# Food Jungles and Retail Chameleons:

## Investigating Consumer Attitudes and Food Access in North Canberra using a Calibrated Disaggregated Spatial Interaction Model

by

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# Candidate's Declaration

This thesis contains no material which has been accepted for the award of any other degree or diploma in any university. To the best of the author's knowledge, it contains no material previously published or written by another person, except where due reference is made in the text.

Brittany Olivia Dahl Date: 27/10/16

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# Abstract

This thesis studies the human-ecological basis of food access among different consumer groups using a geographic information system. Past research on this topic has lacked an integrated socio-spatial modelling approach that takes into account empirical data on consumer behaviours and socio-economic status. A dominant concept in this subject area is the notion of 'food deserts', which focuses on two variables: low socio-economic status, and the distance of consumers to major food retailers. This approach fails to acknowledge the influence of consumer attitudes on food consumption. This thesis addresses this issue through the use of a calibrated disaggregated spatial interaction model to create outputs more representative of actual behaviours. This method calculates the probability of visitation of each retailer, for each consumer subgroup, based on empirically-defined parameter configurations.

Empirical data was collected on consumer attitudes and visitation behaviour to a selection of major food retailers in the area of North Canberra ($n$ = 864). Four factors were found to statistically separate the data. These factors included: *Cost* (1), *Convenience* (2), and *Care* (3), and S*ocio-economic Status* (4); and were used to statistically define five consumer subgroups, named: *Concerned* (A), *Expedient* (B), *Dispassionate* (C), *Calculating* (D), and *Frugal* (E). Socio-economic status played almost no role in the separation of these consumer subgroups, indicating that socio-economic status is less important than attitudes in the measurement of food access in North Canberra. This result challenges the implicit assumptions about socio-economic status and behaviour in the food desert discourse, and highlights the need for greater use of sophisticated, empirically defined models, that can explain underlying behavioural trends.

Unexpectedly, spatial patterns of consumer subgroup visitation to retailers in the study area were comparatively uniform. Aggregate community-retailer visitation patterns also showed that although larger retailers were favoured, proximity was more important. This uniformity revealed that North Canberra is not a typical food desert, but is more characteristic of a 'food jungle', an area with high access to retailers. The statistically measured differences in attitudes between consumers was practically irrelevant for discerning spatial behaviour at this level of analysis. This implies that consumers must either be ignoring their attitudinal values, or acting upon them within stores, at a sub-catchment level. The latter situation is highly likely, as retailers are known to fragment their market share, and act as 'chameleons', by supplying a diversity of food products which cater to a range of consumers. This result suggests that the addition of new retailers for consumers to choose from, is unlikely to realise change in the food system. Instead, regulatory responses (such as a sugar tax), would be more effective if targeted to in-store purchases. This thesis demonstrated that a calibrated disaggregated spatial

interaction model is a useful tool for exploring the influence of underlying contextual and social variables. This method could be used to assess other areas, including those previously labelled as food deserts, for the presence or absence of food jungles and retail chameleons. It could also be applied to other social issues where access and behaviour are fundamental considerations, such as transport, crime, and gambling research.

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In this thesis access is measured as a function of distance and the willingness of the consumer to travel to major food retailers in the study area, based on calibrated parameters. To measure this, a Spatial Interaction Model (taken from Markham *et al.*, 2013) takes the form of:

$$P_{ij} = k \cdot o_j^{\gamma} \frac{\left(\Pi_l \alpha_{il}^{\alpha_l}\right) \cdot f\left(d_{ij}, \beta\right)}{\Sigma_i \left[\left(\Pi_l \alpha_{il}^{\alpha_l}\right) \cdot f\left(d_{ij}, \beta\right)\right]}$$

Where:

$P_{ij}$ is the probability of respondents at origin *j* (household) interacting with destination *i* (retailer);

$o_j$ is the population of the household *j*;

$\alpha_{il}$ is the *l*th variable describing the attractiveness of retailer *i*;

*f* is a negative power function of the distance between household *j* and retailer *i*; and

*k*, *γ* , $\alpha_l$ and β are parameters (to be empirically estimated).

## List of Acronyms and Abbreviations

| | |
|---|---|
| **ABS** | Australian Bureau of Statistics |
| **ACT** | Australian Capital Territory |
| **ACTPLA** | ACT Planning and Land Authority |
| **AFN** | Alternative Food Network |
| **FAO** | Food and Agriculture Organisation (of the United Nations) |
| **G-NAF** | Geocoded National Address File |
| **GIS** | Geographic Information Systems |
| **MAUP** | Modifiable Unit Area Problem |
| **MB** | Mesh Block |
| **PMC** | Department of Prime Minister and Cabinet |
| **SA1** | ABS Statistical Area Level 1 |
| **SES** | Socio-economic status |
| **SIM** | Spatial Interaction Model |
| **UGCoP** | Uncertain Geographic Context Problem |

# *Glossary of Terms*

| | |
|---|---|
| **Buffer** | An area around a feature of a specified distance or time used to measure and analyse the variable of proximity (Esri, 2016c). |
| **Calibration** | The process of adjusting model parameters, using empirical data (Batty and Mackie, 1972). |
| **Disaggregation** | The breakdown of a set of data containing associated features into smaller elements for analysis (Esri, 2016a). |
| **Euclidean distance** | The measurement of the direct distance between an origin and a destination in geographic space (Thornton *et al.*, 2011). |
| **Food access** | The ability to acquire the type, quality, and quantity of food required for a household within a reasonable means (Ingram *et al.*, 2012: 29). This ability depends on allocation, affordability, and consumer preferences (Ingram *et al.*, 2012: 23). |
| **Food accessibility** | A broad term for the state or level of food access in household or wider area (Ingram *et al.*, 2012: 29). |
| **Food desert** | An urban area with socio-economically disadvantaged individuals or households that do not have adequate access to any major food retailers with healthy foods (Leete *et al.*, 2011: 214). |
| **Food environment** | A description of the aspects of the food system in a given geographic location (Lengnick *et al.*, 2015: 587). |
| **Food insecurity** | The state in which individuals, households, or areas have no access to food (FAO, 2016). |
| **Food jungle** | Areas that are not considered food deserts, due to adequate levels of access to major food retailers by socio-economically disadvantaged households in the area. This term implies that there is an underlying complexity to the food environment (Balingasa and Balingasa, 1999; Flaherty *et al.*, 2012; Nestle, 2016). |
| **Food landscape** | A food landscape is considered to be the metaphorical description of the food environment in a given area, based on researched characteristics (Kelly *et al.*, 2008). Examples of this include food deserts (Adams *et al.*, 2010), and food jungles (Flaherty *et al.*, 2012). |
| **Major food retailer** | Major food retailers include supermarkets, grocery stores, and large specialised outlets, including those in the alternative food network, such as farmers' markets. Convenience stores, petrol stations, liquor retailers, cafes, restaurants, and takeaway food services are not included in this definition (ABS, 2010). |

| | |
|---|---|
| **Network distance** | The measurement of distance between an origin and a destination along a network of junctions and lines, such as a roads and footpaths (Thornton *et al.*, 2011). |
| **Retail chameleons** | Retailers who provide a range of products that targets the changing needs of the consumer, allowing each consumer to act upon their attitudinal desires in-store (Burn-Callander, 2013; Kennedy, 2013). |
| **Spatial Interaction Model** | A method to model the movement of people between an origin and a destination across geographical space (Fotheringham and O'Kelly, 1989). |
| **Spatial retailer catchments** | Areas of geographical nature around which a retailer statistically derives the majority of its patronage (Lea, 1998: 140). Spatial catchments are also referred to as retail trade or service areas (Huff, 1963; Lea, 1998). |
| **Uncertain Geographic Context Problem** | The uncertainty of contextual influences of area-based attributes on the geographically defined behaviour of individuals (Kwan, 2012a: 958). |

# Chapter 1: Introduction

## 1.1 *Background and Context*

Food access is a widely debated issue, involving multiple disciplines (Hodgson, 2012; Thornton *et al.*, 2011; Burns *et al.*, 2011). Food access is a combination of allocation, affordability, and preference (Ingram *et al.*, 2012: 23). Taken together, these factors form a vital part of urban community wellbeing (Ingram *et al.*, 2012: 23). Lack of access is thought to directly impact on behavioural patterns of consumption, nutrition, and physical activity across the world (FAO, 2016). Even in high-income countries such as Australia, at least five percent (5%) of individuals are believed to consistently lack access to food (see the 1995 Australian National Nutrition Survey in Burns, 2004; Rosier, 2011; Ball and Thornton, 2013), and this number is thought to be even greater for marginalised communities (Rosier, 2011; Lindberg *et al.*, 2015).

Researchers investigating the issue of food access have undertaken geographical and spatial analysis of the local retail food environment, household purchases, consumption, and social behaviours (Allard, 2016). The most prominent body of literature on this problem that characterises both social and spatial variables of the issue discusses the concept of a 'food desert' (Desjardins, 2010). The term first emerged in policy debates about known areas of social exclusion and undernutrition in the United Kingdom (UK) in the late 1990s (Wrigley *et al.*, 2002). Since then, food deserts have become metaphorical references to areas characterised by households of low socio-economic status (SES) and relatively poor access to healthy and affordable food (for example, see: Charreire *et al.*, 2010; Desjardins, 2010; Leete *et al.*, 2011; Jiao *et al.*, 2012). This term however, has many different definitions due to its use in diverse fields of study, and the variety of ways access can be assessed (Adams *et al.*, 2010).

Geographic information systems (GIS) have been commonly used to model food access and food deserts, but few examples have incorporated contemporary, sophisticated spatial modelling techniques. Outside of the food access discourse, a substantial body of literature has focused on improving spatial understandings of access in general (Golledge and Rushton, 1976; Golledge and Stimson, 1987; Golledge and Stimson, 1997), and the accuracy of retail location and demand analysis (Reynolds and Wood, 2010; De Beule *et al.*, 2014; Newing *et al.*, 2015). However, a key challenge faced by many researchers is the application of these methods to the food desert concept (Adams *et al.*, 2010). GIS-based research into the socio-spatial nature of food deserts typically measures access to major food retailers (hereafter known as 'retailers') using aggregated geographic zones, such as postal area codes, and ambiguous distance measurements (Thornton *et al.*, 2011; Eckert and Shetty, 2011; Taylor and Ard, 2015; Wang *et al.*, 2016). Commonly, researchers assume that consumers access retailers within a 500 to 1,000 metre distance either represented by straight line distance (for example, Euclidean), or along roads and paths (for example, network distance) from their household location (Charreire *et al.*, 2010). Nevertheless, this approach rarely involves the use of actual measured distances.

In addition, few examples of GIS research have captured the complexities of consumer behaviour, such as individual attitudes. Attitude is a contextual expression of favour towards objects or places, which can influence eating habits and patterns of visitation to retailers (Chetthamrongchai and Davies, 2000; Chen, 2007; De Barcellos *et al.*, 2011). Consumers have complex attitudes and behaviours towards food, which may contextually change with geographic location (Lindeman and Väänänen, 2000; D'Souza *et al.*, 2006). However, contextually-explicit variables are difficult to model spatially. This problem has been described by Chen and Kwan (2015) and Kwan (2012b; 2012b) as the 'Uncertain Geographic Context Problem' (UGCoP). The UGCoP refers to the extent to which "…areal units deviate from the true geographic context" (Kwan, 2012b: 958). UGCoP occurs due to, "…spatial uncertainty in the actual areas that exert contextual influences on the individuals being studied and the temporal uncertainty in the timing and duration in which individuals experienced these contextual influences" (Kwan, 2012a: 245). Most existing food access literature assumes that contextual influences are uniform for all consumers (Charreire *et al.*, 2010; Chen and Kwan, 2015). This ignores the strong likelihood that consumer spatial behaviour is likely to be socially patterned, and correlated with SES and attitudes towards food. This omission may have theoretical and policy implications for food accessibility (Thornton *et al.*, 2011; Thornton *et al.*, 2012).

This thesis uses a calibrated disaggregated spatial interaction model (SIM) to address both of these previously overlooked aspects of food access. Firstly, a calibrated SIM may be useful for mitigating the UGCoP because it models accessibility based on reported spatial behaviour (Chen and Kwan, 2015), rather than assuming that consumers visit their nearest food retailer, or visit retailers within an arbitrary geographic distance. Secondly, disaggregation by consumer subgroups may be useful for comparing the behaviours of consumers differentiated by social variables. Integration of these characteristics into a spatial model should result in outputs that are more representative of actual consumer behaviour.

## 1.2 *Significance of Research*

This thesis makes three distinct contributions to knowledge:

Firstly, this is the first study that the author is aware of that examines how different consumer subgroups, based on attitude, translate directly into modelled spatial behaviour to major food retailers. For example, although Dagevos (2005) and Verain *et al.* (2016) discuss transitions in consumer preferences towards foods and retailers, neither model these behaviours spatially. In addition, while Shannon (2015), and Horner and Wood (2014), explore different consumer spatial behaviours, their results only show individualistic consumer behaviours, rather than those representative of a community and its food environment.

