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Developing a flow-based spatial algorithm to delineate hospital service areas

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ABSTRACT

Hospital service areas (HSAs) capture most of local patient-to-hospital travel flows, and have been accepted as the most basic unit for analyzing local hospital utilization and hospitalization patterns. If a given HSA includes multiple hospitals providing care for its residents, it is complicated to assign responsibility for small-area variation in hospital performance or healthcare costs to specific hospitals without established HSA managers. The goal of this study is to produce HSAs with the fewest number of hospitals within an HSA unit. Only a very limited number of studies are related to the HSA delineation. This study reviews the existing approaches to delineate a broader range of service areas besides HSAs. A spatial algorithm named *Travel-to-Hospital Algorithm (TTHA)* was developed and implemented using the individual hospital discharge records from the Florida State Inpatient Database for 2011. The final output, named the *TTHA-derived HSAs*, included 14 more eligible divisions in Florida than the HSAs produced by the traditional approach (92 *vs.* 78), with the degree of self-containment comparable between the two sets of HSAs. The TTHA provides insight into the patterns of hospital visits and holds great value for the delineation of other types of service and catchment areas.

1. Introduction

Hospital service areas (HSAs) have been generally accepted as the most basic analysis unit for studying a wide range of healthcare-related issues such as hospital resource utilization, local hospitalization, and healthcare quality and costs (Lewis, Colla, Carluzzo, Kler, & Fisher, 2013; Ricketts & Belsky, 2012; Schroeck et al., 2014). However, all existing studies in the U.S. have still been using the *Dartmouth HSAs* produced on the basis of 1992–93 Medicare records (Center for Evaluative Clinical Sciences, 1999), which were recently described as outdated and unrepresentative and urgently needed to be re-delineated (Jia, Xierali, & Wang, 2015). The goal of delineation is to produce a set of self-contained functional areas with weak links between each other, which indicates that most of the spatial interactions of destinations should occur within rather than between functional areas. To the best of the author's knowledge, only Jia et al. (2015) made the effort to produce a set of contemporary HSAs by using the hospital attributes considered attractive to patients (e.g., number of beds) to weigh hospitals in the classical Huff model (Jia et al., 2015). As individual hospitalization records became increasingly available, Klauss, Staub, Widmer, and Busato (2005) produced HSAs in Switzerland using locations of patients and hospitals by assigning a zip code to the hospital most frequently visited by the patients in that zip code (Klauss et al., 2005).

Over the past two decades, the Big Data era has made obtaining hospital attendance and discharge records easier than ever, particularly in developed countries (Hodgson, 1988). Especially in the U.S., the Agency for Healthcare Research and Quality (AHRQ) has assembled, edited, and standardized the State Inpatient Databases (SID), State Ambulatory Surgery and Services Databases (SASD), and State Emergency Department Databases (SEDD) across states and for multiple years, as part of the Healthcare Cost and Utilization Project (HCUP). However, few attempts have been made to analyze these abundant hospital data for HSA delineation.

A main criterion to judge the performance of various HSA delineation methods in this study is to produce as many eligible self-contained HSA units as possible, with each unit including as few hospitals as possible. If a given HSA includes multiple hospitals providing care for its residents, it is complicated to assign responsibility for small-area variation in hospital performance or healthcare costs to specific hospitals without established HSA managers, which indicates that associated HSA research may not be

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useful for managerial and policy recommendations (Shwartz, Pekoz, Labonte, Heineke, & Restuccia, 2011). Although there is only a limited body of knowledge related to the methodology for delineating the HSAs (Center for Evaluative Clinical Sciences, 1999; Jia et al., 2015; Klauss et al., 2005), a multitude of methods have been proposed for delineating service areas for different purposes, such as trade areas (TAs), labor market areas (LMAs), and housing market areas (HMAs), from which HSA delineation could significantly benefit with appropriate adaptation.

This study reviews the main approaches of delineating various service areas in addition to HSAs. After determining advantages and disadvantages of different methods, an algorithm named *Travel-to-Hospital Algorithm (TTHA)* was developed, which is explained in detail below. The resulting HSAs were compared to the ones produced by the traditional approach, with the preferred production derived from the TTHA in terms of number of eligible HSAs. The TTHA also holds great value for the delineation of other types of service areas.

