households without a vehicle in above-average census tracts demonstrates that these two groups enjoy better access to the COVID-19 vaccination. Census tracts with high poverty percentages and no vehicles are concentrated in the inner-city areas of Cincinnati, Columbus, Cleveland, and Toledo, which explains why poverty and people with no vehicle access enjoy better access to the COVID-19 vaccination.

Table 3
Test of statistical difference in percentages of demographic groups

VARIABLE	PERCENT WITH ACCESSIBILITY SCORE		DIFFERENCE IN PERCENT	t VALUE
	> 19.70 (1658 census tracts)	< 19.70 (1290 census tracts)		
Race groups				
White	81.91	90.053	8.143	15.508***
Minority	49.868	38.088	-11.780	-9.926***
Age Groups				
>65 (Elderly)	17.625	19.039	1.414	6.603***
Socioeconomic Status				
Poverty	25.880	21.576	-4.304	-7.664***
No car	8.293	7.006	-1.287	-4.871***

4.3 RQ3. Examining the relationship between the SVI and accessibility

4.3.1 Spatial lag model

To further reveal inequalities in the access to permanent COVID-19 vaccination sites, the results of the spatial lag model are shown in Table 4. All the themes are significantly related to accessibility. The coefficient of socioeconomic status with accessibility is negative, meaning that the census tracts with low socioeconomic status suffer from low access to permanent COVID-19 vaccination sites. This finding is not consistent with the findings in 3.2.2, where WOLS indicates that census tracts with low socioeconomic status (high vulnerability in this theme) have high access to permanent COVID-19 vaccination sites. People with low socioeconomic status tend to cluster in the inner-city areas and thereby enjoy high access, so the sign of the coefficient should be positive. To make sense of the coefficient sign, Pearson correlation is adopted to examine the correlation between socioeconomic status vulnerability and accessibility for each urbanicity category. A Similar contradiction appeared in Tao's research; they also used Pearson correlation to explore this contradiction (Tao et al. 2020). The results show that correlation is only significant for the large central metro and large fringe metro; for the large central metro, the correlation is 0.101, and for the large fringe metro, -0.167. The stronger correlation between socioeconomic vulnerability and accessibility in the large fringe metro dominates the socioeconomic coefficient in the model, causing the outcome to contradict the former finding in section 4.2.2. The coefficient of this theme is -0.325 and only significant on the 0.1 level; compared to other themes' coefficients in this spatial lag model, the relation between socioeconomic status and accessibility is relatively weak.

Another variable that is weakly but significantly related to accessibility is housing type and transportation. This theme is determined by the percentage of housing in structures with 10 or more units, mobile homes, crowded living situations, households without a vehicle, and group quarters. The coefficient sign is positive, indicating that the worse living and transporting situation comes with the high access to COVID-19 vaccination. The second theme: household composition and disability coefficient, is also weak compared to coefficients of the third theme and spatial lag variable. This theme is a composite of percentages of persons aged 65 and older, 17 and younger, disability, and single parent. The sign of this coefficient is positive, which shows that the census tracts with a higher proportion of potential disadvantaged contribute to high accessibility to the COVID-19 vaccination.

The most significant correlated theme is minority status and language, and the contribution of this theme to the model is the highest among the four themes. The coefficient is positive, meaning that the census tracts with more minorities or people who speak English less than well benefit from high accessibility. Understandably, minorities tend to concentrate in the urban areas where the accessibility scores are high.

The performance of the spatial lag model is decent, with an R-square of 081. However, the spatial lag coefficient is 0.908, which means the relationships between the four themes and accessibility are nonstationary and vary across the study area. It is also an indicator that an analysis of relationships at the local level is needed, which will be shown and discussed in the next part.