Secondly, this study is significant methodologically in its adoption of a calibrated disaggregated SIM to assess retailer visitation. Most researchers interested in visitation behaviours implement a spatially implicit approach, while spatially-explicit studies tend to assume consumers visit the retailers closest to consumer households, or those within an arbitrary distance (for example, see: Ball and Thornton, 2013; Burns *et al.*, 2011; Thornton *et al.*, 2011; Thornton *et al.*, 2012). This study aims to lessen these limitations by incorporating reported spatial behaviour rather than assumed spatial behaviour, thereby reducing the impact of the UGCoP. In addition, this study uses the Geocoded National Address File (G-NAF, see PMC, 2016) to run the SIM at a household-level. This is a more precise spatial scale than previous food desert studies, which generally use data defined by postal code (see Jiao *et al.*, 2012). Use of the G-NAF also eliminates the need for the time-consuming process of geocoding household addresses.

Lastly, this study will improve the practical understandings of the spatial behaviours of contemporary consumers in the study area. This research will address the knowledge gaps outlined in Turner *et al.* (2012), who highlighted the need for a better understanding of the availability, consumption, and behaviours towards food among different groups of consumers in North Canberra. Access to safe, ethical, and nutritious food has also been a key policy concern of local non-governmental organisations such as the Conservation Council ACT Region (2015), who also benefit from improvements to food access policy because of locally-based research.

## 1.3 *Research Aims and Questions*

This thesis aims to address the social-spatial dimensions of food accessibility through the integration of statistical and spatial methods. This thesis will investigate the following research question:

*Question:* To what extent do socio-economic status and attitudes towards food influence spatial patterns of food access and consumer visitation to major food retailers?

*Hypothesis:* Consumer attitudes are hypothesised to have a strong influence over spatial patterns of visitation to major food retailers in the study area. For example, it is thought that consumers with strong environmental attitudes towards foods will be more likely to visit retailers in the alternative food network (AFN). SES is also expected to have a strong influence on spatial patterns of visitation, due to its prevalence in food desert literature (Charreire *et al.*, 2010; Walker *et al.*, 2010b). It is assumed that attitudes and SES will separate consumers into multiple subgroups, which will display differing geographic patterns of access to food. This hypothesis is supported by a long history of theorised retail-based typologies of consumers, that speculate the existence of varying behaviours based on consumer attitudes and values (for example, see: Stone, 1954; Williams *et al.*, 1978; Lesser and Hughes, 1986; Dagevos, 2005). The influence of attitudes will be understood through statistical analysis of empirical data, to disaggregate the SIM by subgroups (as seen in Markham *et al.*, 2013, who used this method for investigating gambling behaviour).

## 1.4 *Thesis Scope*

This thesis focuses on modelling spatial behaviours in a specific study area. The scope of this project is geographically limited to the area of North Canberra, in the Australian Capital Territory (ACT), Australia. This area was chosen due to the diversity of major food retailers and the distribution of advantaged and disadvantaged households, which will be discussed further in *Chapter 3: Methods.* It is important to note that this thesis analyses geographic and human ecological concepts from an interdisciplinary perspective. This thesis does not take an holistic approach to investigating the urban food system in the study area, nor does it investigate the food chain, food-miles, or food waste of consumers in the study area. No efforts were made to discuss whole food systems, undertake life-cycle analyses, urban and rural metabolism, or the surrounding agricultural landscape. In addition, this thesis will not attempt to tally or analyse individual food purchases. Consumer subgroups are determined statistically using data collected on attitudes and SES, were mapped in aggregated form to avoid third party identification of the respondents. Modelling in this thesis is also limited temporally to a fourteen-day timeframe.

## 1.5 *Thesis Structure*

This thesis is presented using a standard scientific structure. *Chapter 2: Literature Review* explores contemporary understandings of consumer behaviour in urban food systems and how GIS methods have been used to model consumer attitudes and food accessibility. *Chapter 3: Methods* explains the research design, study area, and methods chosen to address the research question. This design includes two-stage approach, of 1) data collection from a questionnaire and 2) statistical and spatial analysis, through a factor-cluster analysis to determine the consumer subgroups, and a calibrated disaggregated SIM to model community-retailer visitation patterns. *Chapter 4: Results* presents key findings on consumer demographics, subgroups, and disaggregated comparisons of consumer visitation to food retailers in the study area. *Chapter 5: Discussion* involves an interpretation of results, with both theoretical and practical implications for the study area. Lastly*, Chapter 6: Conclusion* presents conclusions to the research question.

# Chapter 2: Literature Review

Contemporary spatial modelling methods rarely encompass the sociological complexities of food accessibility and consumer behaviours. This review of literature first discusses the complex interaction of accessibility and contemporary consumer behaviour in urban food systems. Following this, consumer attitudes are examined in terms of how they translate into spatial behaviour; and contemporary methods of food access modelling in a GIS for different consumer subgroups are critically reviewed. Lastly, the use of a calibrated disaggregated SIM to address the UGCoP and theoretical understandings of consumer behaviour are discussed.

## *2.1 Food Access*

Access to food is arguably the most crucial aspect of a healthy and equitable food system (Rosier, 2011). Food systems are complex socio-ecological multi-faceted entities, with multiple activities and outcomes (Ericksen, 2008; Anderson, 2015). Environmental, economic, and social processes impact on the availability, utilisation, and access of food on varying spatial and temporal scales (as illustrated in Figure 1; Sali *et al.*, 2014; Hodbod and Eakin, 2015: 4). Access to food is influenced by three main variables: 1) allocation, defined as the proximity of the consumer to food; 2) affordability, the price of the food; and 3) preference, defined as the choice behaviours determined by consumer attitudes, motivations, and values (see Figure 1, and Ericksen, 2008). This thesis attempts examine all three variables of access, which is unusual for food access studies (Charreire *et al.*, 2010). Many studies of food access in urban areas have focused solely on the variable of allocation, through the investigation of retailer scarcity (for example, see: Nayga and Weinberg, 1999; Smoyer-Tomic *et al.*, 2008; Morton and Blanchard, 2007; Larsen and Gilliland, 2008; Desjardins, 2010; Charreire *et al.*, 2010: 1781). This is a problem because consumer preferences are considered to shape the urban food environment (Desjardins, 2010). A vast volume of literature has demonstrated how consumer attitudes and SES play a vital role in determining eating behaviour (for example, see: Roos *et al.*, 1998; Wilcock *et al.*, 2004; Vereecken *et al.*, 2005; Landais *et al.*, 2015; Hebden *et al.*, 2015; Cecchini and Warin, 2016); yet, less research has examined the role of attitudes in food access. Desjardins (2010: 88) argues that the economic impact of consumer attitudes and choices has caused a rise in large retailers dominating the traditional 'Western' food system. This system, in affluent capitalist societies, is built on the assumption that consumers prefer large and convenient retailers (Dagevos, 2005; Ericksen, 2008), and therefore, it is important to consider all variables, including preference, that may influence retailer accessibility.

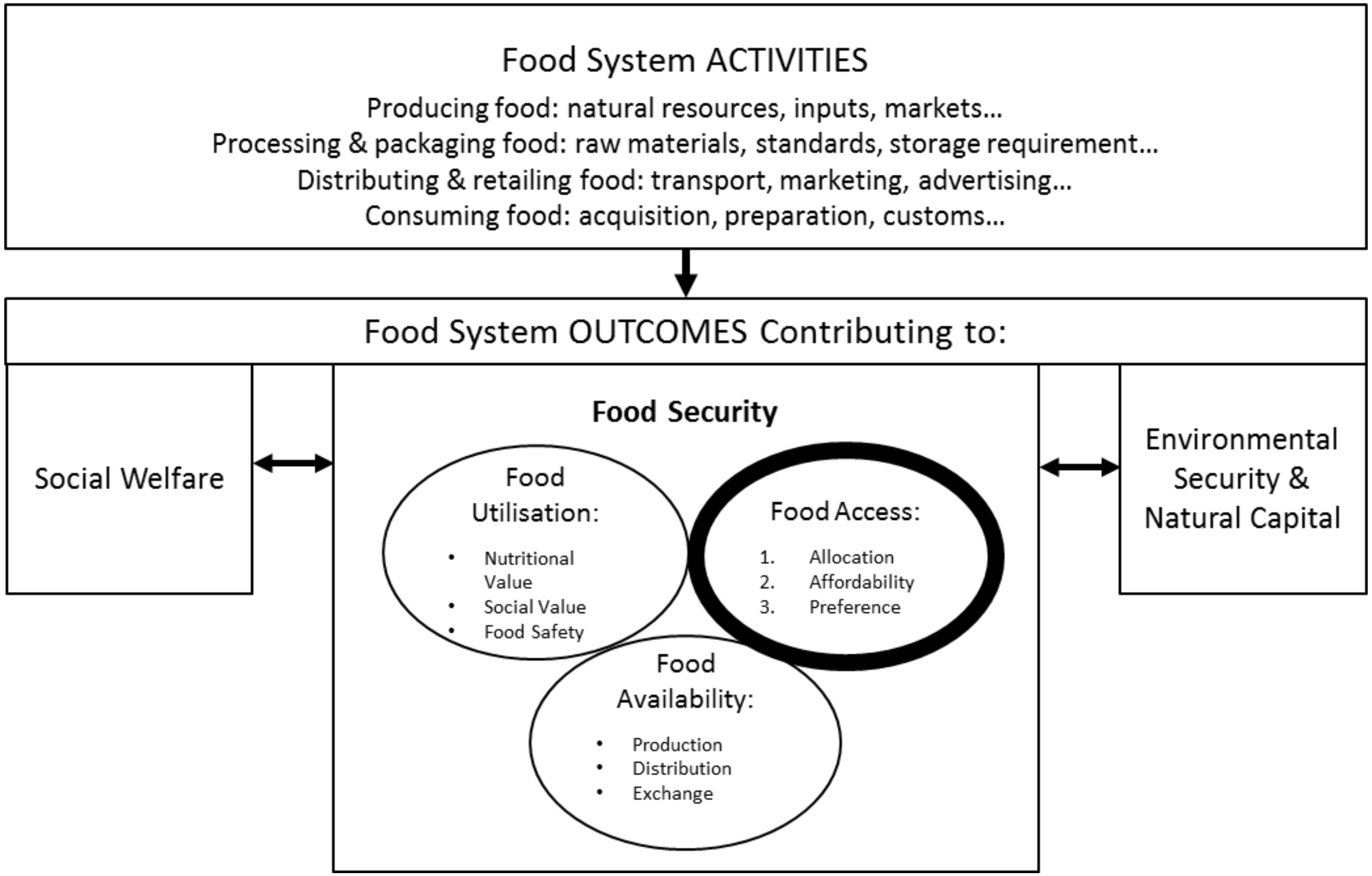



**Figure 1: A schematic version of a functioning food system (adapted from Ericksen, 2008: 234; Ingram *et al.*, 2012: 28).** The bold circle highlights the variable of focus for this thesis.

The majority of food access research in urban areas has focused on one of two research agendas: health, or social equity. However, neither approach regularly incorporate all three key variables of food access (as outlined by Ericksen, 2008). For example, the first research agenda adopts a health reformation lens, focusing on the first variable of food access: allocation. Researchers commonly investigate the distribution of healthy food sources and how these relate to dietary and bodily characteristics (Cummins and Macintyre, 2002: 436). For example, research by Dyball (2006); Pollan (2008); Newell *et al.* (2008); Harray *et al.* (2015); and Aschemann-Witzel (2015), has shown that food systems become obesogenic environments when access is too high to energy-dense nutrient-poor foods. Further research by Burns *et al.* (2011); Thornton *et al.* (2011); and Thornton *et al.* (2012) has shown that spatial access can affect the healthiness of diets, as consumers may choose to eat more unhealthy foods when they are most convenient. Spatial research from this lens has focused on 'food swamps', described as areas where households have access to too many unhealthy retailers, such as fast food restaurants and convenience stores (Taylor and Ard, 2015).

In contrast, the alternative research lens is that of social equity, focusing on the second variable of food access: affordability. Through this agenda, the attention is on disadvantaged households of low SES, to understand how poor access to affordable food affects those most vulnerable in the community (for example, see: O'Dwyer and Coveney, 2006; Sharkey and Horel, 2008; Smoyer-Tomic *et al.*, 2008; Walker *et al.*, 2010a; Desjardins, 2010; Charreire *et al.*, 2010; Leete *et al.*, 2011; Walker *et al.*, 2011; Jiao *et al.*, 2012; Wang *et al.*, 2016). For instance, research by Charreire *et al.* (2010); and Jiao *et al.* (2012), demonstrated that disadvantaged SES households, with low income and social power, have lower levels of access to food retailers than advantaged SES households. To that end, the term food desert was coined, and has subsequently been used to describe areas of low SES households with poor access to retailers (Wrigley *et al.*, 2002). However, differences in local geography has led to alternative terms, such as 'food mirage', to describe areas with high access to retailers, but inaccessible foods, due to inordinately high prices of products (Breyer and Voss-Andreae, 2013).

