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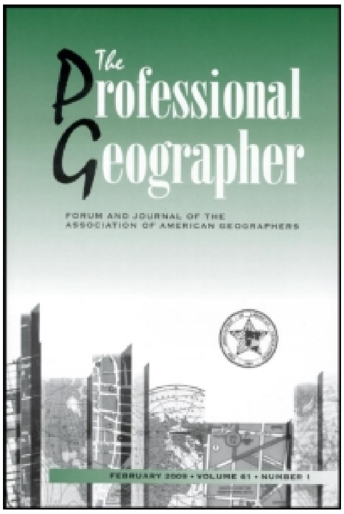

The Professional Geographer

Publication details, including instructions for authors and subscription information:
http://www.informaworld.com/smpp/title~content=t788352615

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Online publication date: 13 May 2010

To cite this Article Langford, Mitchel and Higgs, Gary(2006) 'Measuring Potential Access to Primary Healthcare Services: The Influence of Alternative Spatial Representations of Population', The Professional Geographer, 58: 3, 294 — 306
To link to this Article: DOI: 10.1111/j.1467-9272.2006.00569.x
URL: http://dx.doi.org/10.1111/j.1467-9272.2006.00569.x

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Measuring Potential Access to Primary Healthcare Services: The Influence of Alternative Spatial Representations of Population

Mitchel Langford and Gary Higgs
University of Glamorgan

Spatial accessibility measures are an important policy tool for managing healthcare provision and reducing health inequality. The two-step floating catchment area technique, in common with many alternative methodologies, requires that demand-side population be estimated using spatial interpolation techniques. This article studies the implications of adopting differing spatial representations of population on healthcare accessibility modeling outcomes. Results indicate that a dasymetric model yields lower accessibility scores than a standard pro rata model. More important, the difference is spatially disproportionate, suggesting that the degree of disadvantage experienced in rural areas may be greater than has previously been recognized.
Key Words: dasymetric mapping, healthcare provision, population, spatial accessibility, spatial representation.

Accessibility planning is centrally placed in the present U.K. government's agenda to improve social inclusion and social justice policy. There is a requirement, for example, that accessibility strategies be included in the Local Transport Plans currently being prepared by local transport authorities as part of partnership approaches to improving accessibility for all covering the period 2006 to 2011 (Social Exclusion Unit 2003). In addition, one of the key priorities in meeting this agenda, as set out in the new NHS (National Health Service) Priorities and Planning Framework 2003–2006 (Department of Health 2002), is the requirement for equal access to a range of both primary and secondary health services for disadvantaged groups with the aim of contributing to a reduction in health inequality (Department of Health 2003). In response to this policy agenda, many authorities are currently in the process of monitoring, evaluating, and assessing existing accessibility problems through mapping audits of NHS services and transport provision prior to developing detailed local accessibility action plans and providing targets for improving accessibility.

The increasing availability of geographical information systems (GIS) within the NHS, together with the proliferation of spatially disaggregate data in the United Kingdom, has led to an improved analytical and evidence base with which to identify and target those groups and areas with poorer accessibility. GIS can be used to examine access needs, to monitor the impacts of intervention policies within action plans, and to model the effects of service relocation or changes in delivery on resultant accessibility levels. A number of service providers have utilized GIS when developing measures of access to healthcare and in identifying poorly served areas through combinations of data relating to sociodemographic circumstances, supply/demand characteristics, and appropriate transportation information. Often such work is undertaken as part of an overall health impact assessment exercise in authority areas.

Traditional approaches to measuring geographical barriers to health services have been based on *potential* and *realized* accessibility measures. In the former, health provision measures are examined in relation to demand among those potentially accessing the service; that is, they are primarily concerned with *opportunities* available to residents within administrative areas generally. In the latter approach, researchers draw on utilization data (e.g., postcoded patient lists, referral and/or attendance records, and actual travel behavior) that permit measures of accessibility to be directly calculated. In the absence of such detailed patient-level information, most studies to date have developed potential measures of access based on either straight-line

The Professional Geographer, 58(3) 2006, pages 294–306 © Copyright 2006 by Association of American Geographers.
Initial submission, March 2005; revised submission, July 2005; final acceptance, October 2005.
Published by Blackwell Publishing, 350 Main Street, Malden, MA 02148, and 9600 Garsington Road, Oxford OX4 2DQ, U.K.

or travel-time distances between health services and demand points. Such measures are then used to identify areas where provision is poor and where additional health facilities are needed to improve levels of access. A recent Health Development Agency report (2004), for example, found that over 10 percent of households in rural areas outside the South East of England were more than seven miles from their nearest hospital. Some studies have compared the relative utility of both approaches in association with socioeconomic characteristics of areas, often with contrasting findings. Inevitably these studies tend to make assumptions related to patient behavior, most notably that individuals attend the nearest facility and that there is no cross-boundary flow of patients. There has been some research into the impacts of using different GIS-based techniques on resultant accessibility measures (e.g., Brabyn and Barnett 2004), but other confounding factors have received little focus, one such issue being the estimation of potential population demand.

