

Spatial accessibility assessment of COVID-19 patients to healthcare facilities: A case study of Florida

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ABSTRACT

During the COVID-19 pandemic, healthcare facilities worldwide have been overwhelmed by the amount of coronavirus patients needed to be served. Similarly, the U.S. also experienced a shortage of healthcare resources, which led to a reduction in the efficiency of the whole healthcare system. In order to evaluate this from a transportation perspective, it is critical to understand the extent to which healthcare facilities with intensive care unit (ICU) beds are available in both urban and rural areas. As such, this study aims to assess the spatial accessibility of COVID-19 patients to healthcare facilities in the State of Florida. For this purpose, two methods were used: the two-step floating catchment area (2SFCA) and the enhanced two-step floating catchment area (E2SFCA). These methods were applied to identify the high and low access areas in the entire state. Furthermore, a metric, namely the Accessibility Ratio Difference (ARD), was developed to evaluate the spatial access difference between the models. Results revealed that many areas in the northwest and southern Florida have lower access compared to other locations. The residents in central Florida (e.g., Tampa and Orlando cities) had the highest level of accessibility given their higher access ratios. We also observed that the 2SFCA method overestimates the accessibility in the areas with a lower number of ICU beds due to the “equal access” assumption of the population within the catchment area. The findings of this study can provide valuable insights and information for state officials and decision makers in the field of public health.

1. Introduction

Rapid population growth, urbanization, and economic development have been creating challenges in providing transportation-based accessibility to all segments of the population over the last decade (Litman, 2020; Ozel et al., 2016). This is especially critical when we consider ensuring the transportation-based accessibility to essential facilities such as healthcare providers since these facilities provide important services to people (Freeman et al., 2020; Ghorbanzadeh et al., 2020a). During a disaster such as the COVID-19 pandemic, this issue becomes all the more confounding since these facilities play crucial roles in helping their communities to better prepare and recover from this uncontrolled outbreak (Carteni et al., 2021; Shamshiripour et al., 2020). For example, over the last six months, a drastic increase in the number of coronavirus

patients caused a shortage of healthcare resources such as Intensive Care Unit (ICU) beds and ventilators in the U.S. (White and Lo, 2020; Xie et al., 2020). The high demands for these services led to a reduction in the efficiency of the entire healthcare system (Hao, 2020; Mangan and Schoen, 2020).

The World Health Organization (WHO) announced more than 94 million confirmed COVID-19 cases worldwide as of January 19, 2021 (World Health Organization WHO (2021)). The U.S. with approximately 24 million COVID-19 cases and over 400,000 total deaths ranked first in comparison to other countries. Among the U.S. states, Florida is among the top three states with regard to the high number of cases (CDC, 2021). On January 19, 2021, the Florida Department of Health announced 1,589,097 cases and 24,436 deaths due to coronavirus throughout the state, which have been gradually increasing (Florida Department of

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Health, 2021). According to the Centers for Disease Control and Prevention (CDC), the older population (65 +) and those with serious medical conditions such as lung disease, diabetes, liver disease, and other chronic issues are at a higher risk to get infected with COVID-19 (CDC, 2020; Govindan et al., 2020). Especially since Florida is a state with a substantial aging population, with people living in assisted living facilities or independently, the issue becomes even more challenging. As such, understanding the extent to which Florida healthcare facilities are available to the public in both urban and rural areas is crucial (Dejen et al., 2019; McLafferty, 2015).

