Health & Place 98 (2026) 103608

Contents lists available at ScienceDirect

Health and Place

journal homepage: www.elsevier.com/locate/healthplace

Measuring maternal healthcare accessibility in Florida by a data-driven extension of V2SFCA

Hanqi Li [a,b,g], Fahui Wang [a], Ran Zhang [c], Andy Qin [b,g], Emily Javan [d], Rajesh Reddy [e], Lorie Harper [e], Peiyin Hung [f], Yuhao Kang [b,g,*]

[a] Department of Geography and Anthropology, Louisiana State University, Baton Rouge, LA, USA
[b] GISense Lab, Department of Geography and the Environment, The University of Texas at Austin, Austin, TX, USA
[c] Department of Health Promotion, Education, and Behavior, Arnold School of Public Health, University of South Carolina, Columbia, SC, USA
[d] Department of Integrative Biology, The University of Texas at Austin, Austin, TX, USA
[e] Department of Women's Health, The University of Texas at Austin, Austin, TX, USA
[f] Department of Health Services Policy and Management, University of South Carolina Arnold School of Public Health, Columbia, SC, USA
[g] Population Research Center, The University of Texas at Austin, Austin, TX, USA

ARTICLE INFO

Keywords:
Maternal healthcare
Accessibility
Variable catchment 2SFCA (V2SFCA)
Patient flow data
Area-specific modeling
Rural healthcare

ABSTRACT

Maternal healthcare accessibility is a key determinant of maternal and newborn outcomes, yet the United States continues to experience disproportionately high maternal mortality rates compared with other high-income countries. Efforts to address this problem are hampered by substantial spatial disparities, especially in large states like Florida. Existing methodologies for evaluating healthcare access, such as the widely used Generalized Two-Step Floating Catchment Area (G2SFCA) method, may not accurately capture real-world circumstances because they often rely on assumed, uniform parameters that overlook contextual heterogeneity in travel behavior. However, maternal patients in different geographies experience drastically different transportation barriers and varying tolerance for distance and travel times, underscoring the need for more granular, area-specific modeling. This study proposes a data-driven Variable Catchment 2SFCA (V2SFCA) framework to estimate maternal healthcare accessibility across Florida. Leveraging observed patient flow data, we employed gravity models to empirically calibrate distance decay functions and separately defined catchment thresholds specific to each area type. These data-driven, area-specific parameters enable the framework to more accurately reflect behavioral heterogeneity in maternal healthcare utilization. Applied to Florida, the model reveals substantial accessibility disparities across the four area types, including metropolitan, micropolitan, small town, and rural. It also demonstrates improved behavioral realism compared with conventional approaches, offering actionable insights for equitable maternal care planning and resource allocation.

1. Introduction

Maternal healthcare plays a critical role in safeguarding the health and well-being of both mothers and newborns, directly influencing maternal and perinatal morbidity and mortality (Souza et al., 2024). Reports from the National Center for Health Statistics (NCHS) E-Stats indicate that the U.S. maternal mortality rate was 18.6 deaths per 100, 000 live births in 2023, reflecting a decline from previous years (Hoyert, 2025). However, this rate remains substantially higher than that of other high-income countries, where maternal mortality has stabilized at 2 to 3 deaths per 100,000 live births (World Health Organization, 2023), (Abbasi, 2023). While many health system initiatives have improved the availability and quality of care, these improvements alone do not guarantee care is geographically accessible to all who need it (Attanasio et al., 2022). Spatial accessibility, defined as the relative ease with which individuals can physically reach and obtain appropriate services (Wang and Liu, 2023a), is a determinant of health outcomes (Graves, 2008). Evidence indicates that greater difficulty in spatial access to maternal healthcare is associated with delayed initiation of prenatal care, higher rates of preterm birth, and increased maternal morbidity (Nesbitt et al., 1990), (Fontenot et al., 2024), (Haiman and Cubbin, 2023). Given the impact on maternal and newborn outcomes, accurate measurement of spatial accessibility is essential for identifying underserved populations and guiding targeted interventions.

* Corresponding author. GISense Lab, Department of Geography and the Environment, The University of Texas at Austin, Austin, TX, USA.
E-mail address: yuhao.kang@austin.utexas.edu (Y. Kang).

https://doi.org/10.1016/j.healthplace.2026.103608
Received 1 September 2025; Received in revised form 25 November 2025; Accepted 4 January 2026
Available online 22 January 2026

The burden of maternal mortality is disproportionately distributed across U.S. communities, particularly between rural and urbanized areas (Darville et al., 2025), (Harrington et al., 2023). Similarly, access to maternal healthcare varies across geographic contexts. Rural residents often encounter longer travel times, fewer local facilities, limited provider options, and, in some regions, the complete loss of local obstetric units, all of which contribute to reduced accessibility (Hung et al., 2017), (Kozhimannil et al., 2018), (Probst et al., 2019). These geospatial disparities in access are key indicators of the structural inequities in healthcare, requiring detailed and context-sensitive metrics to capture their complexity and facilitate data-driven solutions (Obeidat and Alourd, 2024).

Researchers have employed multiple approaches to measure healthcare accessibility, each with distinct strengths and limitations. Provider-to-Population Ratios (PPR) remain widely used because they are easy to compute, interpret, and apply in maternal health research (DeSisto et al., 2022), (Tian and Pan, 2021). However, these ratios are constrained by administrative boundaries (e.g., State/County boundaries), overlooking the actual spatial separation between patients and providers as well as cross-boundary healthcare-seeking behaviors. Travel impedance metrics, including straight-line distance, network-based driving distance, and travel time, incorporate spatial separation and transportation infrastructure into accessibility assessment (Delamater et al., 2012), (Rayburn et al., 2012). However, these measures typically focus on physical distance or time alone and do not integrate the balance of healthcare supply and demand. The Two-Step Floating Catchment Area (2SFCA) method addresses this gap by incorporating both spatial impedance and provider-to-population ratios within a defined catchment area, enabling a more comprehensive representation of accessibility (Luo and Wang, 2003). Variants of the 2SFCA method incorporating different distance decay functions, collectively referred to as generalized 2SFCA (G2SFCA), have been widely adopted in health geography to measure accessibility to primary care, specialist services, and maternal healthcare (Luo and Qi, 2009), (Delamater, 2013), (Delamater et al., 2019), (Mao and Nekorchuk, 2013), (McGrail and Humphreys, 2009).

Although the G2SFCA method allows the incorporation of various functions to model distance decay effects, G2SFCA applications often rely on predefined functional forms and its associated key parameters, such as the travel friction coefficient and catchment size, which introduces subjectivity and may not accurately represent real-world travel behaviors. Sensitivity analysis of these parameters can only assess the robustness of accessibility estimates but does not provide a definitive basis for parameter selection. To address this limitation, researchers advanced the G2SFCA framework by adopting data-driven approaches in which key model parameters are derived from observed healthcare-seeking behaviors rather than predefined assumptions. For example, Tao et al. (2020) analyzed infant delivery care visits to empirically determine travel thresholds and distance decay patterns for accessibility measurement (Tao et al., 2020). Similarly, Wu et al. (2024) examined nighttime hospital navigation data to capture the characteristics of medical services, enabling parameter calibration that reflects real-world utilization patterns (Wu et al., 2024). These approaches reduce reliance on arbitrary parameter choices and improve the behavioral realism of accessibility estimates. Nonetheless, deriving friction parameters from real-world data requires disentangling the distance decay effect from the broader spatial interaction process, often via spatial interaction models (e.g., gravity models) to control for confounding factors (Jia et al., 2019). This step has been addressed only to a limited extent in existing accessibility studies (Tao et al., 2020).

Additionally, applying uniform parameter settings may overlook important behavioral differences across diverse geographic contexts (Bauer and Groneberg, 2016). Empirical evidence consistently shows substantial differences in travel behavior across different geographic areas when seeking healthcare. For example, rural populations generally travel longer distances and tolerate higher travel costs, particularly for services requiring automobile travel, compared to their urban counterparts (Liu et al., 2025), (Mseke et al., 2024). These differences reflect not only the relative scarcity of nearby healthcare facilities in rural areas but also varying perceptions of acceptable travel distances and times across geographic contexts (Pot and Piesch, 2024). Such heterogeneity emphasizes the importance of incorporating area-specific travel behaviors into spatial accessibility models to more accurately represent real-world healthcare utilization patterns.