2. Literature review

2.1. HSAs

The currently used *Dartmouth HSAs* in the U.S. were defined in the Dartmouth Atlas of Health Care project (Center for Evaluative Clinical Sciences, 1999) through a four-step process: assigning each hospital to a city by location; assigning each zip code to the city containing the hospital that most patients in that zip code visited; grouping zip codes assigned to each city into an HSA; and reassigning each disconnected zip code to an adjacent HSA to ensure the geographic contiguity of all zip codes in one HSA. Thus, 3436 HSAs were produced for all 50 states and the District of Columbia. This is also referred to as the *Dartmouth approach*, representing the earliest effort to develop HSAs using 1992–93 Medicare hospitalization records.

The *Swiss approach* is an improved version of the Dartmouth approach, which was introduced to produce HSAs in Switzerland by similar steps: assigning each hospital to a census region by location, referred to as a *hospital region*; assigning each census region to the hospital region that most patients in that census region visited; grouping census regions assigned to each hospital region into an HSA; reassigning each disconnected census region to an adjacent HSA to ensure the geographic contiguity of all census regions in one HSA; and, finally, merging each HSA with more patients visiting another HSA into that HSA, also referred to as *plurality rule* (Center for Evaluative Clinical Sciences, 1999). This approach was adapted to delineate HSAs in Florida, U.S., using overall patient data in 2011, also termed *Dartmouth–Swiss hybrid method*.

Jia et al. (2015) brought the Huff model (Huff, 1964) into HSA delineation, considered as the *flow-based Huff approach*, through the following steps:

(1) using the power function with preassumed parameters to fit individual hospitalization data under each assumed threshold of travel distance:

$$P_{ij} = S_j^{\alpha} d_{ij}^{-\beta} \Big/ \sum\nolimits_{k=1}^{n} S_k^{\alpha} d_{ik}^{-\beta}, \qquad (1)$$

where P_{ij} = probability of visiting hospital j by zip code i, $S_{j(k)}$ = number of beds in hospital $j(k)$, $d_{ij(k)}$ = travel time from zip code i to hospital $j(k)$ in minutes, α = elasticity of hospital capacity, β = distance decay friction factor, and n = total number of hospitals accessible to the patients in zip code i;

(2) selecting the model producing the minimum difference between theoretical and actual hospital visits:

$$min\left[\sum\nolimits_{t=1}^{m}\sum\nolimits_{k=1}^{n}(V_t P_{tk} - A_{tk})\right], \qquad (2)$$

where P_{tk} = probability of visiting hospital k by zip code t from Equation (1), V_t = actual number of patients in zip code t, A_{tk} = actual number of visits from hospital k to zip code t, n = total number of hospitals accessible to the patients in zip code t, and m represents all zip codes;

(3) using the selected model to calculate attractiveness of each hospital to each zip code, and assigning each zip code to the hospital that most attracts that zip code; and
(4) grouping zip codes assigned to each hospital into an HSA, and merging each HSA with more patients actually visiting another HSA into that HSA.

2.2. Delineation of other functional areas

One of the simplest and most intuitive approaches is the *ring-based approach* (Patel, Fik, & Thrall, 2008), in which a circle is drawn around a provider to capture a specified number or percentage of customers. This approach is easy to implement and interpret under the assumption that customers are evenly distributed around providers by adjusting the radius uniformly in all directions. Similarly, the *patient origin method* captures a certain percentage of customers or a number of area units closest to the provider. This method can be easily extended by replacing Euclidean distance with network distance or travel time. With more accurate travel distance (or time), the buffer zone within a certain travel distance (or a certain period of travel time) can be used to represent the service area of a provider, such as 15 miles (or 30 min) (Luo & Wang, 2003). One common disadvantage of both approaches above is that the specified number or percentage is subjective, varying by the analysts, such as 60% (Garnick, Luft, Robinson, & Tetreault, 1987), 75%, and 85% (Shortt, Moore, Coombes, & Wymer, 2005). More importantly, as customers living in one region may have different choices, multiple service areas may overlap with one another and not be mutually exclusive.

