Urban population distribution models and service accessibility estimation

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Abstract

This paper examines the influence of alternative population distribution models on GIS-based spatial accessibility analyses using the two-step Floating Catchment Analysis technique. Two population models were tested: the de facto standard of even-distribution within census tracts and a dasymetric-based approach. The latter builds on previous research through the use of a novel methodology that integrates raster map data with a recently built mailing information database in order to enhance the precision with which residential areas are identified. Analysis was conducted for a case study area (Cardiff, South Wales) in order to examine variations in accessibility to a number of public services in the city. The dasymetric model showed a general tendency to report lower accessibility scores, but detailed patterns depended on local factors and, to some extent, on modelling assumptions and methodological issues. A paired T-Test analysis demonstrated that significant differences in outcomes were dependant on the population model adopted. Accessibility-based measures are increasingly being incorporated into deprivation indicators and the paper concludes by suggesting that, if such analysis is to inform urban planning, local service provision and the spatial allocation of financial resources, greater attention needs to be given to the method of population representation utilised in such models.

Keywords: Population estimation models; Dasymmetric techniques; Accessibility measures; Floating catchment analysis; GIS

1. Introduction

Information contained in government instigated national censuses typically forms the foundation of most geodemographic analyses undertaken in urban areas (Harris & Longley, 2002). This is to be expected since they invariably offer the most authoritative, accurate and nationally complete record of both geographical patterns and socioeconomic characteristics amongst the urban population. Despite these strengths, an over-reliance on census-based inputs for GIS model building can diminish the accuracy and value of any subsequent simulation or analysis as they also suffer from a number of well-documented weaknesses. Chief amongst these concerns are the fixed set of areal units over which data are aggregated prior to their release, and the timeliness of the information as the period between censuses elapses.

Spatial aggregation is essential to maintain confidentiality requirements, and also helps reduce data volumes to manageable levels. However, a key strength of GIS is its ability to integrate data from disparate sources facilitating all manner of spatial analyses to be undertaken. This typically results in a need to acquire geodemographic measures for alternative discrete geographies that are spatially incompatible with those supplied by the Census. For example, population counts may be required for areas defined by a computed distance from particular objects or facilities. Similarly, given suitable information resources it is relatively straightforward to generate travel-time zones around particular features of interest, or to create entirely new ana-
litical zones from the spatial intersection of alternative urban geographies such as postal delivery units, travel-to-work areas, healthcare administration zones, and so on.

Although the ease with which new analytical zones can arise during GIS based studies is a potential problem for urban analysts, GIS technology also offers prospects of a solution. Its capabilities enable relatively sophisticated areal interpolation procedures to be undertaken, allowing data aggregated across the fixed geography of the census to be re-estimated for any alternative spatial divisions. At its simplest, a pro-rata redistribution of census counts into overlapping areal units using just the geometric intersection of the two geographies can provide an initial estimate of the attribute across any non-census zone. The real strength of GIS, however, is to combine geometric intersection with additional resources that help to elucidate the true, or at least the most-likely, distribution within census tracts. These intelligent areal interpolators may be expected to yield estimates for target units that are significantly more accurate, which in turn must enhance the quality and accuracy of urban modelling and simulation, and hopefully lead to better urban planning and management.

The remainder of this paper considers service accessibility estimation; an example of a GIS application in which population estimates for non-census geographies form a critical input to the modelling process but where, to date, there has been little research and less appreciation of the importance of population representation on model outcomes. In Section 2 of the paper, we provide a brief review of the accessibility literature as it pertains to the present study before outlining in Section 3, the methodology adopted in this study highlighting the significance of the population estimation process on which it is based. We focus in particular on population modelling strategies, both simple and intelligent, and describe how using innovative techniques, geospatial data integration can yield a highly sophisticated population surface model from which population counts for any arbitrary areal unit may be derived. In Section 4, the influence of alternative population models on accessibility modelling outcomes is explored through a worked example for an urban area (Cardiff, South Wales). Finally, we conclude by emphasising the importance of the choice of population estimation method on model outcomes and by highlighting the policy relevance of such research at a time when government-based measures are increasingly incorporating accessibility indicators.

2. Service accessibility modelling

A number of studies have used GIS in order to examine spatial inequalities in health care delivery using accessibility measures (e.g., McLafferty & Grady, 2004; Phillips, Kinman, & Lindbloom, 2000; Rushton, 1999). Such measures typically involve counting the number of services contained within census tract boundaries (e.g., Lin, 2004), or reporting the number of facilities inside a given Euclidean or Travel-Time distance of demand points. Luo (2004), for example, employed circular buffers around census tract population-weighted centroids to compute a physician-to-population ratio from the number of enclosed facilities. It was argued that this ‘floating catchment area’ (FCA) method allows cross-boundary flows by extending the buffer beyond the borders of the census tracts. An enhancement of this gravity-type accessibility measure is the two-step floating catchment analysis method introduced by Radke and Mu (2000), further developed by Wang and Luo (2005), and recently applied to measure accessibility in family physician utilisation by different ethnic groups in Toronto, Canada (Wang, 2007). This is not the place to describe the two-step FCA method in detail (see for example Luo, 2004; Luo & Wang, 2003; Wang & Luo, 2005) but in this paper we are primarily concerned with the potential refinement of such measures using dasymetric population distribution models.