There are several studies in the literature that have focused on measuring transportation-based accessibility to different public service facilities such as healthcare facilities (Paez et al., 2010; Shah et al., 2016), libraries (Ghorbanzadeh et al., 2020b), supermarkets (Niedzielski and Kucharski, 2019; Widener et al., 2015), shelters (Kocatepe et al., 2016), and urban parks (Chang et al., 2019; Omer, 2006). Different methods have been employed to evaluate spatial accessibility including gravity models (Joseph and Bantock, 1982; Luo and Wang, 2003), regional availability models (Khan, 1992), and kernel density models (Gaugliardo, 2004). Among the gravity models, the two-step floating catchment area (2SFCA) method has been widely used in the literature for measuring accessibility due to its ease of applicability (Wang, 2014). The basic 2SFCA method was defined by Radke and Mu (2000) as a special form of the gravity model and later modified by Luo and Wang (2003). The 2SFCA approach measures the spatial accessibility through a two-step procedure based on the interaction between supply and demand within a certain catchment, as a ratio of physician-to-population (Radke and Mu, 2000). Numerous studies have utilized the 2SFCA method in order to measure the spatial accessibility to healthcare facilities (Chen and Jia, 2019; Dai and Wang, 2011; Zhu et al., 2018). For example, Ngamini Ngui and Vanasse (2012) conducted a 2SFCA analysis to assess the spatial accessibility of mental health services in the southwest of Montreal, Canada. The findings of this study revealed the areas without access to these facilities.

In addition to the 2SFCA, the enhanced two-step floating catchment (E2SFCA) area and three-step floating catchment area (3SFCA) methods also can measure spatial accessibility (Luo and Qi, 2009; Wan et al., 2012). For example, Wan et al. (2012) applied the 3SFCA method to identify the areas with a healthcare shortage in the Austin-San Antonio area. This method was intended to reduce the demand overestimation problem inherent of previous models. Rekha et al. (2017) conducted a 3SFCA method to evaluate the accessibility to healthcare facilities in a case study in India. Chen et al. (2020) proposed a reliability-based 2SFCA method to measure healthcare accessibility under travel time uncertainty. Kocatepe et al. (2017) conducted an empirical-Gaussian two-step floating catchment area (EG-2SFCA) method to assess the proximity of different age groups to severe injury crash hotspots in the Tampa Bay region, Florida. Luo et al. (2018) conducted an E2SFCA method to measure the accessibility to medical services in Wuhan, China with a focus on the aging population. The findings showed that approximately 50% of the aging population had the highest level of accessibility to medical centers within 10 min distance (Luo et al., 2018). In another study, Donohoe et al. (2016) applied the 2SFCA method by considering different decay weights (fast-decay and slow-decay) and catchment sizes to assess the spatial access to mammography centers in the Appalachia region in the U.S. The results revealed that urban areas had the highest access; however, the Philadelphia region obtained poor access scores. Another interesting finding of their study is that rural eastern Kentucky obtained the highest access scores, probably due to the low population density and even spatial distribution of mammography centers in the state.

There is still a research gap in the literature with regards assessing the spatial access to healthcare facilities during a global pandemic such as the COVID-19 outbreak in which the demand for this type of facility increases dramatically. As such, this study aims to measure the spatial accessibility of COVID-19 patients to healthcare facilities in the State of

Florida. For this purpose, the 2SFCA and E2SFCA methods were utilized in order to identify the areas with high and low levels of accessibility to healthcare services given the number of confirmed coronavirus cases (demand) and the number of ICU beds (supply). More specifically, this study aims to answer the following research question: *To what extent do potential COVID-19 patients in Florida have access to healthcare resources and which areas may experience potential resource shortages during the pandemic?* The findings of this study can provide crucial and valuable insights for the field of public health that can lead to providing better access to healthcare resources. The modeling approach and results will be discussed in detail in the following sections.

2. Study area and data description

Based on the 2014–2018 American Community Survey (ACS) estimates, as of 2018, the total population of Florida was more than 20 million people where 4,064,376 of them were age 65 years and over. This is more than 20% of the total population in the state (American Community Survey (ACS), 2020). Fig. 1 depicts an overview of the study area. In this study, different data sources were employed including the confirmed COVID-19 cases in Florida at the zip code level, healthcare facilities as well as counts of the corresponding ICU beds to care for COVID-19 patients in these facilities, and the roadway network. The COVID-19 cases data were provided by the Florida Department of Health (Florida Department of Health, 2020). Furthermore, the data related to the healthcare providers and ICU beds were based on the Definitive Healthcare and Healthcare Cost Report Information System (HCRIS) (COVID Care Map, 2020). According to these resources, there are a total number of 208 facilities that provide medical services to COVID-19 patients in Florida with the capacity of 6,062 ICU beds. It should be noted that the current study is conducted based on the available data as of October 13, 2020. Fig. 2a and Fig. 2b illustrate the spatial distributions of the healthcare facilities along with the corresponding ICU beds in the entire state, respectively. As seen, most of these facilities in the state are located close to large cities such as Miami, Tampa, Orlando, and Jacksonville. More specifically, there are many facilities in southern and central Florida. Similarly, there are many ICU beds in proximity to these cities. On the other hand, Fig. 2c shows the spatial distribution of COVID-19 cases in the State of Florida at the zip code level. As seen in Fig. 2c, most of the areas in the state recorded a total number of cases less than 500 or 1000. However, the highest number of COVID-19 patients were observed in the southern Florida regions. Some areas in the northern Florida also reported a high number of cases. Additionally, the roadway network was obtained via the Florida Standard Urban Transportation Model Structure (FSUTMS) model (Florida Statewide Network Model, 2018). The roadway network in the entire state is presented in Fig. 2d.