Traditionally the total population (or relevant subgroups) potentially able to access health facilities is derived by computing Euclidean or drive-time catchments around healthcare delivery points. An estimated population count is then obtained using spatial interpolation techniques. For example, point-in-polygon analysis may be used to compute the population, as represented by the geographic or population-weighted demand points that lie within the catchment. Problems associated with representing demand as a single point within a census tract are well recognized when using spatial analytical techniques such as location-allocation modeling, and previous work has explored potential implications of generalizing demand at a single point with potential location uncertainties (e.g., Hewko, Smoyer-Tomic, and Hodgson 2002).

Several areal interpolation tools have also been tried for estimating catchment population, such as counting only those census tracts entirely enclosed within the catchment, or also including those that only partially intersect the catchment, or including the population of partially intersecting tracts on a pro rata basis determined by the area of overlap. The population assignment technique chosen inevitably impacts on estimates of those deemed to be within reach of health facilities and each method has limitations, suggesting that careful attention be given to the methodology used. For example, in the complete intersection technique we ignore populations in tracts not completely bounded by the travel catchment, in the pro rata intersection technique we are assuming equal distribution of population within census tracts, and in the centroid approach we are allocating (or not) the entire population of a tract on the basis of just one representative point.

We argue that those techniques that provide a more detailed understanding of the population geography within census tracts should offer more accurate estimates of potential demand, but it is important that the nature of any disparities with population assignment from "traditional" approaches is provided. The importance of population assignment strategy has been shown recently in a study of environmental (in)justice by Most, Sengupta, and Burgener (2004), investigating the impacts of noise levels around a large airport. In this article we examine the consequences of using different population assignment strategies when measuring potential access to primary healthcare services. Specifically we are concerned with comparing demand-side measures based on areal interpolation by dasymetric mapping with those derived from more established approaches. Although there has been recent interest in the use of dasymetric approaches in crime mapping (e.g., Bowers and Hirschfield 1999; Poulsen and Kennedy 2004), little attention has been paid to its potential for aiding the computation of accessibility measures in health studies.

Previous Approaches to Deriving GIS-Based Accessibility Measures

As stated earlier, most studies of spatial inequalities in healthcare delivery to date have measured potential accessibility to services (e.g., Rushton 1999; Phillips, Kinman, and Lindbloom 2000; Haynes, Lovett, and Sunnenberg 2003; McLafferty 2003). Table 1 (adapted from Talen 2003) shows healthcare examples related to traditional approaches to measuring accessibility. In examining potential accessibility, researchers are largely concerned with variations in availability of service rather than the relationship between availability and service utilization. Some recent studies have adopted kernel density estimates (KDE) to represent the geographical availabi-

Table 1 *Measurement of accessibility (with examples from the health sector)*

Approach	Definition	Healthcare example
Container	The number of facilities contained within a given unit	Number of GP surgeries in census ward
Coverage	The number of facilities within a given distance from a point of origin	Number of hospitals 10 km from a population centroid
Minimum distance	The distance between a point of origin and the nearest facility	Distance between village center and nearest pharmacy
Travel cost	The average distance between a point of origin and all facilities	Average distance between centroid of census tract and all GP surgeries
Gravity	An index in which the sum of all facilities (weighted by size or supply-side characteristics) is divided by the ''frictional effect'' of distance	All GP surgeries (weighted by list size) or those with, for example, specialized services or female GPs, divided by distance

Source: Adapted from Talen (2003).
Note: GP = general practitioner.

lity of services. These surfaces are then compared to population need, represented either as population-tract centroids (Guagliardo et al. 2004) or by the addresses of particular subgroups (e.g., births data; McLafferty and Grady 2004) whereby the density value of facilities are assigned to each individual health record based on the mother's census tract of residence, and then characteristics of mothers are compared to the availability of services. Both of these studies were conducted in urban areas of the United States, so they may be less relevant in rural contexts where the density of clinics or surgeries is lower and hence the use of KDE in creating a surface of general practitioner (GP) facilities without a consideration of travel distances can be questioned.

In the absence of individual-level health data, measures are often based on a count of services within census tracts or, alternatively, the number of facilities within a certain Euclidean distance or drive-time of single demand points (e.g., Lin 2004). Luo (2004), for example, used simple circles of varying radii centered at census tract centroids from which a physician-to-population ratio was computed using the number of facilities found within each. This floating catchment area (FCA) method still makes assumptions regarding the availability of services to the population contained within the circular area—that those services are equally available to all residents regardless of distance from the facility. Although this method overcomes assumptions regarding cross-boundary flows by extending the radius of the circle outside the immediate census zone, it is still limited by the use of a single point with which to represent population demand.