To address such heterogeneity, the Variable Catchment 2SFCA (V2SFCA) method was developed, allowing the size of the catchment area to vary across providers or regions (Luo and Whippo, 2012). Luo and Whippo (2012), who introduced this method, advocated defining demand-side catchment sizes based on reaching a predefined population-to-provider ratio (PPR) threshold (Luo and Whippo, 2012). Zhou et al. (2021) applied catchment thresholds of 2, 5, and 15 miles for urban, suburban, and rural areas, respectively, to estimate access to pharmacies in the U.S. (Zhou et al., 2021). However, the V2SFCA method should be applied with caution. If the catchment sizes in the first step (supply side) and the second step (demand side) are not consistent, the same origin–destination pair may receive different weights in each step. This inconsistency violates the original "supply-demand balance" property of the G2SFCA, a theoretically important feature that ensures both consistency and interpretability in the spatial allocation of resources (Wang and Liu, 2023a), (Shen, 1998). Misapplications of V2SFCA that disregard this weight-symmetry requirement can lead to systematic bias of accessibility estimates. Moreover, when employing V2SFCA to highlight the disparities across different area types, it is crucial to account for the substantially smaller population base in less populated areas. In some implementations, catchment size of the urban-located hospital is set as the value that a specific percentage of trips to the hospital are included in the catchment area (Tao et al., 2020). This procedure may disproportionately include urban patients while excluding a significant share of rural residents, thereby underestimating the supply of services available to more distant areas.

Florida, the third most populous state in the United States with over 22 million residents in 2022, is geographically and topographically diverse, surrounded by a rim of coastal residential areas (U. C. Bureau). Compared with major metropolitan coastal areas, less urbanized inland regions face more limited access to maternal services. Fewer than 20 % of rural counties in Florida have obstetric care facilities, placing the state among the lowest nationally in rural obstetric service availability (U. S. G. A. Office). Between 2018 and 2022, Florida's maternal mortality averaged 24.1 deaths per 100,000 live births, exceeding the national average (March of Dimes). Barriers such as scarce obstetric units, long travel distances, and transportation challenges continue to hinder adequate access to prenatal and intrapartum care. The state's pronounced spatial disparities make it a compelling case for analyzing maternal care accessibility.

Although maternal health disparities in Florida have drawn increasing attention, there has been no prior application of the V2SFCA approach to measure maternal healthcare accessibility, largely due to the lack of empirical parameters or real-world data on maternal healthcare travel behavior. This study is the first to develop a data-driven extension of the V2SFCA framework by incorporating statewide electronic birth record–derived patient flow data from Florida, which directly link maternal residences to obstetric hospitals. Leveraging these observed flows, we empirically calibrate distance decay functions and catchment thresholds separately for the four area types (i.e., metropolitan, micropolitan, small town, and rural). These area-specific parameters enable a more behaviorally valid representation of maternal healthcare accessibility and explicitly account for inter-area heterogeneity. In addition, we conduct a comparative analysis with the traditional binary-weighted 2SFCA method to provide parameter references for area-specific accessibility estimation in situations where empirical travel data are unavailable.

2. Study area and data

This study investigates spatial behaviors and potential accessibility to maternal healthcare services in the state of Florida. Administratively, Florida consists of 67 counties and 1008 ZIP Code Tabulation Areas (ZCTAs) (). The Florida Department of Health (DOH) has a binary classification with 32 counties as rural and 35 as nonrural (Florida, 2023). To capture finer-scale heterogeneity, we further adopted the U.S. Department of Agriculture's Rural–Urban Commuting Area (RUCA) classification, which categorizes Florida's ZCTAs into four area types: metropolitan (n = 849), micropolitan (n = 28), small town (n = 20), and rural (n = 51) (Fig. 1) ("Rural-Urban Commuting Area Codes"). The population distribution is highly uneven across the state, with the majority of residents concentrated in metropolitan areas, whereas central and northern inland areas are characterized by lower population densities and limited healthcare infrastructure.

Two primary datasets from the 2022 were utilized to analyze travel patterns and evaluate spatial accessibility to maternal healthcare services in Florida: electronic health records (EHRs) for all recorded births, and detailed information on maternal healthcare facilities. **(1) Birth Electronic Health Records (EHRs):** Statewide aggregated birth records at the ZCTA level were obtained from the Florida Department of Health's Bureau of Vital Statistics and were linked to all-payer hospital discharge data provided by the Florida Agency for Health Care Administration (AHCA). In total, 223,309 births were recorded in Florida in 2022. Each record includes information on the mother's residential ZCTA and the name and identifier of the birth facility. Based on the facility identifier, delivery locations were classified into three categories: licensed healthcare facilities, non-hospital settings, and unknown delivery locations. **(2) Maternal Healthcare Facility:** Data on maternal facilities, including hospitals and birthing centers, were obtained from the Florida Agency for Health Care Administration (AHCA) and the American Hospital Association (AHA) Annual Survey. In 2022, a total of 258 licensed healthcare facilities were identified across the state. Among them, 74 facilities were designated as obstetric hospitals (OBHOS), which served as the supply side of maternal healthcare services. For each OBHOS, facility name, geographic coordinates (i.e., latitude and longitude), and the number of obstetric-designated staffed beds (OBBD) were collected, with OBBD used as a proxy for service capacity.

We linked birth records to OBHOS facility dataset using facility names. This study established a supply-demand framework for analyzing spatial behavior in maternal healthcare and quantifying potential accessibility, with patients representing demand and OBHOS representing supply. We systematically cleaned and integrated the demand and supply data (Fig. 2). On the demand side, we started with 223,309 birth records from Florida's 2022 Electronic Health Records (EHRs). We first matched residential ZIP codes with ZCTAs using geographic correspondence engine GeoCorr 2022, resulting in 188,651 births with identifiable 966 ZCTAs (MCDC 2022). We then limited the dataset to births occurring in OBHOSs, reducing the total to 186,196 records. To focus specifically on obstetric care, we retained only births delivered in OBHOSs, yielding 112,313 records, which accounted for 50.29 % of all births in 2022 and 60.3 % of the births in licensed facilities. On the supply side, we identified 74 OBHOSs among 258 licensed healthcare facilities based on the presence of OBBDs. Finally, we matched 71 OBHOSs to the patient birth records, producing a final set of supply-demand pairs suitable for modeling maternal healthcare accessibility.

This integration enables the identification of actual supply-demand interactions and supports the examination of maternal healthcare-seeking behaviors and preferences, thereby offering insights into realized accessibility based on observed patient choices. Fig. 3 illustrates these patterns, with straight lines representing travel flows between patients' residential ZCTAs and obstetric hospitals. The underlying choropleth shows the spatial distribution of aggregated total birth records at the ZCTA level across Florida, providing a general overview of maternal demand.

3. Methods

This study developed a data-driven framework to measure spatial accessibility by deriving distance decay functions from observed

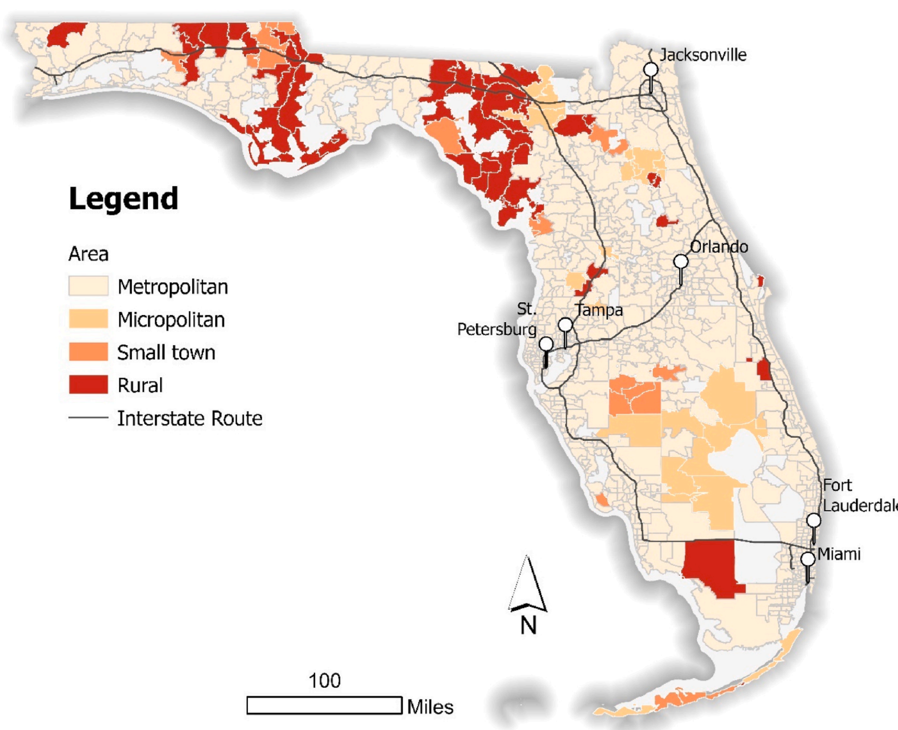

Fig. 1. Four-level classification of Florida ZCTAs by area type.