This thesis aims to integrate these two research approaches with the last key variable of access: preference. This study does not address specific questions of health or social equity directly, but considers allocation, affordability, and preferences to measure food access. Data on consumer preferences are collected to investigate the spatial behaviour of consumers. It is anticipated that better understandings of consumer spatial behaviour will assist policy-makers, to construct interventions aimed at addressing problems of ill health and social injustice. The approach of this thesis is from a geographic perspective, focused on spatially-explicit behaviour, interpreted through established sociological understandings of consumption. These understandings are explored in the next section.

## *2.2 Understandings of Consumer Behaviour*

### 2.2.1 Subgroups and Consumer Attitudes

Research into consumer preferences commonly splits consumers into different subgroups based on a diverse range of factors influencing behaviours. An indication of the range of variables used to describe consumer subgroups in food-based studies is shown in Table 1. In particular, it is well established that social 'consumptive values', such as consumer attitudes, beliefs, and cultural factors, impact on retailer selection and result in differences in-store purchasing behaviours (Grunert, 2002; Eertmans *et al.*, 2005; Brimblecombe *et al.*, 2014; Chen and Yang, 2014; Machín *et al.*, 2014; Cruwys *et al.*, 2015; Higgs, 2015; Lee *et al.*, 2015). Knowledge of these values have been used to theorise separation of consumers into subgroups, known as 'typologies'. These typologies are sometimes derived statistically from empirical data, and are consequently described as 'behavioural' subgroups, or market 'segments' depending on the data source (for example Verain *et al.*, 2012; Verain *et al.*, 2016). While developed in the field of market research, typologies have become popular for the investigation of ecologically sustainable food choices and green consumerism (Gunderson, 2014). In this example, consumers are divided into groups based on their attitudes towards 'immaterial values' of alternative, locally-sourced, and organic foods (as described in: Lindeman and Väänänen, 2000; D'Souza *et al.*, 2006; and for examples of these values, see: Lockie, 2009; Pearson *et al.*, 2011; Som Castellano, 2016). Lee *et al.* (2015) argues that research into this area is typically used for marketing products to consumers with high environmental values (see Figure 2).

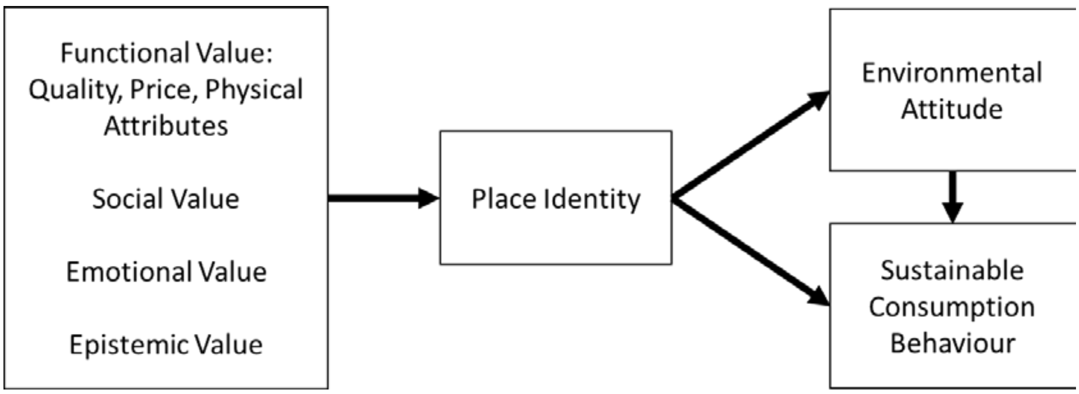



**Figure 2: Factors influencing consumer behaviour (Lee *et al.*, 2015).**

**Table 1: Examples of food-based literature that identify typologies, behavioural consumer subgroups, and market-based consumer segments.** Studies are listed in reverse chronological order below. Note that typologies have been theorised since the 1950s.

| Study | Number of respondents (n) | Number of subgroups | Variable of differentiation | Consumer subgroups |
|---|---|---|---|---|
| Verain *et al.* (2016) | 942 | 3 | Food-category attributes | 1) Pro-self<br>2) Average<br>3) Conscious |
| Turner *et al.* (2012: 21) | n/a (a priori) | 7 | Food-choice motivations | 1) Quality<br>2) Community<br>3) Confidence<br>4) Health<br>5) Green<br>6) Pluralist<br>7) Enrichment |
| Kornelis *et al.* (2010) | 1,844 | 7 | Socio-demographic profile | Un-named groups: A, B, C, D, E, F, G |
| Janssen *et al.* (2009) | 149 | 4 | Buying behaviour | 1) Organic buyers<br>2) Additive avoiders<br>3) Concerned about animal welfare<br>4) Conventional buyers |
| Mostafa (2009) | 418 | 4 | Psychographic variables | 1) True greens<br>2) Reluctant greens<br>3) Basic browns<br>4) Potential greens |
| Bernabéu *et al.* (2008) | 400 | 3 | Consumer socio-economic and lifestyle traits | 1) Price<br>2) Origin<br>3) Price and type |
| Kihlberg and Risvik (2007) | 184 | 2 | Age | 1) Aged >30<br>2) Aged <30 |
| D'Souza *et al.* (2006) | 155 | 2 | Perceived product benefits and cognitive perspectives | 1) Environmentally green<br>2) Price-sensitive green |
| Chryssohoidis and Krystallis (2005) | 205 | 4 | Personal attributes | 1) Health conscious<br>2) Organic loyal<br>3) Explorers<br>4) Independent |
| Dagevos (2005) | n/a (a priori) | 2 | Materialism and collectivism | 1) New<br>2) Old |
| Tivadar and Luthar (2005) | 1,147 | 6 | Food preferences | 1) Male traditionalists<br>2) Yes sayers<br>3) Male modernists<br>4) Weight watchers<br>5) Carefree hedonists<br>6) Health-conscious hedonists |
| Geuens *et al.* (2001) | 72 | 6 | Shopping segments | 1) Convenience<br>2) Low-price<br>3) Social<br>4) Intense social<br>5) Experiential |

| | | | | |
|---|---|---|---|---|
| | | | | 6) Recreational |
| Piacentini *et al.* (2001) | 21 | 5 | Shopping segments | 1) Apathetic<br>2) Convenience<br>3) Economic<br>4) Ethical<br>5) Recreational |
| Said (1997) | 1,200 | 6 | Market segments | 1) Brown bombers<br>2) Light brown battlers<br>3) Lip service greens<br>4) Grudging greens<br>5) Nurturing greens<br>6) Living greens |
| Lesser and Hughes (1986) | 6,808 | 10 | Psychographic market variables | 1) Inactive<br>2) Active<br>3) Service<br>4) Traditional<br>5) Dedicated fringe<br>6) Price<br>7) Transitional<br>8) Convenience<br>9) Coupon-saver<br>10) Innovator |
| Darden and Ashton (1974) | 120 | 7 | Preference for supermarket attributes | 1) Quality-orientated<br>2) Fastidious<br>3) Convenience<br>4) Demanding<br>5) Trading stamp<br>6) Stamp avoiders<br>11) Apathetic |
| Williams *et al.* (1978) | 298 | 4 | Perceived attributes of preferred grocery stores | 1) Low-price<br>2) Convenience<br>3) Involved<br>4) Apathetic |
| Stone (1954) | 124 | 4 | Attitude towards shopping | 1) Economic<br>2) Personalizing<br>3) Ethical<br>4) Apathetic |

Note: Literature compiled from search terms 'food', 'access', 'consumer', and 'subgroups' in Web of Science; and from references in Geuens *et al.* (2001); Dagevos (2005); Verain *et al.* (2012); Turner *et al.* (2012). Unclassified and indeterminate consumer subgroups were not included in this table.

Dagevos (2005) provides one example of a typology based on consumer attitudes. His research is an exemplary approach to food access (as argued in Verain *et al.*, 2012; Kraus, 2015), because of the focus on preference (Nocella *et al.*, 2012), which is the last aspect of Ericksen's (2008) description of accessibility. Dagevos' (2005) consumer subgroups are described by two dimensions of attitude-based consumption (see Figure 3). The first dimension is that of materialist values. Materialistic consumers have price and product driven attitudes, and care about physical characteristics, such as "nutritional value, taste, or texture" (Dagevos, 2005: 34). In contrast, non-materialistic consumers have emotional, ethical, or ecological attitudes. The second dimension of consumption identified by Dagevos is that of individualist versus collectivist values. Individualistic consumers behave with an aim to satisfy personal needs, while collectivist consumers are more likely to be "concerned with social or cultural structures" (Dagevos, 2005: 34). Dagevos argues that collectivists behave with socio-cultural conformity. While Dagevos' (2005) argument is based on previous empirical research, his consumer subgroups are only discussed theoretically. Dagevos provides no evidence of these subgroups existing empirically, or how they influence spatial patterns of consumerism. Readers are left to speculate about how these consumptive values might translate into consumer spatial behaviour, and this leaves a gap in the knowledge of the influence of consumer attitudes on spatial patterns of visitation.

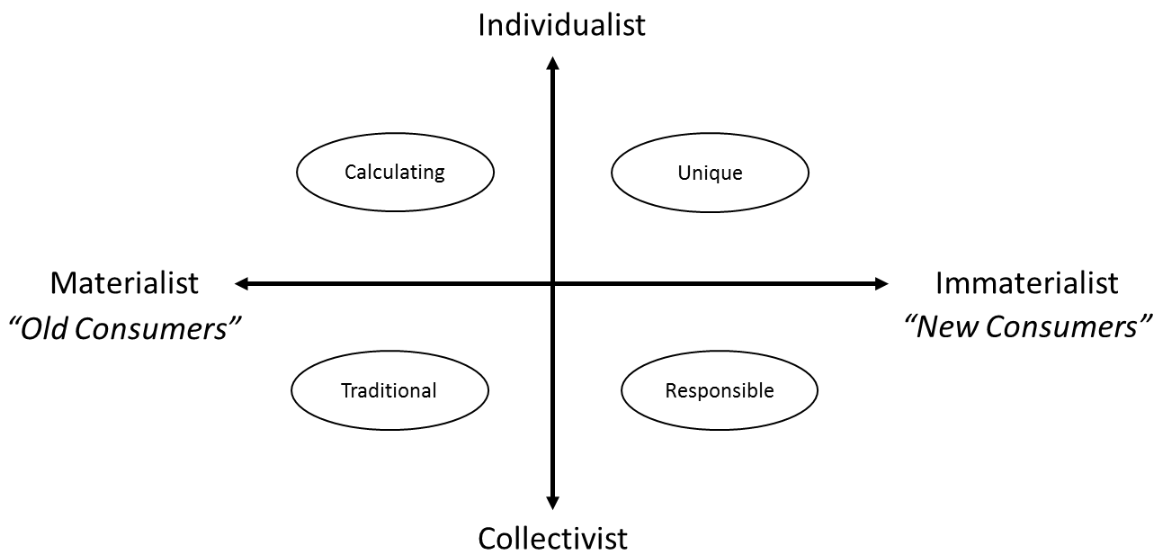



**Figure 3: An example of consumer subgroups based on attitudes and preferences (adapted from Dagevos, 2005: 35).** Dagevos outlines two main consumer groups, 'old' and 'new' consumers based on previous research by Holbrook (1999) and Lewis and Bridger (2001). Old consumers are described as 'calculating' and 'traditional'; and are conformists and laggards in the adoption of new consumer trends. In contrast, new consumers are described as 'unique' and 'responsible'; and are innovators and early adopters of changes in consumer culture (Dagevos, 2005: 38).

## 2.3 Integration of Spatial Behaviour and Consumer Attitudes

Despite the amount of research on the subject consumer behaviour, the spatial characteristics of consumer attitudes are rarely explored. Although food access is an inherently spatial field of study (Thornton *et al.*, 2011; Ball and Thornton, 2013), it is somewhat surprising that, to date, there has been relatively few studies that have explicitly used GIS to investigate attitudinal consumer subgroups. Although there is a long history of economic and retail-based spatial modelling research (Britt, 1966; Bacon, 1984), much of this research has neglected the consumer attitudes. For example, contemporary research by Newing *et al.* (2015), which could be considered state-of-the-art in technical terms (Karlsson *et al.*, 2015), does not address consumer attitudes. Newing *et al.* (2015) only address consumer values through the simplified construct of brand preference. Thus, the next part of this review will explore the use of GIS modelling in food access research, and the work by Newing *et al.* (2015), to show how SIMs can be utilised as a dependable and emerging method for investigating consumer spatial behaviour based on the integration of attitudes.