An enhancement of this methodology is the two-step FCA approach introduced by Luo and Wang (2003), building on earlier work by Radke and Mu (2000). This relatively sophisticated technique better accounts for the interactions between patients and physicians across administrative boundaries. It evaluates accessibility as the ratio between supply and demand, both determined within travel-time catchments. In step one, catchments are computed around each supply point **j** (e.g., a GP practice) and from the estimated population and the number of doctors within the practice, a physician-to-population ratio (***Rj***) is established. In step two, travel-time catchments are computed around demand centers (e.g., population-weighted centroids) and service accessibility is measured by summing all ***Rj*** values contained within this zone. The final accessibility measure (***Af***) reports the balance between doctor availability (physician-to-population ratio) and service accessibility (sum of all supply points within a given travel-time of the demand center), returning higher values as accessibility increases.

Wang and Luo (2005) illustrated the application of the two-step FCA method in the State of Illinois. Physicians were geocoded to point locations using zip codes, and demand centers were represented by population-weighted centroids of census tracts. Travel time catchments using a 30-minute threshold were computed from a vector road network with travel speeds determined by a combination of road classification and an urban/suburban/rural differentiation. They demonstrated how, when all supply and demand centers are repositioned onto the road network, it is possible to implement the two-step FCA by a combination of relational joins between database tables. The parameters contained within the model inevitably affect final outcomes. For example specific road speeds adopted will influence catchment size, as too does the threshold travel time chosen. Any variation in parameters (e.g., specifying different road speeds for different times of day) requires recalibration of the model. Christie and Fone (2003), for example, used travel times to estimate total population (and subgroups based on age, deprivation, and rurality) at specified drive times from tertiary hospital sites in Wales under differing hypothetical changes in service configuration. Their study demonstrates the considerable sensitivity to the road speeds adopted. Our argument in this article is that, although sensitivity to road speeds is fairly self-evident, the influence of differing spatial representations of population on modeling outcomes is less immediately apparent, yet it demands to be better understood.

Horner and Murray (2004) have already highlighted the importance of this factor in a transportation study. They were interested in bus service provision which, like heathcare accessibility, utilizes estimated population in service catchments as a critical modeling input. They were particularly concerned with impacts arising from whether population is represented by points (centroids) or areal units (polygons), and to this end investigated outcomes arising from four different population estimation techniques. Results clearly illustrate the sensitivity of estimated transit service provision to spatial representation and interpolation issues, with bus service coverage levels ranging from 67 to 85 percent of the total population. Similar impacts caused by modeling choices must be expected when measuring access to healthcare facilities, but this issue has currently received little attention. Therefore the specific questions this research aims to address are: First, what are the implications of using differing spatial representation of population and interpolation methods when measuring potential accessibility to primary healthcare facilities? Second, can we begin to utilize more accurate population demand estimates by adopting dasymetric techniques to model population distribution more realistically within census reporting tracts?

Methodology

Our approach uses an adaptation of the two-step floating catchment area method, and investigates the influence of three alternative spatial representation models of the population:

1. Population is modeled by a single representative point in the census tabulation zone (we use the population–weighted centroid supplied by the Office for National Statistics [ONS]).
2. Population is evenly distributed within the census tabulation zone.
3. Population is dasymetrically distributed within the census tabulation zone.

Method 1 is the same as that used, for example, by Wang and Luo (2005) and Christie and Fone (2003). Method 2 is essentially the pro rata method, often referred to as "areal weighting" in the areal interpolation literature, and it may offer more accurate estimates than Method 1 provided uniform distribution is a valid assumption. In a dense urban environment this may be plausible, but it is much less safe in a rural setting where population is almost certainly concentrated into small settlements separated by tracts of unoccupied land. Method 3 offers the prospect of a more realistic representational model, particularly in rural and urban-fringe situations, and requires some further explanation.

Dasymetric modeling utilizes ancillary information resources to internally redistribute variables within the limits of their tabulation zone so as to create subzones of relative homogeneity and thereby ensure that mapped discontinuities better reflect the true underlying geography. By facilitating the spatial refinement of aggregated data, dasymetric maps can better show, in the case of population statistics, the places where people actually reside. Although introduced as a cartographic technique (Wright 1936), it has since found considerable value as an areal interpolation tool (Fisher and Langford 1995, 1996; Martin, Tate, and Langford 2000; Eicher and Brewer 2001). It should be noted that although we utilize a dasymetric approach, other surface modeling and areal interpolation methods exist by which population residing inside travel time catchments could be calculated (e.g., see Martin 1996; Flowerdew and Green 1994; Mugglin et al. 1999).