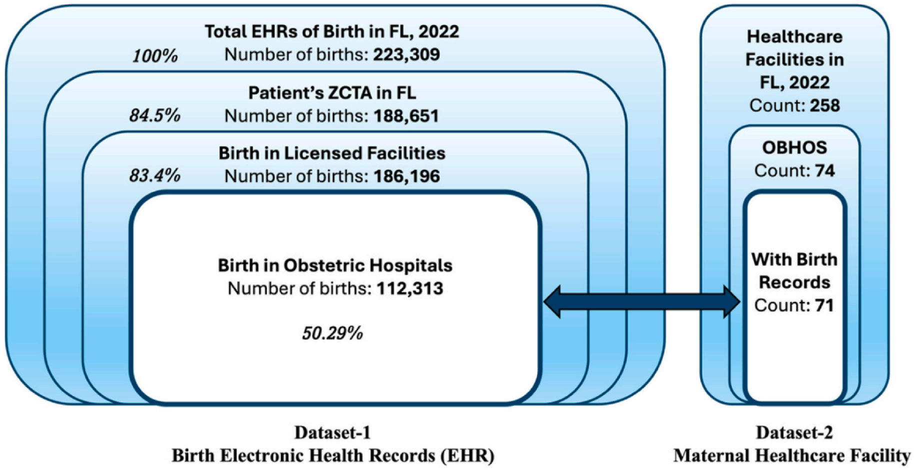

Fig. 2. Data cleaning and integration process.

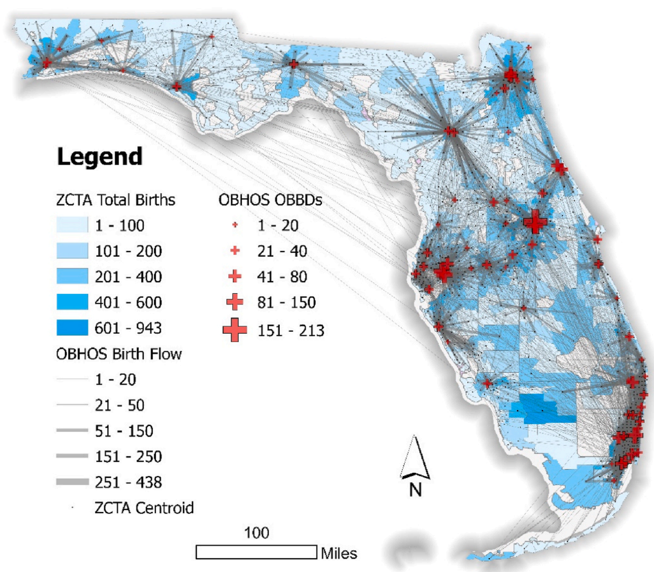

Fig. 3. Birth-related patients flow from residential ZCTAs to obstetric hospitals (OBHOSs).

healthcare-seeking behaviors through a spatial interaction model. To account for heterogeneity in travel behavior across different area types, we implemented an area-specific V2SFCA model with empirically calibrated catchment sizes and distance decay functions for metropolitan, micropolitan, small town, and rural areas. In addition, we conducted a comparative experiment with the traditional 2SFCA to identify appropriate catchment sizes for areas lacking empirical healthcare-seeking data.

3.1. Calculating travel distance and time

This study constructed an origin-destination (OD) matrix linking residential ZCTA to obstetric hospitals (OBHOS) using birth visit records. The population-weighted centroid of each ZCTA was computed based on the geographic centroids of its constituent census tracts, weighted by tract-level population, and served as the origin point representing patient departure locations. The travel distance and time between each OD pair were estimated using the Google Maps API, which accounts for real-world road network conditions and routing algorithms (Google Maps Platform Documentation). While both driving distance (in miles) and driving time (in minutes) were obtained, driving time was adopted as the primary travel cost metric in this study, as it better reflects perceived accessibility and real-world constraints, with its practical relevance emphasized in recent studies (Balsa-Barreiro et al., 2025), (Clark et al., 2025).

To explore spatial variation, patients were then classified into four groups (i.e., metropolitan, micropolitan, small town, and rural) based on their residential ZCTAs. This classification enabled comparative analysis of travel patterns across different geographic contexts. Histograms of travel frequency were used to visualize the distribution of patient travel behavior. Because the travel time data were highly right-skewed and approximated a log-normal distribution, a log-transformed interquartile range (log-IQR) method was applied to identify and remove extreme outliers (Rousseeuw and Hubert, 2011), (Feng et al., 2014). This approach effectively eliminated abnormally long birth-related trips while preserving typical travel patterns within each group.

3.2. Modeling distance decay effect

Although travel cost in this study is measured by driving time rather than distance, the term distance decay function is retained, as it is the conventional terminology in accessibility research. To model the distance decay effect for use in accessibility computation, a spatial interaction model is needed. Healthcare-seeking travel is fundamentally a spatial interaction process, where the volume of patient flows is influenced not only by travel distance or time, but also by several confounding factors—such as the relative size of the supply capacity and demand populations, perceptions of hospital quality, and patient needs (Fotheringham and O'Kelly, 1989).

In this study, we adopted the gravity model, the most foundational approach in spatial interaction modeling, to estimate the distance decay effect embedded in aggregated travel flows (Stacherl and Sauzet, 2023), (Erlander and Stewart, 1990). In the context of maternal healthcare travel, the model effectively incorporates the number of patients at each origin and the service capacity at each destination, both of which are key determinants of flow size and are available in our dataset. Specifically, a generalized gravity model assumes that the flow volume T_{ij} between an origin i and a destination j is proportional to the product of their respective masses, O_i and D_j, and also related to a function of the travel distance or time between them, $f(d_{ij})$, which characterizes the distance decay effect. The parameter a serve as a scaling constant that adjusts the overall magnitude of the predicted flows. The general form of the model is:

$$T_{ij} = a \cdot O_i \cdot D_j \cdot f(d_{ij})$$

This formulation allows us to quantify the influence of travel time while accounting for population demand and facility capacity.

To identify the most appropriate distance decay form $f(\cdot)$, following the previous studies, we tested several common forms (Table 2), including: (1) Power function, (2) Exponential function, (3) Square-root exponential function, and (4) Normal exponential function, and (5) Lognormal exponential function (Wang and Liu, 2023b), (Wang et al., 2021). For comparability and ease of interpretation, each function was simplified to include a single positive friction parameter $\beta > 0$, where larger values of β indicate a steeper rate of decay.

These five candidate functions were independently fitted to travel time across the entire study area and four area-specific groups. The modeled flow T_{ij} represents the number of recorded birth-related visits from origin ZCTA i to hospital j, with origin demand O_i proxied by the total number of departures from ZCTA i, and destination supply D_j represented by the number of obstetric beds (OBBDs) at hospital j. In addition, since the distance decay effect operates only within the effective interaction range, there is no decay effect for the distance from a patient's location to the nearest hospital, as patients have no choice within this segment. Therefore, in this study, d_{ij} was adjusted using the observed minimum travel time in each area type, ensuring that the decay effect begins at the travel time to the nearest hospital. The *curve_fit* function from the SciPy Python package was used to estimate the parameters of these nonlinear fittings (Virtanen et al., 2020). Model performance was evaluated using goodness-of-fit statistics, such as the pseudo-R^2, and the function with the best performance was selected as the best-fitting model (Jia et al., 2019).

3.3. Refining accessibility measurement by data-driven V2SFCA

The Generalized Two-Step Floating Catchment Area (G2SFCA) method measures accessibility in two steps.

Step 1, for each hospital j, a catchment area was delineated (typically within a threshold distance d_o), and the supply-to-demand ratio R_j was calculated as:

$$R_j = \frac{S_j}{\sum\limits_{k \in \{d_{kj} \le d_o\}} D_k \cdot f(d_{kj})}$$

where S_j is the supply capacity of hospital j (e.g., number of obstetric beds (OBBDs)), D_k is the demand (e.g., total number of births) originating from ZCTA k, d_{kj} is the travel distance or time from k to j, d_0 is the distance threshold of the searching catchment area, and $f(\cdot)$ is a predefined distance decay function.

Step 2, for each demand area i (e.g., residential ZCTA), the accessibility score A_i is calculated by aggregating the weighted supply ratios from all hospitals j within the threshold distance:

$$A_i = \sum_{j \in \{d_{ij} \le d_o\}} R_j \cdot f(d_{ij})$$

The conventional G2SFCA method relies on a predefined decay function $f(\cdot)$ and a fixed global catchment threshold d_o, based on the assumption that patient travel behavior conforms to these rules, primarily due to the lack of empirical data. In this study, the decay function was instead derived from the observed travel behavior using a spatial interaction model, thereby more accurately capturing the decline in maternal healthcare travel frequency with increasing travel time. And the catchment threshold was determined as the maximum observed travel time after outlier removal.

