Applied Geography 75 (2016) 137–143

Contents lists available at ScienceDirect

Applied Geography

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

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

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ARTICLE INFO

Article history:
Received 13 January 2016
Received in revised form
2 August 2016
Accepted 8 August 2016
Available online 27 August 2016

Keywords:
Hospital service area (HSA)
Regionalization
Travel flow
State Inpatient Database (SID)
Florida

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the basis of 1992–93 Medicare records (Center for Evaluative Clinical Sciences, 1999), which were recently described as outdated and unrepresentative and urgently needed to be re-delineated (Jia, Xierali, & Wang, 2015).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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http://dx.doi.org/10.1016/j.apgeog.2016.08.008
0143-6228/

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:

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

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:

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

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