GIS-Based Accessibility Measures and Application

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INTRODUCTION

Accessibility refers to the relative ease by which the locations of activities, such as work, shopping and healthcare, can be reached from a given location. Access varies across space because of uneven distributions of supply and demand (*spatial factors*), and also varies among population groups because of their different socioeconomic and demographic characteristics (*nonspatial factors*). Taking healthcare access for example, spatial access emphasizes the importance of geographic barrier (distance or time) between consumer and provider, whereas nonspatial access stresses non-geographic barriers or facilitators such as social class, income, ethnicity, age, sex, and so forth. Since the 1960s, health policymakers in the United States have attempted to improve health care for the citizenry by considering aspects of both spatial and nonspatial factors. Such efforts are exemplified in designations of Health Professional Shortage Areas (HPSA) and Medically Underserved Areas or Populations (MUA/P) by the U.S. Department of Health and Human Services (DHHS), for the purpose of determining eligibility for certain federal health care resources. The DHHS is considering consolidating the HPSA and MUA/P designations into one system because of their overlapping criteria (U.S. DHHS, 1998). See guidelines at http://bphc.hrsa.gov/dsd (last accessed April 1, 2004).

BACKGROUND

Measuring Spatial Accessibility

According to Joseph and Phillips (1984), measures of spatial accessibility include *regional availability* and *regional accessibility*. The former is expressed as a demand (population) to supply (i.e., practitioner in the case of healthcare access) ratio within a region, and it is simple and easy to implement. The latter considers complex interaction between supply and demand in different regions based on a gravity kernel, and it is less intuitive and requires more computation.

The regional availability approach has two problems: interaction across regional boundaries is generally not adequately accounted for and spatial variability within a region is not revealed (Wing & Reynolds, 1988). Several methods have been developed to mitigate the problems. For example, Luo (2004) uses a *floating catchment area (FCA) method* for assessing physician accessibility. Assuming a threshold travel distance of 15 miles for primary health care, a 15-mile circle is drawn around a residential tract as its catchment area. The circle with the same radius (i.e., catchment area) “floats” from the centroid of one tract to another, and the physician-to-population ratio within each catchment defines the accessibility there. The underlying assumption is that services that fall within the circle are fully available to any residents within that catchment. However, not all physicians within the catchment are reachable within the threshold distance by every resident in the catchment, and physicians on the periphery of the catchment may also serve nearby residents outside the catchment and thus may not be fully available to residents within the catchment.

A method developed by Radke and Mu (2000) overcomes the above fallacies. It repeats the process of “floating catchment” twice (cone on physician locations and cone on population locations), and can be easily implemented in a geographic information system (GIS) (Wang & Luo, 2004).

First, for each physician location j, search all population locations (k) that are within a threshold travel time (d_0) from location j (i.e., catchment area j), and compute the physician to population ratio R_j within the catchment area:

$$R_j = \frac{S_j}{\sum_{k \in \{d_{kj} \le d_0\}} P_k}, \qquad (1)$$

where P_k is the population of tract k whose centroid falls within the catchment (i.e., $d_{kj} \le d_0$), S_j is the number of physicians at location j, and d_{kj} is the travel time between k and j.

Next, for each population location i, search all physician locations (j) that are within the threshold travel time

(d_0) from location *i* (i.e., catchment area *i*), and sum up the physician to population ratios R_j at these locations:

$$A_i^F = \sum_{j\in\{d_{ij}\le d_0\}} R_j = \sum_{j\in\{d_{ij}\le d_0\}} \left(\frac{S_j}{\sum_{k\in\{d_{kj}\le d_0\}} P_k}\right), \tag{2}$$

where A_i^F represents the accessibility at resident location *i* based on this two-step FCA method, R_j is the physician to population ratio at physician location *j* whose centroid falls within the catchment centered at *i* (i.e., $d_{ij} \le d_0$), and d_{ij} is the travel time between *i* and *j*.

One may notice that it draws an artificial line (say, 30 minutes) between an accessible and inaccessible physician. Physicians within that range are counted equally regardless of the actual travel time. *A gravity model* such as the one in Joseph and Bantock (1982) can be used to weight a nearby physician higher than a remote one. The gravity-based accessibility A_i^G at location *i* can be written as:

$$A_i^G = \sum_{j=1}^{n} \frac{S_j d_{ij}^{-\beta}}{V_j}, \text{ where } V_j = \sum_{k=1}^{m} P_k\, d_{kj}^{-\beta}, \tag{3}$$

where *n* and *m* indicate the total numbers of physician and population locations, respectively, and all other variables are the same as in Equation (2).

Luo and Wang (2003, p.874) have proven that the two measures A_i^F and A_i^G are equivalent. The only difference is except that travel time impedance is dichotomous in Equation (2) but continuous in Equation (3). The measure A_i^F by the two-step FCA method may be a more favorable choice for practical uses. First, it is simple and can be easily adopted by state health departments. Secondly, it is intuitive as it compares supply vs. demand and does not need to define the travel friction coefficient b in the gravity model. Defining bð is particularly troublesome since its value varies from place to place and also over time. Finally, the FCA method is particularly suitable for identifying areas with low accessibility, as the gravity-based method tends to conceal local pockets of poor accessibility (Luo & Wang, 2003, p.876).

Analyzing Nonspatial Factors

Population subgroups differ in terms of needs and accessibility according to their age, sex, social class, ethnicity, and other nonspatial characteristics. For example, Field (2000) compiled a list of factors affecting healthcare access, standardized all indicators according to a normal distribution, and then combined them to produce a final composite index of relative advantage.

Possible nonspatial factors for healthcare access include:

(1) Demographic variables (such as age and sex). For example, populations with high needs include seniors with ages above 65, children with ages 0-4 and women with ages 15-44.
(2) Socioeconomic status. Low socioeconomic status may incur important barriers to health access and lead to ill health. Variables may include population in poverty, female-headed households, home ownership and median income.
(3) Environment. Overcrowding or poor living conditions may contribute to higher levels of ill health (e.g., Field, 2000, p.315). Variables may include households with an average of more than one person per room and housing units lack of basic amenities (lacking complete plumbing or kitchen facilities).
(4) Linguistic barrier and service awareness. Minorities or lower educational attainment may be associated with lower service awareness (e.g., Field, 2000, p.317), and linguistic isolation may create an important barrier to healthcare access (e.g., U.S. DHHS, 1998). Variables may include non-white minorities, population without a high-school diploma and households linguistically isolated.
(5) Transportation mobility. People dependent solely on public transit may have less mobility and their accessibility to physicians is diminished to a great degree (e.g., Field, 2000). Variables may include households without vehicles.

As these variables are often correlated, a simple aggregation of the indicators may not be appropriate. Wang and Luo (2004) use the factor analysis to consolidate nonspatial factors, and identify three major factors (i.e., socioeconomic disadvantages, socio-cultural barriers, and high healthcare needs).

FUTURE TRENDS

The spatial accessibility measure and nonspatial factors need to be integrated together for assessing accessibility. In evaluating healthcare access, one may assign larger weights to population subgroups with high healthcare needs and directly incorporate this factor into the spatial accessibility measure such as Equation (2). The spatial accessibility measure can be used to identify the first type of physician shortage areas (i.e., *geographic areas* as in the official HPSA designation guidelines). Nonspatial factors (e.g., the "socioeconomic disadvantages" and "socio-cultural barriers" factors) can be used to identify the second type of physician shortage areas (i.e., *popu-*

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