Moreover, recognizing that patient travel behavior varies across geographic contexts, we considered a single global distance decay function and catchment threshold to be insufficient to represent these differences. To address this limitation, we further enhanced the data-driven G2SFCA by applying distinct decay functions and catchment sizes for four groups of populations based on the patients' residential location, adopting the concept of the V2SFCA. The extended equations for the area-specific V2SFCA are as follows:

$$f(d_{ij} \text{ or } d_{kj}) = \begin{cases} f_{metro}(d_{ij} \text{ or } d_{kj}), \text{if } i \text{ or } k \in \text{Metropolitian Set}, \\ f_{micro}(d_{ij} \text{ or } d_{kj}), \text{if } i \text{ or } k \in \text{Micropolitian Set}, \\ f_{smalltown}(d_{ij} \text{ or } d_{kj}), \text{if } i \text{ or } k \in \text{Small Town Set}, \\ f_{rural}(d_{ij} \text{ or } d_{kj}), \text{if } i \text{ or } k \in \text{Rural Set}. \end{cases}$$

$$d_0 = \begin{cases} d_{metro}, \text{if } i \text{ or } k \in \text{Metropolitian Set}, \\ d_{micro}, \text{if } i \text{ or } k \in \text{Micropolitian Set}, \\ d_{smalltown}, \text{if } i \text{ or } k \in \text{Small Town Set}, \\ d_{rural}, \text{if } i \text{ or } k \in \text{Rural Set}. \end{cases}$$

The decay function $f(d_{ij})$ or $f(d_{kj})$ was determined based on the patient's area of residence. Specifically, each area type adopted its own empirically calibrated decay function, with corresponding catchment thresholds applied accordingly.

In addition, this area-specific V2SFCA ensures that the same origin–destination pairs receive the same weights across the two steps, preserving the desirable "supply–demand balance" property that the demand-weighted average accessibility equals the ratio of total supply to total demand.

$$W = \sum \left(\frac{D_i}{D}\right) A_i = \frac{1}{D} \sum D_i A_i = \frac{S}{D}$$

The ZCTA and county FIPS affiliations of each patient were available. Accessibility was first computed at the ZCTA level and then assigned to each patient, followed by aggregating to the county level using population-weighted averages. This approach allows travel distances to be estimated using more precise ZCTA-level patient locations while preserving the intrinsic "supply–demand balance" property. Aggregating to the county level provides greater practical relevance, as counties serve as fiscal entities with the authority to allocate healthcare resources. This capacity enables counties to influence resource distribution and implement targeted interventions, thereby directly shaping the regulation of maternal healthcare accessibility.

3.4. Estimating binary-weighted V2SFCA catchment sizes

Detailed patient flow data are often unavailable, making it difficult to empirically calibrate catchment thresholds and distance decay functions. In such cases, the binary-weighted (0 or 1) 2SFCA remains widely used because of its simplicity and minimal data requirements. However, this approach still requires predefined catchment sizes, and the selection of these thresholds is typically arbitrary (Luo and Wang, 2003).

To provide empirical reference values for 2SFCA applications under data-scarce conditions, we conducted a comparative experiment between the binary-weighted 2SFCA and the data-driven area-specific V2SFCA described above. For the 2SFCA, to enhance practical usability and computation efficiency, catchment thresholds for four types of areas were systematically varied from 0 to 200 min at 5-min intervals, and accessibility scores were calculated for each threshold combination. The resulting 2SFCA estimates were compared with the empirical area-specific V2SFCA outputs, and Pearson correlation coefficients were computed to identify the thresholds that achieved the strongest alignment (Luo and Wang, 2003). The identified thresholds were then considered as empirical references for 2SFCA-based accessibility estimation in different areas if detailed patient-level data were unavailable.

4. Results

After integrating the datasets, as illustrated in Fig. 2, we compiled maternal healthcare demand data encompassing 112,313 birth records linked to 71 obstetric hospitals across Florida in 2022. The births were distributed across all 67 counties (35 nonrural and 32 rural) and originated from 949 ZCTAs, including 849 metropolitan ZCTAs with 107,754 births, 28 micropolitan ZCTAs with 1770 births, 20 metropolitan ZCTAs with 896 births, and 51 rural ZCTAs with 1893 births. This integrated dataset provides a robust basis for examining spatial accessibility patterns and assessing geographic disparities in maternal healthcare.

4.1. Heterogeneity in travel behaviors by area type

The road network driving time (in minutes) for all birth-related electronic health record (EHR) visits were computed, and their distributions were examined using histograms. The raw data exhibited substantial right skewness, with extreme values reaching a maximum of 697.95 min, which were unlikely to reflect typical patient road travel behavior for childbirth-related care (Table 1). The median travel time of the entire study area was 19.88 min (SD = 24.64), indicating substantial variability in travel behavior. Observations with travel time exceeding 1.5 times the log-IQR above the third quartile (upper limit as shown in Fig. 4) were identified as outliers and excluded from subsequent analyses, accounting for approximately 1 % of the total records (Rousseeuw and Hubert, 2011), (Feng et al., 2014).

Fig. 4 presents stacked histograms of the frequency of travel time for patients across different types of area. The metropolitan group accounts for the majority of observations (over 95 %), while the patients from the other three groups tend to experience longer and more variable travel times.

A single, global upper threshold would misclassify many legitimate long-distance trips from micropolitan, small town, or rural areas as outliers. To account for regional variability, the log-IQR outlier removal method was applied separately to each group, ensuring that outlier detection reflects the heterogeneity in travel behavior among groups. The resulting upper limits for driving time are summarized in Table 1. For metropolitan areas, the upper limit was 95.18 min, whereas for micropolitan areas the threshold was substantially higher at 173.83 min, more than nearly twice that of metropolitan areas, reinforcing the need for area-specific treatment in analysis. Similarly, the upper limits for small-town and rural areas were 164.25 min and 141.61 min, respectively.

After removing extremely long travel observations within each group, the distributions of driving time by area type were visualized in Fig. 5. The median travel time was highest in rural areas (approximately 68 min), followed by micropolitan (56 min), small-town (48 min), and metropolitan areas (20 min). Statistically, Welch's ANOVA (appropriate for unequal variances) and subsequent pairwise comparisons confirmed that the differences in travel time among all four groups were significant. These findings further highlight the distinct birth-Related travel behavior patterns across area types and underscore the necessity of conducting area-specific analyses.

4.2. Empirical distance decay fitting

Five spatial interaction models, each incorporating a distinct form of distance decay function, were independently fitted using travel time data adjusted by the statistical minimum time, for the overall study area and for each of the four area-specific groups. Model performance was assessed using Pseudo-R^2, as summarized in Table 2. All fitted models were statistically significant at $p < 0.0001$, and the best-fit model for each group is highlighted in bold. Because travel flows from metropolitan areas dominate the total sample size, the best-fitting decay form for the overall area consistently aligns with that of the metropolitan group, with only slight differences in parameter estimates and goodness-of-fit values. The key comparison lies in examining the best fits across the four area groups. The log-normal exponential decay function provided the best fit for metropolitan area, with a Pseudo-R^2 value of 0.2194, explaining about 22 % of the variation in birth-related travel flows in metropolitan areas. The normal exponential decay functions performed best for micropolitan and small town, with Pse-R^2 values of 0.12 and 0.43, respectively, indicating a clear distance decay effect, particularly pronounced in small-town areas. These levels of explanatory power are considered reasonable, given that no patient-level socioeconomic or behavioral factors were incorporated, and are consistent with existing studies (Jia et al., 2019). In contrast, the best-fitting model for rural areas followed a log-normal exponential decay function with a Pseudo-R^2 of only 0.0476, suggesting that the distance decay effect does not work well in rural areas.

Furthermore, the best-fitted decay curves are presented in Fig. 6, visualizing the distance decay patterns for both the overall dataset and each of the four area types. Each curve depicts how the likelihood of patients traveling to a hospital decreases with increasing travel time, beginning from the minimum travel time observed in each area. By design, all fitted curves start at 1 at the minimum travel time, indicating full travel probability, and gradually approach 0 as travel time increases, reflecting declining accessibility with distance.

