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# Estimating attractiveness, hierarchy and catchment area extents for a national set of retail centre agglomerations

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ABSTRACT

There is a legacy of research aiming to conceptualise and empirically estimate retail store catchment areas, however, a dearth that frames such considerations within the context of retail agglomerations and their position within regional or national networks. As a result, this paper provides an extension to single store or shopping centre retail catchment estimation techniques, and presents an empirically specified and tested production constrained model for a national network of retail centres in the UK. Our model takes into account the spatial interactions between potential customers and a hierarchical network of retail centres to estimate patronage probabilities and catchment extents. The model is tested for a large metropolitan area vis-à-vis real world shopping flows recorded through a survey of shoppers. Finally, we present an open source software tool for custom model fitting, and discuss a range of theoretical and empirical challenges that such a model presents.


## 1. Introduction

A retail catchment can be defined as the areal extent from which the main patrons of a store or retail centre will typically be found. The concepts of retail catchments have a substantial legacy of academic enquiry (e.g. Huff, 1964; Fotheringham, 1983; Wilson, 2010) including literature that provides a comparative review of analytical techniques (Joseph and Kuby, 2011; Yrigoyen and Otero, 1998), model input considerations (Birkin et al., 2010; Burger et al., 2009; Hu and Pooler, 2002) and uncertainty analysis (Rasouli and Timmermans, 2013). There is a large body of literature exploring various aspects of retail catchments for a single store or single shopping centre (Huff, 1964; Converse, 1949; Openshaw, 1973; Jones and Simmons, 1993; Lea, 1998; Dramowicz, 2005; Birkin et al., 2010); however, where a larger agglomeration of stores for a regional or national extent are considered, the empirical evidence is more sparse (De Beule et al., 2014).

Indeed, a large proportion of academic and commercial studies are focused on estimating retail store sales or predicting locations for new stores and shopping centres. Within these contexts, retail markets are often geographically limited to a local or subnational extent; however, in reality customers shop in continuous geographical space (Dennis et al., 2002; Birkin et al., 2010), and therefore, an argument can be made that the consistency in the modelling of catchments can be only achieved through a boundary-free approach where model parameters are calibrated at a national level (Birkin et al., 2010). In addition, generating catchment extents that are estimated consistently so that they enable cross-regional statistics to be derived involves modelling at a national scale. Such a task is complex, and not only requires significant computational resource, but more importantly, requires a trade-off between a number of challenges such as the degree of generalisation and the availability of data to inform model specification.

In this paper we provide an extension to a single store or shopping centre retail catchment estimation technique, presenting a model for a national network of retail agglomerations. The methodology we propose is theory led and estimates catchments for more than 1300 UK retail centres, taking into account spatial interactions between potential customers and these destinations within an estimated hierarchical network of retail centres. The model is fitted at a Lower Super Output Area (LSOA – zones of approximately 672 households; ONS, 2012) level of granularity based on retail centre attractiveness that declines as the distance between consumer domiciles and shopping destinations increases.

Although this paper presents and then empirically tests a model for a UK case study, we would envisage that the presented model with similar inputs, would also be applicable within other international contexts. The commercial and empirical value of such a study is potentially very significant, as the method could be implemented in a wide range of applications that require local insight for a national or regional extent, for example, feeding into broader debates on town centre performance, such as those related to the impact of online sales or other factors impacting demand. Additionally, this study provides an open source software

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tool that enables custom model fitting. It is anticipated that this tool will be useful to various stakeholders such as academics, planners and town centre managers.

This paper also discusses a range of theoretical and empirical challenges that such a model presents. For example, how can a range of retailer types and linked consumer behaviour be measured for a national extent? Or, how can geographic differences that emerge between different facets of the retail centre hierarchy be measured and incorporated into the modelling framework? The paper concludes with discussion on model calibration, including validation methods and recommendations about how we might overcome emergent challenges for estimation of traditional retail catchment models.

## 2. Theoretical and empirical considerations

The general concept of a retail catchment comprises three major components: supply factors, demand factors and consumer interactions (Birkin et al., 2010); however, when considering a network of retail centres there are a number of other, equally important dimensions and constraints that require consideration (Birkin et al., 2010; Cheng et al., 2007; Clarke, 1998; Dennis et al., 2002). The first of which is the position of a retail centre within a hierarchy of other retail centres. Typically such hierarchy relate to the size, attractiveness and the geographical extent of their composite retailers influence, with those centres towards the upper end of a hierarchy typically offering a 'multi-purpose and comparison shopping' experience and acting as a regional hub for employment (Dennis et al., 2002; Teller and Reutterer, 2008), and as such, drawing consumers from a wider area. Conversely, smaller town or district centres will typically serve a different function, be more embedded in local economies (Guy, 1999; Powe and Shaw, 2004), and therefore be patronised more prevalently by local communities.

The relationship between the functional roles of centres with different sizes have historically been modelled through central place theory (Christaller, 1933), which maintains some relevance within the contemporary context (Dennis et al., 2002); however, from the perspective of retail catchment estimation, there are some serious limitations. An assumption of a relatively uniform distribution of population and therefore static distribution of goods and services are problematic within large urban areas such as London or the post-industrial cities of northern England where polycentric and dispersed spatial structures are characterised by a higher degree of market fragmentation, and as a result, more intense competition between retail centres (Burger et al., 2014). In general terms, retail centre distributions influence competition between groups of centres, driven by the location, form and function of a centre, and how such attributes affect shoppers' choice behaviours. As such, establishing the position of a retail centre within a hierarchy becomes an important component for modelling of interactions with competitors (Berry, 1963; Fotheringham, 1986; Dennis et al., 2002; Borchert, 1998). There are various ways of establishing retail centre hierarchy that are implemented within both national and international contexts (e.g. Experian,[1] Venuescore[2] by Javelin Group or International Council of Shopping Centers); however, the methods or metrics used are far from uniform and of varying degrees of transparency. In addition, there is no agreement about how many distinct types of retail centres there are, nor how individual centres should be assigned to the various categories (DeLisle, 2005). Within the UK context, Government guidelines on defining the network and hierarchy of centres are available (e.g. Planning Policy Statement 4; DCLG, 2009), although they exclude out of town shopping centres and retail parks.

A second consideration when delineating a retail catchment is the selection of one or more threshold values representing the proportion of customers likely to patronise a certain store or retail centre – also referred to as primary, secondary or tertiary catchments. However, although it could be argued that there is some ambiguity when drawing a distinction between primary and secondary retail catchments (Guy, 1999), the most common approach adopted by the leading commercial consultancies (e.g. CACI,[3] Savills[4]) defines the primary catchment as the areal extent representing the flow of at least 50% of a particular centre's shoppers (Savills, 2005; CACI, 2007). The secondary retail catchment area would typically see patronage probability levels between 25% and 50%, and the tertiary above 10%. It should be noted that although these thresholds are useful from an operational perspective, they are pragmatic rather than theory driven choices, and as such, are by no means consistent between applications.

Further to considerations of hierarchy and appropriate threshold values for catchment extents, there are also different theoretical and empirical constraints when modelling retail centres versus those for an individual business. Importantly, the potential catchment areas for various retail or service types are likely to vary substantially as consumers would typically travel greater distances to purchase comparison goods, offered by higher order centres, compared to convenience goods, more prevalently available locally (Dennis et al., 2002; Finn and Louviere, 1990; Fotheringham, 1986; Joseph and Kuby, 2011). Indeed, operationalizing the estimation of catchment areas for retail agglomerations requires some generalisations, as it is not feasible for all potential influences to be quantified when broadening analysis to an entire retail centre or system. A further constraint pertains to the validation of catchments derived for a network of retail centres. Most large retailers collect detailed data on their customers, based on actual purchases and spending patterns, and often these can be used to determine the de facto aerial extent of where patronage is drawn. Similarly, there are commercial survey data available on consumer flows to particular shopping destinations in the UK; however, such data are not nationally comprehensive. Lastly, there is a dearth of empirical evidence about the universality of catchment models, and under what circumstances national models break down. For example, retail catchments in rural areas will typically comprise lower competition and customers will tend to travel longer distances (Calderwood and Freathy, 2014); and as such, may create significantly larger extents than a centre with similar attractiveness located within an urban area.