Two-step FCA first examines each service provision point (e.g., School, Post Office, etc.) and computes the population potentially able to access it given a user-specified travel time. Using road network and/or other transport system data stored in the GIS a zone is constructed around each service point defining the region in which it is possible to reach the service point within the specified time limit. This is illustrated in Fig. 1, in which the area deemed to be in reach of a service provision point is shown based on travel via the road network at UK national speed limits and adopting a 5-minute time threshold. Clearly, each such zone is unique to the particular service point, and depends on the spatial arrangement of the transport network in its vicinity, the specified speeds of travel and the time limit stipulated. An estimate of the population contained within these zones is the next step in the procedure.

It can be seen in Fig. 1 that travel-time zones do not readily align with census tract boundaries so an estimated count is required, the value of which will be influenced by the interpolation method and underlying population model adopted. Once a population count is established an availability score (or $R_f$ value) for the service is computed by dividing supply volume (e.g., the number of GPs working in the practice) by the estimated population count. It should be noted that an inherent assumption here is that consumption of services is linearly related to the demand population, but this has been standard practice in the majority of studies to date where potential rather than realised measures of accessibility are computed. Indeed, to accomplish the latter researchers must have access to detailed utilisation data, which are difficult or costly to acquire. Nevertheless, potential measures have been widely used to identify areas of poor provision and highlight where additional facilities may be needed to improve access.

In the second step, travel-time buffers are similarly computed around service demand centres (typically represented by population-weighted census tract centroids), and the sum total of all service availability scores contained inside
each zone yields a final accessibility measure (or $A_f$ value).
As more service centres fall within the zone, or as service availability at any of the enclosed provision points increases, the final accessibility score will rise. A critical step in the calculation of the two-step FCA accessibility measure is clearly the estimated population in travel-time catchments. Exactly how we derive these counts from the spatially incompatible census geography (which offers the only source of true population counts on a nationally consistent basis) will, it is postulated, influence modelling outcomes. The generation of estimated population counts is essentially an areal interpolation problem, the solution of which is considered in the next section of the paper.

3. Population distribution modelling

The simplest approach, as adopted by most practitioners, is to distribute the head count for any census tract evenly within the limits of its boundaries. This model is a good choice only in those situations where no other information is available. In practice it is most unlikely that the internal distribution of population is spatially uniform – residential housing is typically concentrated into villages and towns that occupy only a small part of a census tract whilst the remainder is essentially devoid of population. UK Census geography is space-filling in the sense that every location belongs to one unique census tract, but in truth many areas are actually unoccupied and this characteristic should be recognized in the population distribution model if possible.

Dasymetric mapping is a technique well suited to this situation. A definition of dasymetric mapping is “...a technique that involves estimating the distribution of aggregated data within the units of analysis, by adding additional information that provides insights on how these data are potentially distributed” (Poulsen & Kennedy, 2004). Although dasymetric mapping is less common than area-value or choropleth mapping it offers a number of potential advantages. Chief amongst these is its ability to achieve a more faithful representation of the true underlying geography, minimizing misconceptions of within-zone uniformity and removing the abrupt, and often false, differences that arise along census tract boundaries. By partially disaggregating census data dasymetric mapping provides a finer-grained analysis of population distribution. Dasymetric mapping has seen a resurgence of interest in recent years in a number of application areas with the widespread adoption of GIS technology and as various detailed geospatial datasets have become more widely available (see for example Bowers & Hirschfield, 1999; Chen et al., 2004; Eicher & Brewer, 2001; Holt, Lo, & Hodler, 2004; Langford, 2003; Mennis, 2003).

In this particular application the task is to differentiate occupied from unoccupied space, and then redistribute population accordingly. The concept is illustrated in Fig. 2. In the upper left diagram no internal differentiation of the census tract is shown. The reported population is thus modelled as being uniformly spread across the entire area, as seen on the right. In the lower diagram the census tract is internally divided with only dark areas deemed, from an additional data source, to be occupied. The dasymetric population model shown on the right distributes population evenly within this spatial subset, leaving other areas empty. The total population is identical in both models, only its spatial distribution within the census tract is modified.

To construct a population distribution model of this type requires information to differentiate occupied from unoccupied space. Any source able to provide a more realistic estimate of population distribution than the
even-spread assumption is an option, and the possibility of small errors arising in the precise definition of occupied or unoccupied space should not be taken as a reason to abandon the effort altogether. To date most practitioners have used multi-spectral satellite imagery as their ancillary information input, identifying areas of residential housing using standard image classification tools (e.g., Langford & Unwin, 1994; Eicher & Brewer, 2001; Yuan et al., 1997). Among the advantages of this approach are the ready availability of such imagery for almost any area of interest, the fact it is a relatively cheap data resource when large areas need to be covered, and the potential to select an acquisition date close to that of the Census itself. However, potentially negative aspects also exist such as the considerable data storage and processing requirements and, perhaps most significantly, the need for specialist skills to carry out statistical classification and other image processing operations; generally speaking those professionals most likely to encounter a need for population interpolation (e.g., local planners and decision makers) are unlikely to be familiar with this skill set. Furthermore, classification error remains an issue and is clearly of some significance if precise mapping of residential areas is considered to be important.