## 2.4 Modelling Food Access Using GIS Methods

Accessibility modelling has been used extensively in urban and social applications of GIS, including access to food sources. Accessibility is the ease of access an individual or household has to a particular destination, based on distance, time, and financial resources (Thornton *et al.*, 2011: 3). GIS has been used to measure access for service delivery (Jung *et al.*, 2006), policy assessment (Wright *et al.*, 2009; Markham and Doran, 2015), health services (Craglia and Maheswaran, 2004), education (Alleman and Holly, 2011), retail (Huff, 1963; Jones, 1984; Golledge and Stimson, 1997; Beare and Szakiel, 2009) and impacts of gambling (Markham *et al.*, 2013; Markham *et al.*, 2014). A vast body of literature has explored food accessibility in both Australia (for examples see O'Dwyer and Coveney, 2006; Burns *et al.*, 2011; Thornton *et al.*, 2012; Innes-Hughes *et al.*, 2012; Breyer and Voss-Andreae, 2013; Ball and Thornton, 2013; Pollard *et al.*, 2014; Lê *et al.*, 2015), and around the world (see Charreire *et al.*, 2010; LeClair and Aksan, 2014; Martin *et al.*, 2014; Neumeier, 2015; Shannon, 2015; Taylor and Ard, 2015; Wang *et al.*, 2016; Sadler *et al.*, 2016). Many of these studies examine food deserts from a health or a social equity point of view. Only a few consider consumer attitudes in their methods through model calibration and disaggregation of results (see Table 2). As Table 2 suggests, spatial research often investigates SES, but rarely interrogates its interaction with consumer attitudes.

**Table 2: Methods and characteristics of recent GIS food access studies.** Examples from the time period of 2010 – 2016.

| Study | Location | Study objective | GIS Method | Calibration? | Disaggregation? | Conclusions |
|---|---|---|---|---|---|---|
| Wang *et al.* (2016) | Canada | Fresh food access to grocery stores | Network distance to closest retailer | Based on goodness-of-fit criteria only | Disaggregation by minority groups, seniors, car and public transport access | Accessibility varies for different subgroups |
| Neumeier (2015) | Germany | Street petrol station access | Travel time by network distance | No | Disaggregation by type of access (foot, car) and time | Regions with no supermarkets accessible by foot or car, also had no petrol stations accessible |
| Newing *et al.* (2015) | Cornwall, U.K. | Consumer demand to major supermarkets | Calibrated SIM | Yes – store loyalty card data | Disaggregation by SES, seasonal visitor demand, and type of supermarket chain | Predictions of store patronage and revenue can be determined through SIMs |
| Shannon (2015) | Minnesota, U.S.A | Patterns of individual food access | Geographic tracking on daily mobility created using GPS | Yes – interviews, and photographs | No | Available transit options shape decisions about how and where to get food |
| Taylor and Ard (2015) | Detroit, U.S.A | Access to all food sources | Visualisation of the food environment | No | No | Supermarkets and grocery stores in Detroit are less than three percent of the food retailers in the city |
| LeClair and Aksan (2014) | Bridgeport, U.S.A | Food access using the price–distance Relationship | Euclidean distance buffers 0.5 mile around stores | Yes – survey data | No | Increasing the availability of public transport is not enough improve food access |
| Caspi *et al.* (2012) | Boston, U.S.A | Diet and access to supermarkets | Network distance from home within 1 kilometre (km) | Yes – survey data | Disaggregation by income | Low-income housing residents in greater-Boston have adequate access to food sources. However, fruit and vegetable intake is low, and not associated with geographic access |
| Jiao *et al.* (2012) | Seattle–King County, U.S.A | Measuring physical and economic access to supermarkets | Network service areas based on travel time | No | Disaggregation by low cost and high cost supermarkets | The definition of low-income status and access affects estimates of food deserts |
| Leete *et al.* (2011) | Portland, U.S.A | Coverage of different food desert definitions | Euclidean distance buffers 1 km radius from supermarkets | No | No | Using the definition of food hinterlands can map all those considered to have low accessibility |
| Russell and Heidkamp (2011) | New Haven, U.S.A | Loss of a supermarket | Network service areas of the major supermarkets | No | No | The loss of one retailer has detrimental effects on food access |
| McEntee and Agyeman (2010) | Vermont, U.S.A | GIS methods for rural food deserts | Mean network distance by census tract | No | No | Food deserts are areas where individuals experience inadequate access through multiple measures |
| Paez *et al.* (2010) | Montreal, Canada | Assessing accessibility deprivation indicators | Multivariate, spatially expanded models of distance | No | Disaggregation by, income and vehicle ownership | Low-income households have better food access near the centre of the city |

Note: Literature was compiled from search terms ‘food’, ‘access’, ‘calibration’, and ‘disaggregation’ in Web of Science; and from references in Charreire *et al.* (2010).

### 2.4.1 Assumptions of Space-time Sensitivity

Whilst attitude is a social variable assumed to be contextually consistent across all consumers in a wide body of literature, contemporary food access research also contains many other methodological and spatio-temporal assumptions, which has seen limited testing. Table 2 above, lists and compares the most recent GIS-based food access studies and their use of calibration and disaggregation. A close examination of these studies reveals two problematic contextual assumptions:

First, spatially-explicit studies tend to assume that the consumer residence is the origin point for visits to retailers. This overlooks the fact that consumers may purchase foods during transit to work or other destinations (Kwan, 1999; Chen and Clark, 2013; Horner and Wood, 2014). A lack of regard for contextual influences on individual eating habits is reflected in the UGCoP outlined by Chen and Kwan (2015) and Kwan (2012b; 2012b). The UGCoP refers to the lack of individual behaviours recorded in area-based studies, due to how contextual units are geographically defined (Kwan, 2012a). Because food access studies assume that point of origin is the same contextually for all consumers (this being their household), differences in food preferences and temporal changes in proximity to food are generally ignored.

The second contextual assumption is that many spatially-explicit studies assume that consumers visit the closest retailer to their household within an arbitrary distance. For example, Caspi *et al.* (2012); LeClair and Aksan (2014) use distance-based 'buffers' to model access to the closest supermarket. While Caspi *et al.* (2012) uses a half-mile area measured from each store, LeClair and Aksan (2014) uses one kilometre measured along roads from the respondent's homes. Use of arbitrary distances makes it difficult to compare studies and the validity of claims to areas being actual food deserts. Adams *et al.* (2010) ascribes this problem to lack of spatial clarity within the definition of food deserts itself. Researchers generally used their own definition, and various GIS methods to model access. Thornton *et al.* (2012) highlights that distance measures of road network distance, Euclidean and road network buffers, and kernel density estimates have all been used as methods to model the same pattern of food access with varying results (see Figure 4).

Similarly, many spatially-explicit studies assume that consumers visit a retailer within a given spatial zone (such as a census tract or statistical local area). Although, the official USDA definition of 'food deserts' is made upon this basis (Walker *et al.*, 2010b), such an assumption compounds the problem of arbitrary food buffer distances described above with the Modifiable Areal Unit Problem (MAUP). The MAUP occurs is when "…areal units can take any shape or size, resulting in complications with statistical analysis related to both scale and the method used to create the areal units" (Dark and Bram, 2007). The MAUP applies to these studies because the differences in scale between arbitrary food buffer distances can cause variations in results. This makes such an approach unsuitable for predicting food deserts and individual behaviour (Kwan, 2012a).

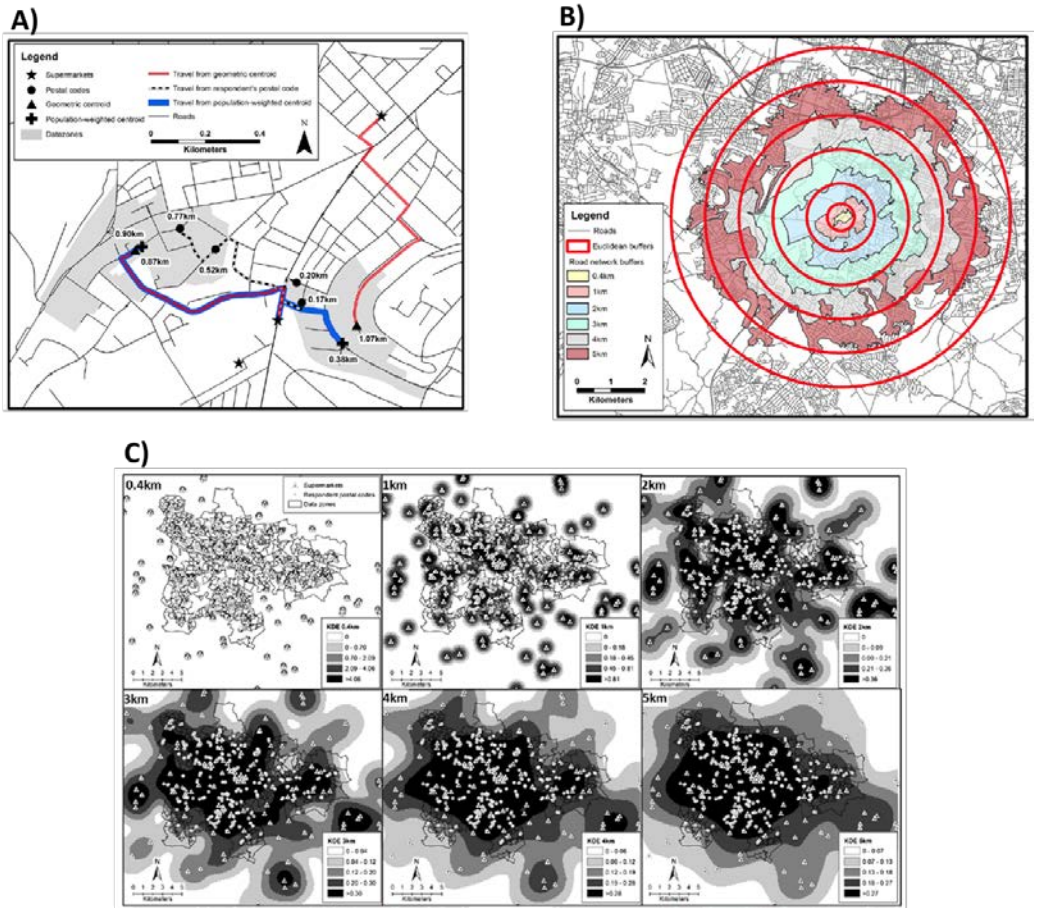



**Figure 4: Multiple GIS modelling methods used to measure distances of food access (Thornton *et al.*, 2012).** A = Road network distance, B = Buffers, C = Kernel Density estimations. Road network distances are measured as the total distance in meters or kilometres from a household to the retailer. Buffers are set distances surrounding a retailer, either by Euclidean (straight-line distance, seen in red), or network distances. Kernel Density estimations are predictions of catchment areas around retailers based on an arbitrary distance measure. In all diagrams, areas in white represent areas with low accessibility.

### 2.4.2 The Utilisation of Spatial Interaction Modelling

To mitigate the limitations of the methods described above, a modelling method is required which takes into account the complexity of actual consumer behaviour without making crude assumptions about the point of journey origin, travel distances to visit retailers and is less vulnerable to the MAUP. While travel diary or GPS tracking methods can be used to address these issues (Chen and Kwan, 2015), this type of data collection is very burdensome for respondents, and can be expensive to collect and difficult to analyse (Shannon, 2015).

To better understand how consumer attitudes influence spatial behaviour, a more sophisticated set of GIS tools can be used. A SIM is useful for mitigating the UGCoP because it models accessibility based on reported spatial behaviour, rather than assuming that consumers visit their nearest retailer or only visit retailers within an arbitrary geographic distance. SIMs are designed to estimate the probability of an individual or household spatially interacting with each destination (Huff, 2003). Many types of SIM take into account the ‘attractiveness’ of a destination (such as a ‘gravity model’, see Cox, 1972; Ottensmann, 1997; Fotheringham, 2007), and assume competition between sites (such as a ‘Huff model’, see Huff, 2003). These models are better aligned to human behaviour than other types of models, because they factor in multiple alternative behaviours (Fotheringham *et al.*, 2000). Specifically, calibration of a SIM requires survey respondents to list the number of times they visited specific retailers within a specific time period (Markham *et al.*, 2013). SIMs can also be calibrated using pre-recorded or survey data about the destinations to determine the ‘attractiveness’ of retailers (for examples see Markham *et al.*, 2013; and Suárez-Vega *et al.*, 2014). In the context of a study of food retailers, elements of attractiveness often include “store size, brand name, and range of products stocked” (Newing *et al.*, 2015).

A SIM can be used to investigate consumer subgroups through disaggregation. Disaggregation of a SIM allows for the model calibration of different groups of respondents in the data. For example, Newing *et al.* (2015), used this method to highlight differences in purchasing behaviours of consumer subgroups for different seasons in the year. In this case, a SIM can be used to differentiate the spatial behaviour of groups defined according to external variables. This method is more suitable for food access studies, as it allows a comparison of travel behaviour between different groups, defined by SES and attitudes. As such, this kind of research design meets the criteria of Charreire *et al.* (2010), who argued that the ideal research study design for examining the food environment combines GIS and survey approaches to look at both social and spatial accessibility. This thesis aims to combine sociological theory with spatial modelling to investigate spatial variation in consumer behaviour.

