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Identifying areas of potential critical healthcare shortages: A case study of spatial accessibility to ICU beds during the COVID-19 pandemic in Florida

Kyusik Kim,*, Mahyar Ghorbanzadeh, Mark W. Horner, Eren Erman Ozguven

**A R T I C L E   I N F O**

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**A B S T R A C T**

Healthcare resource availability is potentially associated with COVID-19 mortality, and the potentially uneven geographical distribution of resources is a looming concern in the global pandemic. Given that access to healthcare resources is important to overall population health, assessing COVID-19 patients’ access to healthcare resources is needed. This paper aims to examine the temporal variations in the spatial accessibility of the U.S. COVID-19 patients to medical facilities, identify areas that are likely to be overwhelmed by the COVID-19 pandemic, and explore associations of low access areas with their socioeconomic and demographic characteristics. We use a three-step floating catchment area method, spatial statistics, and logistic regression to achieve the goals. Findings of this research in the State of Florida revealed that North Florida, rural areas, and zip codes with more Latino or Hispanic populations are more likely to have lower access than other regions during the COVID-19 pandemic. Our approach can help policymakers identify potentially possible low access areas and establish appropriate policy intervention paying attention to those areas during a pandemic.

**1. Introduction**

Since COVID-19 first appeared at the end of 2019 in Wuhan, China, most countries have suffered catastrophic economic and health problems. As of December 2020, the cumulative number of COVID-19 cases has exceeded 14 million in the United States and 67 million worldwide (WHO, 2020). There have been various health policies, guidelines, and efforts, such as quarantines, lockdowns, and travel restrictions to mitigate the spread of the virus. Although there was a significant decrease of daily COVID-19 cases as of August 2020 in the U.S., the number of cases increased again in the winter given greater indoor activity.

There have been substantial research efforts with a focus on transport policy against the COVID-19 pandemic. A study by Zhang et al. (2020) that conducted a world-wide expert survey for COVID-19 and transportation noted that preparation for the current COVID-19 pandemic was not sufficient and stressed that preparedness plays an important role in preventing and mitigating the adverse impacts of pandemics. In that vein, Zhang (2020) has proposed a PASS (Prepare-Protection-Provide, Avoid-Adjust, Shift-Share, Substitute-Stop) approach targeting transportation-related stakeholders such as users, operators, and governments. Likewise, responsible transport as a new concept has been proposed to mitigate the impacts of pandemics on our society, highlighting individuals’ awareness and responsibility on their travel behavior (Budd and Ison, 2020).

Empirically, it has been highlighted that transportation is intricately linked to outcomes of the COVID-19 pandemic, which supports the importance of a transport policy intervention. For example, some studies conducted in Japan (Zhang et al., 2020a) and Italy (Carteni et al., 2021) demonstrated that transportation accessibility has a positive association with COVID-19 infections, and a study by Li et al. (2021), which highlighted the role of inter-city travels, suggested that limiting inter-city travels may help mitigate the spread of COVID-19 in China. Moreover, given the finding that transportation insecurity is likely to correlate with a higher risk of COVID-19 infection, the importance of transport policy aimed at managing risk during the COVID-19 pandemic can not be underemphasized.

In addition to transport policy, it is also important to provide disbursed healthcare resources such as intensive care units (ICU) beds and ventilators for recovering COVID-19 patients because there are potential associations between COVID-19 mortality and healthcare resources availability (Ji et al., 2020). However, the uneven geographical distribution of hospitals with ICU beds could lead to unequal access of...
COVID-19 patients to needed healthcare resources (Zhang et al., 2020b). In terms of socio-demographic characteristics, existing research focusing on COVID-19 suggests that minority status and one’s native language were associated with COVID-19 outcomes, and this association tends to be stronger in rural communities than in urban communities (Cheng et al., 2020; Khazanchi et al., 2020). It is implied then that the uneven distribution of healthcare resources makes a difference in COVID-19 outcomes between rural/urban and race/ethnicity.