The *wedge-based approach* adds a component of directionality to the origin–destination (O–D) distance by dividing a region into a certain number of sectors or wedges, and specifying an incremental distance based on analysts' experiences. The procedure starts from a small core region around the provider. In each iteration, only the wedge that would capture the maximum number of customers by its incremental extension is extended. The iteration stops when a specified number/percentage of customers is reached or no additional increment is gained by the extension in all directions (Patel et al., 2008). This approach identifies spatial heterogeneity of travel willingness and patterns in different directions. However, subjectivity in multiple steps can lead to introduction of errors and inability to replicate results, such as determination of how many sectors are needed and how long an incremental distance is. Moreover, if a large number of customers are clustered farther than a specified incremental distance from a wedge's current radius, they cannot be captured by only one incremental extension. In that case, the wedge would not be allowed to extend, and hence those customers would not be detected and included in the service area of that provider. This could create holes in coverage, also referred to as artificial discontinuity.

The *proximal area method* is another simple geographic approach (Ghosh & McLafferty, 1987), which considers only travel distance (or time). Customers are assigned to their nearest providers, and all customers assigned to the same providers constitute service areas. This approach weakly assumes that customers always choose the nearest service providers.

Another group of approaches defines service areas according to the flows of customers in relation to supply and demand (Brown & Hincks, 2008). To measure independence of one service area from others, *self-containment* for a given service area is defined as percentage of the residents (customers) interacting with the providers within that area, also termed as *localization index* (LI) in some other studies (Jia et al., 2015; Klauss et al., 2005). A degree of self-containment is set for all flow-based approaches, below which a service area should not be regarded as independent and must be merged with another for a higher self-containment than previously set. Although the precise level of threshold of self-containment remains unanswered (Jones, 2002), it has been suggested as 50% (Jones, 2002) or 70% (Pieda, 2004) in existing studies.

The approach utilized to delineate the LMAs in Sweden uses the intensity of commuting flows from living to working places within and between municipalities to group municipalities into LMAs (Carlsson, Johansson, Petersson, & Tegsjö, 1993). Two major steps are involved in this approach: some municipalities form initial LMAs by themselves if (1) >80% of employed residents commute to work within their municipalities and (2) the percentage of employed residents commuting to any other individual municipality is <7.5%; and each remaining municipality is assigned to an LMA to which most of their employed residents commute. However, such a threshold of 80%, plus 7.5% for the maximum percentage of commuters going outside the service area, can lead to a small number of LMAs and may not be necessary in other contexts.

The *Synthetic Data Matrix* (SDM) is devised to integrate the service areas derived from a variety of datasets in order to create an one-size-fits-all boundary that could serve multiple disciplines, including local institutions, demography, economy, facilities, and landscape (Coombes, 2000). This approach focuses on broad, common features instead of specific features of different localities, which, however, is difficult to realize, as the aforementioned notions are conceptually different (e.g., local institutions *vs.* demography).

The *Travel-to-Work Algorithm* (TTWA) was developed for producing a set of nonoverlapping functional areas by identifying potential foci by specific criteria, merging strongly interlinked foci, expanding foci into initial functional areas, allocating residual basic units to initial functional areas, and disassembling and reallocating the initial functional areas not satisfying the population size and self-containment criteria (Coombes, Green, & Openshaw, 1986). This algorithm has been reviewed and adjusted per decade because of changes in commuting patterns over time (Coombes, 2010).

3. Data

Florida was selected as a study area because of its relatively isolated geographic location from neighboring states and, thus, the reduced likelihood of patients going outside of the state for hospitalization. Records from 221 hospitals (i.e., 22 acute long-term care hospitals and 199 general medical and surgical hospitals) in Florida in 2011 were extracted from the SID by the AHRQ (Agency for Healthcare Research and Quality, 2011). Each record represents a discharge record of one inpatient. A total of 2,376,743 discharge records were successfully geocoded to 983 zip codes in Florida and included in this study. The detailed screening process has been described elsewhere (Jia et al., 2015).