3. Methodology

This study includes four main steps to measure the spatial accessibility of Floridians to healthcare providers during the COVID-19 pandemic. In the first step, the data related to healthcare facilities with the corresponding ICU beds as well as the number of COVID-19 patients were extracted for the entire state. Second, the travel times between the centroids of zip codes and each healthcare facility were calculated using the O-D cost matrix function of the ArcGIS Network Analyst. The travel times in the roadway network were obtained via the FSUTMS model built-in CUBE software. In the current study, the congested travel times on the roadways were used. In the next step, the 2SFCA and E2SFCA methods were applied to obtain the accessibility scores at the zip code level in order to identify the areas with the high and low level of accessibility to healthcare resources in Florida. Ultimately, a metric, namely the Accessibility Ratio Difference (ARD), was developed in this paper to compare the level of access obtained through the models. It is important to note that, in this study, the healthcare

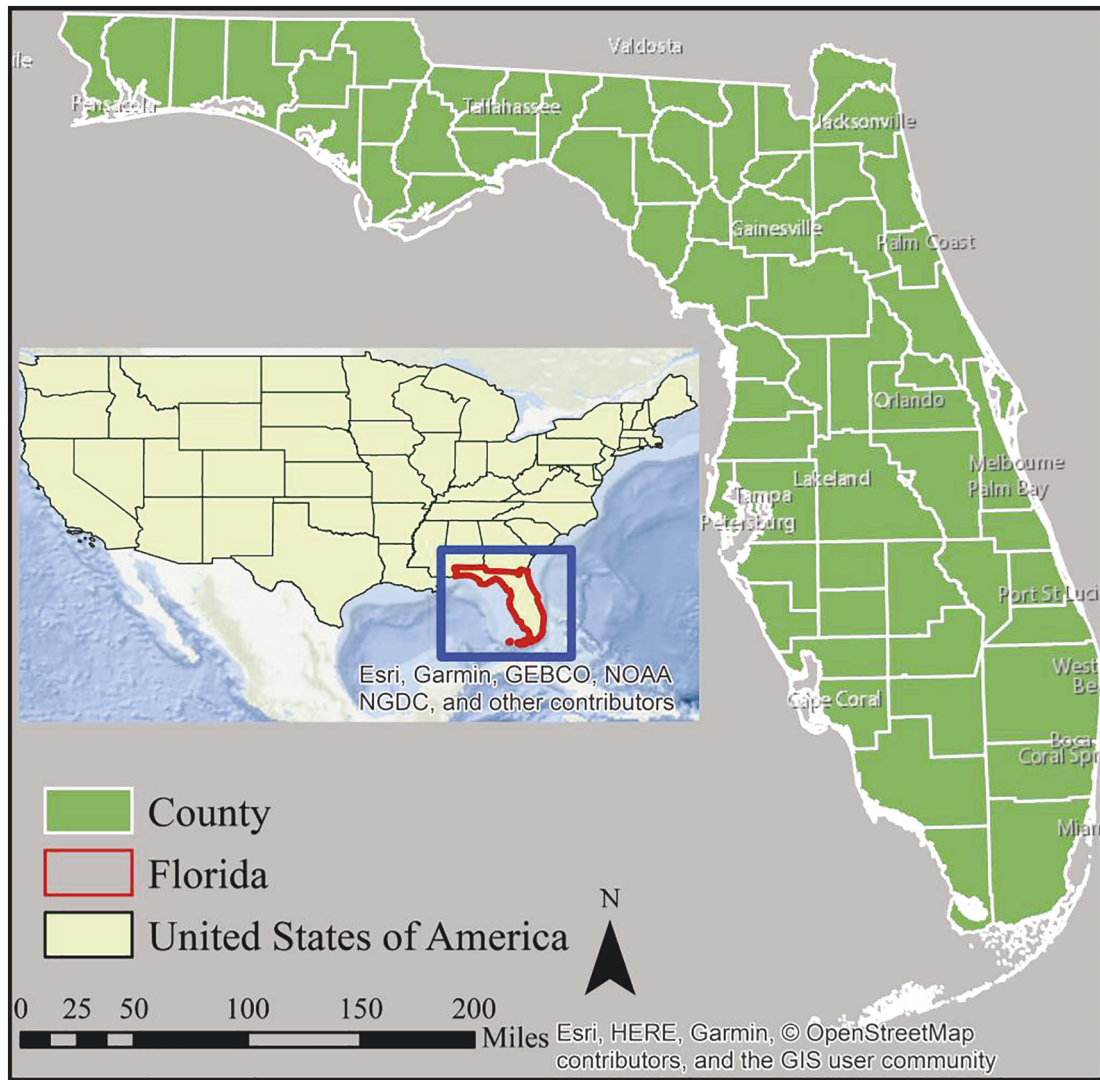


Fig. 1. Study area.

facilities that hospitalize COVID-19 patients and are equipped with ICU beds in Florida were selected. The results of the modeling approaches are shown in Fig. 3 and Fig. 4.

3.1. Two-step floating catchment area

As previously stated, the 2SFCA and E2SFCA models were conducted to calculate the accessibility of COVID-19 patients to the facilities in the State of Florida. In order to conduct these methods, the number of ICU beds in each facility along with the number of COVID-19 patients at the zip code level were considered respectively as the supply and demand in the proposed methodology. The basic 2SFCA method has two steps. In the first step, all populations within the