In the broader literature, it has been recognized that access to healthcare resources is critical to overall population health (Guagliardo, 2004), and numerous researchers have investigated accessibility to healthcare resources and facilities (e.g., Apparicio et al., 2008; Ghorbanzadeh et al., 2020; Langford and Higgs, 2006; Luo and Qi, 2009; Luo and Wang, 2003; Yin, 2018). However, given the recent timing and onset of this disaster, there have been limited studies examining accessibility to healthcare resources in the context of the COVID-19 pandemic. As Zampieri et al. (2020) noted, people having poor access to hospitals with ICU beds during this pandemic may be one of the influential factors decreasing mortality. Along these lines, it was found that geographical access to ICU beds was associated with case fatality ratio (CFR) due to COVID-19 in Europe (Bauer et al., 2020). Researchers concluded that low accessibility to ICU beds was related to a higher ratio (CFR) due to COVID-19 in Europe (Bauer et al., 2020).

Outside the U.S., Pereira et al. (2021) observed socioeconomic, demographic, and spatial disparities in spatial accessibility to ICU beds in Brazil. In the context of Wuhan, China, Zhou et al. (2021) examined accessibility to healthcare facilities associated with COVID-19 symptoms, using travel distance and time collected by API of online map services. The study found notable disparities in service areas, which implies spatial inequity of services. Given the range of approaches available for addressing accessibility to healthcare, the two-step floating catchment area (2SFCA) method-based accessibility measures have been applied to different types of healthcare facilities; for instance, hospitals (Delamater, 2013), primary cares (Gilliland et al., 2019; Langford and Higgs, 2006; Luo and Qi, 2009; Luo and Wang, 2003; McGrail and Humphreys, 2009; Wan et al., 2012), and mental healthcare (Ghorbanzadeh et al., 2020; Ngamini Ngui and Vanasse, 2012). The 2SFCA method, introduced by Luo and Wang (2003), combines an accessibility metric based on service coverage with a measure of provider-to-population ratios. More generally, the 2SFCA method considers the geographical distribution of patients and physicians. Another advantage of this method is that the method can control capacity restrictions, local competition for services, and cross-border healthcare-seeking behavior (Neutens, 2015; Page et al., 2018). However, the method also has a limitation, which is the overestimation of patient demand since local needs are redundantly calculated at the physician locations.

Since Luo and Wang (2003) introduced this approach, the method has been incrementally enhanced, including the incorporation of variable catchment size (McGrail and Humphreys, 2009), distance decay effects (Enhanced 2SFCA) (Luo and Qi, 2009), age-adjusted health care demand (Ngamini Ngui and Vanasse, 2012), multiple transportation modes (Multimode 2SFCA) (Mao and Nekorchuk, 2013), and the consideration about overestimation of demand (3SFCA) (Wan et al., 2012). Nevertheless, recent studies of COVID-19 have applied only the basic forms of 2SFCA, such as the general 2SFCA (Tao et al., 2020) and P-E2SFCA (Kang et al., 2020), although there have been other methodological advances in the 2SFCA approach as mentioned above.

To better understand the COVID-19 pandemic through the lens of spatial accessibility, we seek to contribute to the literature of spatial accessibility to COVID-19 healthcare resources and transportation/public healthcare policy by answering the following three research questions in this paper. First, when we focus on different time periods according to COVID-19 confirmed case patterns, is the COVID-19 infections pattern stable across space and time? Previous literature, in general, has utilized the cumulative number of COVID-19 cases (e.g., Ghorbanzadeh et al., 2021; Kang et al., 2020), whereas the number of COVID-19 patients at a given time varies by the number of recovered patients and mortality rates. Second, is spatial accessibility of COVID-19 patients to healthcare resources stable given the dynamic spatial patterns in the number of COVID-19 cases? In other words, which areas are more likely to be overwhelmed by the COVID-19 pandemic than others? Lastly, what are the socioeconomic and demographic characteristics of low accessibility areas across different time periods? In order to respond to these questions, we examine different space-time patterns of COVID-19 cases and compute spatial accessibility to healthcare resources by using the 3SFCA method with the spatial distribution of COVID-19 cases accounting for recovery and mortality. Using local Moran’s I, the areas with high and low access to healthcare resources across time periods are identified. Lastly, employing logistic regression, we attempt to explore potential associations between low access areas and their socioeconomic and demographic characteristics. This approach will help policymakers who are involved in transportation and public healthcare better understand the spatial dynamics of the COVID-19 pandemic. It will also help allow them to establish policy interventions to deal with the current health crisis and prepare for future pandemics.