The *Huff-based HSAs* including 81 units produced by the *flow-based Huff approach* and the *2011 overall-derived HSAs* including 78 units produced by the *Dartmouth–Swiss hybrid method* were obtained from a previous study for comparison purposes (Jia et al., 2015). Two sets of boundaries were proved comparable with each other in that study, especially in terms of number of eligible self-contained HSA units, which was the main criterion for judging the performance of different methods under the specific context of this study. Therefore, the resulting HSAs from this study were only compared to the *2011 overall-derived HSAs*, because of the similarity of both methods that purely depended on O–D flows.

4. Methods

After compromising the fit of the methods to hospital discharge data and ease of implementation, the TTHA was developed on the basis of the TTWA, which was mainly divided into two stages and five steps: Stage 1 (Steps 1–3) and Stage 2 (Steps 4 and 5), illustrated in Fig. 1 and described as follows:

4.1. *Step 1: identify independent HSA foci*

All zip codes within which at least one hospital was located were considered as *HSA foci*. All hospital discharge records were converted into O–D patient flows according to patients' zip codes and hospital locations, based on which the percentage of discharges from each hospital to each zip code was computed. LI, indicating the percentage of patients visiting local hospitals within a given area, was calculated for each HSA focus with the basic unit (a patient) replaced with a hospital visit of a patient. All HSA foci with $LI \geq 0.5$ were considered as *independent HSA foci*.

4.2. *Step 2: merge zip codes with HSA foci for independent HSA foci*

Those HSA foci with $LI < 0.5$ were ranked in descending order of LIs. According to the Queen Contiguity rule that all zip codes sharing at least a point-length border with a given HSA focus were defined as *neighboring zip codes* (or *neighbors*) of that HSA focus (the hospital within that HSA focus was called *focus hospital* for its neighbors), the neighbors of each HSA focus, if not HSA foci and with the focus hospital(s) discharging ≥50% of their patient records, were extracted. The neighbor with the highest percentage of discharges from the focus hospital(s) was first merged with a given HSA focus, and the new LI was calculated. If $LI \geq 0.5$, the combined HSA focus was considered as an independent HSA focus; otherwise, the neighbor with the next highest percentage of discharges from the focus hospital(s) continued to be merged with the combined HSA focus, until $LI \geq 0.5$. If all extracted neighbors were merged but LI remained <0.5, the combined HSA focus was then dismantled into individual zip codes.

4.3. *Step 3: amalgamate residual HSA foci for independent HSA foci*

The remaining HSA foci with $LI < 0.5$ were ranked in descending order of LIs. Each HSA focus was merged with a different HSA focus that discharged the highest percentage of patient records to that HSA focus, and the LI of the combined HSA focus was calculated. If $LI \geq 0.5$, the combined HSA focus was considered as an independent HSA focus; otherwise, this combined HSA focus continued to be merged with another HSA focus discharging the highest percentage of patient records to the combined focus, until $LI \geq 0.5$. All HSA foci were independent by the end of this step.

4.4. *Step 4: expand HSA foci into proto HSAs*

The percentage of discharges was recomputed from each independent HSA focus to each remaining zip code that was not part of any HSA focus. Each HSA focus was iteratively expanded outward to