## 3. Catchment area estimation techniques

There are numerous ways in which catchments can be delineated depending on the requirements for a particular study, available data, software used or the analytical capability of a practitioner or researcher. The simplest techniques might be to draw buffer rings around a store, or to generate polygons based on the distance and time that customers are willing to travel to a particular centre (Segal, 1999). Drive distance and drive time methods are generally considered to be most valid for convenience store scenarios, where patrons are expected to go to the closest or

[1] http://www.experian.co.uk/marketing-services/news-retailscape-uk-retail-centres-best-placed-to-thrive.html.

[2] http://www.javelingroup.com/retail_consulting_services/locations_analytics/location_consumer_data/.

[3] http://www.caci.co.uk/.

[4] http://www.savills.co.uk/.

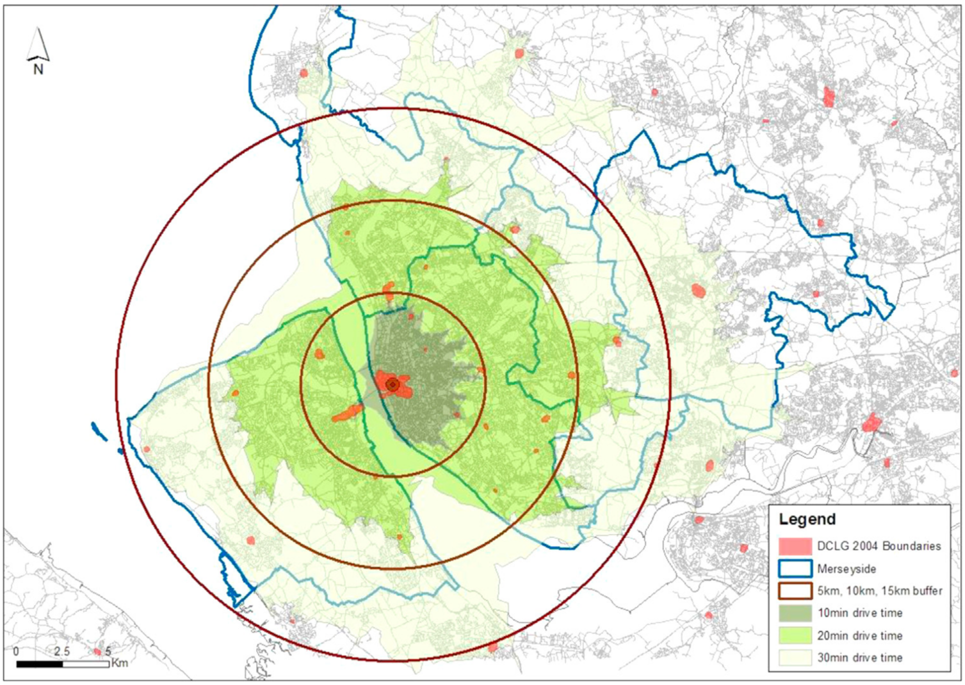


**Fig. 1.** Drive time polygons of 10 min, 20 min and 30 min generated for Liverpool Central.

most logistically convenient location; however, when an entire town centre or shopping street is considered, such techniques are unlikely to sufficiently capture the complexity of those different attributes that may influence true catchment extent (Birkin et al., 2010; Dramowicz, 2005).

Moreover, as consumers will typically use more than one place to shop, retail catchments may overlap, and especially so in densely populated urban areas where shopping choice is greater (Gonzalez-Benito and Gonzalez-Benito, 2005). For instance, Fig. 1 shows the extent of trade areas for Central Liverpool generated for 10, 20 and 30-min drive times using road network data, alongside measures derived as buffers. Such models imply that the centre has a monopoly over a depicted area, which oversimplifies the complexity of real-world consumer patronage behaviour.

A key objective of this paper is to extend catchment modelling from single stores to retail agglomerations, and such undertaking needs to implement a range of sophisticated modelling techniques, capturing multiple variables of influence, while simultaneously depicting the spatial interaction between particular retail centres and the population of the surrounding geography (Fotheringham, 1986; Benoit and Clarke, 1997; Lea, 1998; Dennis et al., 2002; Wilson, 2010; Birkin et al., 2010, Newing et al. 2015). Such techniques typically apply Newtonian laws of physics to the modelling of shopper behaviour, and approximate a store or retail centre catchment area by considering the spatial distribution of competing locations and evaluating their relative attractiveness to different population groups (Davies and Rogers, 1984; Segal, 1999). Catchment areas derived from early gravity models, such as those developed by Reilly (1931) and extended by Converse (1949) comprised break points between the distance that customers would be willing to travel to a set of competing destination (e.g. a town centre or store), and were calibrated using a number of location factors such as city population, price and the selection of offered goods. Although Reilly's gravity concept had limited ability to deal with multiple stores or retail centres, and assigned all potential sales within a trading area to only one town centre/store, it has underpinned the development of other more complex methods of patronage prediction (Dramowicz, 2005; Joseph and Kuby, 2011).

One of the most enduring catchment area models was introduced by Huff (1964), and is calibrated using three main variables: distance, attractiveness and competition (Dramowicz, 2005). The probability ($P_{ij}$) that a consumer located at $i$ would choose to shop at retail centre $j$ is calculated according to the following formula (Huff, 2003).

$$P_{ij} = \frac{A_j^{\alpha} D_{ij}^{-\beta}}{\sum_{j=1}^{n} A_j^{\alpha} D_{ij}^{-\beta}} \tag{1}$$

where:

$A_j$ is a measure of attractiveness of retail centre $j$, such as square footage,
$D_{ij}$ is the distance from $i$ to $j$,
$\alpha$ is an attractiveness parameter estimated from empirical observations, and
$\beta$ is the distance decay parameter estimated from empirical observations.

The major advantage of the Huff Model is an allowance for the simultaneous estimation of a customer's patronage probabilities for many retail centres, including those with overlapping trade areas, while at the same time, identifying break points in the distribution of retail influence between competing retail centres/stores (Joseph and Kuby, 2011).

Some other prominent examples include entropy maximisation models (Wilson, 1970, 2010), the competing destinations model (Fotheringham, 1983), the multipurpose shopping model (Arentze and Timmermans, 2001) and the travel-to-store-area method (Pratt et al., 2014). The family of spatial interaction entropy maximising models (Wilson, 1970), employ statistical mechanics to '*represent our knowledge of the system in a set of constraint equations and find the most probable state—which then becomes the model equations—by maximizing the entropy subject to these constraint's*' (Wilson, 2010, p. 367). Such entropy maximising spatial interaction models have been applied in many areas of urban geography and regional science and their utilisation within the retail context has underpinned the intelligence of store location amongst a variety of major retailers (Wilson, 2010; Birkin et al., 2010). An alternative competing destination framework was proposed by Fotheringham (1983) which assumed that the spatial arrangement of destinations in a geographical system would influence trip distribution, and therefore patronage of certain destinations. The relative location of destinations was found to have a strong effect on the distance decay parameter estimates, and was addressed by adding an accessibility variable to the traditional gravity model. The multipurpose shopping model is an activity-based approach where consumer choice of shopping destination is linked to a trip purpose (Rasouli and Timmermans, 2013).