Table 4
Spatial Lag model results

Variables	Coefficient	Standard Error	z-value	Probability
Constant	1.376	0.183	7.526	0.000
Socioeconomic Status	-0.325	0.190	-1.713	0.0867
Household Composition and Disability	0.352	0.169	2.083	0.0373
Minority status and Language	0.632	0.135	4.678	0.000
Housing and Transportation	0.254	0.146	1.747	0.0806
Spatial lag	0.909	0.0081	111.569	0.000
R-square: 0.815; ACI: 13099.6; # observation: 2948; degrees of freedom: 2942				

4.3.2 Bivariate Local Moran's I analysis

Bivariate Local Moran's I analysis is adopted to view the relationship between individual themes and the accessibility scores, which varies across the study area. It measures the first variable x in location i, and the second variable *y* in *i*'s nearby location. This method, unlike most regression models where the focus is the *y* variable, puts the first variable x in the spotlight. Because the focal point of this study is accessibility, *x* variable is denoted as accessibility score and *y* variable as the four themes of SIV. The results of Bivariate Local Moran's I are shown in Fig. 4 below.

Figure 4 (a) has 433 high-high census tracts, the second highest among the four themes. These tracts are primarily located in urban areas, including Cleveland, Columbus, Toledo, and Dayton. It confirms that the urban areas with high access to permanent COVID-19 vaccination sites are also those with high vulnerability in socioeconomic status. Figure 4 (a) has the highest number of census tracts belonging to the high-low category, and those tracts are concentrated in the outskirts of those cities mentioned above. Interestingly, this pattern fits the "white flight" phenomenon in which middle-class Whites relocated to suburban regions in the middle and late 20th century. Suburban areas have a population with relatively high socioeconomic status and, therefore, have low levels of vulnerability. Moreover, as indicated before, those areas are also enjoying high accessibility to permanent COVID-19 vaccination sites. Therefore, it is not surprising to see that the high-low census tracts are concentrated chiefly in suburban areas.

For the theme 2: household composition and disability (Fig. 4 (b)), which considers the percentage of people under the age of 17, age above 65, single parents, and disability, the pattern is similar to Fig. 4 (a). However, the number of census tracts in each category is lower than Fig. 4 (a). The tracts that belong to the high-high category concentrate in urban areas but compared to the first category, the pattern is less clustered, especially in Dayton and Columbus. The high-low category still concentrates in the outskirts only with a smaller number of census tracts. Figure 4 (d) shows a similar pattern with the first two themes but with fewer census tracts categorized. The concentration of high-high category in urban and high-low category clusters in the outskirts is less obvious than the first two themes. This is consistent

with the finding in the OLS model and spatial lag models, which shows the coefficient of theme 4 is the lowest among 4 themes. The resemblance of patterns of these three themes may indicate that socioeconomic status correlated to or similar with each other.

5. Conclusion

Our analysis in this paper found several interesting patterns with respect to geographic access to permanent COVID-19 vaccination sites. First, the accessibility scores decrease as the urban-rural hierarchy decreases except for the medium metros. The large central metro has the highest accessibility to permanent COVID-19 vaccination sites, followed by the median metro, large fringe metro, micropolitan, and non-core areas. Second, disparities across different demographic groups exist. White and elderly have relatively low access to permanent COVID-19 vaccination sites because they concentrate in the tracts with below-average accessibility scores. Minorities, people below poverty have better access because they are clustered in the urban areas where the proximity to the COVID-19 vaccination is high. This “reversed racial advantage” finding is counterintuitive but coherent with the former studies (Xu et al. 2017, McLafferty et al. 2011). However, the groups with better access do not necessarily mean that those groups utilize vaccination services. In fact, even though minorities enjoy better access to permanent COVID-19 vaccination clinics, the actual African Americans vaccination rate is lower than their proportionate share in the Ohio population. The possible reasons are time conflicts (clinics’ operation times conflict with their working time) and willingness (people do not believe the vaccinations are safe and/or do not believe the government). To iron out the inequalities, pop-up clinics are organized in those communities with low vaccination rates. Third, the vulnerability themes are positively correlated to accessibility in urban areas. For theme 1, 2, and 4, vulnerability rankings are negatively correlated to accessibility in suburban areas, but no specific patterns are observed in the rural areas. For theme 3, positive correlations were observed in the rural areas, whereas no significant patterns were found in suburban areas.

All the findings are related to features and characteristics of urbanicity. For example, people in poverty tend to live in the inner city as the living and commuting cost are relatively low compared to living in the suburban areas, and often there is collinearity between people in poverty and race. So, one would observe that census tracts in the urban areas possess a high vulnerability. From the accessibility side, because of the high population density in the urban areas, more services would be located there, and many permanent COVID-19 vaccination providers are set based on the existing services like pharmacies, hospitals, and grocery stores, which makes the number of permanent providers high, thus directly contributing to high accessibility for the inner-city residents. Combining these two reasons, we can see how demographic features relate to accessibility.