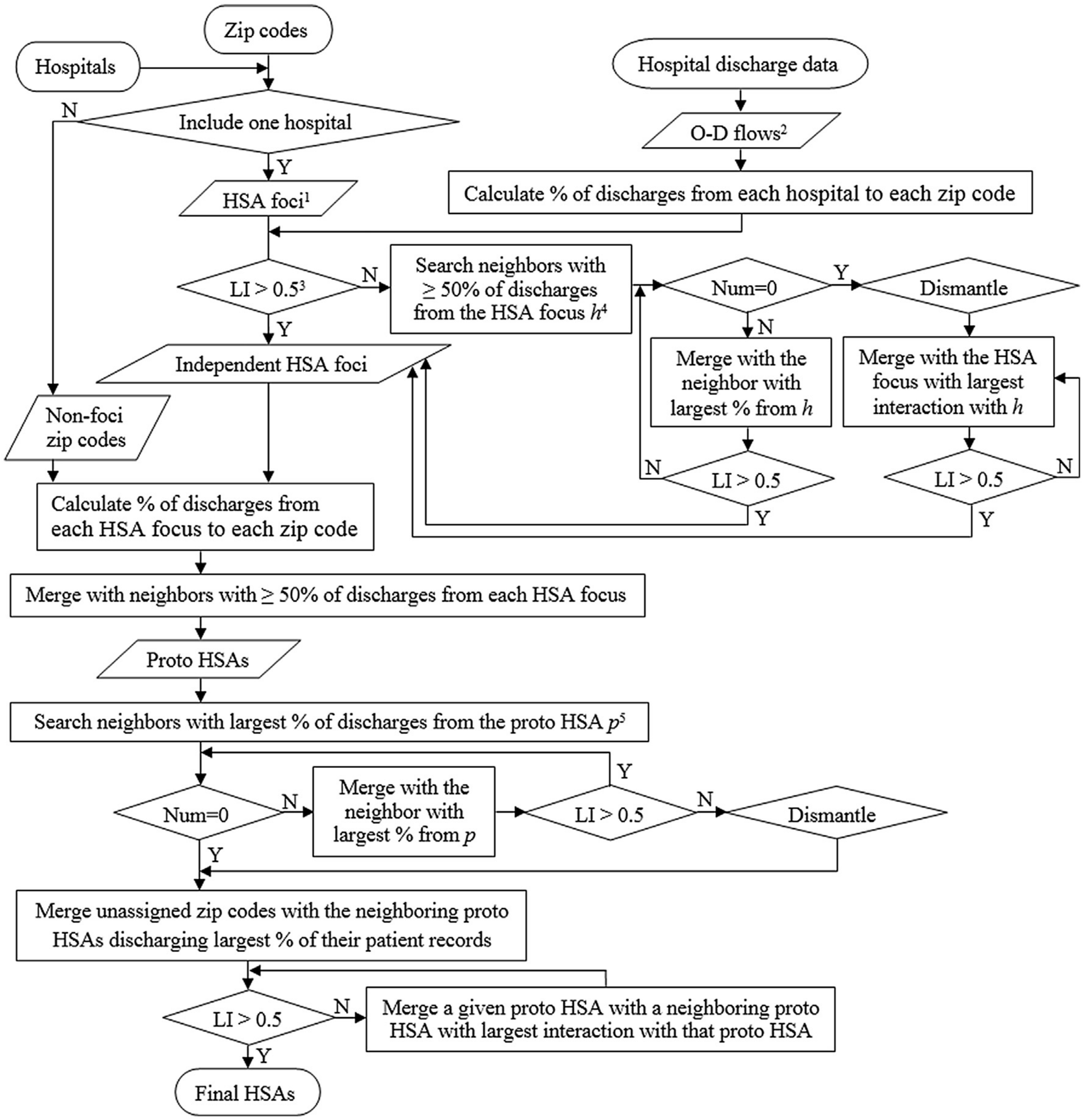

Fig. 1. Flowchart for generating the *TTHA-derived HSAs* (starting from "Zip codes" and ending with "Final HSAs"). Note: [1]Hospital service areas; [2]Origin–destination; [3]Localization index; [4]h denotes each of the HSA foci with LI < 0.5; [5]p denotes each proto HSA.

merge with all neighbors with the focus hospital(s) discharging ≥50% of their patient records. Each expanded HSA focus was considered as a *proto HSA* at the end of this step, with the LI recalculated.

4.5. Step 5: allocate residual zip codes to proto HSAs

The proto HSAs were ranked in descending order of LIs. The neighbors of each proto HSA with the highest percentage of their patient records discharged from the focus hospital(s) were extracted; the neighbor with the highest percentage relative to other extracted neighbors was first merged with a given proto HSA, and the LI of the combined proto HSA was calculated. If LI < 0.5, merging was rescinded and processing moved to the next proto HSA; otherwise, the neighbor with the next highest percentage continued to be merged with that combined proto HSA, until either LI < 0.5 or all extracted neighbors had been merged. Each remaining zip code unassigned was merged with a neighboring proto HSA (according to the Queen Contiguity rule) that discharged the highest percentage of its patient records, which sometimes may lower the LI of present proto HSAs below 0.5 to make them ineligible for being independent HSA units. In those cases, a given proto HSA (LI < 0.5) was merged with a neighboring proto HSA that had the largest interaction with that proto HSA, until LI ≥ 0.5. The final output was named the *TTHA-derived HSAs*.