## 2.5 Summary

As explored above, food accessibility and consumer subgroups are inherently complex. To understand the role of the consumer in these systems, food access has typically been researched from a health or socio-equity approach, incorporating key access variables of allocation and affordability. However, a limited amount of research has focused on spatially modelling consumer subgroups based on both approaches, and the final key variable of preference. In addition, most research focused on consumer subgroups lacked integration with spatial behaviour. This leaves a knowledge gap in our understandings of the interrelation between all three dimensions of food accessibility.

Additionally, food access studies are inherently spatial, and accessibility has a long history in the field of GIS research. However, there has been limited use of advanced GIS techniques to address socio-spatial assumptions currently prevalent in food access modelling. The use of a calibrated disaggregated SIM can address these assumptions, and is better aligned to human behaviour than other modelling techniques. A SIM is used in this thesis to combine sociological theory with spatial modelling. Use of a SIM encompasses the contextual sociological complexities of contemporary consumers to address the methodological concerns of the UGCoP and the MAUP. This method is explored further in the next chapter.

# Chapter 3: Methods

This chapter describes the methods designed to investigate the research questions introduced in the introduction and literature review. This study uses quantitative methods to identify consumer subgroups using SES and food choice motivations, and determines the importance of proximity and retailer attributes for visitation by these subgroups.  This chapter also briefly describes the study site.

## *3.1 Research Design*

This study investigates the spatial behaviour of food consumers using a two-stage approach (see Figure 5). The first stage involved a postal survey of households in North Canberra, designed to collect data about residential location, socio-economic and demographic characteristics, food shopping behaviour, and food choice motivations as a measure of consumer attitudes towards food. This was required to collect the basic data used in the analysis. The second stage involved partitioning survey respondents into separate groups based on their socio-economic status and food choice motivations. This was required in order to delineate consumer subgroups whose spatial behaviour would then be compared. The spatial behaviour of these consumer subgroups was analysed using a calibrated disaggregated spatial interaction model (SIM). This approach was adopted because it combines spatial behaviour and social composition to understand how urban geography, socio-economic status and motivations produce food purchasing outcomes, an approach that has been recommended for cross-sectional food studies (Charreire *et al.*, 2010).

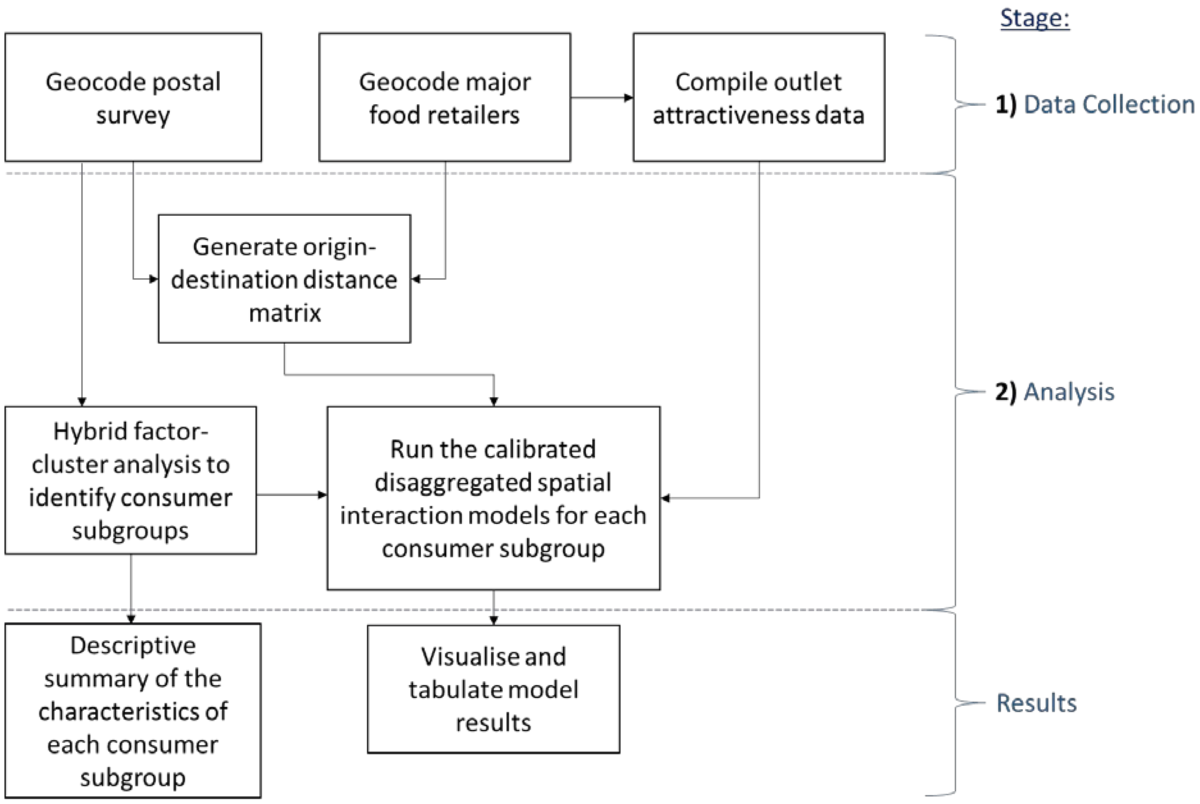



**Figure 5: Schematic representation of the research design.** Numerals in bold denote each major stages of the research approach, as described above.

## 3.2 Study Site

Northern Canberra, in the Australian Capital Territory (ACT), provides a suitable study area for this thesis. The ACT covers over 235,000 hectares and contains a residential population of over 380,000 people (ABS, 2015). The vast majority of this population lives in the nation's capital, Canberra. On average, Canberrans are wealthier and better educated than the rest of the Australia (ABS, 2013; Dyball, 2015). At least 25% of Canberrans have a university degree, compared to the national average of 14% (ABS, 2013). In 2011, the median household with children earned over $3,000 per week, compared to a national average of $2,300 per week; and the unemployment rate was 3.6%, compared to the national average of 5.6% (ABS, 2013). Yet, the wealth of the city generally 'hides' the large distribution of disadvantaged individuals (Anglicare and Red Cross, 2013). Canberra's highly planned urban structure has distributed advantaged and disadvantaged households relatively evenly across the city, with relatively little residential segregation relative to other Australian cities (Tanton *et al.*, 2013). This makes Canberra an optimal site for investigating accessibility for both advantaged and disadvantaged individuals, as socio-economic advantage is only weakly correlated with urban structure (Baum *et al.*, 2006).

Previous research has also documented diverging consumer behaviours towards food in Canberra (ACTPLA, 2010; ACTPLA, 2011). According to Turner *et al.* (2012:5), "…ACT residents have become increasingly interested in food and its social, economic and environmental impacts over the last decade." However, Anglicare and Red Cross (2013) have also documented the existence of extremely disadvantaged households in the region with inadequate access to food. This report was the first study to examine the concept of food deserts in the ACT. Yet, the report failed to identify community-retailer visitation patterns of access, that are generally used in the classification of food deserts (Thornton *et al.*, 2011). Instead, it described the experience of extremely disadvantaged individuals. Consequently, little is known about the interaction of consumers and the retail endpoints of the food system in Canberra.

This thesis will focus specifically on the sub-region of North Canberra, located close to the city's central business district (see Figure 6). This area includes suburbs: Watson, Dickson, Downer, Hackett, Ainslie, Braddon, Lyneham, O'Connor, Turner, Acton, City, Reid, Campbell, and Russell (outlined by ABS, 2015 as SA3 80105). The area was chosen for the diversity of food retailers present and the mixed socio-economic status of its residents. North Canberra contains four major supermarket chains, a food co-operative, a local produce green grocer, and a large range of smaller food retail stores (see Figure 6). In addition, directly outside of this area is a large farmers' market, operating every Saturday. These retailers are examples of all food system domains described by Anderson (2015:550, see Figure 7), and cover a wide range of business models (Table 3). Consumers have a wide variety of choice of food retailers in this area.