facility's j catchment are identified. That is, the provider-to-population ratio is calculated by dividing the capacity of each facility by the total population within the catchment j (Eq. (1)). The second step identifies all the facilities of a population location within the catchment size. This is obtained by summing up all provider-to-population ratios in the first step. Accessibility index (A_i) is calculated as follows (Eq. (2)):

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

$$A_i^F = \sum_{j \in d_{ij} \leq d_0} R_j \quad (2)$$

where R_j is the provider-to-population ratio of any facility j , S_j is the number of ICU beds at location j , P_k is the number of COVID-19 patients of any unit (zip code) within the catchment size, d_0 is the catchment size, and d_{kj} is the travel time from k to j .

However, the 2SFCA method has a limitation and it assumes equal access for all the population in the catchment (Luo and Qi, 2009). In order to address this issue, the E2SFCA method was applied to measure the spatial accessibility of COVID-19 patients to healthcare facilities by including a distance decay function (Luo and Qi, 2009). As such, the Gaussian function was added to the model for the effect of distance decay. A catchment size of 30 min has been suggested in the literature for assessing the spatial access to healthcare facilities (Wan et al., 2012). Also, catchments in this study were divided into three time zones: 0–10, 11–20, and 21–30 min. The distance weights 1, 0.68, and 0.22, were applied at each zone. These weights correspond to 0–10, 11–20, and 21–30 min. time zones (39). Similar to the basic 2SFCA method, the E2SFCA approach also has two steps. First, the weighted provider-to-population ratio is computed (Eq. (3)). Next, all the facilities within the catchment size for each population location i are identified (Eq. (4)).