5. Results

The 221 hospitals were geocoded to 197 zip codes, of which 93 were considered as independent HSA foci (LI ≥ 0.5). Two of the remaining 104 HSA foci became independent HSA foci after merging with neighboring zip codes with ≥50% of discharges from the focus hospitals. After merging with one another based on interaction between them, 13 HSA foci formed five independent HSA foci; the remaining 89 foci were merged with 100 existing independent HSA foci in the way described in the methodology section. After merging with all nonfoci zip codes, eight proto HSAs had an LI < 0.5 and hence were merged with their neighboring proto HSAs having the largest interaction with them. A total of 92 continuous HSA units with LI $\geq$ 0.5 were ultimately produced.

According to the evaluation criterion adopted in this study that a preferred method should produce more eligible self-contained HSA units, the TTHA outperformed the traditional method by producing 14 more eligible HSA units (92 *vs.* 78). This contributed in part to the varying numbers of the HSAs within each LI category (Fig. 2). The cumulative probability curves from histograms showed that the proportions of LIs of two sets of HSAs were similarly distributed. However, there were more HSA units with a relatively lower LI (0.5–0.8) and fewer units with a higher LI ($\geq$0.8) in the *TTHA-derived HSAs* than in the *2011 overall-derived HSAs*.

However, the means of LIs of the TTHA-derived HSAs and of the 2011 overall-derived HSAs were comparable (0.62 *vs.* 0.65). A natural log transformation was conducted to alleviate the skewed distribution of two groups of LIs, and a *t*-test was used for assessing if the difference between the two groups of LIs was significant. There was no difference in the log-transformed LIs for the TTHA-derived HSAs (M = −0.488, SD = 0.162) and the 2011 overall-derived HSAs (M = −0.446, SD = 0.177); t (168) = 1.612, $p = 0.109$ (two-tailed). Therefore, we concluded that despite an obvious increase in the number of HSA units from 78 to 92, there was no significant decrease in degree of self-containment on average.

The boundaries of the *TTHA-derived HSAs* were overlaid with those of the *2011 overall-derived HSAs* (Fig. 3). There were considerable inconsistencies between two sets of boundaries, observed more often in metropolitan areas such as Jacksonville, Miami, Tampa, Clearwater, and Orlando, where some medium-size hospitals (100–300 beds) formed self-contained service areas on their own or with close competitors when the threshold level was set at 50%.

6. Discussion

Despite abundant and detailed hospital admission and discharge data available, only a very limited number of studies are related to the HSA delineation. The goal of this study is to develop an efficient spatial algorithm to produce as many eligible self-contained HSA units as possible within a given area. The TTHA meets this criterion by producing an apparently larger number of HSAs than traditional methods. The skeleton of the algorithm is primarily composed of iterative spatial computation and spatial neighbor searching, which have been well supported and facilitated by Geographic Information Systems (GIS) and could be easily automated. In addition, a select review of literature on the delineation of HSAs and other types of service areas is presented, which serves as an important step forward to enable the adaptation of more traditional classical methods to healthcare facility catchment area delineation.

An eligible self-contained HSA unit was defined as an area with LI $\geq$ 0.5, which followed the same setting of LI in previous studies for an easy comparison. When the threshold of LI changes from 50% to a higher level, such as 70% or 80%, delineation was expected to change as well; however, although more research is warranted, on the basis of the nature of the algorithm and results from this study, it can be reasonably hypothesized that the TTHA would still outperform the traditional method regardless of threshold.

Some limitations exist in this algorithm. First, implementation of the TTHA is heavily dependent on actual individual hospitalization data, which may not be available in many areas such as in low- and middle-income countries. Nevertheless, the TTHA works better in a different context where hospitalization data are abundant, especially when a larger number of resulting service areas is preferred. The TTHA can take full advantage of these data to maximize eligible catchment areas in a given area.