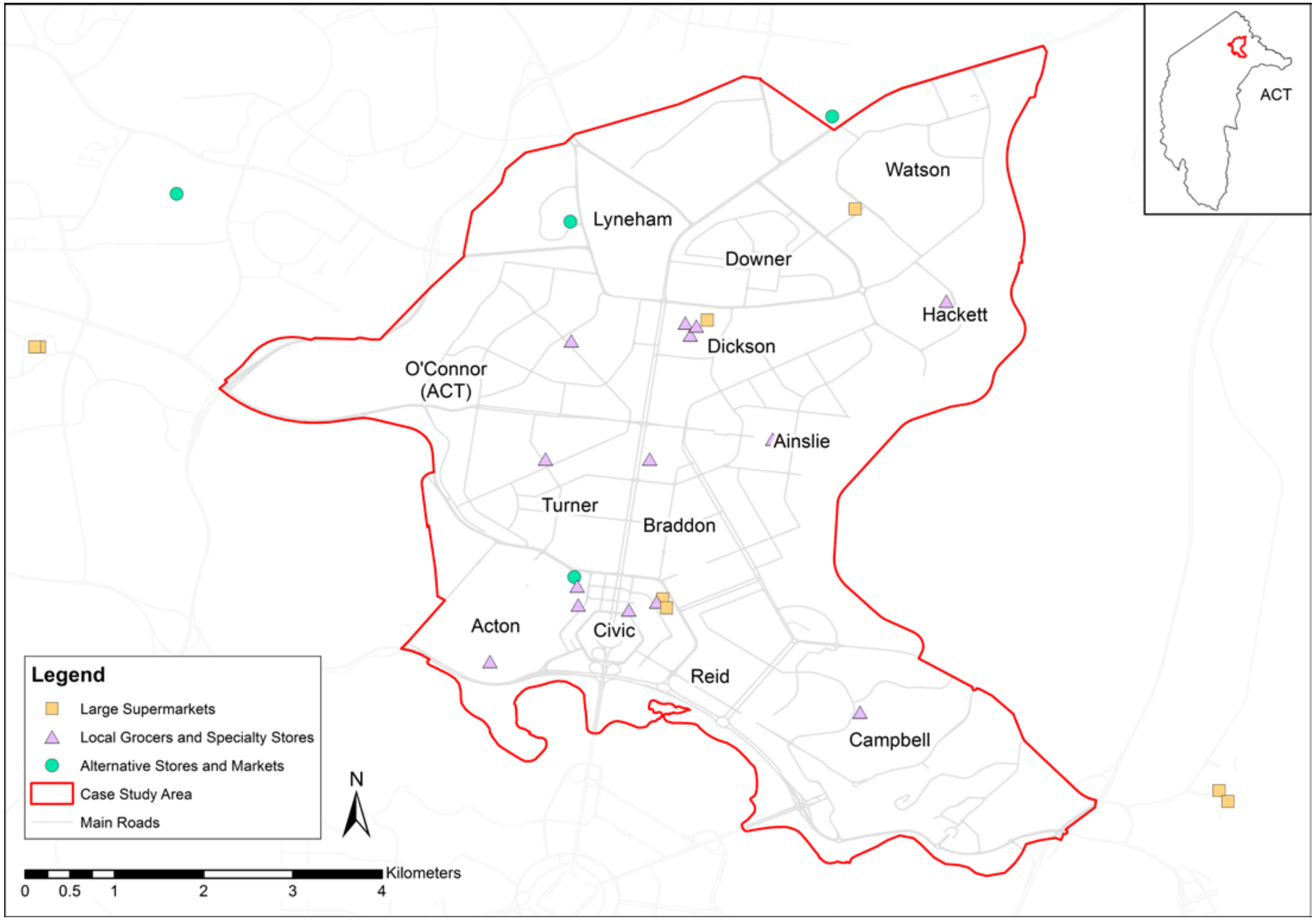



**Figure 6: Locations of major food retailers in North Canberra**

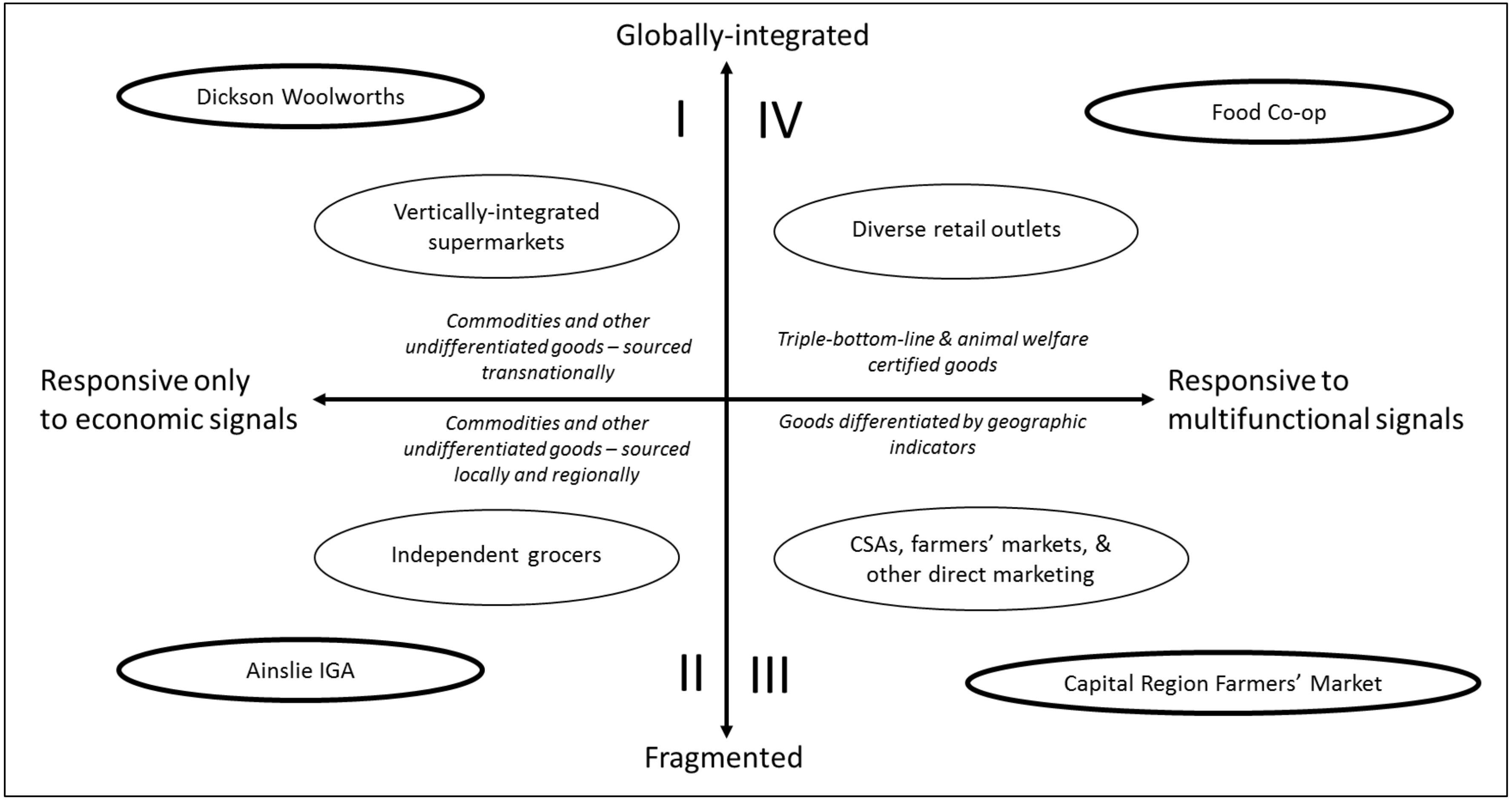



**Figure 7: Four food system domains (Anderson, 2015).** North Canberran retailers are listed as examples in bold text bubbles.

**Table 3: Major food retailers in North Canberra.**

| Major Food Retailers | Location (Suburb) | Type of Retailer | Food System Domain | Description of Business Model | Floor Area ($m^2$) | Business-District Area ($m^2$) | Participation in the AFN? |
|---|---|---|---|---|---|---|---|
| **Dickson Woolworths** | Dickson | Large Supermarket | I | Dominate market - low prices, multi-option shopping, emphasis on brands and marketing | 3055 | 91602 | No |
| **Dickson specialty stores** | Dickson | Small Retailer | II | Speciality goods – up-selling of high valued products and goods unavailable elsewhere | 170 | 91602 | No |
| **Canberra Centre Supabarn** | City East | Large Supermarket | I | Similar model to Woolworths and Coles – but with a wider range of speciality goods | 3700 | 163851 | No |
| **Canberra Centre Aldi** | City East | Large Supermarket | I | Lowest prices – competitive advantage through efficiency and cost control | 50 | 163851 | No |
| **Canberra Centre specialty stores** | City East | Small Retailer | II | Speciality goods – up-selling of high valued products and goods unavailable elsewhere | 176 | 163851 | No |
| **East Row IGA X-Press** | City West | Independent Grocer | II | Speciality goods – emphasis on customer service, convenience and impulse purchases | 401 | 25677 | No |
| **Watson Supabarn Express** | Watson | Independent Grocer | II | Similar model to Woolworths and Coles – but with a wider range of speciality goods | 338 | 338 | No |
| **Hackett IGA** | Hackett | Independent Grocer | II | Speciality goods – emphasis on customer service and community | 887 | 887 | No |
| **Ainslie IGA** | Ainslie | Independent Grocer | II | Speciality goods – emphasis on customer service and community | 1200 | 1200 | No |
| **O'Connor IGA** | O'Connor | Independent Grocer | II | Speciality goods – emphasis on customer service and community | 385 | 385 | No |
| **Lyneham IGA** | Lyneham | Independent Grocer | II | Speciality goods – emphasis on customer service and community | 559 | 559 | No |
| **Campbell IGA** | Campbell | Independent Grocer | II | Speciality goods – emphasis on customer service and community | 280 | 280 | No |
| **Spar, Canberra City** | City West | Independent Grocer | II | Speciality goods – emphasis on customer service, convenience and impulse purchases | 472 | 1698 | No |
| **Choku Bai Jo, North Lyneham** | Lyneham | Small Retailer | IV & III | Alternative products – emphasis on quality and local products, goods differentiated by geographic indicators | 4430 | 4430 | Yes |
| **The Food Co-Op, ANU** | Acton | Small Alternative Retailer | IV | Alternative products – emphasis on quality, local products, and certified goods | 9481 | 9481 | Yes |

Note: Business-district area includes the approximate area of the shopping centre or collection of businesses adjacent to the retailer. If the retailer is not part of shopping centre or a collection of retailers, then this number is the same as the floor area. AFN = Alternative Food Network.

## 3.3 Stage 1: Data Collection

### 3.3.1 Sample Frame

This study sought to gain responses from a representative sample of private households in the study area. This excluded all hotels and motels, hostels, boarding houses, residential colleges and halls, hospitals, nursing homes and retirement villages, corrective and welfare institutions, convents and monasteries, caravan parks, camping grounds, and marinas (ABS, 2011a; ABS, 2011c). The Geocoded National Address File (G-NAF) was used to create the sample frame for the postal survey of this area (PMC, 2016). The G-NAF is a database of geocoded street addresses compiled from 13 government agencies, including Australia Post and the Australian Electoral Commission (Markham *et al.*, 2013). The G-NAF contains longitude and latitude co-ordinate pairs for more than 13 million residential, commercial, and industrial addresses in Australia (PMC, 2016). The G-NAF was recently released as an open dataset by the Department of the Prime Minister and Cabinet under *The National Innovation and Science Agenda* (Turnbull, 2015). The G-NAF is currently the most frequently updated and finest scale of geocoded address data available in Australia (see *Appendix A: Metadata*), and was chosen for use in this study for this reason.

The initial sample frame was created by clipping the G-NAF for the whole of the ACT to Statistical Area Level 3 (SA3) of North Canberra. The sample frame was refined using several measures to avoid posting questionnaires to non-residential addresses. First, residential addresses from this subset were excluded if the Mesh Block in which they were located was not zoned as *residential* (ABS, 2011b). However, one exception to this, a new development in Watson (Mesh Block ID 80042482000 and 80042470000) was manually included in the sample frame, as it was not yet zoned in 2011 when the Mesh Block land use classification took place. Second, the sample frame was checked for duplicates, which were removed. Third, all addresses were individually screened by *building name* to remove unoccupied and public dwellings, including: shops, churches, toilet blocks, nursing homes, hotels, hostels, and student residences. Fourth, all addresses without a unit, street, or flat number were removed. Fifth, addresses classified as 'shop', 'office', or 'suite' in the *flat type* field were removed.

### 3.3.2 Participants

Questionnaires were mailed to 5,000 randomly selected households within the redefined sample frame. This number of participants was selected to ensure the collection of a sample large enough for analysis, and yet, small enough to not exceed financial constraints. Previous research by Markham *et al.* (2013) conducting a similar G-NAF survey (*n* = 7,000) had a response rate of 14.5%, suggesting that this project should conservatively receive at least 500 responses. This was considered a sufficient sample size for statistical analysis. Participants were sent a cover letter, participant information sheet and a reply-paid envelope with the questionnaire (see *Appendix B: Survey Material*). All documents were printed through the Australian National University Printing Service, and mailed to respondents through Australia Post. A unique identifier referencing the respondent's G-NAF was included on the questionnaire to enable the returned questionnaires to be precisely geocoded (Markham *et al.*, 2013). The questionnaire could be returned by post in the provided reply-paid envelope, or completed and returned online using a link to the questions in Google Forms. The cover letter requested that a person over the age of 18 who completes most of the household shopping should complete the enclosed questionnaire. This method was approved by the Human Ethics Officer of the Australian National University (protocol no. 2016/078; see *Appendix C: Ethics Approval*), as per the university's guidelines.

### 3.3.3 Variables

The questionnaire was designed to obtain information on residential location, retailer visitation and expenditure, dietary behaviours, socio-economic status and demographics, and food choice motivations. Residential location was tracked using the G-NAF identifier. Food retail visitation and expenditure was assessed by asking respondents to indicate which major food retailers they had visited in the last 14 days (Question 2), how much income was spent at each retailer (Question 3), and the number of times they had visited each retailer (Question 2). To reduce respondent burden, a list of the major supermarkets, farmers' markets, and large retailers in the AFN close to North Canberra was provided. In addition, an 'Other' box was provided for respondents to write in an unlisted retailer. Dietary behaviours were assessed with one question (Question 13), asking how many standard servings of the vegetables, fruit, and lean meat, the respondent consumes on a daily basis (based on Townsend *et al.*, 2003; Thompson and Subar, 2008: 3).

Socio-economic and demographic characteristics of respondents were elicited with a series of questions, including: length of stay at household (Question 1), number of people in household (Question 4), and number of people regularly shopped for (Question 5). In addition, year of birth

(Question 6), gender identity (Question 7), weekly household income before tax (Question 12), highest level of education (Question 9), usual main occupation (Question 11), main employment status (Question 10), and car access and ownership (Question 8) were elicited through questions based on Caspi *et al.* (2012); ABS (2013); and Dubowitz *et al.* (2015).

Respondent attitudes towards food was obtained using a modified, brief subset of the Food Choice Questionnaire (FCQ) instrument (Question 14). The original FCQ is a set of 36 questions assessing the reported importance of nine general factors that influence food choice (Steptoe *et al.*, 1995; Fotopoulos *et al.*, 2009). These factors include: convenience, price, health, sensory appeal, familiarity, mood, natural content, ethical concern, and weight control (Steptoe *et al.*, 1995). Research by Lindeman and Väänänen (2000) included the inclusion of ecological welfare, political values, and religion as additional factors. For the FCQ respondents rate the importance of each attribute affecting their food choices on a 'typical' day using a 4-point Likert scale (1 = "not at all important" to 4 = "very important"). The FCQ has been used extensively to assess food choice motives across multiple countries and social contexts (see Pollard *et al.*, 1998; Pollard *et al.*, 2002; Lockie *et al.*, 2005; Chen, 2007; Kornelis *et al.*, 2010; Machín *et al.*, 2014; Markovina *et al.*, 2015).

For this study, the FCQ was modified to include 12 questions based on convenience, price, familiarity, ecological welfare, and political and social values (see Table 4). These dimensions of food choice were selected from the original FCQ because they satisfy each dimension of Dagevos' (2005: 35) consumer typology (see Figure 8). Social values were added as an additional factor, as they were considered an important aspect of food choice behaviour in the case study area (Turner and Hope, 2015; Turner *et al.*, 2012). A shortened FCQ instrument was used in order to reduce respondent burden and increase the response rate. It should be noted that the FCQ is not designed to determine consumer behaviour. Instead, it is used to characterise respondent attitudes towards food (for literature on the 'attitude-behaviour gap' see Young *et al.*, 2010; and De Barcellos *et al.*, 2011). The FCQ was considered a more suitable instrument than other longer shopping-based motivational scales (such as Westbrook and Black, 1985).