This research measured and identified the patterns of accessibility of permanent COVID-19 vaccination centers. The limitations of this study, however, need to be acknowledged. First, this study does not include the mobile and pop-up vaccination clinics, which administered a large number of vaccinations and temporarily increased accessibility for people living in some census tracts. As pop-up clinics are only in

operation for a very short time and their locations change, considering them in our research would require a spatial-temporal model. Second, this study only considers driving as the transportation mode, while in reality, walking and public transportation are also options. Other transportation modes are not considered because 96.8 percent of people in Ohio have access to cars, and it is hard to identify the number of people who regularly adopt transportation modes other than driving. Third, no capacity data of vaccination clinics are available, so estimation must be made by assuming that each county's capacity is the highest number of doses administered in a day and all the clinics in a county administer the same doses.

In terms of future studies, we suggest including pop-up and mobile clinics to gain a more comprehensive understanding of access to COVID-19 vaccinations. A comparison study of accessibility, which includes and does not include pop-up and mobile clinics, could be done to see if and how pop-up and mobile clinics change accessibility.

Declarations

Ethical Approval and Consent to participate

Not applicable.

Consent for publication

Not applicable.

Availability of data and materials

The datasets used and/or analyzed during the current study are available from the first author on reasonable request.

Competing interests

The authors declare that they have no competing interests.

Funding

Not applicable.

Authors' contributions

YY and YX designed the original study. YY performed analyses and drafted the manuscript. NR, TH and YX participated in discussion of results of the original manuscript. All authors read and approved the final manuscript.