This study focuses on the State of Florida which is the third most populous state in the U.S. Florida also ranks third after California and Texas in the number of positive COVID-19 cases (CDC, 2020). Furthermore, the Florida Department of Health provides disaggregate data on COVID-19 cases publicly available based on zip code areas. With this rich source of information on COVID-19, we anticipate that this paper will help better understand the COVID-19 pandemic and facilitate new insights for planners charged with appropriate responses.

The remainder of this paper is organized as follows. The next section describes the study area and data sources that were used in this paper. In the third section, we present the methodology, which includes the 3SFCA method, local Moran’s I, and a logistic regression. Section four presents the results of our analyses. In the last section, we conclude with a discussion about COVID-19-focused accessibility and its policy implications for future pandemics.

2. Study area and data

The State of Florida is the third most populated state in the U.S. During the COVID-19 pandemic, the cumulative total number of cases exceeds one million in Florida as of December 2020. In this paper, both spatial accessibility and clusters are computed using information such as the number of COVID-19 cases at the zip code level, hospitals with ICU beds, and travel times. Moreover, the relationships between socioeconomic and demographic characteristics and spatial accessibility to healthcare services are also examined.

Fig. 1 illustrates the study area with urban and rural zip codes and locations of hospitals along with the number of ICU beds in Florida. Most of North Florida and South Florida’s inland areas are considered as rural as seen in Fig. 1a. This rural and urban classification of zip codes was done with a definition on “rural” given by the Florida Department of Transportation – Office of Policy Planning (FDOT OPP) (Florida Department of Transportation Office of Policy Planning, 2018, p. 6) and the Federal Office of Rural Health Policy (FORHP) (Health Resources and Services Administration, 2017). By combining rural zip codes provided by FDOT OPP and FORHP, 157 rural zip codes and 782 urban zip codes were identified in Florida. The ICU bed data are collected by the Florida Department of Health (FDH), the Federal Office of Rural Health Policy (FORHP), and the Federal Office of Rural Health Policy (FORHP). More specifically, the number of COVID-19 cases accounted for recovery and mortality.

For this study, we focus on the crowdsourced location data of COVID-19 patients in Florida, which were collected and made publicly available by the Florida Department of Health (FDH). The data include the number of positive COVID-19 cases publicly available based on zip code areas. With this rich source of information on COVID-19, we anticipate that this paper will help better understand the COVID-19 pandemic and facilitate new insights for planners charged with appropriate responses.
Definitive Healthcare and Healthcare Cost Report Information System (HCRIS) via the CovidCareMap (CovidCareMap, 2020) and presented in Fig. 1b. There are 208 hospitals with 6062 ICU beds. Hospitals with more than 200 ICU beds are located in Alachua County and Orange County, and hospitals with 50–100 ICU beds are mainly located in large metropolitan areas such as the cities of Jacksonville, Tampa, and Miami. As shown in Fig. 1b, ICU beds are scarce in Northwest Florida (i.e., around the City of Tallahassee). It may imply that people there would be more vulnerable to a potential COVID-19 crisis.

We collected the COVID-19 cases data set from the Florida COVID-19 Hub (Florida COVID-19 Hub, 2020), which provides the archive of COVID-19 daily data at county and zip code levels since April 2020. According to this data, the number of daily COVID-19 cases sharply increased in the middle of June, peaked in the middle of July, and then decreased as of August (Fig. 2). While various criteria determine the recovery period (e.g., the World Health Organization (WHO): 4–8 weeks, the Centers for Disease Control and Prevention (CDC): 2 weeks), considering the average recovery period suggested by WHO, we divide the whole period into three with four weeks: early, spreading, and stable. Thus, the early period is from May 15th to June 15th, the spreading period is from July 1st to July 31st, and the stable period is from September 1st to September 30th. The number of COVID-19 cases is 33,145 in the early period, 312,016 in the spreading period, and 79,437 in the stable period.

We collected socioeconomic and demographic information obtained from the American Community Survey (ACS) 2019 5-year estimates provided by the U.S. Census Bureau in terms of potentially vulnerable populations. This data is available at the zip code level and used to explore associations between areas with poor access to ICU beds and their socioeconomic and demographic characteristics. The data are pulled with the census Application Programming Interface (API) from the U.S. Census Bureau. Selected socioeconomic and demographic population groups consist of age (65-year-old or over), race/ethnicity (Asian, Black or African Americans, Latino or Hispanic, White), and poverty level.