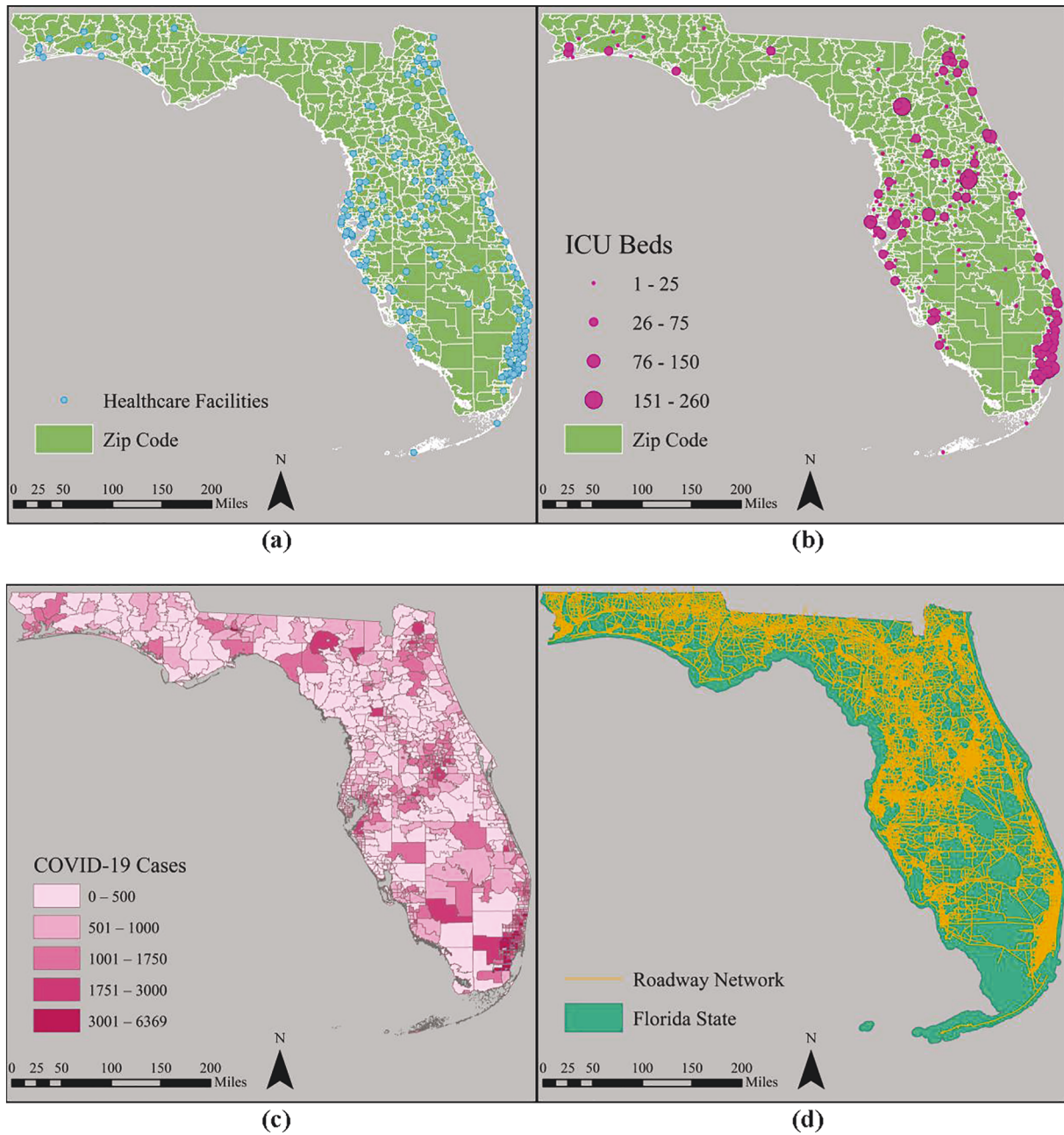


Fig. 2. (a) Spatial distribution of healthcare facilities; (b) ICU beds; (c) COVID-19 cases; (d) Roadway network.

$$R_j = \frac{S_j}{\sum_{k \in d_{ij} \in D_r} P_k W_r} \quad (3)$$

$$A_i^F = \sum_{j \in d_{ij} \in D_r} R_j W_r \quad (4)$$

where D_r is the r th time zone ($r = 1-3$), W_r is the distance weight for the r th travel time zone calculated from the Gaussian function, and A_i^F is the accessibility of population at location i to facilities. Also, in order to compare the two methods in terms of the level of accessibility, a metric namely the Accessibility Ratio Difference (ARD), was developed. The ARD is defined as follows (Eq. (5)):

$$ARD_i = \frac{A_i^{E2SFCA}}{\max(A^{E2SFCA})} - \frac{A_i^{2SFCA}}{\max(A^{2SFCA})} \quad (5)$$

where A_i^{E2SFCA} and A_i^{2SFCA} are the accessibility of population at

location i to facilities through the E2SFCA and 2SFCA methods, respectively. Effectively this measure looks at the difference between the two measures for a given zip code i .