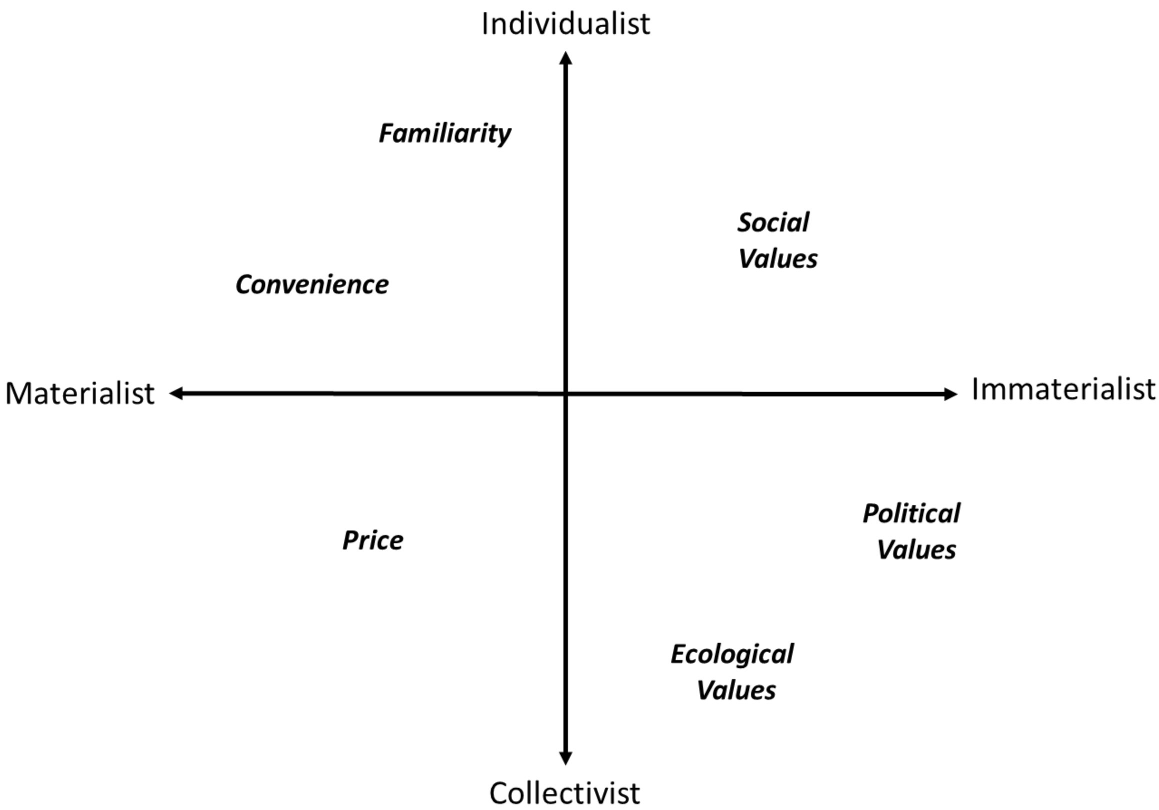



**Figure 8: FCQ motives in relation to Dagevos (2005) consumer typology.** The FCQ motives are seen in bold italicised text, and are taken from Steptoe *et al.* (1995); Lindeman and Väänänen (2000); Fotopoulos *et al.* (2009).

**Table 4: Brief FCQ.** Respondents were asked: "On a daily basis, how many standard servings of the selected food groups do you consume?" with respect to the importance statements listed below (Fotopoulos *et al.*, 2009; Steptoe *et al.*, 1995).

| Question | | "Motive" | "Importance Statement" |
|---|---|---|---|
| Q14 | 1 | Convenience | Easy to prepare |
| | 2 | Price | Not expensive |
| | 3 | Familiarity | Like the food I ate as a child |
| | 4 | Ecological Welfare | Produced in an animal friendly way |
| | 5 | Political Values | Traded in a fair way |
| | 6 | Price | Good value for money |
| | 7 | Social Values | Purchased from a community I want to support |
| | 8 | Ecological Welfare | Produced in an environmentally friendly way |
| | 9 | Familiarity | What I usually eat |
| | 10 | Social Values | Purchased from a store that I enjoy spending time in |
| | 11 | Convenience | Ready to be cooked very quickly |
| | 12 | Political Values | Comes from a country I approve of politically |

Raw data collected from the questionnaire was entered into *Microsoft Excel* (2013) using the unique G-NAF as an identifier, and coded for statistical analysis. Any responses written as a range were entered at the middle of the range. Non-numerical answers from Question 2 (such as crosses in the number boxes) were counted as a '1'. Box deliveries and home-grown food sources were not counted as appropriate answers to Question 2. An independent coder was appointed to code a portion of the questionnaires, and was given clear guidelines for each question (see *Appendix D: Coding Guidelines*). The independent coder was used to minimise the chance of errors and improve the reliability of the data. The demographics and food choice motivations of each respondent were then tabulated.

### 3.3.4 Major Food Retailers

In order to assess respondents' access of food retailers, data regarding major food retailers in and around the study was collected. Retailers were considered in scope if they were located in the geographic sub-region of North Canberra (SA3 80105), and if they were a supermarket, grocery store, or a large specialised food retailer. Convenience stores, petrol stations, liquor retailers, cafes, restaurants, takeaway food services, community gardens, and home-grown foods were not included in scope (ABS, 2010). For each in scope food retailer, the following data were collected: geographic co-ordinates (latitude and longitude), floor area ($m^2$), business-district floor area ($m^2$; this includes the approximate area of the shopping centre or collection of businesses adjacent to the retailer), and participation in the AFN. Geographic coordinates were collected from Google Maps through a search of the retailer's name (see *Appendix E: Manually Geocoded Food Retailers)*. Retailer floor area was collected from Martin (2009). Business-district (shopping centre) floor area, and the floor area of newer retailers not featured in Martin (2009), were manually estimated using the measure tool in *ArcMap* (10.4.1). Retailers were considered to participate in the AFN if they sold primarily organic or local foods (Som Castellano, 2016).

## *3.4 Stage 2: Analysis*

### 3.4.1 Subgroup Identification

A hybrid factor-cluster analysis was conducted to identify consumer subgroups in the sample. This was run in the *R* statistical environment (version 3.2.4; R Core Team, 2016) and its associated graphical user interface *RStudio* (version 0.99.892). A fully reproducible script of commands and packages used is included in *Appendix F: R Commands* and *Appendix G: Installed R Packages*.

In this two-phase approach, questions regarding a large number of characteristics are first summarised into a small number of empirically defined factors. A factor describes a construct using a single variable, even though several questions might be used to elicit information about that construct. For example, in this study the socio-economic status construct was assessed by asking questions about unemployment, household income, occupation, education, and car ownership and accessibility. Each respondent is then assigned a factor score for every factor identified in the data. In the second phase, a cluster analysis is run on the basis of the factor scores to identify relatively homogenous groups of respondents. Each cluster was named, and descriptive statistics were compiled to characterise the respondents allocated to each cluster.

This method was used to empirically define clusters of respondents on the basis of their socio-economic status and food choice motivations. Alternative methods for defining clusters include the use of pre-defined typologies or taxonomies (for examples see Geuens *et al.*, 2001; Findlay and Sparks, 2002; Tregear, 2007). In addition, it is possible to define factors and subgroups using other statistical methods (Bower, 2013); however, a hybrid factor-cluster analysis was used because it is a widely accepted method to group observed data on consumers into meaningful structures (Vichi and Kiers, 2001; Dolnicar and Grün, 2008).

While a cluster analysis could be run on the basis of all the input variables without first running a factor analysis, a 'raw' cluster analysis has two shortcomings. First, it may be biased in the presence of multicollinearity. Multicollinearity involves the presence high correlations among independent variables (Hair *et al.*, 2006:456). In a cluster analysis, multicollinearity effectively weights the analysis to pay more attention to those constructs about which the most questions have been asked. Second, the resulting clusters may be easier to interpret as a smaller number of independent variables are directly assessed in the cluster solution.

It should be noted that a hybrid factor-cluster analysis has been criticised on the basis that data is discarded at the factor analysis stage which could be useful when delineating clusters (De Sarbo *et al.*, 1991; Arabie and Hubert, 1994; De Soete and Carroll, 1994; Vichi and Kiers, 2001; Dolnicar and Grün, 2008). However, statistical methods for overcoming this shortcoming are still relatively experimental. Two of these methods, 'factorial k-means' and 'reduced k-means' were tested to produce preliminary analyses using the *clustrd* package in R (De Soete and Carroll, 1994; Vichi and Kiers, 2001; Markos *et al.*, 2013). As neither of these methods produced clusters solutions that were satisfactory in terms of being interpretable or homogenous, the classic hybrid factor-cluster approach was preferred.

### 3.4.2 Factor Analysis

An ‘R-type’ exploratory factor analysis was run using the protocol outlined by Hair *et al.* (2006). This protocol is outlined in Figure 9. An exploratory factor analysis was chosen as there were no strong *a priori* consensus regarding how the underlying social variables should be reduced into factors for the cluster analysis. The following 17 variables were entered into the factor analysis: car ownership and accessibility, household equivalised income, unemployment, occupation, education; and the 12 FCQ motivations, which included two variables on the importance of each food choice motivation: convenience, price, familiarity, ecological welfare, and social and political values. Non-numeric socio-economic variables were converted into ‘dummy variables’ (Hair *et al.*, 2006: 100). The sample size and total number of variables for the factor analysis were checked against the guidelines given by Hair *et al.* (2006: 99). To assess intercorrelation the data were visually inspected, and tested with Bartlett’s test of sphericity and the measure of sampling adequacy (MSA). Responses containing missing data for the factor analysis input variables were removed from the dataset.

Separate factor analyses were conducted for the FCQ and socio-economic status variables using the *fa* function in the *psych* package (Revelle, 2014). Factor solutions were calculated using Ordinary Least Squares (OLS) to find the minimum residual solution. The function repeated the analysis 5,000 times on a bootstrapped sample, and used this to rotate the axes and transform the original solution using the ‘oblimin’ oblique rotational method from the *GPArotation* package (Bernaards and Jennrich, 2005; Revelle, 2014). An oblique rotation was selected as it was desired that factors could be correlated (Everitt and Hothorn, 2011: 146). To determine the number of factors to extract a ‘Scree’ test and parallel analysis were performed (Hoyle and Duvall, 2004). Then the percentage of variance criterion and Eigen values (latent root criteria) was calculated and interpreted (Yong and Pearce, 2013:85). A correlation-preserving rotated factor-loading matrix was produced, and the variables with significant loadings (>0.5), and loadings meeting the minimal level for interpretation of structure (>0.3) were interpreted to label the identified factors (as described in Hair *et al.*, 2006: 118).