We employ the Open Source Routing Machine (OSRM) to compute travel times between demand locations (i.e., zip code centroids) and service site (i.e., hospitals), which is executed in R (R Core Team, 2020). OSRM allows us to find the shortest paths using a detailed road network and returns the travel times between locations based on OpenStreetMap (Haklay and Weber, 2008).

Fig. 1. Illustration of the study area. (a) Urban and rural zip codes, (b) locations and number of ICU beds in Florida.

Fig. 2. Daily COVID-19 cases.
3. Methods

We measure the spatial accessibility of COVID-19 patients to healthcare resources, explore spatial clusters of the spatial accessibility, and then finally estimate which areas are more likely to be possibly overwhelmed by a shortage of COVID-19 healthcare opportunities. Specifically, the spatial accessibility is measured by 3SFCA, the spatial clusters are explored by local Moran’s I, and the logistic regression is used to estimate the odds of being a low access area. This series of analytic procedures have been adopted elsewhere (e.g., Andresen, 2011; Tsai et al., 2009) and it will help us answer the above-mentioned research questions. To find and understand clusters with high and low values in the procedures, local Moran’s I, G*, and z-scores have been employed (e.g., Andresen, 2011; Kang et al., 2020; Tsai et al., 2009). For COVID-19 healthcare accessibility research, while Kang et al. (2020) used z-scores, we applied local Moran’s I to explore statistically high and low access areas (i.e., determining hot and cold spots of accessibility statistically), which reflects local relationships. Combining this analytic framework with the statistical methods will help us to better understand spatial variations in COVID-19 healthcare opportunities allowing officials to target resources towards areas overwhelmed by these kinds of pandemics. These analyses and visualizations were implemented in an R environment, which is open-source software for statistical computing (R Core Team, 2020).

3.1. 3SFCA

Since Luo and Wang (2003) introduced the 2SFCA method, numerous variants of the method have been developed and the basic 2SFCA method still has been widely used to assess spatial accessibility to healthcare services. In this paper, noting a shortcoming of the 2SFCA method that local demand is overestimated, we use the three-step floating catchment area (3SFCA) method developed by Wan et al. (2012) that takes into account the overestimation issue and focus on accounting for the 3SFCA method since the basic 2SFCA method has been well explained elsewhere (e.g., Luo and Qi, 2009; Luo and Wang, 2003; Wan et al., 2012). The 3SFCA method is computed with three steps, as the name implies.

In the first step, a selection weight between demand location and service site is computed with Gaussian weight. Wan et al. (2012) suggested that 3SFCA employs the Gaussian function for the distance impedance because it has been revealed better than other types of weight functions.

\[
G_{ij} = \exp\left(-\frac{d_{ik}}{\tau_0}\right)
\]

where \(G_{ij}\) is the selection weight between demand location \(i\) and service site \(j\), \(\text{Dist}(i,k)\) is the travel cost (distance or time) from \(i\) to any service site \(k\) within the catchment, and \(d_0\) is the predefined catchment size.

In the second step, the provider-to-population ratio of \(j\) is computed, dividing catchment areas into several sub-zones that helps minimize the problem of overestimation of local demand.

\[
R_j = \sum_{s \in r=1,2,3,4,5} S_j G_s P_s W_r
\]

where \(R_j\) is the provider-to-population ratio at service site \(j\). \(S_j\) is the healthcare resources of service site \(j\), which means the number of ICU beds of \(j\)th hospital, \(W_r\) is the impedance of the \(r\)th sub-zone \(D_r\), \(G_k\) is the selection weight between demand location \(k\) and service site \(j\), and \(P_k\) is the demand size of \(k\). In this study, \(P\) is the number of COVID-19 cases and \(j\) is the number of ICU beds of the hospital \(j\). While the original 3SFCA method considers four sub-zones (10, 20, 30, 60, 130 min), this study considers five sub-zones (10, 20, 30, 60, 130 min) to include an area with the minimum travel time to the nearest hospital. Each sub-zone’s average travel time is represented as 5, 15, 25, 45, and 95 min and used to compute \(W_r\). The impedance value is 1960 so that the Gaussian weight for the last zone is always greater than 0.01 (Kwan, 1998).