In terms of its actual implementation, dasymetric mapping lacks a standardized methodology and variations are possible in terms of the choice of ancillary data used or the degree of internal differentiation attempted. Some studies have investigated a three-tier density classification scheme (e.g., Eicher and Brewer 2001;

Mennis 2003; Langford 2006), but there is little evidence to date of any clear benefit over the simpler two-tier, binary dasymetric method; we therefore adopt the latter in this study. The binary method consists of internally mapping each census tabulation zone into subareas identified as either occupied or empty, then allocating the population count uniformly to only the occupied portion. For the ancillary data source, most practitioners to date have used information derived from classified satellite imagery to identify occupied areas (e.g., Yuan, Smith, and Limp 1997; Eicher and Brewer 2001; Mennis 2003; Holt, Lo, and Hodler 2004), but this is not an essential feature of the technique. What is important is that the chosen ancillary data correspond well with the true population distribution and, in the case of the binary method, are able to accurately separate occupied from unoccupied space. The final decision on ancillary data will inevitably depend on local circumstances and available resources. Using existing map data is an obvious alternative to using satellite imagery, and Moon and Farmer (2001) have demonstrated the creation of a dasymetric population density surface using manually digitized housing polygons. We elect to adopt a more automated approach using information extracted from Ordnance Survey (OS, the U.K. national mapping agency) 1:50000 scale raster maps.

This product is a general-purpose topographic map base, typically used for background and context mapping. It provides full U.K. coverage and carries details of roads, footpaths, woods, water features, buildings, and contour heights. Data are supplied in GeoTIFF format with an 8-bit color-palette and a 5-m grid cell resolution. A wealth of information is present visually but, like satellite imagery, additional data processing is needed in order to extract the thematic information into a form suitable for further assimilation within the GIS.

Information content is portrayed visually by color and physically by each pixel's color palette index code. A binary mask (i.e., a map separating occupied from unoccupied land) is created simply by isolating all pixels that possess the color palette index numbers (i.e., color) associated with the depiction of buildings. To further improve clarity, a low-pass spatial filtering operation is then applied which removes isolated pixels and generally smoothes the output. The procedure is illustrated in the left panel of Figure 1, which is reproduced in monochrome although the original data are color coded. The area highlighted represents the extent of a single Output Area, the finest unit of data tabulation in the U.K. census and broadly equivalent to a U.S. Census Block. It is apparent from a visual inspection that the residential population of this Output Area is unlikely to be uniformly distributed across the zone, but will be concentrated into the buildings on either side of the road that traverses from north to south. It is equally clear that a single representative point, such as the population-weighted centroid supplied by the ONS, will be a crude simplification of the true geography. The binary dasymetric mask extracted from the OS raster map source is seen in the right panel of Figure 1. Although not without some problems and potential sources of error on its own (to be discussed later), mapping census population into the occupied space (i.e., the white areas) would seem to offer the most plausible representation of where people truly reside. The areal interpolation performance of a dasymetric map based on this data source has been shown by Langford (2004, forthcoming) to be comparable to that attained from a classified Landsat Enhanced Thematic Mapper image, and both resources considerably improved on the results obtained by a simple pro rata distribution model.

Figure 2 summarizes the three alternative representations of population within the same example Output Area. To evaluate the impacts of these models, a data set containing all primary healthcare services within Wales was assembled. This contained a total of 2,010 GPs distributed across 485 practices, geocoded to point locations using the NHS postcode directory, which has a quoted positional accuracy of 1 m (left map of Figure 3). In this investigation we concentrate our attention on three contrasting unitary authorities within Wales (see the right map of Figure 3): Ceredigion, a predominantly rural region of Wales; Rhondda Cynon Taff, characterized by distinctly linear urban development along north-south trending valleys; and Cardiff, which contains the capital city and is the most highly urbanized region of Wales.

Travel-time catchments were computed using a road network derived from the Ordnance Survey's Meridian© dataset (which is marketed as a medium-scale vector database and contains various feature layers including a detailed road

Figure 1 *On the left a single census zone (Output Area) is highlighted together with its corresponding Ordnance Survey raster map data. The binary mask of buildings extracted from this map is shown on the right.*

network). Although no formal scale is reported for this dataset, visual inspection reveals it to closely match road information contained in 1:50000 scale raster maps. In contrast to Wang and Luo (2005), we performed all of our analysis in a raster environment because this most readily facilitates the incorporation of a dasymetric population distribution model. Thus the vector road network, clipped to the Welsh national boundary, was rasterized to a grid with a 25-m posting. The road classification scheme provided in Meridian© was used to assign travel speeds, which were set broadly in line with national legal limits (see Table 2). However, to better reflect true driving conditions, speeds were modified (i.e., reduced) along road sections contained within the limits of the urban area polygons that form part of the Meridian© dataset. For example, A–road sections lying within urban polygons are assigned a travel speed of 35 mph; outside urban areas this rises to 55 mph. Grid cells not deemed to be part of the road transport system received a transit speed of 3 mph representing typical walking velocity. This is a simplification since maintaining this speed through a forest or, worse still, over a water body might prove difficult if not impossible. However, we assume that in general the vast majority of the population lives fairly close to the road transport network and can reach it along pathways that afford relatively little impedance. The final result was a travel cost raster from which a travel-time catchment could be computed for any designated location using any specified threshold time limit.