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Figures

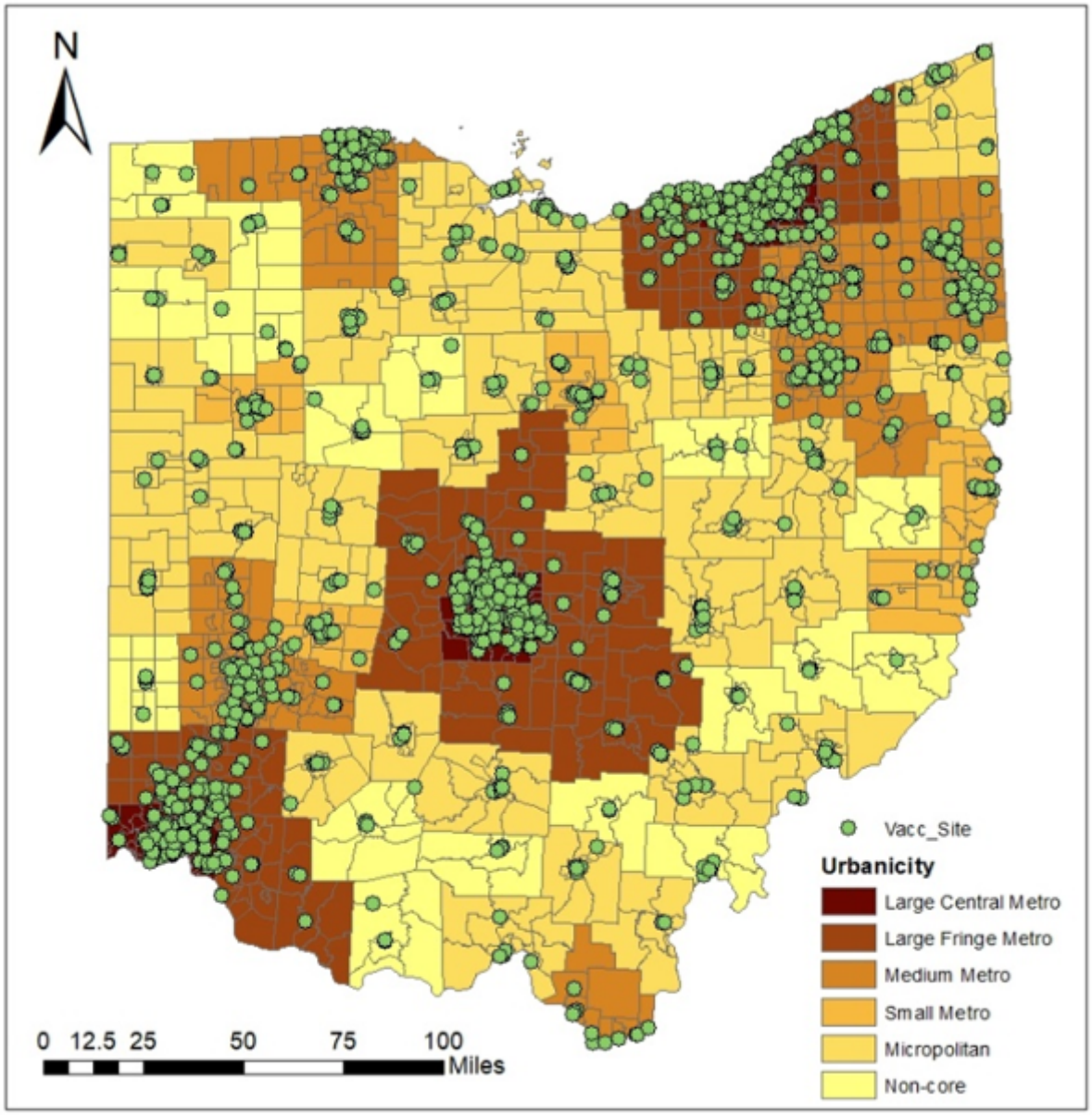


Figure 1

Distribution of COVID-19 vaccination clinics and Urban-Rural classification of Ohio census tract