4. Results and discussions

As discussed in the previous sections, the 2SFCA and E2SFCA methods were utilized in this study to measure the spatial accessibility of COVID-19 patients to healthcare services in the State of Florida. Fig. 3a and Fig. 3b show the results obtained by the 2SFCA and E2SFCA models, respectively. In these figures, the green and red colors represent the higher and lower accessibility ratios obtained by the models, respectively. Both methods approximately reveal the same accessibility patterns over the entire state. As shown in Fig. 3a and Fig. 3b, those regions are mainly located in the northwest and southern portions of Florida and seem to have low spatial accessibility ratios which are shown in red.

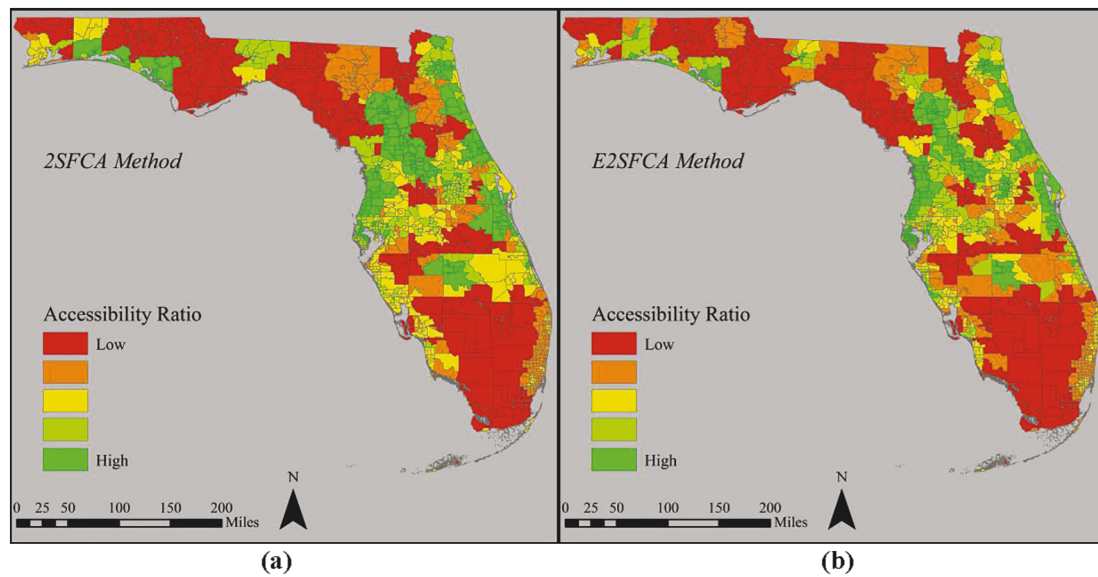


Fig. 3. (a) Results of the 2SFCA method; (b) Results of the E2SFCA method.