In the third step, the spatial accessibility of demand location \(i\) is computed as follows.

\[
A_i^s = \sum_{r=1,2,3,4,5} G_{ij} R_j W_r
\]

where \(R_j\) is the provider-to-population ratio of demand location \(j\) derived from the second step, \(G_{ij}\) is the selection weight between \(i\) and \(j\), and \(W_r\) is the Gaussian weight of the \(r\)th sub-zone \(D_r\).

Like other accessibility measures, a high value means better accessibility. However, since there are no criteria for what low accessibility is, it is difficult to identify areas potentially overwhelmed with COVID-19. As such, to identify these areas, local Moran’s I is utilized in order to find spatial clusters.

3.2. Local Moran’s I

In order to find spatial clusters of areas with high or low spatial accessibility to healthcare resources, local indicators of spatial association (LISA) can be employed. As Anselin (1995) noted, LISA can be any statistic that satisfies two requirements: (1) the LISA for each observation gives an indication of the extent of significant spatial clustering of similar values around that observation. (2) the sum of LISAs for all observations is proportional to a global indicator of spatial association. While there are various types of LISA such as Getis-Ord local G statistic and local Geary’s c, local Moran’s I have been employed to attempt capturing both spatial clusters and outliers.

\[
I = \frac{\sum_{i,j} w_{ij}(y_i - \bar{y})(y_j - \bar{y})}{\sum_{j}(y_j - \bar{y})^2}
\]

where \(I\) is the indicator of local Moran’s I, and spatial weights, \(w_{ij}\), is determined by first-order queen contiguity weights. Local Moran’s I generates four types of spatial associations: high-high, high-low, low-high, low-low. High-high type means the spatial cluster with high values, and low-low type indicates the spatial cluster with low values. In other words, high-high type clusters can be interpreted as a set of areas with high accessibility and low-low type clusters will be those with low accessibility. On the other hand, high-low and low-high types indicate the spatial outliers or spatial pockets that different values surround an area.

In this analysis, we focus on the low-low type clusters more than...
other types because the identified low-low type clusters represent areas where their residents may struggle to find healthcare resources due to poor access to ICU beds. However, given that local Moran’s I is determined by a global mean and local relationships, it would not necessarily be the case that areas identified as low-low clusters have the lowest accessibility overall or globally. Nevertheless, based on the conducted state-level analysis, calculating a local Moran’s I value can enable us to find a set of low access areas at a sub-regional level in Florida.

3.3. Logistic regression

To identify socioeconomic and demographic characteristics of low access areas during the COVID-19 pandemic, a logistic regression is implemented to estimate the odds of being a low access area. As an outcome variable, two types of areas are employed: high access area and low access area, which are thought of as binary outcomes that take on the values 0 and 1, respectively, obtained from the local Moran’s I analysis.

Since the logistic regression is well suited for describing associations between the outcome variable and explanatory variables (Peng, 2016), it has been used to describe possible relations between low accessibility and an area’s socio-demographic characteristics. The purpose of this regression analysis is to capture which socioeconomic and demographic properties are related to being low access areas during the COVID-19 pandemic. Thus, we model the relationship, considering four-type explanatory variables, such as rural/urban, older population, race/ethnicity, and poverty. During this modeling, we refer to studies by Kang et al. (2020) that used a social vulnerability index consisting of socioeconomic status, minority status, and age composition in households and Pereira et al. (2021) that compared accessibility by age, income, and race. The linear form of the logistic regression is as follows.