Map-based information is an alternative source for driving the dasymetric mapping process yet few examples exist to date of solutions utilising this approach. Moon and Farmer (2001) discuss potential advantages of using cartographic inputs rather than remote sensing derivatives, and provide an example that uses residential housing polygons mapped and maintained by Arkansas Highway Transportation Department from 1:12,000 scale base maps. In the UK a wealth of high quality digital mapping products are supplied by the national mapping agency (the Ordnance Survey – OS) many of which could be used to implement dasymetric mapping. The choice of which product to use will ultimately depend on issues relating to cost, areal coverage, data volume, how up-to-date the resource is or needs to be, and whether or not such data are already available within an organization – perhaps having been purchased to support other tasks. In this study we employ 1:50,000 raster pixel maps. These are a comparatively cheap information source in respect to their areal coverage, and provide broadly comparable information content to typical satellite imagery such as Landsat ETM+, or SPOT XS. Furthermore, they are widely held by both local government and non-governmental agencies in the UK.

We also make use of the mailing information database called CodePoint supplied by the OS. This provides a geographical coordinate for each unit postcode in Great Britain and is largely promoted as a tool for market analysis, sales targeting and resource allocation. However, it also has potential for urban modelling and geodemographic analysis when linked to other information resources (e.g., Harris, 2003; Harris & Chen, 2005; Mesev & McKenzie, 2007). The manner in which we utilise and combine these two products is detailed below.

3.1. Initial dasymetric mask

In this study a two-stage process for constructing the dasymetric population distribution model is developed. The first step is identical to that documented in previously published articles (Langford, 2004, 2007) and therefore
only a brief summary account is provided here. Firstly built-up areas are extracted from the raster maps, primarily on the basis of colour (or more accurately, the colour palette index value assigned to each pixel) using a simple recode operation. This yields a binary map of buildings versus non-buildings. The process is somewhat analogous to the process of identifying residential land cover via the classification of multi-spectral satellite imagery. Further spatial filtering operations are then applied to enhance the final product, suppressing isolated erroneous pixels and removing areas of annotation (i.e., black ink associated with place names and various point symbols). The final binary mask (Fig. 3) has been shown to perform in areal interpolation tasks about as well as similar products derived from classified satellite imagery (Langford, 2007).

Using this dasymetric mask the population of each census tract (i.e., 2001 Output Area) is redistributed internally such that it lies only in built areas. This model was illustrated conceptually in Fig. 2, and a real-world example is shown in Fig. 4 where built areas within Output Areas are indicated by the dark shading. Clearly, an estimated head count in travel-time zones will be influenced by whether population is modelled pro-rata or dasymetrically, particularly given the inclination for built areas to concentrate close to transport networks and thus be spatially heterogeneously distributed across census tracts.

Thus far the dasymetric mask identifies areas occupied by any type of building, and from the raster map source alone it is impossible to further differentiate houses and other residential structures from factories, shops or commercial premises. To achieve this objective we turn attention to the CodePoint dataset which allows further enhancement of the dasymetric mask using a process not previously reported in the literature.

3.2. Enhancing the dasymetric mask

UK postcodes are an alphanumeric abbreviated address developed by the Royal Mail to assist in sorting and delivering mail. A full 7-digit code called the Unit Postcode (UPC) provides the finest level of spatial differentiation, with approximately 1.76 million locations maintained by

Fig. 3. A sample of 1:50,000 raster map data (left), and the first-stage dasymetric binary mask extracted from this source (right). © Crown Copyright/database right 2005. An Ordnance Survey/EDINA supplied service.

Fig. 4. The potential influence of a dasymetric distribution model on estimated travel-time catchment population.
the Royal Mail across the UK. Each UPC typically identifies a set of approximately 15 adjacent postal delivery points. UPCs have enjoyed widespread use in GIS applications, particularly in areas of marketing, health, education and geodemographics, where they provide a convenient discrete spatial referencing system.

This later point is of interest here because UK postcodes are essentially a non-space-filling point dataset. The CodePoint product collects all postal delivery points that make up each UPC and computes their centroid location. The delivery point lying closest to this position is then assigned as the CodePoint geo-reference for the UPC; thus ensuring that it lies within the extent of the UPC boundary. UPC boundaries are an entirely fabricated construction created by tessellating individual postal delivery points, and clipping the resultant boundaries to various features such as transport systems, natural features and various administrative boundaries. These boundaries are constrained only by the requirements to fill space and to enclose all relevant postal delivery points – they have no real-world foundation and could be drawn anywhere subject to meeting these basic rules. UPC boundaries thus provide a full non-overlapping polygon coverage of Great Britain allowing any location to belong to a UPC but, like census tracts, much of the enclosed area in reality may be devoid of habitation and lie a considerable distance from the nearest actual postal delivery point (especially in rural areas).