Travel-time catchments, using a 10-minute threshold, were computed for each GP practice in turn using the *CostAllocation* function in

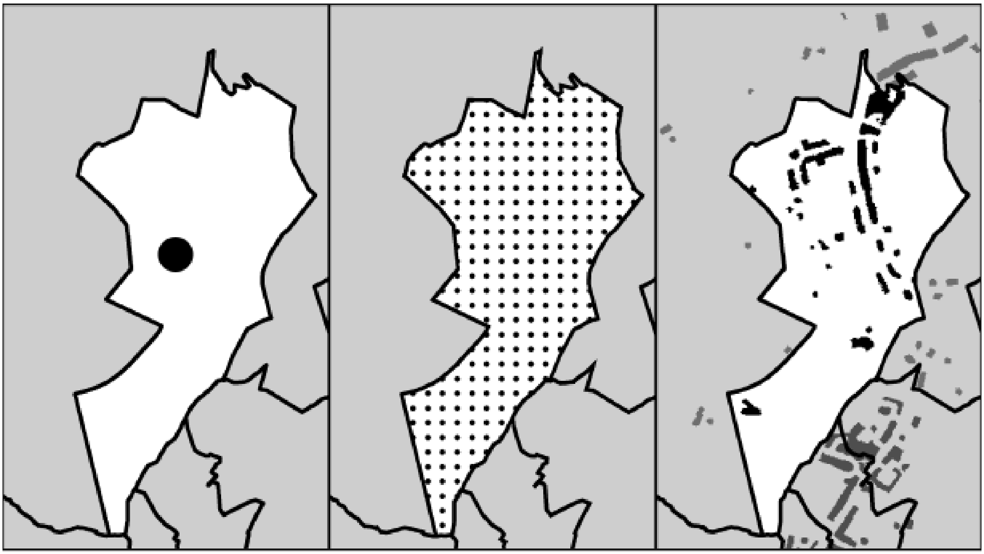

Figure 2 *The three alternative representations of population used in healthcare accessibility modeling: (left) using a single representative point, (center) evenly distributed throughout the census zone, (right) a dasymetrically distributed model.*

ArcGIS 9.0; some example outputs are illustrated in Figure 4. Once each catchment had been computed, the total population contained within it was estimated using the three spatial representational models reported earlier, yielding corresponding physician-to-population ratios (i.e., $\mathbf{R}_j$). This process is computationally intensive and would be extremely laborious to execute manually for each GP practice via the menu interface. It was therefore automated by a

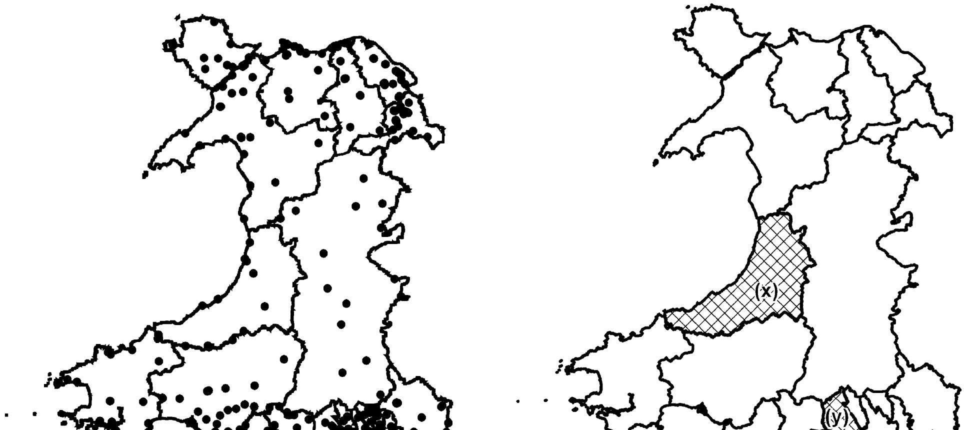

Figure 3 *Locations of 485 general practitioner practices in Wales (left), and the three unitary authorities (right) selected for investigation: (x) Ceredigion; (y) Rhondda Cynon Taff; (z) Cardiff.*

Table 2 *Allocated travel speeds (mph)*

Area type	Road type				
	Motorway	**A-class road**	**B-class road**	**C-class road**	**Nonroad**
Within urban polygon	70	35	25	25	3
Outside urban polygon	70	55	40	30	3

VBA (Visual Basic for Applications) script that cycled through each GP practice in turn, computing travel-time catchments and performing raster overlays with each population surface to determine the **R***j* values.