$$\logit(Y) = \alpha + \beta_1 X_1 + \beta_2 X_2 + \ldots$$

(5)

where the outcome variable, Y, takes 1 or 0 according to the area’s cluster type. Explanatory variables, Xi, represent the aforementioned four-type explanatory variables and βi is the coefficient of each explanatory variable. Explanatory variables include urban/rural, age, race/ethnicity, and poverty as socioeconomic and demographic characteristics and the number of COVID-19 cases as a control variable. Specifically, for each explanatory variable, we anticipate that the number of COVID-19 cases will be positively associated with increasing odds of being a low access area. Rural and urban zip codes were classified by using the FDOT OPP and FORHP definition as illustrated in Fig. 1a. In general, given that transportation networks are less developed and less dense in rural areas than urban areas, rural zip codes are more likely to be associated with being low access areas than urban zip codes. The age variable focuses on older populations. Since the older populations with age 65 or over tend to be more vulnerable to COVID-19 (Blackburn et al., 2020), a positive association between older populations and low access areas will indicate a negative sign. Race/ethnicity is divided into four groups: Asian, Black or African Americans, Latino or Hispanic, and White. With these variables, we will be able to capture race/ethnicity differences. Lastly, populations below the poverty level is an indicator of income and is included in the model since low-income populations may face a lack of available transportation options to healthcare resources (Syed et al., 2013).

4. Results

Fig. 3 shows the spatial distribution of the number of COVID-19 cases and their corresponding variations over periods. In the early period, the areas with less than 100 cases accounted for the most in Florida. As the number of COVID-19 cases increases, the areas with more than 500 cases increased during the spreading period. In the spreading period, most urban areas had suffered increased COVID-19 cases, for example, Miami, Tampa, Orlando, and Jacksonville. In the stable period, when the number of COVID-19 cases was only double of the cases in the early period, the spatial distribution looks different. South Florida seems it suffered during the early period, whereas there were more cases in North Florida than South Florida. This pattern implies that the spatial distribution may differ across periods.

4.1. Spatial accessibility to healthcare resources

As seen in Fig. 4, the result of 3SFCA is visualized across three periods. Since the maximum and minimum values of the 3SFCA differ in each period, we do not classify values with a particular classification method. Instead, readers can compare them within a certain period; for instance, the darker blue areas indicate higher spatial accessibility. On the other hand, the darker red areas get lower spatial accessibility they have. The areas colored by yellow indicate an average level of accessibility.

During this pandemic, North Central Florida around Gainesville has higher accessibility than others. In contrast, while the level of accessibility in Northwest Florida around Tallahassee was close to the average in the early period, the level of accessibility has worsened over periods. It is worth noting that the proximity to healthcare resources is crucial to determine the level of accessibility, as the hospital with the large number of ICU beds located in North Central Florida seems to lead high level of accessibility in North Central Florida compared to Northwest Florida, where lacks hospitals with ICU beds (Fig. 1).

![Fig. 3. Changes in the number of COVID-19 cases over time periods.](image-url)
The large urban areas such as Miami, Tampa, Orlando, and Jacksonville have a high level of accessibility compared to their high number of COVID-19 cases during the spreading period. Even though they have a large number of COVID-19 cases, they also have a corresponding number of ICU beds resources in their areas. In contrast to the large urban areas, Northwest Florida and South Florida, a relatively rural area, seem to suffer from a lack of ICU beds resources during the spreading and stable periods.

4.2. Identifying overwhelmed areas

In general, local Moran’s I generates four types of spatial associations: high-high, high-low, low-high, and low-low. However, since our result only shows high-high and low-low types because other types were not detected within a 0.05 significance level, we focus on two types of clusters: high-high and low-low clusters. Typically, the high-high clusters are colored as red and low-low clusters are colored as blue. However, in Fig. 5, the color scheme is reversed because high-high clusters mean a cluster of high accessibility (better than others) and low-low clusters indicate a cluster of low accessibility (worse than others). We refer to them as ‘high access area’ and ‘low access area,’ and we also consider the low access area as ‘the area overwhelmed by COVID-19’ because people living in low access area are more likely to struggle to get access to healthcare resources than people living in high access areas.

Similar to the patterns of spatial accessibility of Fig. 4, high access areas were clustered around North Central Florida and low access areas were clustered in Northwest Florida across time periods (Fig. 5). In addition, South Florida was detected as low access area across the periods. In terms of the number of each cluster, the number of high access areas has monotonically decreased (134–126–72). On the other hand, the number of low access areas has increased then decreased (65–158–104). In particular, during the spreading period, Miami-Dade County may have suffered from the pandemic; however, the low access areas have disappeared after this period.

It is observed that low access areas have more expanded to rural areas than urban areas. As low access areas disappeared in Miami-Dade County, some high access areas appeared in the Tampa Bay area, and then low access areas expanded to Northwest Florida during the stable period. This implies that rural areas are more likely to suffer from the COVID-19 pandemic than urban areas.