### 3.1. Calibration of gravity models

Spatial interaction approaches such as the Huff model require calibration of individual model parameters that capture the effects of different types of retail centres, distance between origin and destination locations and local demographic characteristics. In the context of building such models for retail centres rather than individual stores, a series of specific considerations are required, including: the extent of the retail centre; how the defined centre sits within a hierarchy of national or regional retail centres; how the effects of such differentiation can be modelled by disaggregated distance decay parameters; and finally, the extent to which a comprehensive and multidimensional attractiveness measure for retail centres can be captured for national extents? Employing a systematic measure of retail centre extent is of high importance, so a like-for-like set of measures can be extracted. In the case of UK town centres, such boundaries were developed by Thurstain-Goodwin and Unwin (2000) and consequently adopted by the Department of Communities and Local Government (DCLG) in 2004.

The decay of patronage linked with duration of travel can be adjusted by assigning a power value to the $\beta$ parameter, with larger values representing a more rapid decay (Joseph and Kuby, 2011). A substantial body of literature has evaluated various aspects of the distance decay parameter and estimation of its values, often through survey or study of transaction data (e.g. Huff, 1964; Dennis et al., 2002; Gonzalez-Benito and Gonzalez-Benito, 2005; Birkin et al., 2010). For instance, different types of retail centres were found to have variable estimated decay exponents, ranging from 0.97 for regional centres through to 2.3 for local centres (Young, 1975). Additionally, Drezner (2006) also suggested moving away from a fixed distance decay parameter to a stratified value depending on the centre size or position within the hierarchy of a retail system. Furthermore, it has been suggested that the parameter $\beta$ should also be disaggregated by origin and/or person type e.g. car owner vs. non-car owners, socio-economic status (Wilson, 2010; Birkin et al., 2010) or geodemographics (Singleton et al., 2011), as such factors are argued to affect both mobility and spending power.

The issue of retail centre attractiveness has also received considerable attention of both academics and practitioners (Guy, 1998; Mintel, 1997; Arentze and Timmermans, 2001; Drezner and Drezner, 2002; Teller and Reutterer, 2008; Teller and Elms, 2010). As the market share captured by a retail centre and the extent of a catchment area is related to its competitive advantage (Drezner and Drezner, 2002), the most common measures of retail centre attractiveness are related to their size, typically proxied through gross or net selling area (Dennis, 2005; Gonzalez-Benito and Gonzalez-Benito, 2005) or the number of retail/service units (Mintel, 1997; Reynolds and Schiller, 1992).

However, it is important, to note that single measures of attractiveness are far from comprehensive (Birkin et al., 2010; Timmermans, 1996), and therefore other significant factors found to influence the patronage of a particular town centre such as the presence of specific anchor stores (Finn and Louviere, 1996; Feinberg et al., 2000), retail tenant mix (Teller and Reutterer, 2008; Teller and Elms, 2010) and 'non-retail tenant mix' such as leisure outlets (Reimers and Clulow, 2009) should be considered. Empirical evidence also implies that choice of store or retail centre is determined by a wider suite of qualitative indicators, such as the age of a centre, cleanliness, convenience, accessibility including car parking facilities, perception of safety and trading hours (Guy, 1998; Timmermans, 1996; Teller and Elms, 2010; Arentze and Timmermans, 2001). Nevertheless, it should be highlighted that although such indicators might influence our choice of a shopping destination; it may not be feasible to measure them on a systematic basis across a national extent.

Finally, when estimating retail centre attractiveness, consideration also needs to be given to differences between naturally-evolved retail agglomeration such as town centre or high streets and those that have been planned, such as shopping centres. Research has suggested that large shopping centres offering free car parking are often perceived as more attractive than traditional town centres (e.g. Timmermans, 1996; Teller and Reutterer, 2008; Teller and Elms, 2010), and therefore in modelling such dynamics, scaling up of the attractiveness of large shopping centres by a fixed percentage compared to town centres has also been suggested (Dennis et al., 2002).

## 4. Building a model of retail centre catchment estimates for a national extent

Estimating retail catchment areas for a national extent using a spatial interaction modelling framework is complex, multi-dimensional and requires significant computational resource. As such, some generalisations or simplifications based on assumptions drawn from the literature are necessary for both empirical and pragmatic reasons. For instance, an entropy model could be argued as delivering more accurate results for a single store or a retailer's chain where sales data is available, however, for a national network of town centres, gathering such data for all stores would not likely be feasible. As such, our pragmatic approach given such constraints was to create an $R$[5] package that utilises available data to calibrate a bespoke probabilistic Huff model incorporating various dimensions of town centre attractiveness, and accounting for both competition between retail centres and their position within an overall retail system hierarchy. Additionally, the diverse patterns of patronage for particular centre types were estimated by disaggregating the β and α coefficients by the attractiveness score rank and distance respectively. Thus, variable levels of 'distance friction' ($\beta$) of retail centre attractiveness could be linked to a position within hierarchy, with those centres towards the upper end of the hierarchy displaying lower levels of distance decay. Moreover, we model a non-linear relationship between shopping probability and travel costs by adjusting the α parameters to account for those consumers who are more likely to patronise those retail centres in close vicinity (Guy, 1999). This consideration was required to address the issue of functional differences within town centres, and to avoid situations where a large number of small local centres failed to generate patronage probabilities above those levels required to delineate a catchment area.

The design of the attractiveness measures for retail centres was multi-staged. Occupancy data were derived for the 1312 DCLG specified town centres, of which 25 were classified as free-standing shopping centres (typically out-of-town) rather than an

[5] http://www.r-project.org/.

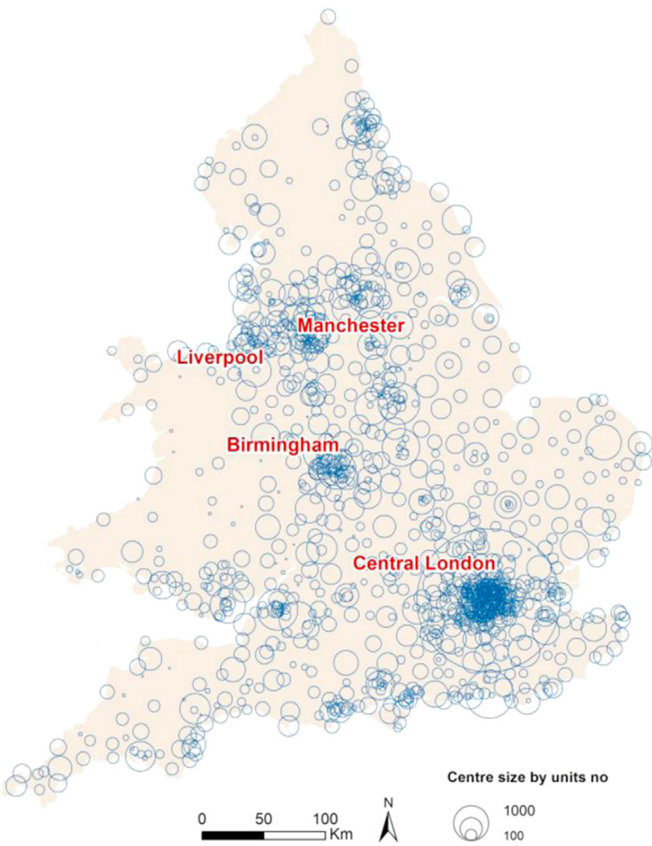


**Fig. 2.** Distribution of the DCLG town centres in England and Wales by size.

integral part of existing town centres (Guy, 1998).[6] The occupancy data were made available through the Local Data Company,[7] who provide various attributes about each town centre including facia, ownership and type of retail[8] or service units (also referred to as outlets); with the data collected every six to twelve months through their own site survey team. Fig. 2 shows the spatial distribution of the DCLG town centres located in England and Wales and depicts their proportional size by the total number of outlets. It is clear from Fig. 2 that town centres are not evenly distributed across the country, and tend to concentrate in the most densely populated urban areas. This can be problematic when attempting to delineate potential catchment areas in the largest conurbations of the country such as Manchester, Liverpool, Birmingham or Greater London.