Once an **R***j* was computed for every GP practice and for each population distribution model, the values were assigned to GP point objects via their attribute tables. To derive an accessibility measure for any point of interest, a travel-time catchment was first created around it using the same threshold time limit. The sum total of **R***j* values contained within that zone yields the final accessibility index (*Af*). Although it is theoretically possible to compute this index for *any* location in the study region, to do so would be computationally impractical. Instead, the index is computed for the population-weighted centroid of each Output Area. Given the previous discussion concerning rural population distribution patterns, it is recognized that in the future it would be desirable to investigate whether multiple demand points within Output Areas could be used to reflect each nucleated settlement contained within an area (perhaps using the Meridian© urban polygons referred to earlier).

Results

Our results show that, in all cases, a dasymetric representational model leads to higher estimates of the floating catchment population than does the pro rata evenly distributed population model. This in turn implies that physician availability is always somewhat lower than might previously have been thought, and consequently computed accessibility measures show a comparable decline in value. Of greater significance than this overall trend is the fact that the degree to which accessibility measures are depressed is

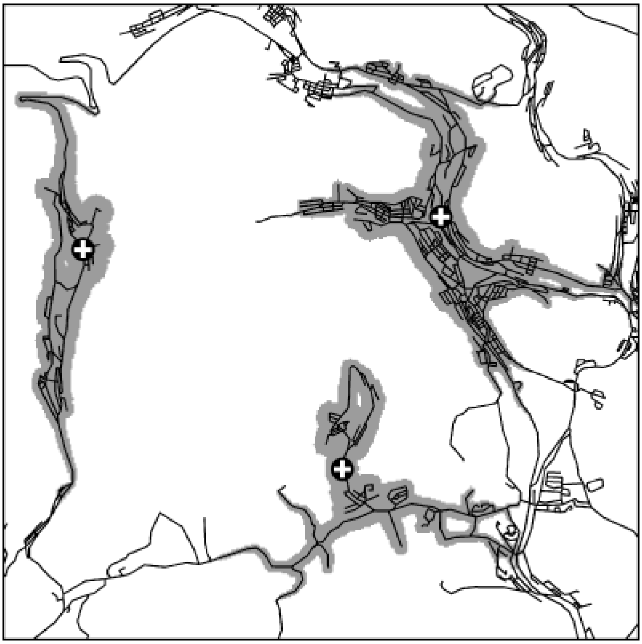

Figure 4 *Floating travel-time catchments (shaded areas) computed for three general practitioner practices within Rhondda Cynon Taff; the influence of the road network on travel times is apparent.*

Table 3 *Mean **A**f scores by unitary authority*

	District		
Model	**Ceredigion**	**RCT**	**Cardiff**
Dasymetric	0.0749	0.0605	0.0784
Weighted centroid	0.0886	0.0689	0.0803
Pro rata area	0.0898	0.0682	0.0799

Note: RCT= Rhondda Cynon Taff.

spatially disproportionate. At a broad scale this is demonstrated by the mean **A***f* score reported in each of the three unitary authorities (see Table 3). Comparing values obtained from the dasymetric and pro rata representations, the difference is relatively small in highly urbanized Cardiff, but becomes larger in Rhondda Cynon Taff, and increases again in highly rural Ceredigion. Results obtained from the representative point model show a greater degree of variability and, though always painting a more favorable picture of healthcare accessibility than the dasymetric model, estimates fluctuate either side of the pro rata model. This is probably a reflection of an inherent weakness in this methodology, whereby results become very sensitive to the exact placement of a centroid since correspondingly either all or none of the associated Output Area population is incorporated into the **R***j* computation.

Although these mean figures are instructive up to a point, the absolute values of **A***f* scores are typically of less importance than are the detailed patterns they exhibit over space, since it is these patterns that help to identify isolated pockets of impoverished healthcare accessibility. Some **A***f* scores for the Cardiff Unitary Authority are plotted in Figure 5 and clear patterns can be seen to emerge. These would evidently be of interest to healthcare providers and planners seeking to improve accessibility and ensure equal access for all. However, the focus of this article is to compare alternative representations of population and therefore it is the