4.3. Associations between low access areas and their socioeconomic and demographic characteristics

Since low access areas, which may struggle to get access to healthcare resources, are of our interest, this section aims to explore associations between low access areas and their socioeconomic and demographic characteristics by estimating the odds of being a low access area. To achieve this goal, the logistic regression is conducted with high access area vs. low access area as the outcome variable and other explanatory variables. Our explanatory variables include the following: rural/urban, age, race/ethnicity, and poverty. Each category is...
represented by proxy variables. As an indicator of each category, rural and urban zip code classification (Rural zip code) represents the rural/urban area, older populations (Older pop, population with 65-year-old or over) is used for age, Asian, Black or African Americans (Black), Latino or Hispanic (Hispanic), and White (alphabetical order) are used for race/ethnicity, and populations below the poverty level (Below poverty) represent the poverty. The number of COVID-19 cases per 1000 populations (Cases/1000 Pop) is included in the models to control the explainable variance of the model. The logistic regression models’ outcome variable is area types, i.e., high access area and low access area are coded as 0 and 1, respectively. Since the reference is high access areas, we convert log odds ratio (\( \log \text{OR} \)) into odds ratio (\( \text{OR} \)) which allows us to interpret the estimates as the percent changes of odds or times. We account for their meanings, focusing on the statistically significant variables with a 0.05 significance level. Cases/1000 Pop was statistically significant and increased the odds of getting into low access areas for a one-person increase in the cases in the early and stable models. For example, when the number of cases per 1000 population increased by one, the zip code area was about 3.17 times more likely to be a low access area in the early period. Rural zip code was statistically significant across all models and had a great association with getting into a low access area compared to a high access area. In particular, rural zip code was about 44 times more likely to be a low access area compared to a high access area. In particular, rural populations may have been more likely to be overwhelmed during the early and stable periods.

According to the results, obviously it can be stated that spatial patterns of COVID-19 cases are not homogeneous. Rural areas’ patients seem to have the most difficulty in accessing healthcare resources, and limited transportation systems may be stressed in coping with the COVID-19 pandemic. It can be easily posed that the distribution of the cases can differ across subregions even though the total number of COVID-19 cases across the state is consistent over the time periods. For instance, while the total number of cases during the stable period was similar to that during the early period, the spatial patterns of cases and accessibility between the two time periods differed in subregions. In addition to these dynamic patterns of COVID-19 cases, the uneven distribution of healthcare resources can lead to substantial variation in spatial accessibility to healthcare resources. As a result, Northwest Florida around Tallahassee, which was an area that was not severely affected by COVID-19, becomes the most vulnerable area during the stable period. That means these areas are under relatively more vulnerable conditions from COVID-19 than other areas. As Bauer et al. (2020) and Ji et al. (2020) noted, low accessibility to ICU beds may result in high COVID-19 related deaths; thus, Northwest Florida, South Florida, and large Latino or Hispanic communities may be vulnerable to COVID-19 mortality due to a shortage of healthcare resources relative to a large number of cases.

The results of the logistic regression analysis presented that areas with more Latino or Hispanic populations were more likely to be low access areas than high access areas during the early and spreading periods. This finding implies that Latino or Hispanic populations living in low access areas may be challenging to cope with the COVID-19 pandemic and shortage of healthcare resources than that of populations living in high access areas during the early and spreading periods. However, this pattern was not presented in the stable period. Policymakers can pay attention to Latino or Hispanic communities during the early period of a pandemic to help Latino or Hispanic populations appropriately access healthcare resources.

Another notable finding from the regression analysis showed that rural areas are more likely to have low access than urban areas across all time periods in Florida. This may be due to the shortage in healthcare resources and less developed transportation systems (e.g., road networks) in rural areas as compared to their urban counterparts. To
promote access to healthcare resources for rural communities that have limited access to healthcare services and public transit, one promising future transport policy intervention that can be recommended is the use of advanced transportation technologies such as Autonomous Vehicles (AVs) and drones (Bernhart et al., 2018). AVs or drones have the potential to significantly help the communities reduce the impacts of such a pandemic by transporting medical supplies, food, and other essential goods to the public in order to cope with the spread of the virus. This can be achieved by limiting the exposure of people and more specifically healthcare personnel. AVs and drone technologies can be utilized widely by delivery and logistics companies to transport goods without putting anyone’s life at risk by getting infected with COVID-19 (Bailey, 2021; Boll, 2020).