Second, the nature and process of the TTHA cannot guarantee that degree of self-containment can always be maximized as a whole. In Step 5, when there are zip codes left unassigned within which patients visit hospitals in multiple HSAs more evenly instead of visiting hospital(s) in one HSA more frequently than in other HSAs, the TTHA continues merging these zip codes into the proto HSAs to a maximum degree, until LI reaches the lower limit of eligibility. Therefore, under the premise of eligibility (LI $\geq$ 0.5), the TTHA pursues a larger number of service areas instead of higher LIs on average, and is specifically geared to the needs of delineation of healthcare facilities catchment areas.

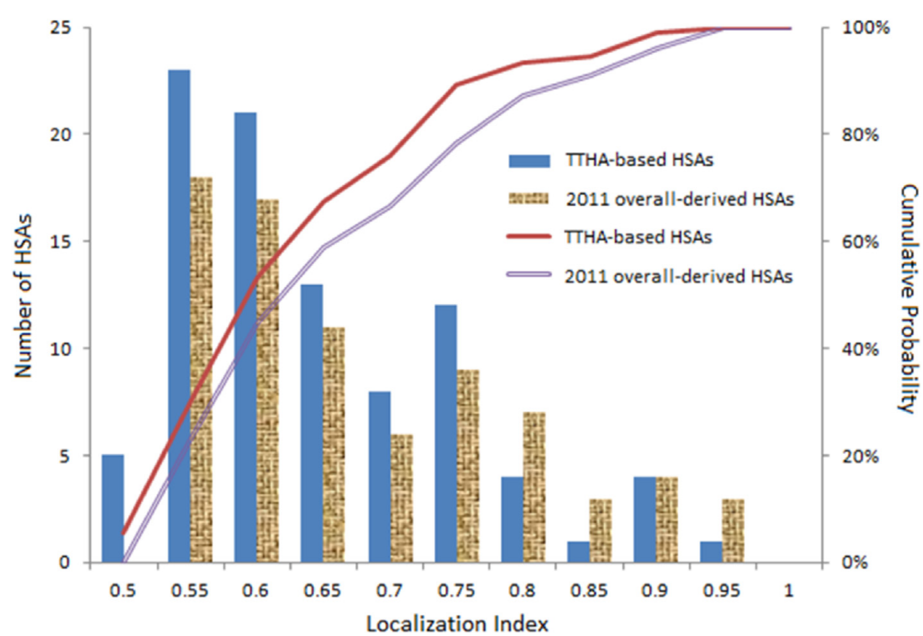

Fig. 2. Histograms and cumulative probability curves of the localization index (LI).