In addition to a geo-coordinate, further attributes are derived from the set of delivery points that comprise each UPC. Of particular interest here is the tally of domestic and non-domestic delivery points, since this can provide a valuable insight into the land use characteristics of the associated UPC. To utilise this information an idea is adapted from the remote sensing literature to construct an index of industrialization. The Normalized Difference Vegetation Index (NDVI) is a measure widely used in remote sensing to report the ratio of Infrared to Red reflectance values; it provides a surrogate measure of vegetation mass and vigour. Similar indices expressing a normalized ratio between two multi-spectral data values have been developed for purposes as wide ranging as delineating water bodies (NDWI, McFeeters, 1996), snow cover mapping (NDSI, Sidjak & Wheate, 1999), and even the identification of urban areas (NDBI, Zha, Gao, & Ni, 2003).

The normalized ratio of domestic to non-domestic delivery point counts for each UPC can be exploited in a similar way to yield a Normalized Industrialised Index (NII), computed thus

\[ \text{NII} = \frac{\left(\# \text{ DOM} - \# \text{ NON}\right)}{\left(\# \text{ DOM} + \# \text{ NON}\right)} / 2.0 + 0.5 \]

where \# DOM is the number of domestic postal delivery points; \# NON is the number of non-domestic postal delivery points.

This index will range in value from +1.0 (all delivery points domestic) to 0.0 (all delivery points non-domestic). A value of 1.0 implies the area inside the UPC boundary is totally residential in character, while a value of 0.0 indicates an area essentially industrial or commercial in character. Intermediate values imply a mixture of land use on a continuous scale between these two end points. By itself this index is not particularly useful, primarily because of the arbitrary nature of the UPC boundaries, as discussed earlier. But when combined with the dasymetric mask generated earlier it allows further differentiation between buildings that are residential and those associated with industry and commerce, and thus becomes a valuable way to enhance the dasymetric mask. The process is illustrated conceptually in Fig. 5.

The upper-right grid represents a census tract composed of 100 pixels, 10 of which are identified as built in the dasymetric mask. If this zone had a population count of 100 each shaded cell would receive a population of 10 using the simple dasymetric model previously described. However, the upper-left grid shows the distribution of NII scores across the same area. These suggest the north-west quadrant is purely residential in nature (NII = 1.0), the south-west quadrant is purely industrial/commercial (NII = 0.0), and the eastern quadrants possess mixed land usage to varying degrees.

Combining these two resources, we extract NII scores for built areas as shown on the right-hand grid. If population is divided by the sum total of NII scores within each census tract, and then each pixel assigned a value based on the NII score multiplied by this ‘per unit’ figure – we derive the enhanced population distribution model shown below. Once again the total population (depicted here as volume) remains identical to that in Fig. 2, but in addition to differentiating built from unbuilt locations, this model further allocates population in accordance with knowledge of probable land use. Thus, built pixels in the north-west quadrant receive proportionally more people than those in the east (where buildings are a mixture of residential and commercial use), and built pixels in the south-west receive no residential population at all because they are recognized as purely commercial in nature.

4. Application to measuring accessibility

To examine the possible influence that population distribution models exert on service accessibility estimation a two-step Floating Catchment Analysis was undertaken within a study area comprising of the City of Cardiff Unitary Authority in South Wales, UK. This administrative boundary approximately defines the metropolitan area of Cardiff City – the capital city of Wales with a population of around 315,000. Within this boundary accessibility levels to five services were investigated: Primary Health Care (i.e., General Practice, or GP), Dentist, Primary School, Pharmacy, and Post Office. These services were selected as they are often used in the calculation of government based deprivation measures, the outcomes of which are crucial to the allocation and distribution of central
governmental funds. The population distribution models studied consisted of (i) the pro-rate (or even-distribution) model, and (ii) a dasymetric model in which resident population was distributed using a buildings mask further enhanced by CodePoint derived NII scores, as described earlier.

In the case of GPs, some information concerning service-side capacity was available, specifically the number of practicing doctors in each surgery. Our results took this into account, weighting accessibility by this volume of service provision. No further information was available for the other services, although in reality many factors could significantly affect a consumer’s perception of service availability. For example, a post office with multiple service counters clearly has more capacity than one with a single counter. However, given the lack of any suitable supply-side information we can only recognize the simplifications that are inherent in our modelling, and accept them as a constraint on the validity of our experimental outcomes. The scores derived for each service were ultimately simply added together to create a single combined measure of accessibility. This implies or assumes that the ratio of provision to people matters equally for all services, although it would be a relatively simple matter to adopt a weighting scheme should there be sufficient strength of argument and available calibration data to justify such an action.

Each service provision point was first located using the CodePoint coordinate of its postcode address. Each point was then re-positioned so as to lie directly on the road network using the ArcGIS NEAR function. Using this tool each point is moved to the nearest ‘as-the-crow-flies’ location on the network, but it should be recognized this will not necessarily be its true access point. The average magnitude of spatial translation was 23 m and the maximum was 195 m. Due to the density of road networks and other factors, any error introduced by this procedure is more likely to be an issue in rural regions rather than our predominantly urban study area.