For example, during the COVID-19 pandemic, AVs have been used in a limited fashion to transport COVID-19 tests from a drive-through testing site to the processing laboratory around the Mayo Clinic campus located in Jacksonville, Florida (Roads and Bridges, 2020). In addition, 104 AVs were used in 17 cities across China to deliver supplies and food to ease the burden of the pandemic (MIT Technology Review, 2020). These technologies such as AVs and drones can play an important role in the upcoming years by supporting the residents and more specifically people who live in the suburban and rural areas due to the lack of healthcare resources in those regions.

Summarily, the findings of this study point out that the number of COVID-19 cases can vary across time periods, and rural areas, where there is a lack of healthcare resources and transportation systems are less developed, are more likely to be overwhelmed by the COVID-19 pandemic, unlike the early period. These findings and obtained knowledge of this study can provide valuable information for public health planners and policymakers to cope with the pandemic and are in line with the need for policymakers to focus on local characteristics to cope with the pandemic (Dandapat, 2020). In particular, from an accessibility perspective, decision-makers can take into consideration not only the number of COVID-19 cases but also the geographical distribution of healthcare resources and the role of transportation systems. For instance, to mitigate potential barriers to healthcare resources, transporting healthcare resources by new transport technologies such as AVs and drones and flexible allocation of ICU beds to rural areas and Latino or Hispanic communities can be considered for this and the next pandemic. Furthermore, while it may be thought that the study time periods were arbitrarily selected given the availability of data and timing of research, the overall benefit of our work is giving additional attention to rural areas. This is very important given for policymakers in future pandemics, given that rural zip codes kept being identified as low access areas.

While these findings are clear to help better understand the COVID-19 pandemic from an accessibility perspective, the outcomes should be treated with appropriate caution with some limitations. First, this study was conducted in the State of Florida. Other states could be analyzed within the same framework. Typically, it has been anticipated that urban areas may suffer more from the COVID-19; however, in Florida, it was found that rural areas are more likely to suffer from the pandemic. Second, the travel time calculation using the centroid of a zip code area might be less accurate in rural areas than urban areas because rural zip code area generally covers a more extensive area than urban zip code area. While some city-level governments provide a more geographically detailed data set, there is no available comprehensive data for the states that we focus on. If the COVID-19 data set is provided at the census tract or census block groups levels, a more detailed statewide accessibility analysis could be implemented. Third, the present paper only considered travel time by a car in measuring accessibility; however, other transportation modes such as walking or public transit might show different accessibility results if they were included. Given that public transit is not generally available across the whole State of Florida (i.e., rural areas have very limited transit services), different transportation modes could not be systematically considered in this analysis. However, this issue could be accounted for a micro-level study (e.g., in a city) where both private vehicles and public transit are available. Fourth, although traffic congestion might produce different accessibility outcomes between urban and rural areas, it was out of scope for our analysis. In particular, given that travel time in urban areas would be longer during rush hours, it would be worth noting that accessibility in urban areas might be overestimated in our results. Lastly, even though spatial accessibility is closely related to land use and transportation, the logistic regression analysis did not account for these elements due to our chosen analytical focus that tried to explore a relationship between low accessibility and residents’ socio-demographic characteristics. If this association was modeled, it may provide insights into areas needing additional mitigation, which would inform planning for a future pandemic.

With regard to our focus on accessibility, various transportation modes would be considered for future study. As we have pointed out, since transportation modes can include walking, car, or public transit usage based on personal and/or regional availability, alternative accessibility measures based on different transportation modes can be developed and evaluated. In addition, for possible future pandemics, we suggest that a geographic surveillance system can be established based on this study’s analytic framework. For example, spatial accessibility analysis based on real-time surveillance of spreading disease and patients with healthcare resources can help policymakers to make resource and tactical decisions. Lastly, since information about COVID-19 mortality has accrued prior to the time before and after completion of this research, the association of accessibility and COVID-19 mortality can be examined in future efforts. This would further highlight the role of spatial accessibility in this pandemic.

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