As a result, we replaced the aggregated occupancy data for Central London-an outlier comprising over 20,000 businesses and outsizing the second largest centre tenfold-with the 27 inner retail cores identified within Central London[9] (see Fig. 3).

There are further issues related to the inclusion of regional and designer outlet shopping centres within the model. Some of the newest regional shopping centres such as Westfield in West London and Stratford were not accounted for by the 2004 DCLG boundaries, and additionally, as suggested by Dennis et al. (2002), the attractiveness scores for the regional and designer outlet shopping centres ideally requires scaling by a fixed percentage as they normally draw customers from larger distances compared to traditional town centres of similar size, measured by total number of units (Guy, 1999; Teller and Elms, 2010). Drawing on the literature outlined above, we created a composite index of attractiveness that assumes a linear relationship between key quantitative attributes found to determine customer's choice of shopping destination. In addition to conventional measures such as size of the retail offering, additional weight was given to retail mix (Teller and Reutterer, 2008), proxied by a retail diversity index (Oxford Institute of Retail Management, 2013), proportion of leisure units which increase the dwelling time (Reimers and Clulow, 2009; Hart and Laing, 2014) and anchor stores, which are empirically shown to generate larger footfall (Teller and Reutterer, 2008; Wrigley and Dolega, 2011; Teller and Schnedlitz, 2012).

As such, our measure of destination attractiveness ($A$) for a given town centre ($_j$) is specified as a sum of retail centre size ($S_j$) measured by the total number of units, retail mix ($\mathrm{RM_j}$) proxied by the diversity index, proportion of leisure units ($L_j$) and proportion of the most attractive/anchor stores ($\mathrm{An_j}$). Additionally, a negative weight was implemented to model the impact of vacant units ($V_j$), which in large numbers have been shown to create a significant deterrent to the perceived attractiveness of a given town centre (Findlay and Sparks, 2010; Wrigley and Dolega, 2011). The method used to create the composite index involved subtracting the number of vacant outlets from the total number of units and then summing the four attributes which were range standardised onto the same measurement scale.

$$A_j = \left(S_j - V_j\right) + \mathrm{RM}_j + L_j + \mathrm{An}_j \tag{2}$$

The attractiveness scores were then divided into five ranks defined by Natural Breaks (Jenks),[10] and used to depict hierarchy and functional differences between UK shopping destinations. This partitioning method establishes break points that are optimised to reduce variance within, and maximise variance between classes. Those scores above 168 indicated the most attractive centres, which typically would draw customers from large areas extending well beyond the local administrative boundaries. These pertained to the metropolitan and major regional centres such as Manchester, Liverpool, Bristol or Brighton. Second within the hierarchy, with scores of between 85 and 168 were those regional and sub-regional centres that typically draw customers from relatively broad areas and are important shopping destinations within a region e.g. Southampton, Cambridge or Leicester. The third group were centres with attractiveness scores ranging from 44 to 85, and were those sub-regional centres and larger market towns such as Truro, Lincoln or Wembley. Fourth, were the district centres and market towns such as Buxton, Sevenoaks or Marlborough. Lastly, ranking fifth comprised over 40% the DCLG centres, and represented the small district and local centres, typically serving local catchments. An example of such retail centre hierarchy for Greater Manchester is shown in Fig. 4.

Travel to a retail centre can be measured in terms of cost, time and distance including transport weighted or Euclidean (straight-line) distance (Wilson, 1974). Given an absence of national coverage data on cost of travel, the shortest road distance was calculated in this analysis using the Meridian 2 road network provided

[6] Boundaries of the central areas of towns were developed by Thurstain-Goodwin and Unwin (2000) and consequently adopted by the Department of Communities and Local Government (DCLG) in 2004. They used kernel density estimation to transform employment, floorspace and retail/service diversity data from 'objects' into continuous surfaces of spatial densities. The derived boundaries comprise all central areas of towns and the major out-of-town regional and designer outlet shopping centres at a time (25 in total).

[7] http://www.localdatacompany.com/.

[8] Categories of retail are shown in Appendix A.

[9] All the major DCLG town centres contained a smaller high density retail cores (see Thurstain-Goodwin and Unwin (2000) for more details). In the case of Central London there were 27 retail cores for which occupancy data was extracted and then used in the model.

[10] Jenks Natural Breaks is a method of data clustering designed to determine the best arrangement of values into different classes. This is done by determining the smallest in-class variance; in other words by minimising each class's average deviation from the class mean, while maximising each class's deviation from the means of the other groups.