Services located some distance beyond the boundary of the study area were also retained in our analysis to avoid introducing boundary effects. This is critical for reliable assessment of accessibility in population centres lying close to the boundary, since nearby services located outside the actual study area would still act as potential service delivery points. A spatial buffer of 8 km around the Unitary Authority boundary was used to select service provision points for inclusion in the analysis. This distance was chosen with reference to the road speeds and travel-time thresholds discussed below, and ensured that all services within any potential travel-time catchment of a population centre within the study area would be included in the analysis.

4.1. Road network and travel-time modelling

Accessibility modelling assumed transport was via car on the road network, or by walking where a road was not present. The road network was derived from the OS Meridian dataset (approximately 1:50,000 scale). In facilitating this model a number of inherent assumptions and
simplifications are made. Firstly, travel speeds were specified using road classifications and UK national speed limits (namely Motorway (70/70); A-Road (55/35); B-Road (40/25); C-Road (30/25); and No road (3/3)). The figures in brackets are miles per hour, with the second value relating to road segments found to lie within urban areas, as defined by Meridian’s Urban Area polygon dataset. This speed reduction in urban areas was intended to reflect, albeit in a rather simplified manner, the effects of congestion, traffic control measures such as traffic lights, and the negotiation of road junctions, on travel times. The vector coverage was converted to a raster grid whose cell values indicated the time taken to traverse each cell according to its road class. A walking speed of 3 miles per hour was assigned to cells where no road was deemed to be present.

4.2. FCA calculations

For step one of the FCA the ArcGIS GRID function CostAllocation was used to compute areas deemed to be in reach of each service provision point. Each point is selected in turn from the Services layer and the raster coverage of road speeds specified as the CostRaster input. Cell values are multiplied by cell size to obtain the time taken to traverse a cell, and this property is accumulated away from the service provision point. A user-supplied time limit determines the final extent of the computed catchment. Although the algorithm used in the CostAllocation function adjusts travel times to take account of diagonal motion between cells there remains an inherent assumption that access to any adjacent cell is always unimpeded. This implies, for example, that on reaching a neighbouring motorway pixel instant access to that cell is available and the travel times will reflect this accordingly. In reality, of course, access to road networks (and particularly motorways) is not freely available at any point since they may only be joined at junctions or other designated access points.

With a total of 698 service points lying inside the 8 km buffer selection zone, operating this model was a computationally demanding and repetitive process. It was essential to automate the task using a bespoke application developed in VBA accessing the necessary functionality through exposed ArcObjects.

The user-specified threshold time is a subjective parameter within the model; we adopted values of 8, 5, and 3 minutes. These were chosen after recognizing the transport system, as modelled, assumes constant unimpeded travel at the speeds listed earlier. No accurate account is taken of delays caused by negotiating junctions, roundabouts, traffic lights and pelican crossings, or for the effects of congestion due to the presence of other road users. Insufficient information was available to us to attempt to vary travel speeds according to the time of day. Furthermore, no account is taken of the time taken in getting to and into the car, joining the road system, parking the car at journey’s end, exiting the car, and so on. Given all these simplifications, and after studying various travel-time zones, these values seemed, in our opinion, to be realistic for a major urban area.

As stated earlier, the final shape of each travel-time zone is uniquely defined by the location of the service point, its relationship to the road network, travel speeds and threshold time limit. Since they bear no similarity with census tracts (with known head-counts) spatial interpolation is required to estimate a contained population. When a travel-time zone is overlaid with census tracts those that are entirely contained within its limits cause no issue, since all their population is added to the estimated tally regardless of how it may be internally distributed. In those that partially intersect only a proportion of the census count should be added to the estimated tally, and this figure will depend on the population distribution model adopted. One clear consequence of this is that as travel zones expand (i.e., a longer travel-time threshold is specified) they can be expected to contain more census tracts in their entirety, and thus any differences arising from distribution models should diminish. In a similar way, there will be a tendency for partial intersection to increase as rurality increases, since census tracts are typically much smaller in urban areas than in rural areas. However, even within a city, areas of high-density housing are likely to have smaller census tracts and exhibit greater internal uniformity of populated distribution than is found in low-density neighbourhoods.

4.3. Availability patterns

In the two-step FCA technique estimated populations initially affect availability scores \((R_j)\) for service provision points, and these in turn ultimately determine accessibility scores \((A_f)\) as they are aggregated within travel-time catchments around population demand centres. Since any differences in reported accessibility due to the use of alternative population distribution models ultimately originate at this stage, the nature of these differences merits some further analysis.

To examine the consequences of adopting alternative drive times, \(R_j\) scores were computed for 8-, 5-, and 3-min drive times. Differences were calculated as the pro-rata score minus the dasymetric score, expressed as a percentage of the pro-rata score. Positive values arise where the dasymetric model predicts lower service availability (due to a larger estimated demand population). A statistical summary is shown in Table 1. Predictably, shorter drive times result in larger differences between modelling outcomes. No matter what threshold time was set, a clear positive skew persisted in the distribution of \(R_j\) scores. In the majority of cases adopting a dasymetric population model produced lower service availability estimates, and in a few extreme cases the differences from a pro-rata model are very substantial indeed (i.e., over 85%). Some cases where the dasymetric model predicted better service availability than the pro-rata model was also a persistent feature.