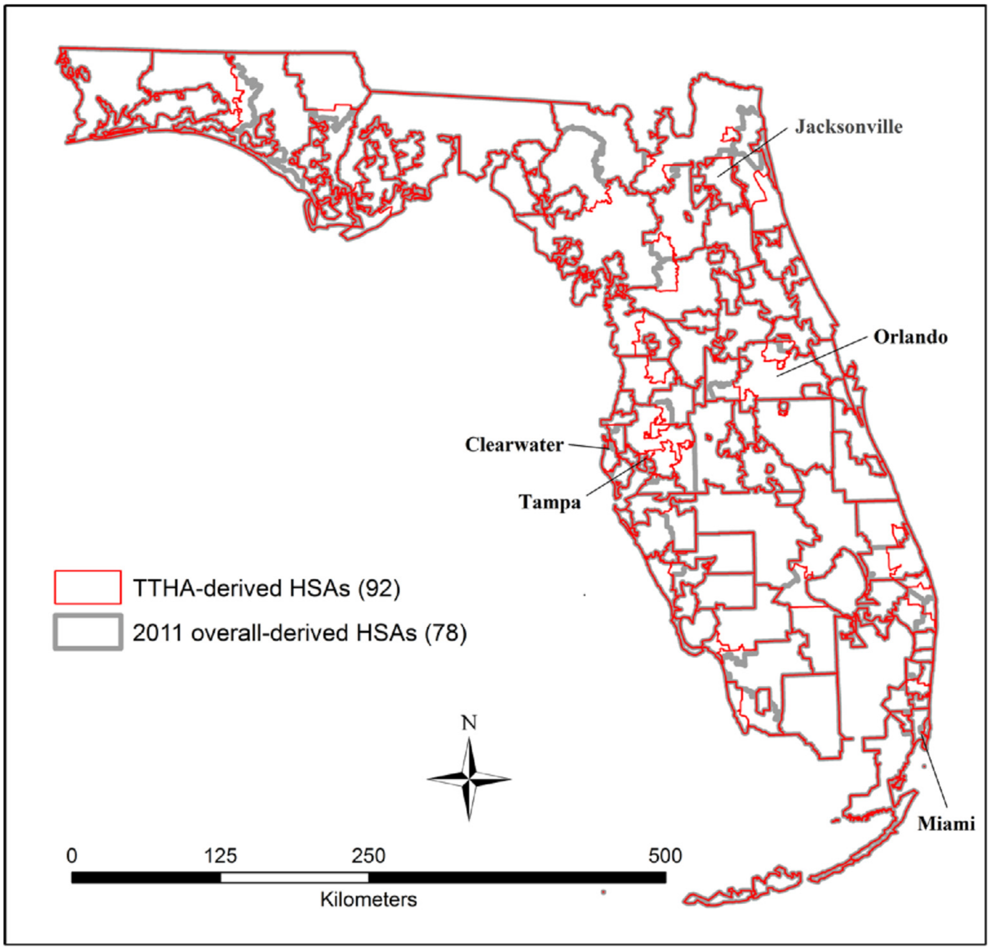

Fig. 3. Boundaries of the *TTHA-derived HSAs* and *2011 overall-derived HSAs*.

Third, the severity or uniqueness of illness is not differentiated in this study. Some specialized patients (e.g., neurological patients) may have to bypass the closest hospital or all local hospitals to visit farther hospitals because of lack of provision of specialized or just adequate care within their own HSAs (Jia & Xierali, 2015). Removal of the influences of this physical restriction requires a clear definition of ranges of services provided by each hospital, which is not conducted in this study. Moreover, such unavoidable physical restrictions also come from more factors than availability of hospital services, such as types of health insurance accepted by local hospitals, car ownership, and public transportation infrastructure. It is difficult to remove all these confounding effects, but how to differentiate general and specialized patients and adapt this algorithm to produce hierarchical HSAs is an important future direction to popularize this algorithm. According to the central place theory (Christaller, 1933), specialized patients generally tend to travel longer than general patients to pursue a higher level of healthcare services (Jia, Wang, & Xierali, 2017). Therefore, exclusion of specialized patients may lead to an even larger number of HSA units than the present number.

Fourth, the criterion used to compare the performance of various HSA delineation methods in this study is never a gold standard, although there has not been any gold standard in this area. The selection of HSA delineation methods should depend on the specific aim of the study. The goal of conducting this study is to facilitate forming a healthcare market where each patient could and would like to visit a nearest hospital to meet his/her demands, such as the ideal mutually exclusive hospital catchment areas. In that case, we would be able to produce a set of HSAs with only one hospital in each unit by only using hospital visit data. The method developed in this study and resulting HSAs well serve the goal by clearly showing which hospitals managed to attract more than half of their surrounding residents independently and which hospitals failed to. This could inform and guide relevant stakeholders to compare two categories of hospitals, seek the reasons why some hospitals lost their neighboring patients, and improve the infrastructures, staffing, services, or quality of hospitals.

Last, this is a pilot study only conducted in one state of the U.S. More studies in other regions using more years' data are warranted to assess the generalizability of this algorithm. Also, methodologically speaking, there are more literature on complex analyses and clustering of travel or other types of flows that was covered in the literature review part of this study due to limited capacity. However, given the specific setting of this study, the majority of HSA delineation methods have been covered. More advanced theories and methods are expected to be used for improving the method developed in this study.

Overall, with the aid of GIS, the TTHA can divide a given region (Florida in this study) into eligible units to a maximum degree once threshold for eligibility is set. Despite more steps involved than traditional methods, the algorithm could be easily automated as most operations include spatial neighbor searching and computation. The TTHA provides deep insight into the patterns of hospital visits during any specific period of time in areas where reliable patient flow data are available. In addition to HSA delineation, this method holds great value for delineation of other types of service and catchment areas where customer (to provider) flow data are available.

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