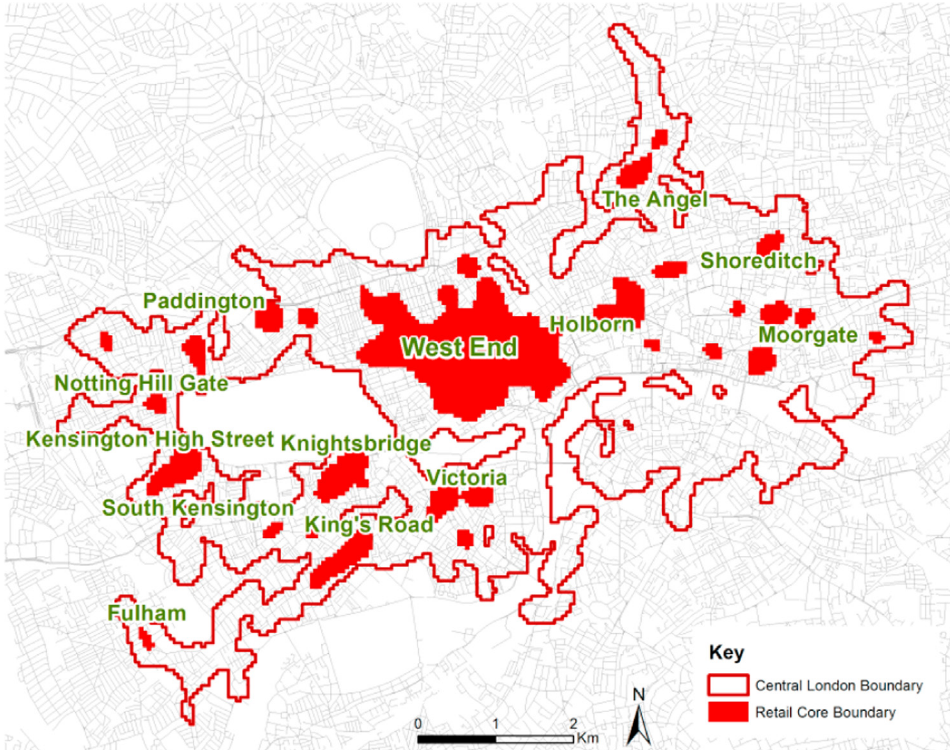


**Fig. 3.** Central London retail cores used in the analysis.

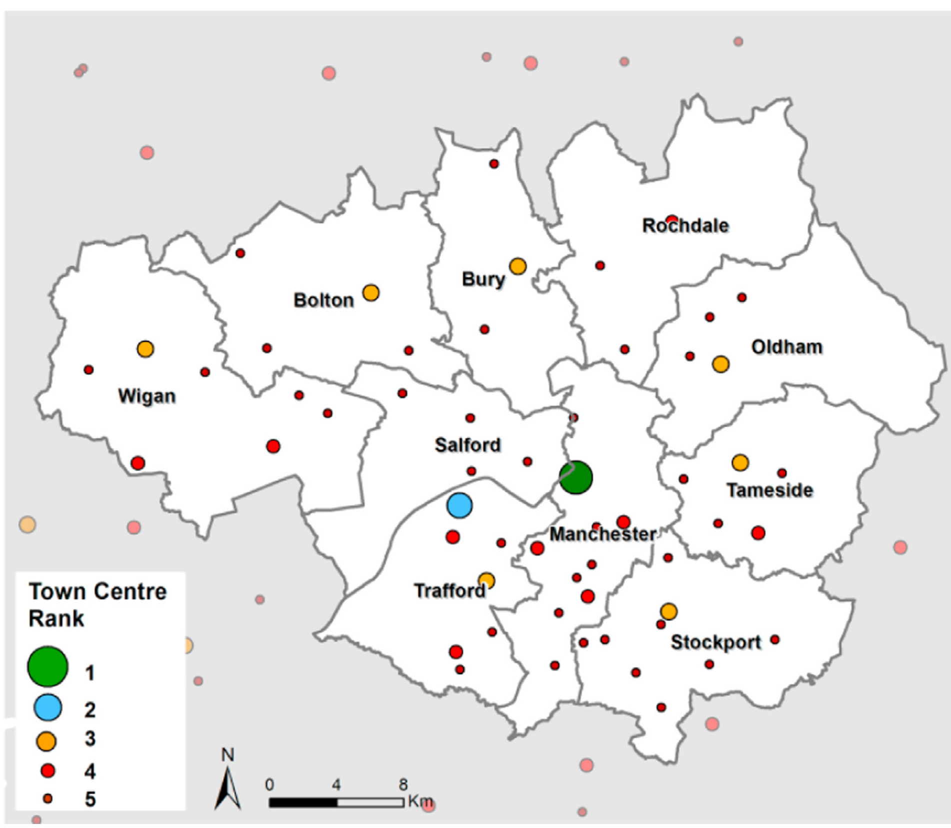


**Fig. 4.** Town centre ranks used by the study for Greater Manchester.

by the Ordnance Survey.[11] The shortest road distance was calculated from each LSOA centroid to the nearest point on the boundary of each retail centre extent, which was found to produce catchments that better accounted for the morphology of each retail centre than when the same models were implemented with distances to the centroid of a retail centre extent. The process used to calculate the pairwise road distances between the centroids of

[11] https://www.ordnancesurvey.co.uk/opendatadownload/products.html.

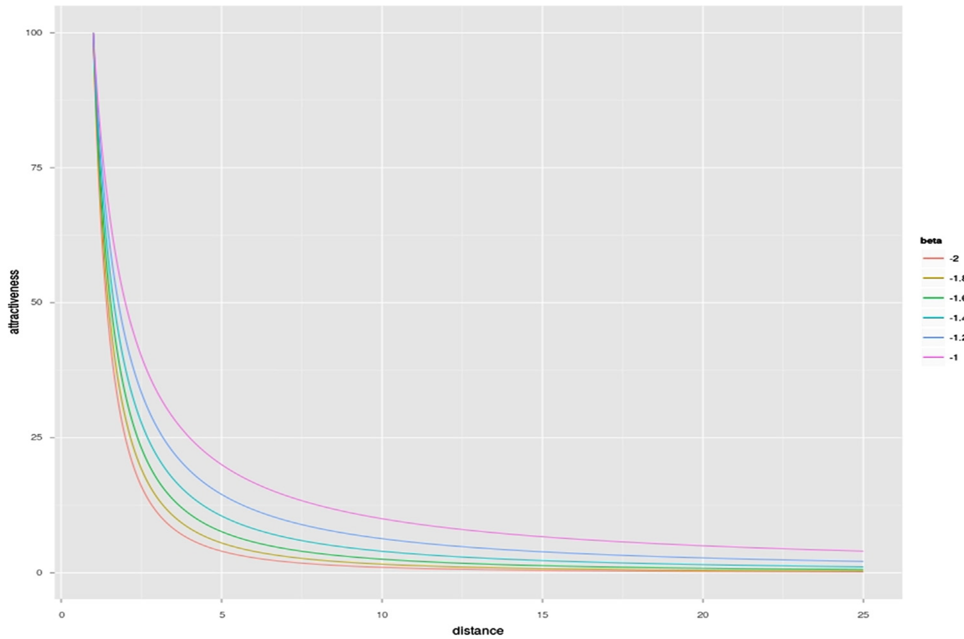


**Fig. 5.** Relationship between retail centre attractiveness and distance for different $\beta$ values.

the LSOAs and the boundaries of the retail centres was as follows. After road network data was collected, it was made "routable" by applying the Depth First Search[12] (Tarjan, 1972) method, which traverses the road network and then decomposes it into self-connected components. The coordinates of the points that defined the retail area boundaries were then extracted and Dijkstra's algorithm (Dijkstra, 1959) was applied in order to calculate the shortest road distances. The analysis was all completed within the statistical programming language R, and integrated into the developed huff-tools library.[13]

Road distances were used to form the basis of the attractiveness score exponent ($\alpha$). In essence, this enables the modelling of nonlinear behaviour of the attractiveness parameter, and within a Huff type model it can be employed to account for various qualitative factors such as the ease of access to a particular retail centre, perception of attractiveness, or trading hours etc. (normally estimated from empirical observations). However, it was not possible to account for these effects universally, and as such, our model considers only the effect of accessibility on the extent of potential catchments. More specifically, any retail centre within a short walking distance (maximum of 0.5 km from the centroid of a LSOA) was assumed to be a primary retail destination, and hence the attractiveness score for that pair was raised to a power of two. For all other distances, a default alpha value equal to 1 was used. The disaggregation of the α value is based on both the literature (Birkin et al., 2010) and empirical observations from the survey presented in the final section of this paper. As such, in our study we make an assumption that 'ease of access' is proxied by a 5 min walk (0.5 km) between the customer origin and shopping destination, and increases the perceived attractiveness of a given centre twofold. For other custom models, such calibration could be adjusted or removed.

The distance to a retail centre is raised to the power of a beta exponent ($\beta$) in order to model the negative relationship between distance and retail attractiveness. Based on the literature (Young 1975; Joseph and Kuby, 2011), the beta exponent usually takes a value of between $-1$ and $-2$, depending on factors such as the type of retail centre or competition. As illustrated in Fig. 5, the lower the value of beta, the steeper the decay of attractiveness becomes. Therefore, lower beta values are assigned to retail centres where the attractiveness (and the probability of patronage) is reduced faster over distance.

In our model we disaggregate the β values by the attractiveness score using the ranks ($s$) described above and the $\alpha$ values by the 'ease of access' ($k$). As such, the bespoke Huff model developed by our study takes the following form:

$$P_{ij} = \frac{A_j^{\alpha k} D_{ij}^{-\beta sj}}{\sum_{j=1}^{n} A_j^{\alpha k} D_{ij}^{-\beta sj}} \tag{3}$$

## 5. Implementing a model to estimate retail centre catchment extents for England and Wales

The model defined in equation 3 was run for all 1312 DCLG retail centres in England and Wales, and was calibrated against the criteria described in the previous section. The denominator of the Huff model provides a way of standardising the numerator so that the sum of probabilities for each point of origin add up to 1; and thus considers the effect of competition between retail centres. By adjusting the gravity model for this origin-specific constraint, we developed what is known as a singly constrained or production constrained gravity model. The patronage probability for each centre was then used to delineate retail catchment areas by selecting threshold values of 50% for the primary, 25% for the secondary and 10% for tertiary catchments, and correspond to thresholds discussed earlier (Savills, 2005; CACI, 2006–2011).