The geographical distribution of these differences across the study area are shown (for a 5-min drive time) in Fig. 6,
with positive differences displayed in white and negative differences in black. A number of observations can be drawn from this map. The largest differences clearly occur at the urban fringe and in the surrounding rural villages. As a consequence, those population centres that lie close to the margins of the city (which is approximated by the Unitary Authority boundary) can be expected to exhibit greater sensitivity in accessibility scores between the models because their travel-time catchments will tend to include these service provision points in step two of the FCA process. This distribution also raises clear issues and implications concerning the making of direct comparisons between accessibility scores reported for predominantly urban versus predominantly rural study areas. In other words, any contrasts in accessibility estimates between rural and urban study areas are likely to be much larger if the underlying population model used to perform the areal interpolation task is dasymetric rather than pro-rata.

Notwithstanding these clear rural/urban differences, variations in modelling outcomes for availability scores are also evident within the city itself. Furthermore, whilst it is still the case that within the urban area the majority of \( R_j \) scores are lower for a dasymetric population model, there are now a substantial number of cases where the opposite trend is seen to be exhibited.

In order to produce a lower \( R_j \) score the dasymetric model must internally redistribute census population such that it tends to lie inside areas of partial intersection with the travel-time catchments constructed around service provision points. We might generally expect this to be the case if we assume that population generally tends to lie close to transport routes. Conversely, to generate a higher \( R_j \) score the dasymetric model must tend to relocate population away from areas in close proximity to transport routes. The reasons behind this situation occurring are less intuitive, but most of the examples that arise in our study area lie along principal arterial routes leading out from the city centre, and this may help to explain the process acting here. The roads in question are dominated by commercial activity (shops and small businesses) and we believe our enhanced dasymetric mask has the sensitivity to detect this land use characteristic using information contained in the CodePoint dataset and is thus able to report lower residential occupancy than a simple pro-rata model when this particular situation arises.

Aside from such localised patterns and processes we can conclude that the dasymetric model places population into areas of housing which in general tend to lie in close proximity to roads. These in turn are areas which tend to become included in travel-time catchments constructed.

### Table 1

<table>
<thead>
<tr>
<th>Drive time</th>
<th>Minimum difference (%)</th>
<th>Mean difference (%)</th>
<th>Maximum difference (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>8</td>
<td>-3.3</td>
<td>+4.5</td>
<td>+54.8</td>
</tr>
<tr>
<td>5</td>
<td>-7.8</td>
<td>+5.9</td>
<td>+68.7</td>
</tr>
<tr>
<td>3</td>
<td>-27.7</td>
<td>+6.6</td>
<td>+87.5</td>
</tr>
</tbody>
</table>

Fig. 6. Difference in \( R_j \) scores (pro-rata minus dasymetric). Positive values are shown white (i.e., the dasymetric model predicts lower availability), and negative values are shown black.
around service provision points. Ultimately, this yields larger estimated population counts, thereby lowering the availability scores reported for services in step one of the FCA analysis process. If this effect were to be uniform across space it would ultimately be of little consequence, but our case study shows that significant variation can exist inside urban areas when residential/non-residential land use is accurately portrayed, and these differences may give rise to a better evaluation of the pattern of accessibility across the urban landscape. We can also predict that any contrasts between pro-rata and dasymetric models will be magnified when applied to rural rather than urban settings, since in this setting there will be an even greater tendency for population to lay in close proximity to transport networks as opposed to being evenly distributed across the entire census tract. Finally, it must be remembered that although $R_j$ scores are clearly affected by an underlying population distribution model, accessibility scores reported by a two-step floating catchment analysis depend on how these data interact with travel zones constructed around population centres in the second stage of the analysis – which is where we turn our attention next.

### 4.4. Accessibility patterns and methodological effects

In step two of the FCA technique, travel-time zones are constructed around demand points of interest and $R_j$ scores contained within are summed to yield a final accessibility measure ($A_f$) for that population subset. In this study we have utilised each census tract’s population-weighted centroid to represent demand points, although it should be noted that a population headcount is also available for each unit postcode which would provide greater spatial detail but at the expense of considerable computational cost.

In our case study the mean $A_f$ score recorded for each individual service tended to reflect the total number of service supply points, although some interesting effects were noted as the threshold travel times were varied (see Table 2). In all cases the mean accessibility score (reported here for the dasymetric model) increased as travel times decreased. The effect of specifying a shorter travel time is to reduce catchment size around both service delivery points and population demand centres. In the former case it yields lower potential demand population leading to better availability and thus higher accessibility scores, whilst in the latter case it reduces the chance of capturing supply centres thus tending to lower reported accessibility. The net effect depends on the trade-off experienced between sharing resources over a larger population, whilst gaining access to more service supply centres. Particularly noticeable within these results is the large rise in reported accessibility to a dentist as drive times are reduced.