The results reveal distinct differences across area types. Metropolitan areas (blue line) exhibit the steepest decay, indicating that patients are less likely to travel long distances for care. This further suggests that residents in these areas can typically find a preferred hospital within a relatively short travel time. In contrast, patients in micropolitan (orange) and small-town (green) areas typically need to travel at least about 6 and 12 min (Table 1), respectively, before reaching the nearest hospital. Their curves decay more slowly, suggesting a higher tolerance for longer travel times and a greater willingness to travel farther for healthcare services (Wang and Liu, 2023a). The rural curve (red) remains relatively flat across a wide range, indicating that rural residents often travel substantially longer distances (at least about 20 min) to access obstetric hospitals. However, once they reach a hospital, the rural curve drops sharply, implying that rural patients tend to adhere to a “nearest-available” principle and are less likely to continue traveling to additional facilities. This also suggests that the explanatory power of the distance decay effect for travel behavior in rural areas is limited. The overall fitted curve (purple dashed line) lies between these area-specific patterns, representing the general decay trend across all regions. Collectively, these findings demonstrate clear heterogeneity in travel behavior across area types and emphasize the importance of applying area-specific decay functions in accessibility modeling, as a single global decay function would fail to capture these nuanced spatial differences.

Table 1
Summary statistics of Drive Time (minutes) by Area Type Before and After Outlier Removal.

Area Type	Count	Mean	Std	Min	25th Pctl	Median	75th Pctl	Max	Upper Limit*	Filtered Count	Retention (%)
Overall	112,313	25.44	24.64	1.92	12.65	19.88	30.49	697.95	109.25	111,198	99.01 %
Metropolitan	107,754	23.66	22.36	1.92	12.48	19.31	28.59	697.95	95.18	106,822	99.14 %
Micropolitan	1770	67.78	41.61	6.20	49.04	56.84	81.93	458.97	173.83	1731	97.80 %
Small town	896	56.24	34.03	11.52	33.39	48.26	63.92	264.80	164.25	885	98.77 %
Rural	1893	72.14	30.24	19.85	56.65	68.72	85.57	443.04	141.61	1881	99.37 %

Upper Limit indicates the outlier threshold used for data trimming.
Retention (%) represents the percentage of records retained after outlier removal.

Table 2
Model comparison for distance decay fitting.

Decay Function	Form	Overall		Metropolitan		Micropolitan		Small Town		Rural	
		β	*Pseudo-R^2*	β	*Pseudo-R^2*	β	*Pseudo-R^2*	β	*Pseudo-R^2*	β	*Pseudo-R^2*
Power	$f(d) = d^{-\beta}$	0.3340	0.0872	0.4592	0.1217	0.4184	−0.1111	0.4752	−0.1526	0.3887	−0.0320
Exponential	$f(d) = e^{-\beta d}$	0.0710	0.2186	0.0714	0.2174	0.0455	0.0905	0.0668	0.2944	0.0342	0.0332
Square-root exponential	$f(d) = e^{-\beta d\hat{}0.5}$	0.5046	0.2204	0.5084	0.2190	0.3708	0.0140	0.4762	0.1216	0.3767	0.0410
Normal exponential	$f(d) = e^{-\beta d\hat{}2}$	0.0018	0.1981	0.0018	0.1967	**0.0008**	**0.1213**	**0.0017**	**0.4318**	0.0003	0.0043
Log-normal exponential	$f(d) = e^{-\beta(\ln d)\hat{}2}$	**0.2016**	**0.2221**	**0.1965**	**0.2194**	0.2297	0.0996	0.2324	0.1024	**0.1962**	**0.0476**

β in all models are significant at the level of 0.0001.
Best fit models in bold.

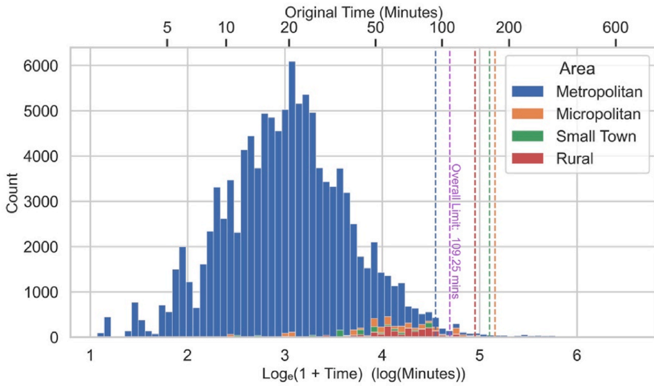

Fig. 4. Stacked histogram of log-transformed birth-related travel time by area type.

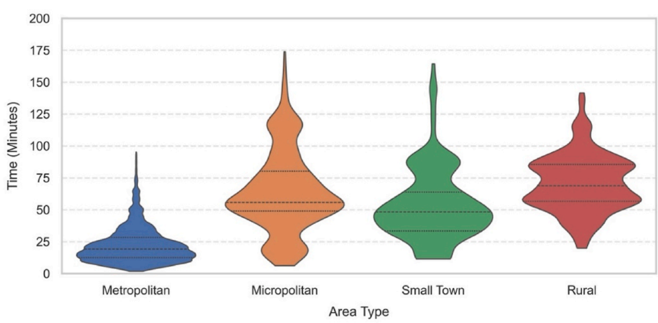

Fig. 5. Violin Plots of birth travel time distribution by area type.

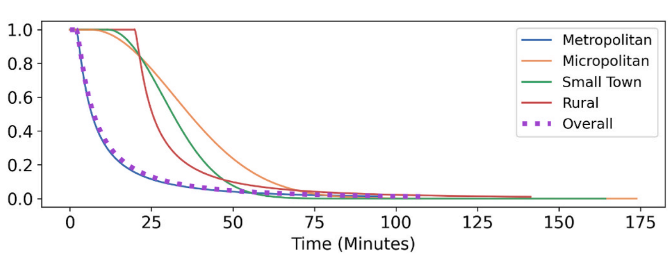

Fig. 6. Empirically fitted decay curves by area type.

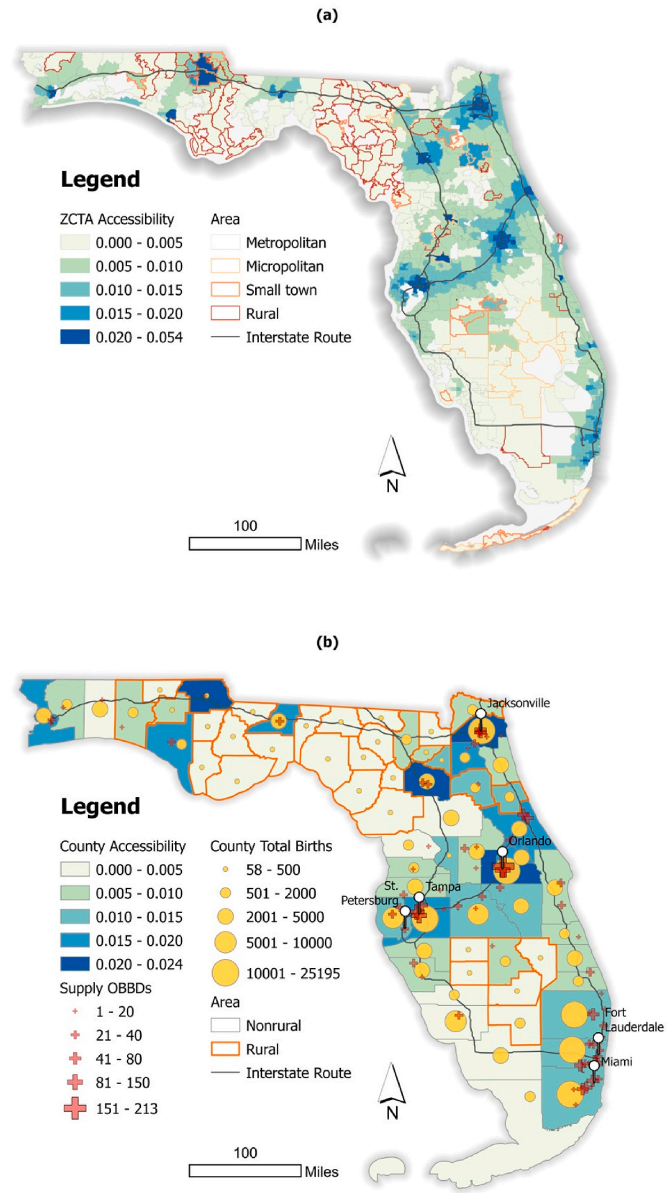

Fig. 7. Spatial distribution of maternal healthcare accessibility in Florida using the data-driven V2SFCA. **(a)** ZCTA-level accessibility scores; **(b)** County-level accessibility scores.

4.3. Data-driven V2SFCA accessibility

Fig. 7 presents the spatial distribution of maternal healthcare accessibility in Florida, estimated by the area-specific V2SFCA model that incorporates empirically derived distance-decay functions and catchment thresholds tailored to four distinct area types. Panel (a) displays ZCTA-level accessibility scores, overlaid with area-type boundaries and major interstate routes, revealing fine-scale spatial variation across the state. Panel (b) aggregates these results to the county level, overlaid with obstetric hospital (OBHOS) locations, total county births, and a simplified rural–nonrural classification defined by the Florida Department of Health (DOH), providing a broader regional perspective.