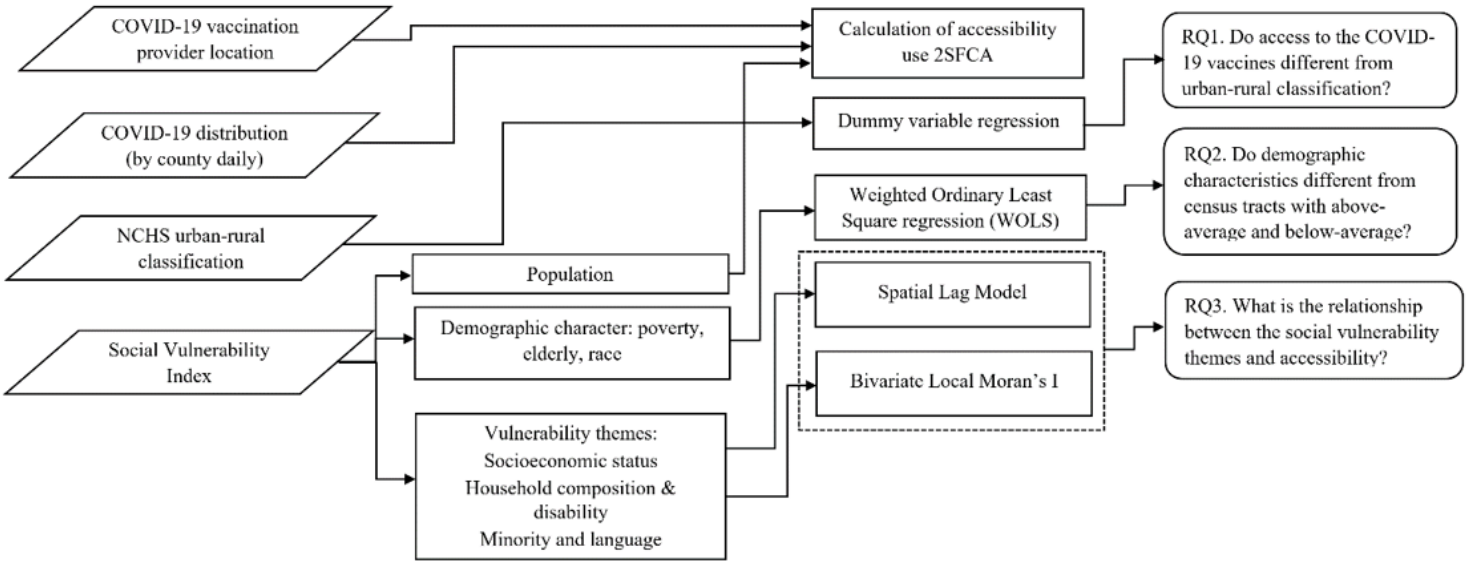
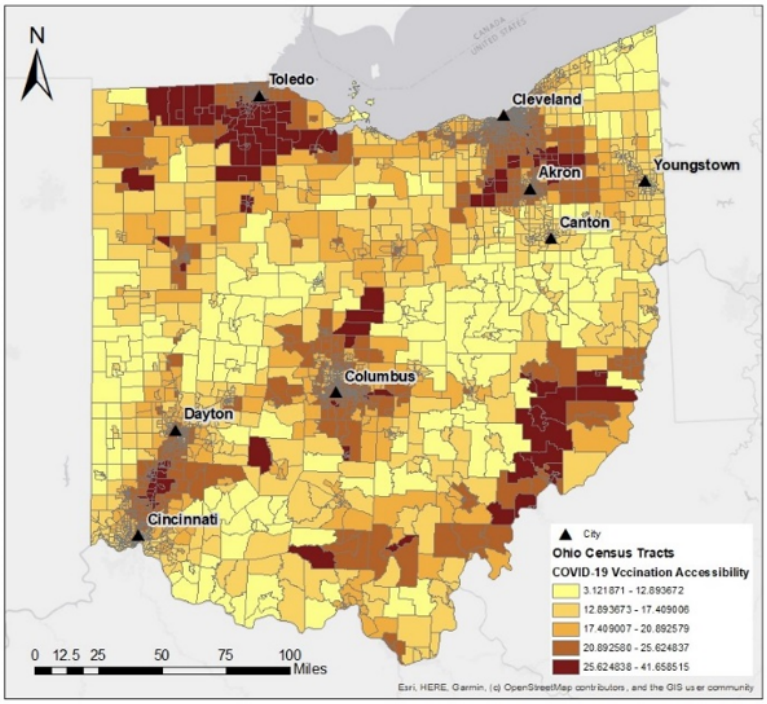
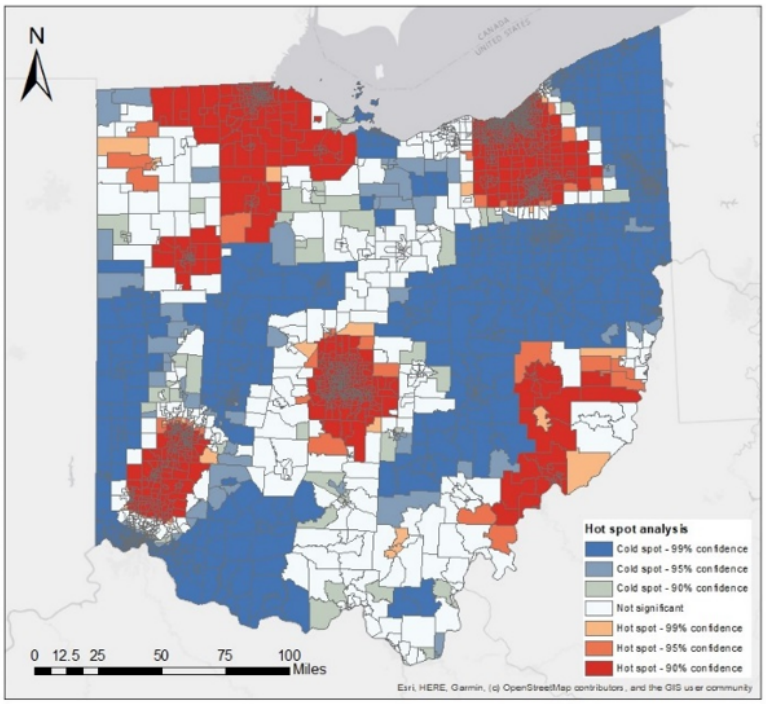


Figure 2

Workflow of this study



(a)



(b)

Figure 3

(a) Accessibility to permanent COVID-19 vaccination the clinics at census tracts level in Ohio; (b) Hot spot analysis for accessibility to permanent COVID-19 vaccination sites

Figure 4

Bivariate Local Moran’s I results of (a) theme 1: socioeconomic status (b) theme 2: household composition and disability (c) theme 3: minority and language (d) theme 4: housing and transportation