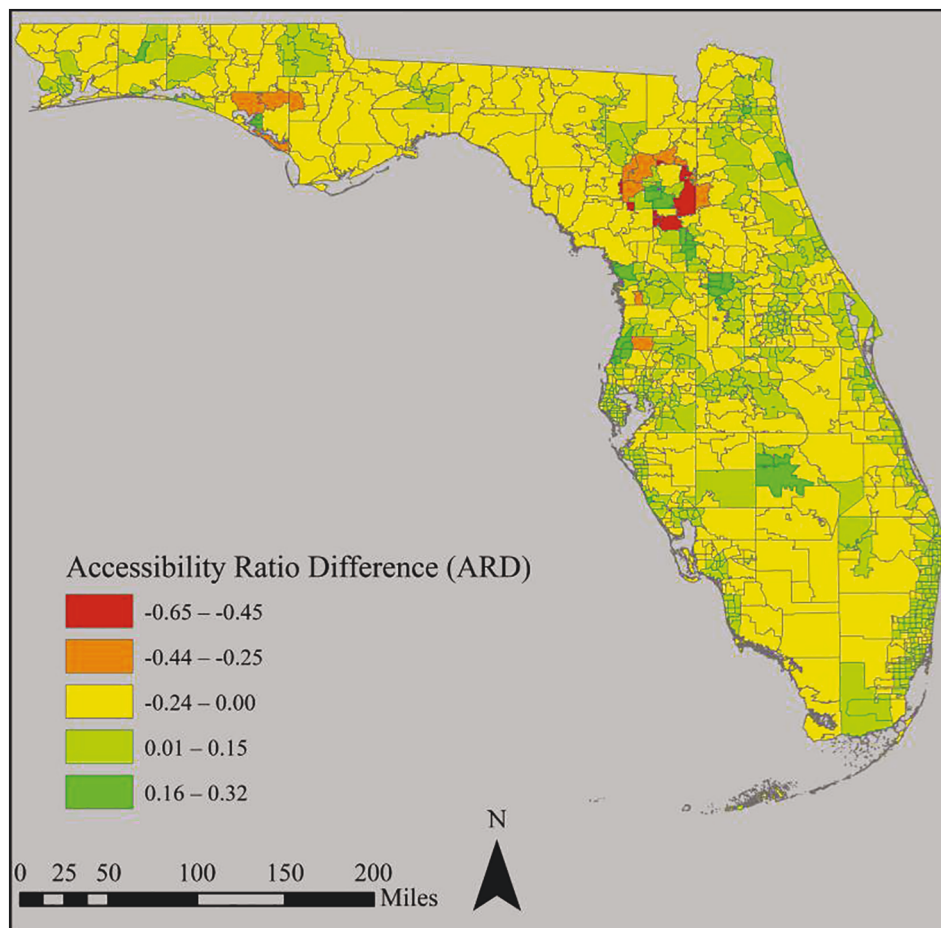


Fig. 4. Results of the accessibility ratio difference (ARD).

Note that the areas in northwest Florida are mostly considered as rural areas. According to Fig. 2c, lower COVID-19 cases were reported for these areas; however, the insufficient number of healthcare facilities and specifically ICU beds led to low access levels for the residents of these areas. In contrast to northwest Florida, as shown in Fig. 2a and Fig. 2b,

there are many healthcare facilities along with more ICU beds in southern Florida. However, the high number of COVID-19 patients in these areas (Fig. 2c) led to findings of low access in these regions given the low computed ratios. On the other hand, the areas with higher access are mainly located in central Florida and close to the cities of Tampa and

Orlando (shown in green). Based on Fig. 2b and Fig. 2c, these regions have a high number of ICU beds along with a low number of confirmed coronavirus cases. Therefore, it can be concluded that the people in the northwest and southern Florida are more likely to experience resource shortages due to an imbalance between supply and demand.

Additionally, in order to evaluate the spatial access difference between the models, the ARD metric was used to provide a detailed comparison of the 2SFCA and E2SFCA methods. The results of this approach are presented in Fig. 4. In this figure, the higher value of difference, the higher the accessibility ratio obtained by the E2SFCA method (shown in green). As seen, the 2SFCA method showed higher access ratios in most parts of the state (shown clearly with the yellow color) due to the negative ARD values. On the other hand, the E2SFCA model shows the higher access ratios in the regions with a higher number of ICU beds which appears in green. One explanation for this finding could be related to the distance decay effect within the catchment area which was considered in the E2SFCA method. According to the results, it can be concluded that the 2SFCA method overestimates accessibility in the areas with a low number of ICU beds due to the equal access of population within the catchment area.