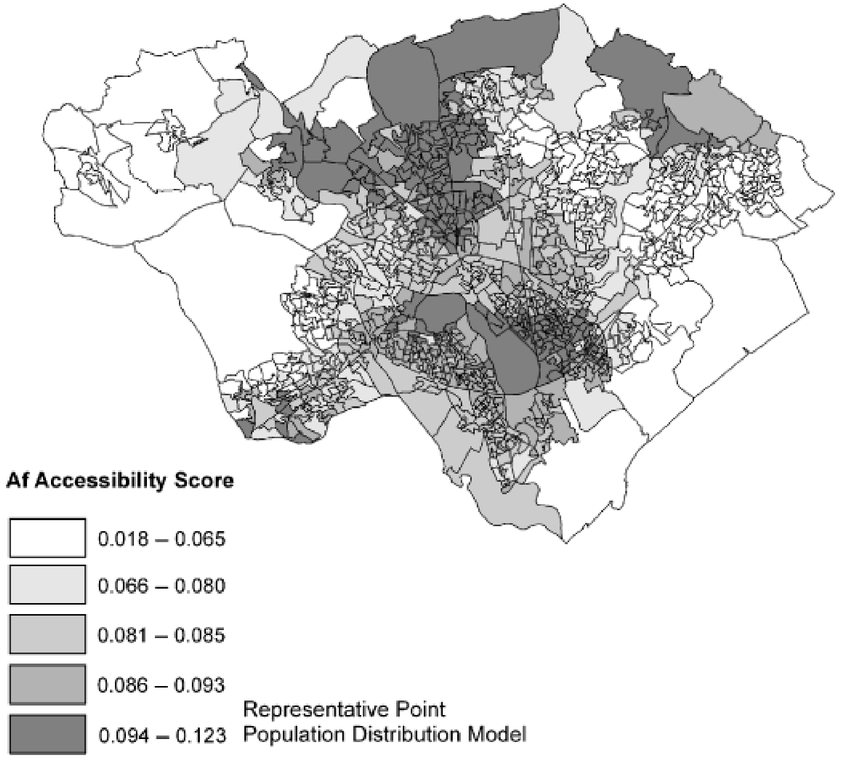

Figure 5 *Accessibility scores (**A**f) plotted for Output Areas in the Cardiff Unitary Authority (representative point population distribution model and ten-minute travel time threshold).*

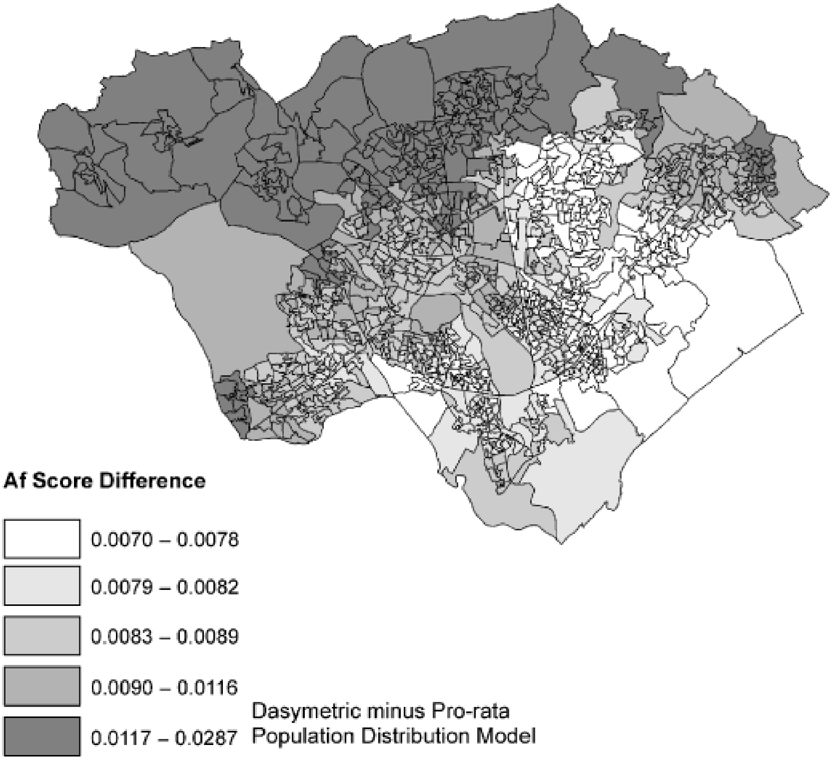

Figure 6 *Absolute difference in accessibility scores for the Cardiff Unitary Authority between the dasymetric and pro rata population distribution models.*

difference in **A***f* values between models that is of real interest to us. In Figure 6 the absolute difference in **A***f* score between the dasymetric and pro rata population distribution models are plotted for the Cardiff Unitary Authority area.

Consistent with the unitary-authority-level comparisons is the fact that in every single Output Area the lowest **A***f* value derives from the dasymetric model, but strong spatial patterns and high spatial autocorrelation are evident too. The overall pattern reinforces the suggestion obtained earlier from the unitary-authority-level comparison: specifically, that the discrepancy between models increases as rurality increase. There is a clear tendency for larger, less-urbanized Output Areas lying beyond the city limits to report the greatest decline in **A***f* score when comparing these two representational models of population. The same pattern was repeated in the other two areas studied.