The vast majority of the retail centres in England and Wales (1294) generated a patronage probability above 25%, but where

[12] Depth First Search (DFS) is a method for traversing a graph data structure, and in this case it is used to identify the self-connected components of the road network of England. The DFS method is applied by beginning from a node in the graph, visiting all the neighbouring nodes for as long as there are unvisited nodes. If at some stage there are no unvisited neighbouring nodes, DFS checks if all of the nodes of the graph have been visited, and if that is not the case, then it then starts traversing the next self-connected component from an unvisited node.

[13] An open source software tool created as part of this research can be found here: https://github.com/ESRC-CDRC/huff – this also enables bespoke model creation for different geographic extents, or for other contexts

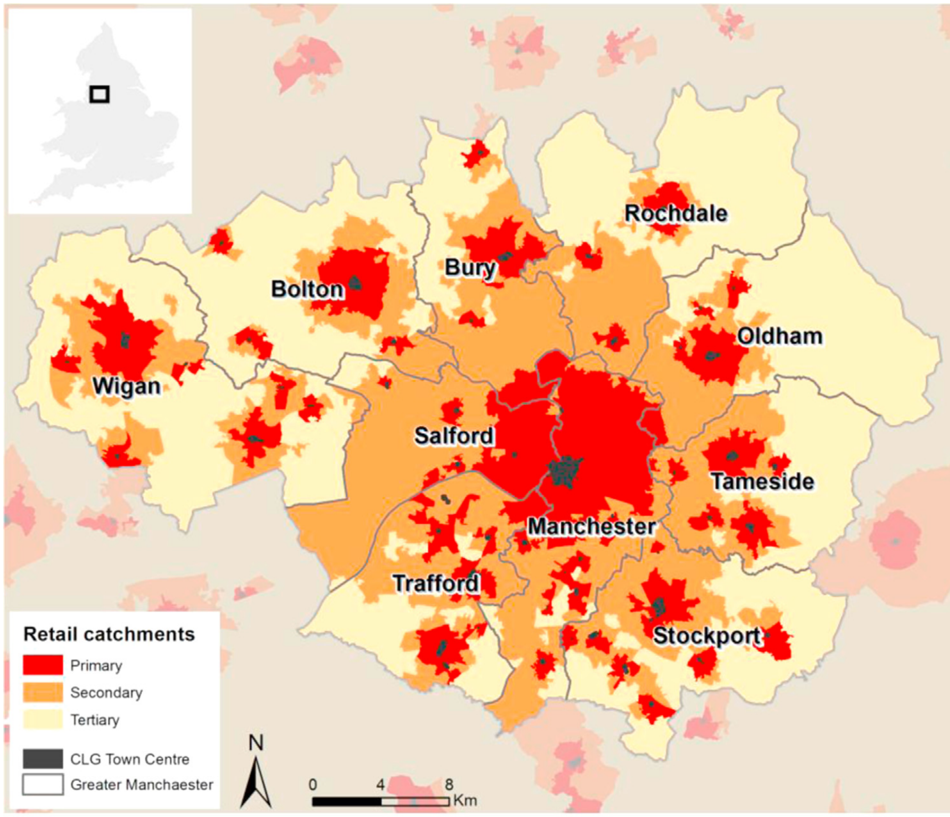


**Fig. 6.** An example of the Huff model output computed at a national scale and presented for Greater Manchester, a large northern metropolitan area of England.

this was not the case, centres were typically very small, and/or in closer proximity to other larger more dominant centres. In general, the extent of a catchment areas is affected by the position of the centre within the retail hierarchy, so rather expectedly, the most attractive shopping destinations become more likely to attract customers from further afield, and as such, were found to serve much larger catchments than those lower within the hierarchy. Visually, the model appears to perform well, assigning patronage probabilities consistent with the attractiveness scores and distances between origins and destinations, while simultaneously accounting for proximity between competitors. Typically, those LSOAs within the immediate vicinity of retail centres displayed a patronage above the 50% level, and those further afield generated lower probabilities given costs associated with travel and the availability of alternative shopping destinations. These effects are illustrated in Fig. 6, which shows the mapped results for the largest urban area in northern England, namely Greater Manchester.

There are strong advantages of this open model which uses a consistent and transparent methodology. It is easy to re-run the model in the case where new data becomes available or there is a need to update the existing parameters. Indeed, it has a range of applications to academia, local authorities or the private sector.

Nevertheless, one needs to be cautious when interpreting the results of the model, and two main limitations emerged. First, accounting for competition was challenging in the case of some centres, which in turn impacted the extent of their catchment areas. We found that in large urban areas, where competition would be significant, our model tended to underperform. This can be illustrated in the context of the West Midlands and includes those centres surrounding and including Birmingham, which are shown in Fig. 7. A number of densely populated LSOAs which are circled in red were not assigned to any town centre as primary or secondary catchments.

This effect occurs due to the close proximity of a large number of competitors within one conurbation such as Birmingham, Merry Hill regional shopping centre and several other large centres. Such spatial distributions are likely to create additional complexity in consumer behaviour regarding patronising certain shopping destinations, and are not accounted by our Huff model particularly well. Secondly, implementation of the Huff model for an entire network of retail centres at a national scale, as opposed to a chain of stores or retail/service types (e.g. convenience, comparison) has implications for validation. For example, we are not aware of any systematic data in the UK that would provide consumer flows to retail agglomerations at a national scale. However, for certain localities such data is available for some retail categories such as comparison (non-food) retailing, and therefore can be used to validate the specifications of our model calibrated to that broad retail type.

### 5.1. A case study calibration of the catchment model framework

Exploration of de facto retail centre catchments for a sample of consumers in Birmingham and surrounding retail centres was explored through a survey supplied by Acxiom Ltd., a marketing technology and services company (http://www.acxiom.com/). This dataset is based on a large sample of customers who provided postcode origins for their domicile and location of principal non-food shopping destinations. The survey was carried out in 2007 and contained 10,800 valid answers on the primary non-food shopping destination within the Birmingham (B) postcode area. Expectedly, the most popular shopping destination in the study area was Birmingham City Centre with 3760 patrons, followed by Merry Hill regional shopping centre, Solihull, Redditch and Sutton Coldfield. With the exception of four LSOAs (where no responses were recorded), between 1 and 26 survey respondents were recorded, with 9 being the average. The frequencies of survey responses are shown in Fig. 8 for the valid responses within the study area.