Overall, maternal healthcare accessibility in Florida exhibits pronounced geographic disparities. The use of ZCTA-level analysis allows these local disparities to emerge clearly, revealing how accessibility can vary sharply even within a single county or metropolitan boundary. County-level aggregation smooths the micro-scale variations visible in the ZCTA-level maps, yet both spatial scales reveal broadly consistent patterns.

Higher accessibility values are concentrated in major metropolitan ZCTAs or nonrural counties along the coast, where hospital supply and birth demand are both dense. Interstate corridors also emerge as critical spatial backbones connecting regions of relatively higher accessibility. At the same time, many nonmetropolitan inland ZCTAs and rural counties remain underserved, reflecting sparse healthcare infrastructure and longer travel distances.

A notable exception appears in a small-town ZCTA in northern Florida, where the presence of a local hospital markedly enhances accessibility despite the limited healthcare supply. Conversely, within several high-demand metropolitan counties, accessibility values are not always among the highest because the large number of births dilute the effect of abundant hospital resources. This pattern is particularly evident in the metropolitan area south of Orlando. These findings highlight that metropolitan accessibility is not universally higher than the accessibility of other areas; instead, accessibility is shaped by the interplay of supply concentration, demand intensity, transportation networks, and cross-boundary healthcare seeking behavior.

Rural areas, in contrast, consistently show the lowest accessibility across the state. From the county-level maps, rural counties located adjacent to high-accessibility nonrural areas tend to exhibit slightly higher accessibility scores than those that are more isolated. This pattern reflects the inherent supply–demand balance characteristic of the 2SFCA framework: as nonmetropolitan areas gain accessibility through expanded catchments, some metropolitan areas experience relative reductions due to resource competition and spatial spillover effects. Together, these findings underscore persistent disparities in maternal healthcare accessibility among populations across different area types.

4.4. Comparison with traditional 2SFCA

Catchment thresholds for the four area types in the binary-weighted 2SFCA model were systematically varied to assess their correspondence with data-driven V2SFCA estimates. The strongest correlation ($r = 0.726$; birth-weighted correlation $= 0.526$) was achieved when thresholds were set to 20 min for metropolitan areas, 40 min for micropolitan areas, 40 min for small-town areas, and 30 min for rural areas. The second-highest correlation ($r = 0.724$; birth-weighted correlation $= 0.522$) occurred when the rural threshold was increased to 40 min. Given the marginal difference between these configurations and for the sake of simplicity, catchment thresholds of 20 min for metropolitan areas and 40 min for all nonmetropolitan areas were adopted for the binary-weighted 2SFCA model.

Using these optimal thresholds, Fig. 8 presents a scatterplot comparing ZCTA-level accessibility derived from the binary-weighted and data-driven V2SFCA models. Each point represents a ZCTA, with dot size proportional to total birth demand. Most metropolitan ZCTAs cluster around the 1:1 line, indicating the agreement between the two models for the type or areas. However, systematic deviations are evident: small-town and rural ZCTAs tend to show higher and more dispersed scores under the binary-weighted model, reflecting the limitations of rigid cutoff thresholds in capturing diverse travel behaviors. The binary-weighted model also produces more discrete value distributions due to its 0–1 weighting scheme, resulting in visible horizontal banding, whereas the data-driven model generates smoother, more continuous estimates that better capture fine-scale spatial variability.

Overall, these findings suggest that the binary-weighted V2SFCA offers a practical approximation for accessibility estimation in data-scarce contexts. In regions with similar geographic contexts and healthcare-seeking behaviors, catchment thresholds of 20 min (metropolitan), 40 min (micropolitan, small-town, and rural) provide reasonable empirical references.

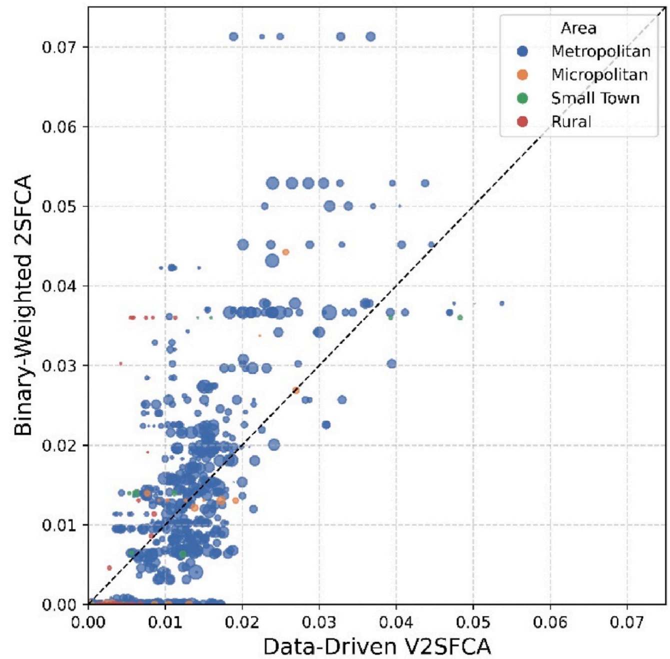

Fig. 8. ZCTA-level comparison of accessibility scores between data-driven and binary-weighted V2SFCA using the optimal thresholds.

5. Discussion

This study aimed to investigate spatial accessibility to maternal healthcare in Florida using a data-driven, area-specific V2SFCA framework that accounts for heterogeneity in travel behaviors, catchment areas, and service utilization. By deriving distance decay functions and catchment thresholds from observed birth-related travel flows, the study sought to provide a realistic, behaviorally informed assessment of maternal healthcare access and to identify geographic disparities that conventional approaches may overlook.

Maternal healthcare is distinct from other forms of care due to its unpredictable and high-intensity nature. This compels patients to actively prepare and engage with the healthcare system, often with significant emotional and financial commitment (Rogers and Lushbough, 2023). In this study, we leveraged birth-record data to represent delivery-related services utilization, capturing the central stage of maternal care, which typically elicits the highest level of patient engagement.

The spatial accessibility metric applied integrates two key dimensions: the supply-to-demand ratio (availability) and spatial impedance. Both are essential determinants of timely access, and insufficiency in either reduces overall accessibility. Metropolitan hospitals, while often densely distributed, attract patients from wide catchment areas, potentially causing congestion and reducing effective availability (Friedman and Holmes, 2022). Conversely, patients living in rural areas may travel longer distances but use lower volume facilities, paradoxically resulting in unexpectedly high accessibility relative to certain urban areas. These dynamics demonstrate that single-dimensional measures, such as provider density or proximity, may misrepresent true access by ignoring the interaction between availability and spatial impedance across geographic contexts.

A key methodological contribution of this study is the application of different decay functions and catchment sizes for different area types to better reflect their distinct geographic contexts, population densities, and travel behaviors. Applying uniform parameters risks underestimating accessibility in rural areas or oversimplifying urban conditions. By calibrating model parameters to local context, the analysis captures realistic travel patterns, supports meaningful comparison among areas, and enhances the validity of accessibility estimates.

From a practical perspective, these findings support maternal care interventions, advocacy, and informed allocation of healthcare resources. First, the area-specific V2SFCA framework enables precise identification of underserved areas and high-risk populations, informing targeted facility placement, capacity adjustments, or transportation interventions. Second, it allows simulation of alternative service configurations in resource-limited settings, facilitating fiscally sustainable planning. Third, in metropolitan areas, the method can detect potential congestion or overutilization, guiding optimization of existing networks. By incorporating local behavioral patterns and service demand, this approach aligns resource allocation with actual utilization, enhancing both efficiency and equity. Furthermore, the data-driven V2SFCA method provides an adaptable foundation for future research investigating the impact of spatial accessibility on maternal and neonatal health outcomes.

Equity-weighting methods have been proposed in U.S. healthcare systems to ensure that rural and disadvantaged populations are not overshadowed in measuring access and allocating resources (Agniel et al., 2023). However, traditional approaches that apply uniform parameters across all regions, pursuing "numerical equality", may lead to inefficient resource allocation. For instance, building high-capacity obstetric facilities in sparsely populated remote areas without sufficient demand may increase fiscal burden and result in underutilized resources. In contrast, our locally calibrated parameters allow our accessibility index to reflect true conditions, guiding resource allocation that is both equitable and financially sustainable, and providing actionable evidence to optimize maternal healthcare networks.