5. Conclusions and future work

In this paper, the 2SFCA and E2SFCA methods were applied to measure the spatial accessibility of COVID-19 patients to healthcare resources in the State of Florida given the number of ICU beds and the number of COVID-19 cases at the zip code level. Additionally, a metric, namely the Accessibility Ratio Difference (ARD), was developed to assess the obtained level of accessibility between the two models. The results of both models revealed that many areas in the state have low access to the facilities given the low access ratios. These regions are mainly located in northwest and southern Florida. In contrast to northwest Florida, there are many healthcare services in the southern parts of the state. However, the high number of COVID-19 cases led to a low access ratio for the residents of these areas. On the other hand, the highly accessible areas are mostly located in central Florida. Also, using the ARD values, a comparison between the 2SFCA and E2SFCA methods was made to show the different access ratios throughout the state. Based on the results, the 2SFCA method represented higher access ratios than the E2SFCA model in most of the areas and more specifically in the areas with a lower number of ICU beds. On the other hand, the E2SFCA method showed higher ratio access in the regions in which more facilities are located. This could be related to the distance decay effect which was considered in the E2SFCA method. This clearly shows the impact of decay on the areas in which the facilities are not distributed evenly.

Returning to the policy front, exploratory analyses such as the present effort can provide key information that could be used by health officials to formulate educational agendas aimed at promoting safety and well-being regarding the risks associated with COVID-19. The problem is so critical that even one or two neglected locations can have dire consequences. Specifically, the 2SFCA and E2SFCA analyses and their comparison, and insights presented in this paper could be a part of efforts to raise awareness of safety issues and make health officials more cognizant of locations near them that might require further care in providing access and support. In addition, with regards to COVID-19 cases, there are several community-oriented organizations charged with assisting them to meet their daily needs. The types of insights produced in this study may have the potential to assist them in their efforts to help people, especially those vulnerable, find the health assistance they need. The obtained knowledge and insights of this study can also be useful for public health planners and decision makers. This information can also help officials to better identify those areas with low access to the healthcare resources that are equipped with ICU beds. In addition, the proposed approach can lead to identifying future candidate facility locations in order to provide better accessibility for those vulnerable areas.

There are limitations to this study worth noting. For example, although it might seem that the weights utilized in our modeling are somewhat arbitrary, these parameters are similar to the distance decay weights offered in the original paper that proposed the E2SFCA. As Wang (2012) suggested, using distance decay weights determined by actual travel behavior is desirable; however, here the travels of COVID-19 patients to healthcare resources across Florida were unknown at the time of the research. In this context, assuming that COVID-19 patients will potentially seek out more distantly located hospitals due to any shortages of resources during this pandemic, we applied slower distance decay weights instead of sharper distance decay weights. As possible future work, alternative distance decay weights can be determined given data availability regarding the actual travel experiences of COVID-19 patients, which could enhance the approaches applied here. Along these lines, distance decay parameter estimation could vary by population characteristics, insofar as future research could explore whether specific population groups were more sensitive to the effects of spatial separation on securing healthcare resources.

In terms of other future extensions, one obvious line of inquiry involves whether diminished accessibility to healthcare resources translates into adverse health outcomes. In this way, questions on whether a lack of spatial accessibility leads to higher mortality rates for COVID-19 patients, or if there is a difference in mortality rates based on the accessibility measures used, are out of scope for the present paper. However, both of these dimensions would clearly be interesting future directions for further research, especially if examined in the context of vulnerable populations. As other potential future research, we note that this study considers only the Gaussian function weight for modeling distance decay. Clearly other functions could be applied with regard to the type of accessibility being measured. Moreover, this study uses the same catchment size for steps 1 and 2 of the 2SFCA and E2SFCA methods. Relatedly, considering variable catchment sizes can be a good direction for future research. Lastly, in the current study, the accessibility analysis was conducted based on the centroids of zip code areas. However, this approach might suffer from aggregation bias. One solution for addressing this issue can be the use of more disaggregated data (Gaboardi et al., 2020).

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CRedit authorship contribution statement

Mahyar Ghorbanzadeh: Conceptualization, Methodology, Software, Formal analysis, Data curation, Writing - original draft, Visualization. **Kyusik Kim:** Methodology, Software, Formal analysis, Data curation. **Eren Erman Ozguven:** Conceptualization, Supervision. **Mark W Horner:** Conceptualization, Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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