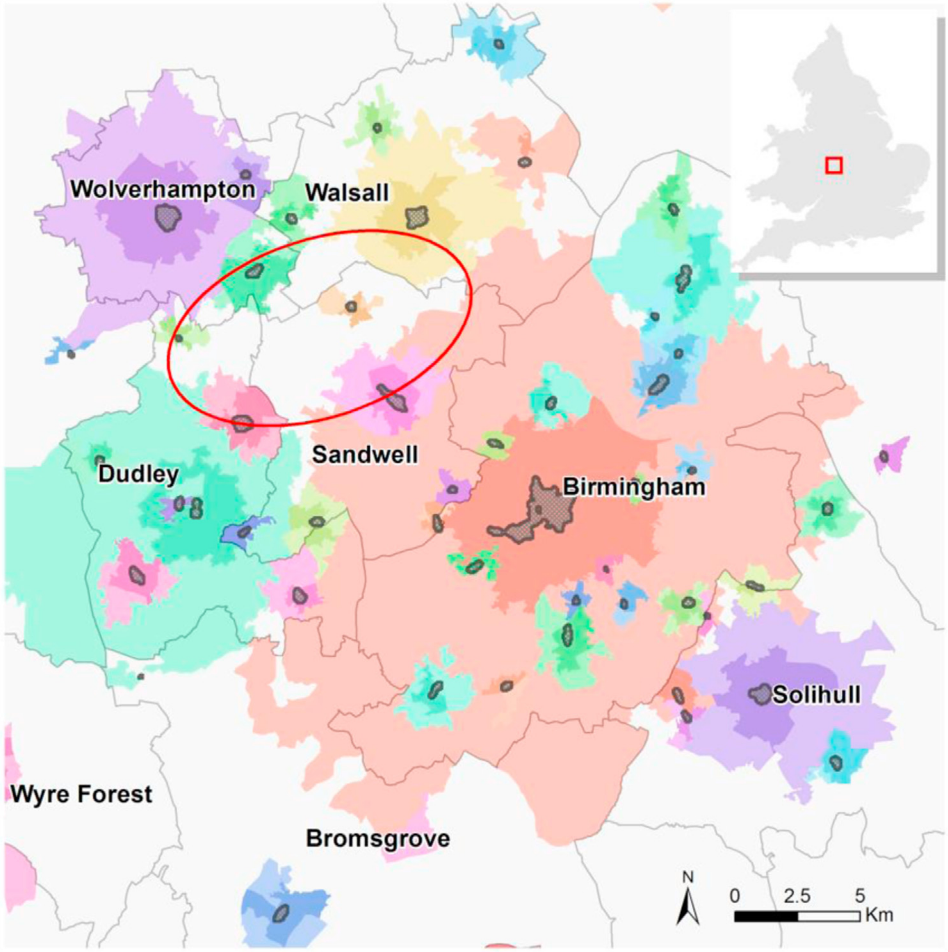


**Fig. 7.** Primary and secondary retail catchments in Birmingham urban area.

The calibration of our model in this case study application was based on comparison of the extents of retail catchments derived from the patronage survey against those estimated by our model output. The Acxiom shopping flow data was used to calculate patronage probabilities for each LSOA in the Birmingham area by dividing the number of patrons of a particular shopping destination by the number of respondents. The thresholds used to establish the primary and secondary catchments based on Acxiom's respondents corresponded to those used in our Huff model. The model used an identical input to the bespoke Huff model described earlier, however, the composite attractiveness index developed for each town centre was altered to incorporate comparison retail units only, supplemented by retail mix, and the proportion of leisure and anchor stores. This adjustment was required to match the focus of the survey data.

The output of the model revealed that 800 of the 1137 LSOAs (70%) within the study area were assigned to the same shopping destination as recorded in the real world patronage data. Although the initial results showed a high degree of correspondence to those patterns recorded in the Acxiom's sample, we attempted to improve the model prediction accuracy through better account for non-linearity in consumer patronage behaviour. After exploration of many different specifications, we found that the most effective was to scale up the attractiveness score for the regional shopping centre Merry Hill by 50%, and adjust the ranking of centres to account for the dynamics of local competition, and furthermore, amend the α values so that they were disaggregated by centre type. This had particular impact in the case of secondary but large centres around the city centre. In this adjusted Huff model, 884 of 1137 LSOAs, (78%), were assigned to the same centre as Acxiom's patronage data indicated. Although calibration of spatial interaction models is common (Birkin et al., 2010; Fotheringham, 1983; Hu and Pooler, 2002; Wilson, 2010), for a national retail system this would be more complex as survey data would be required for a much larger extent. However, as illustrated in this example, the disadvantage of not doing such calibration is that you may not produce an optimised model for a locality, although the variability of such differences may differ depending on local context and complexity of sub-regional retail systems.

The mapped results, shown in Fig. 9, indicate that the match between the real world data and our predictions can be viewed as satisfactory; nevertheless, there are some noticeable differences. This is especially evident in the north-east part of our study area (circled in red), which depicts the Tamworth area. According to Acxiom's data, Tamworth town centre draws its patronage from much larger area than our results indicate. The Huff model probabilities suggest that there is a significant leakage to Birmingham City Centre. This might possibly be explained by the fact that the Acxiom's data is from 2007 and our town centre occupancy data from 2013. Tamworth town centre has been adversely affected since then by the 2007–09 economic crisis – its vacancy levels reached 20%, well above the national average at 14% (Retail Week, 2013)-and the competitive pressure from Birmingham and Ventura Retail Park, which are home to a plethora of anchor retailers and leisure operators (LDC, 2015) are performing exceptionally well.

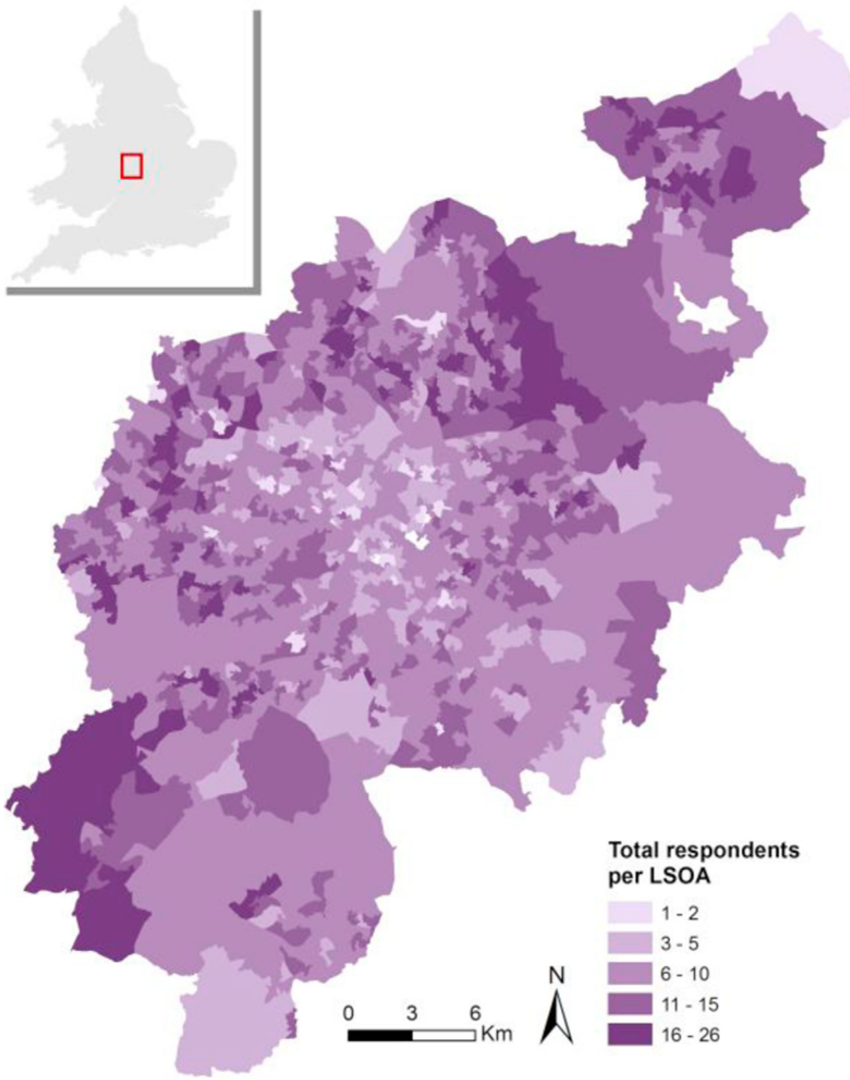


**Fig. 8.** Distribution of valid responses on non-food shopping destination within study area.

## 6. Concluding remarks

The concept of a retail catchment area is well established in the academic literature, and, as discussed in this paper, those methods for estimating such extents have evolved substantially over time. Contemporary models featuring spatial interactions are complex, typically implementing bespoke calibration and validation against customer insight data (Birkin et al., 2010; Huff, 2003; Wilson, 2010). However, these such models become challenging to replicate within the context of a nation system of retail agglomerations.