Despite the contributions of this study, several limitations should be acknowledged. First, we did not include facility-level characteristics, maternal comorbidities, or transportation modes, which may influence atypical travel patterns for high-risk pregnancies. Second, our analysis is limited to Florida and does not capture cross-state deliveries, potentially affecting travel patterns and assessment of access in state border regions. Third, we focused on birth, the most travel-driven maternal care event, as a proxy for service utilization, acknowledging that maternal care is a continuum encompassing prenatal and postpartum stages that may have different accessibility dynamics (Mallenbaum and Meier, 2025), (Cheng et al., 2006), (AAFP, 2020). Future research should extend this framework to include multi-stage maternal care, capturing prenatal and postpartum services to better reflect the cumulative travel burden and access patterns. Moreover, linking spatial accessibility metrics with adverse maternal and neonatal outcomes will clarify how geographic disparities affect health. Such analyses can provide actionable evidence to guide targeted interventions, inform maternal care advocacy, and support equitable allocation of healthcare resources across diverse geographic settings.

6. Conclusion

This study developed and applied a data-driven V2SFCA framework to evaluate maternal healthcare accessibility in Florida, explicitly accounting for different areas' heterogeneity in travel behavior. By deriving distance decay functions and catchment thresholds from observed birth-related travel flows, the model improved the behavioral realism of accessibility estimates compared with conventional approaches. The results reveal pronounced spatial disparities, with accessibility concentrated in metropolitan coastal areas and substantially lower scores in inland rural counties, demonstrating that accessibility is shaped not simply by urbanization but by the interplay of supply distribution, demand intensity, and transportation networks. Comparison with the traditional binary-weighted 2SFCA method further highlights the critical role of data-driven approaches in determining appropriate parameters for accessibility modeling. These findings provide actionable guidance for maternal healthcare interventions, advocacy, and resource allocation: area-specific accessibility measures enable precise identification of service gaps, support equitable distribution of obstetric resources, and account for nonmetropolitan patients' travel tolerance, cross-boundary service flows, and transportation constraints when planning maternal healthcare networks. Moreover, the framework is highly adaptable to other regions and care domains and establishes a robust foundation for future research linking spatial accessibility with maternal and neonatal health outcomes, thereby informing and efficient maternal healthcare planning and interventions.

CRediT authorship contribution statement

Hanqi Li: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Visualization, Writing – original draft. **Fahui Wang:** Conceptualization, Data curation, Investigation, Methodology, Supervision, Writing – review & editing. **Ran Zhang:** Data curation, Investigation, Project administration, Supervision, Writing – original draft, Writing – review & editing. **Andy Qin:** Data curation, Investigation, Methodology, Software. **Emily Javan:** Resources, Writing – review & editing. **Rajesh Reddy:** Writing – review & editing. **Lorie Harper:** Writing – review & editing. **Peiyin Hung:** Data curation, Funding acquisition, Investigation, Resources. **Yuhao Kang:** Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Resources, Supervision, Writing – review & editing.

Declaration of interest statement

Null.

Acknowledgments

This project was supported by grants awarded to the Population Research Center (#P2CHD042849 and #T32HD007081) at The University of Texas at Austin by the Eunice Kennedy Shriver National Institute of Child Health and Human Development. This project was supported by the Health and Health Care Improvement Pilots 2025 Dell Medical School at The University of Texas at Austin. The content is solely the responsibility of the authors and does not necessarily represent the official views of the National Institutes of Health. During the preparation of this work, the authors used ChatGPT in order to as a tool solely for improving language and readability, without contributing any ideas or perspectives to the content of the paper. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Data availability

The data that has been used is confidential.

References

American Academy of Family Physicians. Striving for Birth Equity: Family Medicine's Role in Overcoming Disparities in Maternal Morbidity and Mortality [Online]. Available: https://www.aafp.org/about/policies/all/birth-equity-pos-paper.html. (Accessed 13 August 2025).

Abbasi, J., 2023. US maternal mortality is unacceptably high, unequal, and getting worse—what can be done about it? JAMA 330 (4), 302–305. https://doi.org/10.1001/jama.2023.11328.

Agniel, D., Cabreros, I., Damberg, C.L., Elliott, M.N., Rogers, R., 2023. A formal framework for incorporating equity into health care quality measurement. Health Aff. 42 (10), 1383–1391. https://doi.org/10.1377/hlthaff.2022.01483.

Attanasio, L.B., Ranchoff, B.L., Cooper, M.I., Geissler, K.H., 2022. Postpartum visit attendance in the United States: a systematic review. Womens Health Issues 32 (4), 369–375. https://doi.org/10.1016/j.whi.2022.02.002.

Balsa-Barreiro, J., Batista, S.F.A., Hannoun, G.J., Menendez, M., 2025. Travel-time accessibility and adaptive spatial planning solutions for the healthcare system. Npj Health Syst 2 (1), 24. https://doi.org/10.1038/s44401-025-00028-1.

Bauer, J., Groneberg, D.A., 2016. Measuring spatial accessibility of health care providers – introduction of a variable distance decay function within the floating catchment area (FCA) method. PLoS One 11 (7), e0159148. https://doi.org/10.1371/journal.pone.0159148.

Cheng, C.-Y., Fowles, E.R., Walker, L.O., 2006. Postpartum maternal health care in the United States: a critical review. J. Perinat. Educ. 15 (3), 34–42. https://doi.org/10.1624/105812406X119002.

Clark, N.M., et al., 2025. Travel time as an indicator of poor access to care in surgical emergencies. JAMA Netw. Open 8 (1), e2455258. https://doi.org/10.1001/jamanetworkopen.2024.55258.

Darville, J.A., et al., 2025. Using spatial Bayesian models to estimate associations between structural racial discrimination and disparities in severe maternal morbidity. Soc. Sci. Med. 371, 117932. https://doi.org/10.1016/j.socscimed.2025.117932.

Delamater, P.L., 2013. Spatial accessibility in suboptimally configured health care systems: a modified two-step floating catchment area (M2SFCA) metric. Health Place 24, 30–43. https://doi.org/10.1016/j.healthplace.2013.07.012.

Delamater, P.L., Messina, J.P., Shortridge, A.M., Grady, S.C., 2012. Measuring geographic access to health care: raster and network-based methods. Int. J. Health Geogr. 11 (1), 15. https://doi.org/10.1186/1476-072X-11-15.

Delamater, P.L., Shortridge, A.M., Kilcoyne, R.C., 2019. Using floating catchment area (FCA) metrics to predict health care utilization patterns. BMC Health Serv. Res. 19 (1), 144. https://doi.org/10.1186/s12913-019-3969-5.

DeSisto, C.L., Goodman, D.A., Brantley, M.D., Menard, M.K., Declercq, E., 2022. Examining the ratio of obstetric beds to births, 2000–2019. J. Community Health 47 (5), 828–834. https://doi.org/10.1007/s10900-022-01116-1.

Erlander, S., Stewart, N.F., 1990. The Gravity Model in Transportation Analysis: Theory and Extensions. VSP.

Feng, C., Wang, H., Lu, N., Chen, T., He, H., Lu, Y., Tu, X., et al., 2014. Log-transformation and its implications for data analysis. Shanghai Arch. Psychiatry 26 (2), 105–109. https://doi.org/10.3969/j.issn.1002-0829.2014.02.009.

Statutes, Florida, 2023. Florida rural counties. Florida Statutes [Online]. Available: https://www.floridahealth.gov/programs-and-services/community-health/_documents/Rural_Counties_February_2023.pdf.

Fontenot, J., Brigance, C., Lucas, R., Stoneburner, A., 2024. Navigating geographical disparities: access to obstetric hospitals in maternity care deserts and across the United States. BMC Pregnancy Childbirth 24 (1), 350. https://doi.org/10.1186/s12884-024-06535-7.

Fotheringham, A.S., O'Kelly, M.E., 1989. Spatial interaction models: formulations and applications. In: Studies in Operational Regional Science. Kluwer Acad. Publ, Dordrecht no. 5.

Friedman, H.R., Holmes, G.M., 2022. Rural medicare beneficiaries are increasingly likely to be admitted to urban hospitals. Health Serv. Res. 57 (5), 1029–1034. https://doi.org/10.1111/1475-6773.14017.

"Google maps platform documentation Distance Matrix API (Legacy)," Google for Developers. Accessed: August. 11, 2025. [Online]. Available: https://developers.google.com/maps/documentation/distance-matrix.

Graves, B.A., 2008. Integrative literature review: a review of literature related to geographical information systems, healthcare access, and health outcomes. Perspect. Health Inf. Manag. AHIMA Am. Health Inf. Manag. Assoc. 5, 11.

Haiman, M.D., Cubbin, C., 2023. Impact of geography and rurality on preconception health status in the United States. Prev. Chronic Dis. 20, E101. https://doi.org/10.5888/pcd20.230104.

Harrington, K.A., Cameron, N.A., Culler, K., Grobman, W.A., Khan, S.S., 2023. Rural–urban disparities in adverse maternal outcomes in the United States, 2016–2019. Am. J. Publ. Health 113 (2), 224–227. https://doi.org/10.2105/AJPH.2022.307134.