Although slight differences arose in the figures reported by the pro-rata distribution model, the broad patterns remained identical. The mean $A_f$ scores suggest that restricting travel times leads to better overall accessibility, but they ignore the range and distribution of values which typically exhibit stronger positive skews and higher standard deviations as smaller threshold times are specified. Very short travel times can lead to huge gains in accessibility for the lucky few who live close to the service provision points, but this is at the expense of the rest of the population who see a reduced level of service. The effect is examined in more detail in Table 3 where further statistics concerning accessibility to a dentist are presented. Whilst mean $A_f$ scores are seen to increase, the median scores actually decrease, the range and skewness increase, and the final column shows that an increasing number of census tracts are reported as having no access to a service point at all.

These outcomes are both logical and intuitive – if we consider the extreme situation where all population centres are willing to travel any distance to access a service then accessibility scores become equal. At the other extreme, where populations are not prepared to travel at all those in the immediate vicinity of a service receive excellent accessibility, since they share the service with no one else, but most populations would then be without any access.

The spatial pattern of accessibility across the study area for any given service is best shown in map form and as examples the result for schools is reproduced in Fig. 7, and for a combined accessibility score in Fig. 8. Clearly, such maps would be of interest and value to local government agencies, planners, and such like, concerned with the provision, management, and equitable access to a service. However, the focus of this work is not the specific pattern of accessibility for any given service in our study area, but rather the degree to which any results are methodologically dependent.

To statistically evaluate this a paired-sample $T$-Test was first used to explore whether the average difference between availability scores for each service resulting from the two alternative population distribution models was significant. This revealed, firstly (see Table 4), that a dasymetric model returns a lower mean score for all services. In other words, a dasymetric model suggests lower levels of accessibility across the board compared to the pro-rata model. Paired sample correlations between the dasymetric and pro-rata model scores were consistently high, implying differences were relatively systematic and uniform across space. Finally, all differences (i.e., for each service) were statistically significant; thus the choice of population distribution methodology does have a genuine effect on accessibility modelling outcomes.

<table>
<thead>
<tr>
<th>Drive time</th>
<th>GP</th>
<th>School</th>
<th>Post office</th>
<th>Pharmacy</th>
<th>Dentist</th>
</tr>
</thead>
<tbody>
<tr>
<td>8</td>
<td>0.803</td>
<td>0.322</td>
<td>0.266</td>
<td>0.248</td>
<td>0.212</td>
</tr>
<tr>
<td>5</td>
<td>0.823</td>
<td>0.327</td>
<td>0.267</td>
<td>0.271</td>
<td>0.259</td>
</tr>
<tr>
<td>3</td>
<td>0.897</td>
<td>0.352</td>
<td>0.287</td>
<td>0.298</td>
<td>0.322</td>
</tr>
</tbody>
</table>
Table 3
Further $A_t$ score statistics for dentists by travel time (dasymetric model)

<table>
<thead>
<tr>
<th>Drive time</th>
<th>Mean</th>
<th>Median</th>
<th>Standard deviation</th>
<th>Skewness</th>
<th>Tracts with no reported service</th>
</tr>
</thead>
<tbody>
<tr>
<td>8</td>
<td>0.212</td>
<td>0.218</td>
<td>0.096</td>
<td>-0.05</td>
<td>10</td>
</tr>
<tr>
<td>5</td>
<td>0.259</td>
<td>0.197</td>
<td>1.336</td>
<td>+30.76</td>
<td>40</td>
</tr>
<tr>
<td>3</td>
<td>0.322</td>
<td>0.187</td>
<td>3.056</td>
<td>+30.98</td>
<td>99</td>
</tr>
</tbody>
</table>

Fig. 7. Accessibility pattern for Primary Schools in the study area.

Fig. 8. Accessibility pattern of combined service score. Good accessibility is experienced around the city centre and along main arterial roads running to the north, east and west. Poorer accessibility levels tend to be associated with the urban fringe.
The spatial patterns of difference in scores reported by each of the population distribution models are explored in Fig. 9. This maps the percentage difference in the combined accessibility score, created by summing each of the six services (with GP values re-scaled to account for supply-side volume). The broad pattern in this case study is for progressively lower accessibility to be reported by the dasymetric model towards the urban fringe and in the larger (and essentially more ‘rural’) census tracts. The magnitude of differences are less extreme than the $R_j$ scores reported earlier, but nevertheless both positive and negative values arise within the city boundaries and some scores were seen to differ by more than 5%. It could be argued that there is no one correct answer to evaluating accessibility, since any set of results will to some extent reflect inherent modelling assumptions and scale effects associated with the data sources utilised. What does matter is whether changes in methodology can impart a bias or could adversely affect particular groups of people or places. Accessibility scores are incorporated into deprivation measures, such as the Index of Multiple Deprivation used in the countries of the UK. These, in turn, form the basis of, for example, resource allocation mechanisms and differences of the magnitudes reported here could clearly have consequences in the spatial allocation of funds. For this reason, the choice of population estimation method must be given due attention when designing and implementing resource allocation schemes.