Our approach to address this issue has been to develop a flexible model that utilises a composite index of attractiveness, and considers the impact of the interdependencies between different retail centres, including their function within a retail system hierarchy. This approach involved a series of generalisations or simplifications that were required when expanding the assumptions used to model catchments for a store chain or retail/service category to retail agglomerations. Thus far, statistically significant indicators of retail centre attractiveness or catchment models have typically been demonstrated through various studies derived at a small scale, ranging from one urban area (Timmermans, 1996) to over a dozen shopping centres (Finn and Louviere, 1990; Teller and Elms, 2010). As such, we position our work presented here within the context of national extrapolation.

Through the calibration presented for the case study of Birmingham, we would argue that our model is robust; however, some questions are raised for future research. For instance, how can qualitative factors typically found to affect the perceived attractiveness of a centre such as cleanliness, safety or opening hours (Guy, 1998; Teller and Reutterer, 2008; Timmermans, 1996) be incorporated into a national model? Furthermore, are gravity based models appropriate in urban areas where the large number of competitor destinations creates additional complexity? Similarly, how can global retail centres such as Central London (ATCM, 2013) be better accounted for within such models, where a substantial share of patronage comes from nationwide and overseas visitors? In addition, there is uncertainty regarding the extent to which catchment models may be affected by the flows of residents over the course of the day, in particular the linkages between the location of employment or night-time economies (ATCM, 2013; Roberts and Eldridge, 2009). Furthermore, using town centre boundaries from 2004 has some implications for modelling, as their extents are likely to have changed over the past ten years (Wrigley et al., 2009; Wrigley and Dolega, 2011). If an inaccurate retail centre extent is used, the related attributes such as vacancy rates can skew the attractiveness of a particular centre, and therefore, there is clearly work required on how the temporal granularity of retail centre boundaries can be enhanced.

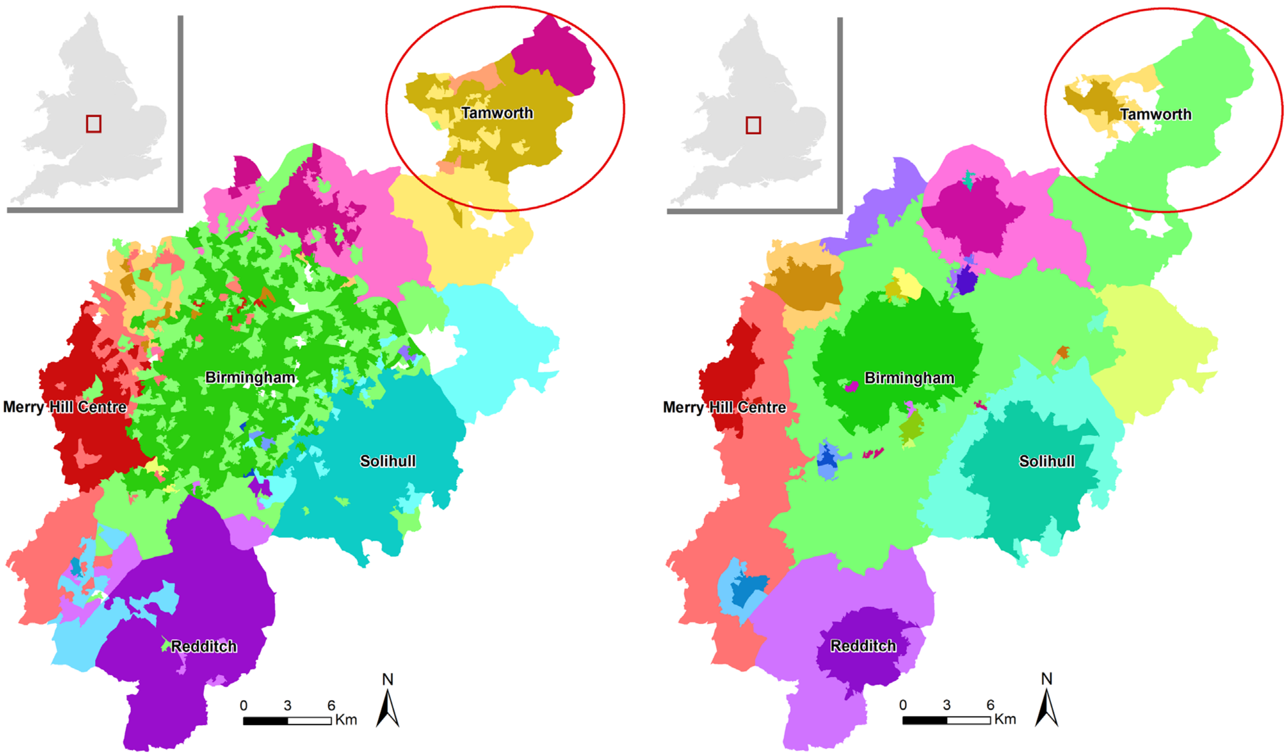


**Fig. 9.** (a) Catchments derived from the Acxiom's patronage data and (b) Catchments derived by the bespoke calibrated Huff model.

Finally, there are important externalities to the dynamic nature of town centres and the impact that these changes have on the extent of catchments areas. For instance, rapidly increasing online sales, which are estimated to exceed 14% of UK retail sales in 2015 (CfRR, 2015), have and will increase impact on retail and town centre configuration. Such issues are however not well understood, and there is a broader agenda for further research into how such changes may impact retail catchment geography.

## Appendix A

Retail and Service Categories & Sub-Classes used by Local Data Company

| Comparison | Convenience | Retail Services | Leisure Services | Financial & Business Services | Vacant Outlets |
|---|---|---|---|---|---|
| Antique Shops | Bakers and confectioners | Clothing and fancy dress hire | Bars and wine bars | Building societies | Vacant retail and service |
| Art and art dealers | Butchers | Dry cleaners and launderettes | Bingo and amusements | Building supplies and services | Other vacant outlets |
| Booksellers | CTN | Filling stations | Cafes | Business goods and services | |
| Carpets and flooring | Convenience Stores | Health and beauty | Casinos and betting offices | Employment and careers | |
| Catalogue showrooms | Fishmongers | Opticians | Cinemas and theatres | Financial Services | |
| Charity Shops | Frozen Foods | Other retail services | Clubs | Legal Services | |
| Chemist and drugstores | Greengrocers | Photo processing | Disco, and nightclubs | Other business services | |
| Children and infant wear | Grocers and delicatessens | Photo studio | Fast food and take away | Printing and copying | |
| Clothing general | Health foods | Post offices | Hotels and guest houses | Property services | |
| Crafts, gifts, china and glass | Markets | Repairs, and restoration | Public Houses | Retail Banks | |
| Cycles and accessories | Off licences | Travel agents | Restaurants | | |
| Department and variety stores | Supermarkets | TV, cable and video rental | Sports and leisure | | |

DIY and home improvements
Electrical and durable goods
Florists
Footwear
Furniture fitted
Furniture general
Gardens and equipment
Greeting cards
Hardware and household goods
Jewellery, watches and silver
Ladies and men wear and acc.
Ladies wear and accessories
Leather and travel goods
Men wear and accessories
Music and musical instruments
Music and video recordings
Newsagents and stationers
Office supplies
Other comparison goods
Photographic and optical
Secondhand goods, books, etc.
Sports, camping and leisure goods
Telephones and accessories
Textiles and soft furnishings
Toiletries, cosmetics and beauty products
Toys, games and hobbies
Vehicle and motorcycle sales
Vehicle accessories
Shoe repairs etc.
Vehicle rental
Vehicle repairs and services
Video tape rental

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