Hoyert, D.L., 2025. Maternal mortality rates in the United States, 2023. NCHS Health E Stats Internet [Online]. Available: https://www.ncbi.nlm.nih.gov/books/NBK611990/. (Accessed 11 August 2025).

Hung, P., Henning-Smith, C.E., Casey, M.M., Kozhimannil, K.B., 2017. Access to obstetric services in rural counties still declining, with 9 percent losing services, 2004–14. Health Aff. 36 (9), 1663–1671. https://doi.org/10.1377/hlthaff.2017.0338.

Jia, P., Wang, F., Xierali, I.M., 2019. Differential effects of distance decay on hospital inpatient visits among subpopulations in Florida, USA. Environ. Monit. Assess. 191 (S2), 381. https://doi.org/10.1007/s10661-019-7468-2.

Kozhimannil, K.B., Hung, P., Henning-Smith, C., Casey, M.M., Prasad, S., 2018. Association between loss of hospital-based obstetric services and birth outcomes in rural counties in the United States. JAMA 319 (12), 1239–1247. https://doi.org/10.1001/jama.2018.1830.

Liu, X., Patel, A.B., Seidel, J.E., Mosher, D.P., Hagens, J., Marshall, D.A., 2025. Informing equitable access to care: a cross-sectional study of travel burden to primary and rheumatology care for people with rheumatoid arthritis. Int. J. Equity Health 24 (1), 84. https://doi.org/10.1186/s12939-025-02439-w.

Luo, W., Qi, Y., 2009. An enhanced two-step floating catchment area (E2SFCA) method for measuring spatial accessibility to primary care physicians. Health Place 15 (4), 1100–1107. https://doi.org/10.1016/j.healthplace.2009.06.002.

Luo, W., Wang, F., 2003. Measures of spatial accessibility to healthcare in a GIS environment: synthesis and a case study in Chicago region. Environ. Plann. Plann. Des. 30 (6), 865–884. https://doi.org/10.1068/b29120.

Luo, W., Whippo, T., 2012. Variable catchment sizes for the two-step floating catchment area (2SFCA) method. Health Place 18 (4), 789–795. https://doi.org/10.1016/j.healthplace.2012.04.002.

Carly Mallenbaum , Travis Meier, "Two-Thirds of Missouri Women Miss Postpartum check-ups," Axios. Accessed: August. 13, 2025. [Online]. Available: https://www.axios.com/local/kansas-city/2025/08/06/nearly-two-thirds-of-missouri-women-miss-postpartum-check-ups.

Mao, L., Nekorchuk, D., 2013. Measuring spatial accessibility to healthcare for populations with multiple transportation modes. Health Place 24, 115–122. https://doi.org/10.1016/j.healthplace.2013.08.008.

March of Dimes, "Maternal mortality rates: florida, 2018-2022," March of Dimes | PeriStats. Accessed: August. 12, 2025. [Online]. Available: https://www.marchofdimes.org/peristats/data?top=6&lev=1&stop=370&reg=99&sreg=12&obj=35&slev=4.

Missouri Census Data Center. Geographic Correspondence Engine (GeoCorr 2022). University of Missouri [Online]. Available: https://mcdc.missouri.edu/applications/geocorr2022.html. (Accessed 22 November 2025).

McGrail, M.R., Humphreys, J.S., 2009. Measuring spatial accessibility to primary care in rural areas: improving the effectiveness of the two-step floating catchment area method. Appl. Geogr. 29 (4), 533–541. https://doi.org/10.1016/j.apgeog.2008.12.003.

Mseke, E.P., Jessup, B., Barnett, T., 2024. Impact of distance and/or travel time on healthcare service access in rural and remote areas: a scoping review. J. Transport Health 37, 101819. https://doi.org/10.1016/j.jth.2024.101819.

Nesbitt, T.S., Connell, F.A., Hart, L.G., Rosenblatt, R.A., 1990. Access to obstetric care in rural areas: effect on birth outcomes. Am. J. Publ. Health 80 (7), 814–818. https://doi.org/10.2105/AJPH.80.7.814.

Obeidat, B., Alourd, S., 2024. Healthcare equity in focus: bridging gaps through a spatial analysis of healthcare facilities in Irbid, Jordan. Int. J. Equity Health 23 (1), 52. https://doi.org/10.1186/s12939-024-02120-8.

Pot, F.J., Piesch, L., 2024. How far is too far? Urban versus rural acceptable travel distances. Transp. Res. Part Transp. Environ. 137, 104474. https://doi.org/10.1016/j.trd.2024.104474.

Probst, J., Eberth, J.M., Crouch, E., 2019. Structural urbanism contributes to poorer health outcomes for rural America. Health Aff. 38 (12), 1976–1984. https://doi.org/10.1377/hlthaff.2019.00914.

Rayburn, W.F., Richards, M.E., Elwell, E.C., 2012. Drive times to hospitals with perinatal care in the United States. Obstet. Gynecol. 119 (3), 611. https://doi.org/10.1097/AOG.0b013e318242b4cb.

Rogers, T.S., Lushbough, B., 2023. Schedule of visits and televisits for routine antenatal care. Am. Fam. Physician 107 (2), 187–190.

Rousseeuw, P.J., Hubert, M., 2011. Robust statistics for outlier detection. WIREs Data Min. Knowl. Discov. 1 (1), 73–79. https://doi.org/10.1002/widm.2.

"Rural-Urban commuting area codes Economic Research Service." Accessed: October. 22, 2025. [Online]. Available: https://www.ers.usda.gov/data-products/rural-urban-commuting-area-codes.

Shen, Q., 1998. Location characteristics of inner-city neighborhoods and employment accessibility of low-wage workers. Environ. Plann. Plann. Des. 25 (3), 345–365. https://doi.org/10.1068/b250345.

Souza, J.P., et al., 2024. A global analysis of the determinants of maternal health and transitions in maternal mortality. Lancet Global Health 12 (2), e306–e316. https://doi.org/10.1016/S2214-109X(23)00468-0.

Stacherl, B., Sauzet, O., 2023. Gravity models for potential spatial healthcare access measurement: a systematic methodological review. Int. J. Health Geogr. 22 (1), 34. https://doi.org/10.1186/s12942-023-00358-z.

Tao, Z., Cheng, Y., Du, S., Feng, L., Wang, S., 2020. Accessibility to delivery care in Hubei Province, China. Soc. Sci. Med. 260, 113186. https://doi.org/10.1016/j.socscimed.2020.113186.

Tian, F., Pan, J., 2021. Hospital bed supply and inequality as determinants of maternal mortality in China between 2004 and 2016. Int. J. Equity Health 20 (1), 51. https://doi.org/10.1186/s12939-021-01391-9.

U. C. Bureau, "New Florida Estimates Show Nation's Third-Largest State Reaching Historic Milestone," Census.gov. Accessed: August. 24, 2025. [Online]. Available: https://www.census.gov/library/stories/2022/12/florida-fastest-growing-state.html.

U. S. G. A. Office. Maternal health: availability of hospital-based obstetric care in rural areas | U.S. GAO [Online]. Available: https://www.gao.gov/products/gao-23-105515. (Accessed 4 August 2025).

Virtanen, P., et al., 2020. SciPy 1.0: fundamental algorithms for scientific computing in Python. Nat. Methods 17 (3), 261–272. https://doi.org/10.1038/s41592-019-0686-2.

Wang, C., Wang, F., Onega, T., 2021. Spatial behavior of cancer care utilization in distance decay in the Northeast Region of the U.S. Travel Behav. Soc. 24, 291–302. https://doi.org/10.1016/j.tbs.2021.05.003.

Wang, F., Liu, L., 2023a. Computational Methods and GIS Applications in Social Science, third ed. CRC Press, Boca Raton. https://doi.org/10.1201/9781003292302.

Wang, F., Liu, L., 2023b. Computational Methods and GIS Applications in Social Science, third ed. CRC Press, Boca Raton. https://doi.org/10.1201/9781003292302.

World Health Organization, 2023. Trends in Maternal Mortality 2000 to 2020: Estimates by WHO, UNICEF, UNFPA, World Bank Group and UNDESA/population Division. World Health Organization.

Wu, X., Huang, Z., Yu, X., 2024. Potential and observed supply–demand characteristics of medical services: a case study of nighttime visits in shenzhen. ISPRS Int. J. GeoInf. 13 (11), 382. https://doi.org/10.3390/ijgi13110382.

Zhou, Y., et al., 2021. An adapted two-step floating catchment area method accounting for urban–rural differences in spatial access to pharmacies. J. Pharmaceut. Health Serv. Res. 12 (1), 69–77. https://doi.org/10.1093/jphsr/rmaa022.