Discussion

A principal finding in this study is that the spatial representation used to model population distribution can exert a significant influence on healthcare accessibility modeling outcomes. Of the three alternatives investigated, the dasymetric model was found to consistently yield proportionately lower estimates of healthcare accessibility (using the floating catchment technique) in rural as compared to urban regions. The dasymetric representation is believed to provide the most detailed and realistic understanding of population geography within census tract boundaries, and therefore should offer the best estimates of potential demand on services. A number of limitations have to be highlighted in the methodology adopted here; many of which are common to other studies of this nature. First, in the absence of detailed utilization patterns and GP registers, we assume patients access their nearest surgery. This may indeed hold for rural areas where there may be less choice, but it may not necessarily be the case in urban areas. Second, the binary mask used in the dasymetric model currently fails to differentiate nonresidential buildings (factories, shops, garages, etc.) from housing, which is a clear source of error. Potential solutions include assimilating the output with multispectral satellite imagery, local authority planning documents, or information contained in mailing list databases, but currently this remains an area for future work. Chronological synchronization between the map base and Census data should also be maximized to avoid introducing error due to land cover changes between dates. Third, in the second stage of the methodology we used Output Area centroids to generate the catchments in order to calculate a final index, although we have the potential to use individual urban areas (e.g., those held by the Meridian dataset). Fourth, we have assumed patients have the means to access such services through, for example, private transport opportunities. Recent research in the United Kingdom has demonstrated how public transport availability and timetables could be incorporated into measures of health services accessibility (e.g., Martin et al., 2002; Lovett et al. 2002), but this was beyond the scope of this particular study.

The primary aim of this article has been to highlight the importance of the spatial representation of population demand on the indices generated in accessibility studies. We have researched this in relation to the floating catchment area methodology, which, it has been argued, overcomes some of the problems inherent in calculating measures of accessibility to health facilities. A number of further strands of research can be offered here. There is clearly scope for conducting sensitivity analysis in relation to, for example, variations in the road speeds specified in the models, in the threshold distances used to generate catchments (perhaps based on any future national service guidelines), or in varying the scale of analysis. In this study we used Output Areas, but U.K. census data are also made available at other spatial scales such as Super Output Areas[1] (built from clusters of Output Areas, in a similar fashion to U.S. Census Block Groups) and Wards. In addition, it would be interesting to apply these techniques to other public services (e.g., schools, post offices, banks, etc.) to see if the results are consistently reproduced across the three types of scenarios studied here (i.e., rural, valley, and urban authorities/regions). We have some supply-side characteristics of the GP practices (such as number of female doctors, age of the doctor), but clearly, given suitable data sources, it may be possible to refine the calculations to take into account the opening times of the surgery, the medical services provided, the specializations of the doctors, as well as other supply-side characteristics that may influence whether patients choose to access such practices. Likewise there are demand-side characteristics contained within the census, such as age groups, which would allow us to determine whether accessibility patterns vary with respect to subpopulations such as the elderly that can typically be expected to require more frequent access to the service.

We have highlighted the use of such techniques as a policy tool for health professionals in identifying areas with poor access to primary health services. The availability of data from the 2001 Census of Population also enables us to calculate, for the same Output Areas areas, deprivation measures that have been used in other health contexts in the United Kingdom—for example, the Townsend measure (Senior 2002) or levels of car ownership—and thus to compare our accessibility indicators with "standard" deprivation scores. In addition, a new classification of urban and rural areas has recently been produced in the United Kingdom, which enables us to examine trends in measures against a typology of Output Areas[2] (e.g., "fringe and small town," "hamlets and dispersed households") in order to examine the differences in the applications of the three techniques according to this classification. Finally, it would be interesting to compare such accessibility measures with health outcomes such as limiting long-term illness (which is available from the 2001 Census) or other measures of health status to see if areas of poorer access also have higher levels of morbidity or mortality.

Conclusions

Our preliminary results show that in all cases a dasymetric model of population distribution leads to higher estimates of floating catchment population than does the pro rata, evenly distributed model, and thus yields lower accessibility scores. It is difficult to prove conclusively that the dasymetric model provides the most accurate estimates of demand-side population, but visual evidence and the fact that the model incorporates powerful information pertaining to likely population placement might lead most observers to accept this assumption. Formal testing of areal interpolation tools has shown dasymetric techniques to outperform simple areal weighting (e.g., Fisher and Langford 1995; Eicher and Brewer 2001), which adds further credence to this argument.

If accessibility scores were found to be uniformly modified over space, the influence of the population model adopted would be of little consequence since absolute values are much less important than the spatial patterns exhibited. However, this study has revealed the influence to be spatially disproportionate, with clear evidence emerging that scores are more strongly depressed in rural areas compared to urban areas. This is an important outcome because, although the relative paucity of healthcare provision in rural areas is already widely documented, it implies the degree of disadvantage is much greater than previously recognized. So far, results generated when population is modeled by point objects tend to lie somewhere close to those from a pro rata areal interpolation, but greater discrepancies are expected to arise as travel time thresholds are varied. ■

Notes

[1] http://www.statistics.gov.uk/geography/soa.asp (last accessed 26 July 2005).

[2] http://www.statistics.gov.uk/geography/urban_rural.asp (last accessed 26 July 2005).

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