The detailed patterns of difference in this case study are clearly linked to specific local factors, suggesting it must be assessed on a case-by-case basis. The important overall message however is that local planners and officers who are charged with resource allocation and decision making in respect to service provision should be aware of the potential for information on which they rely to be influenced by the underlying population distribution model adopted during the modelling process.

While evaluating our case study accessibility maps it also became apparent that considerable care is needed in interpreting detailed patterns since these too potentially

<table>
<thead>
<tr>
<th>Paired differences</th>
<th>t</th>
<th>df</th>
<th>Sig. (2-tailed)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>Std. deviation</td>
<td>Std. error mean</td>
<td>95% Confidence interval of the difference</td>
</tr>
<tr>
<td>Dentist</td>
<td>-.0024</td>
<td>.00217</td>
<td>.000688</td>
</tr>
<tr>
<td>General practice</td>
<td>-.0083</td>
<td>.01225</td>
<td>.003889</td>
</tr>
<tr>
<td>Pharmacy</td>
<td>-.0030</td>
<td>.00247</td>
<td>.000784</td>
</tr>
<tr>
<td>Post office</td>
<td>-.0056</td>
<td>.01103</td>
<td>.003502</td>
</tr>
<tr>
<td>Schools</td>
<td>-.0059</td>
<td>.01024</td>
<td>.003251</td>
</tr>
</tbody>
</table>

Fig. 9. Percentage difference in total accessibility score arising from the use of alternative population distribution models.
result from assumptions and methodological limitations in the modelling process. As an example, Fig. 10a highlights a large Output Area located in the north of the study region. This reported high accessibility levels for most services studied, while its immediate westerly neighbour returned very contrasting low scores. A closer investigation of the respective population-weighted centroids (PWC) and local transport network helps to explain this situation. The PWC of the high-scoring area lies almost directly on the Motorway, although there is actually no access via a junction at this point (the apparent intersection is an overpass). The proximity of the PWC to the motorway and its presence within the census tract leads to an over estimation of accessibility levels to local services in the vicinity. In contrast, the PWC of the neighbouring tract lies at the end of a C-class road, itself some distance from the nearest A-class road. It is highly likely that these two OAs experience similar (i.e., low) levels of service accessibility. In this specific case it could be argued that the motorway should be excluded from the analysis since it is unlikely to be used to gain access to local services, particularly given the limited number of true access/exit points. Another situation is shown in Fig. 10b. Here an Output Area located close to the city centre reports anomalously low scores compared to its immediate neighbours. Again detailed study elucidates the probable cause. Its PWC lies a considerable distance from any road, greatly reducing the size of its computed travel-time zone and lowering its $A_t$ scores. It is doubtful that the population of this tract is truly so isolated; more likely is that the PWC is erroneously placed or that a part of the road network is missing from the transport dataset.

Fig. 10. Examples of local anomalies caused by methodological issues.
5. Conclusions

Although there have been attempts to test the accuracy of different approaches to reassigning population between incompatible spatial units (e.g., Saporito, Chavers, Nixon, & McQuiddy, in press), there has been less research concerned with examining the influence that alternative models of population distribution can exert over GIS-based analyses. This paper represents an attempt to address such research gaps in the context of a service accessibility study using innovative population distribution models which incorporate recently released and detailed UK data sets. Drawing on findings from a case study conducted in the city of Cardiff, South Wales, two population distribution models were considered. The first is the de facto standard which assumes even-distribution of population within census tract boundaries. The alternative uses dasymetric principles to redistribute population internally into those areas considered most likely to be residential in nature. The dasymetric model introduced here contains a number of innovations hitherto unreported in the research literature, most notably in the use of a mailing information database to aid differentiation between residential and commercial built space.

In order to illustrate the implications of these models, accessibility to a number of public services was measured using the two-step Floating Catchment Analysis technique. Despite the relative sophistication of this technique the task of implementing a working model has been shown to be fraught with assumptions, simplifications, and methodological issues that inevitably impact on the nature of the results reported. In particular, careful consideration is needed in interpreting detailed local patterns of accessibility since there are many ways in which anomalous values might arise as a consequence of these problems.

More generally, it has been shown that the choice of population distribution model used to facilitate areal interpolation of population counts from census tracts to analytical travel-time zones, an essential component in the FCA technique, can exert a significant influence on outcomes. In our case study area resultant differences in reported accessibility levels were statistically significant for all services studied, based on a paired T-Test analysis. An aggregate measure of geographical access to services, of the kind typically incorporated into government measures of multiple deprivation, yielded similar results. There was a general tendency for a dasymetric model to report lower accessibility scores, but more importantly the pattern was not spatially uniform. The margin of difference increased towards the urban fringe and was particularly exaggerated in the rural regions surrounding the city. Within the city itself, both lower and higher scores were reported by the dasymetric model. This indicates that the method of population estimation can adversely affect particular groups of people or places, since accessibility scores are often incorporated into resource allocation mechanisms. For this reason, the choice of population estimation method must be subject to more scrutiny when designing and implementing such schemes which may, in turn, have important implications for resource allocation in situations where accessibility measures form the basis of local and central government targeting mechanisms.

References