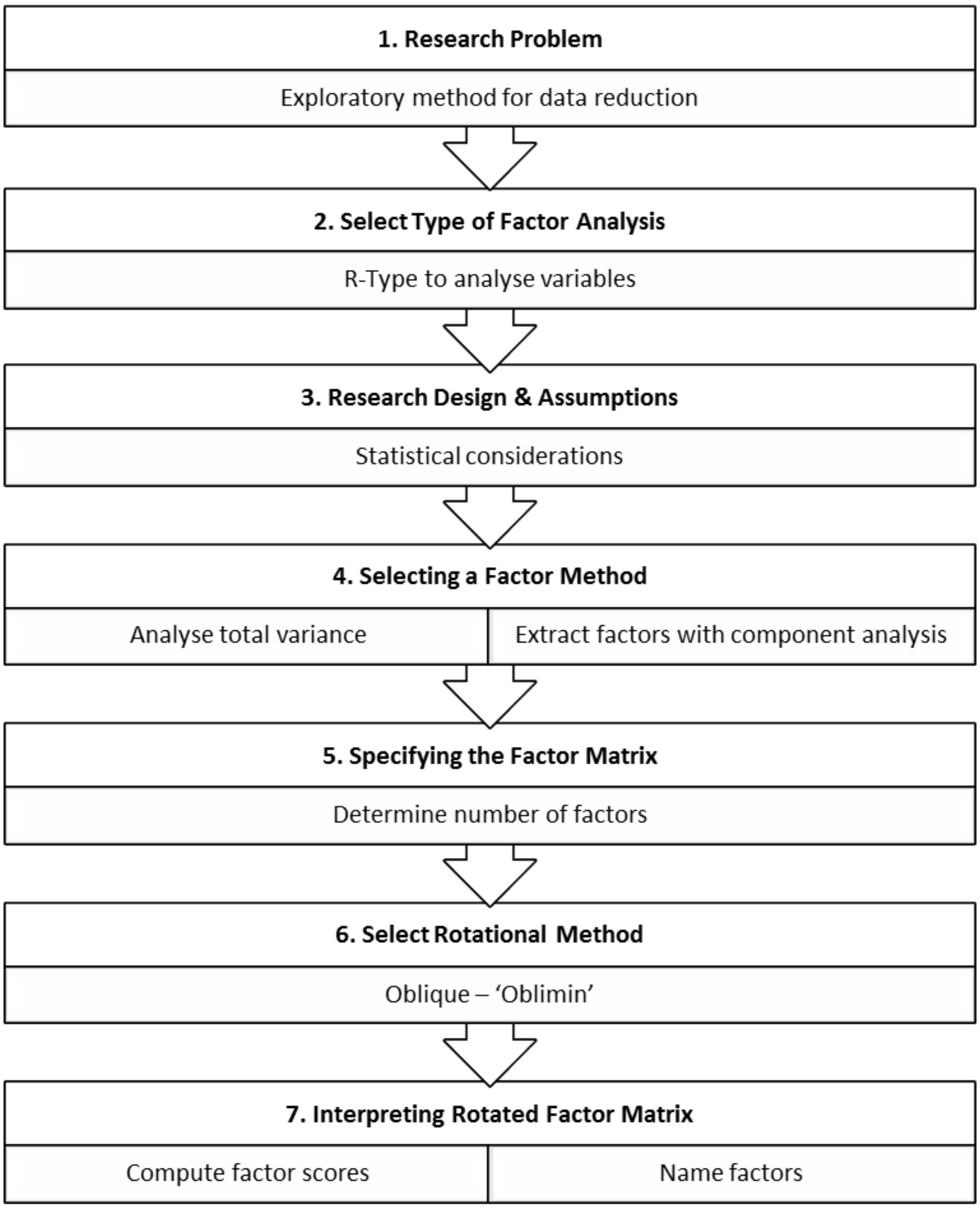



**Figure 9: Schematic representation of the factor analysis process (as described in Hair *et al.*, 2006).**

### 3.4.3 Cluster Analysis

A cluster analysis was also run using the protocol outlined by Hair *et al.* (2006). See Figure 10 for a schematic representation. Following recommendations by Hair *et al.,* an initial hierarchical cluster analysis was conducted to identify the optimal number of clusters and the location of the cluster centres. During the hierarchical analysis, a number of clustering methods were explored using the package *nbclust* (Charrad *et al.*, 2014). These methods included: 'Ward's method', 'complete linkage' and 'single linkage'. The result of each method was plotted using Euclidean distance measures (Duran and Odell, 1974: 19; Späth, 1982; Hair *et al.*, 2006: 441), and scatterplots and silhouette plots to identify the most plausible cluster solutions. Complete linkage allowed for the most compact, variably sized clusters, and was consequently used to select the optimal number of clusters using an ensemble of 30 indices (for a list of the indices see: Charrad *et al.*, 2012; Charrad *et al.*, 2014). The number of clusters was identified by the majority of methods, using the *factoextra* package (Kassambara, 2015).

Once the optimal hierarchical cluster solution was identified, the analysis was re-run using 'k-means'. K-means has been found to produce better delineated clusters, even though it is more difficult to identify the correct number of clusters and the location of initial cluster centres (Hair *et al.*, 2006; Timmerman *et al.*, 2010). This method iteratively partitions the data into the specified number of clusters, from the cluster centers, until convergence to the optimum is complete (Anderberg, 1973; Aldenderfer and Blashfield, 1984; Carlson *et al.*, 2002; Tan, 2006:497). The number of clusters identified by the hierarchical cluster analysis and the cluster centres were used as the basis for the k-means clustering. Silhouette plots and dendrograms were used to confirm that the k-means cluster solution improved upon the hierarchical cluster solution (Romesburg, 1984: 21; Rousseeuw, 1987).

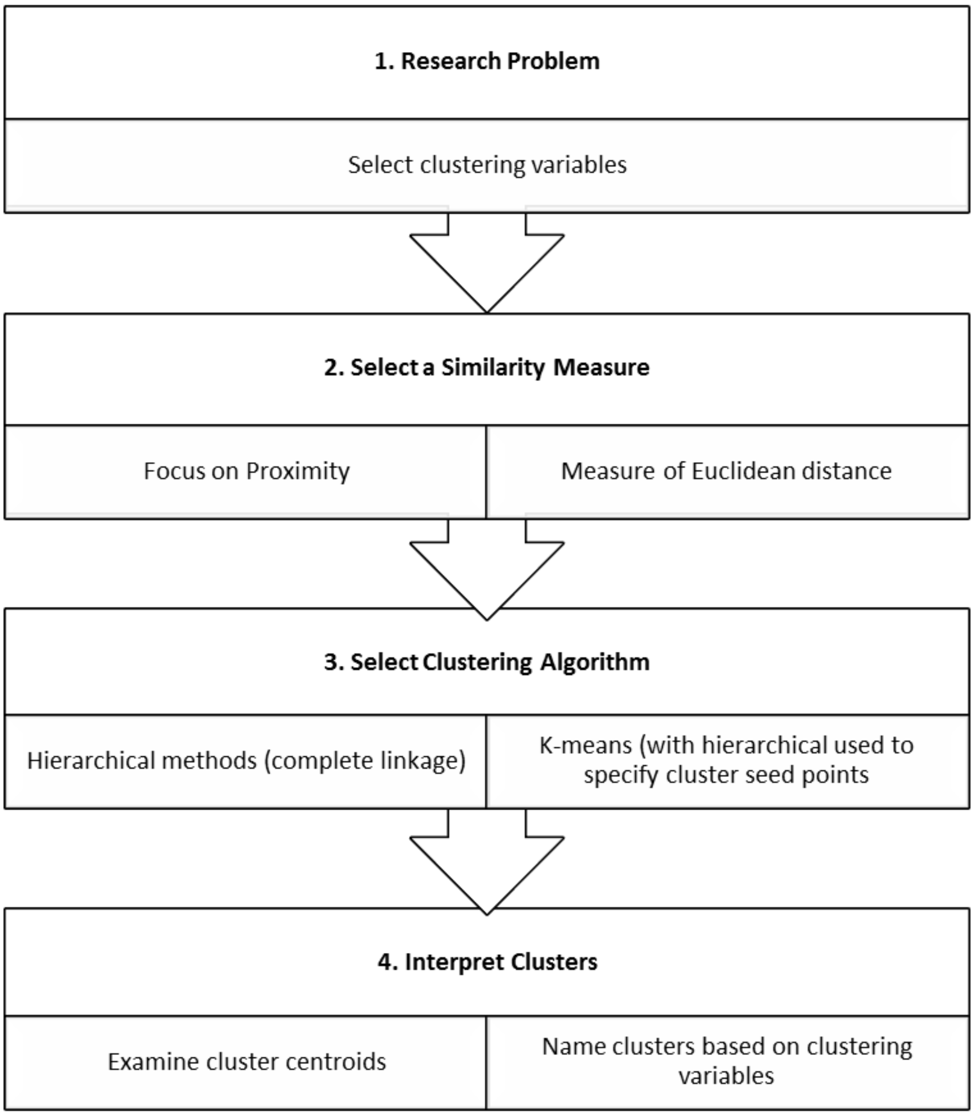



**Figure 10: Schematic representation of the clustering analysis process (as described in Hair *et al.*, 2006).**

### 3.4.4 Spatial Interaction Modelling

A calibrated disaggregated SIM was used to model the patterns of visitation of food retailers in North Canberra for each of the consumer subgroups identified using the factor-cluster analysis. The calibrated SIM results for the whole dataset, and each cluster, were visualised as probability surfaces and exported as spatial catchments for further interpretation. A fully reproducible script of this method is included in *Appendix H: Python Script*. A Huff Model was chosen based on the assumption that all origin points (households) interact with at least one retailer (Huff, 1963; 2003). This model is a well-established method in the literature (Wang, 2006; Greene and Pick, 2012), that accounts for the premise of 'choice behaviour', and competition between retailers. This model assumes that as distance increases and respondents get *further* away from the major food retailer, *less* individuals are attracted to that retailer. For this study, the SIM (taken from Markham *et al.*, 2013; and schematically represented in Figure 11) takes the form:

$$P_{ij} = k \cdot o_j^{\gamma} \frac{\left(\Pi_l \alpha_{il}^{\alpha_l}\right) \cdot f\left(d_{ij}, \beta\right)}{\Sigma_i \left[\left(\Pi_l \alpha_{il}^{\alpha_l}\right) \cdot f\left(d_{ij}, \beta\right)\right]}$$

Where:

$P_{ij}$ is the probability of respondents at origin *j* (household) interacting with destination *i* (retailer);

$o_j$ is the population of the household *j*;

$\alpha_{il}$ is the *l*th variable describing the attractiveness of retailer *i*;

*f* is a negative power function of the distance between household *j* and retailer *i*; and

*k*, $\gamma$ , $\alpha_l$ and β are parameters (to be empirically estimated).

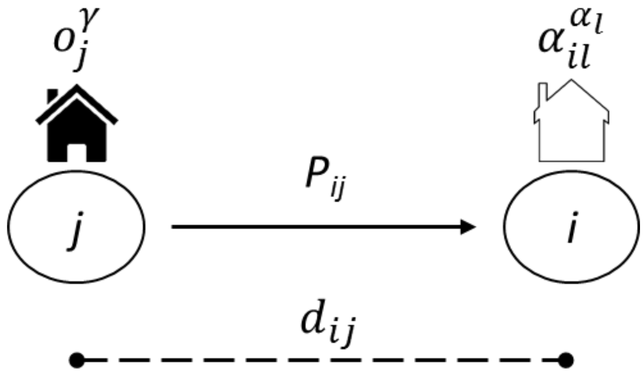
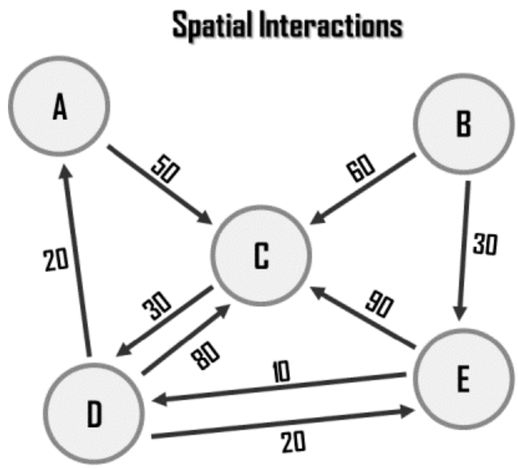



**Figure 11: Schematic representation of the calibrated Spatial Interaction Model (based on Rodrigue, 2016).**

Before the SIM was calibrated, distance calculations were determined, empirical data was spatially aggregated for calibration, and model parameters were estimated. First, responses were aggregated by consumer subgroup and Statistical Area Level 1 (SA1) spatial zones. Second, an origin-distance matrix was created that measured the estimated travel time between each respondent-weighted SA1 centroid and each major food retailer (see Figure 12; and see *Appendix I: Technical Log*). A road network dataset was obtained from OpenStreetMap (2015). Each level in the network hierarchy was assigned a driving speed using ArcCatalog (10.4.1; Esri, 2016b). Network distance was measured, with proximity modelled by travel time (Adams *et al.*, 2010: 60; Charreire *et al.*, 2010: 1782). Next, retailer attractiveness variables were used calculate retailer attractiveness and distance friction coefficients for each cluster and the whole dataset in R (see *Appendix F: R Commands*). These variables included: retailer floor area ($m^2$), and business district (shopping centre) floor area ($m^2$), and participation in the local AFN. No 'propulsiveness' variables were included, except for the number of respondents. Then, the number of visits to each food retailer reported by survey respondents were summed to produce a total for each SA1 and each customer subgroup. These subgroup specific SA1–food retailer visitation matrices were used as the outcome variables against which SIM calibration took place.




**O/D Matrix**

| | A | B | C | D | E | Ti |
|---|---|---|---|---|---|---|
| A | 0 | 0 | 50 | 0 | 0 | 50 |
| B | 0 | 0 | 60 | 0 | 30 | 90 |
| C | 0 | 0 | 0 | 30 | 0 | 30 |
| D | 20 | 0 | 80 | 0 | 20 | 120 |
| E | 0 | 0 | 90 | 10 | 0 | 100 |
| Tj | 20 | 0 | 280 | 40 | 50 | **390** |

**Figure 12: Schematic representation of an Origin-Distance Matrix (Rodrigue, 2016).** Values of zero represent one-way streets.

The aim of SIM calibration is to identify the combination of $k$, $\gamma$ , $\alpha_i$ and β parameter values that best predict the observed visitation patterns reported by respondents using the model described above. Parameter estimation was undertaken separately for each consumer subgroup, using maximum likelihood methods. A maximised log-likelihood equation (adapted from Markham *et al.*, 2013; and Fotheringham and O'Kelly, 1989) was used to compute confidence intervals for estimated parameters. Values for $R^2$, the standardised root mean square error (SRMSE), and the relative number of wrong predictions (RNWP) were used to calculate goodness of fit (Markham *et al.*, 2013). R code used for calibration is listed in *Appendix F: R Commands*.

## 3.5 Summary

This thesis utilises a two-part approach to investigate the spatial influence of consumer attitudes in the study area. This approach involved a survey of households through a questionnaire, a hybrid factor-cluster analysis to determine consumer subgroups, and a spatial analysis of accessibility, with an integration of real-world behaviours output to each consumer subgroup using a calibrated disaggregated SIM. Primary data was gathered through 5,000 questionnaires posted to randomly selected households in North Canberra, and was then used to statistically determine consumer subgroups, and calibrate a spatial interaction model, disaggregated by each consumer subgroup identified. The next chapter will present the outcomes of the methods listed above.

# Chapter 4: Results

This chapter presents results from the questionnaire, the hybrid factor-cluster analysis, and the calibrated disaggregated SIM. First, the response rate, and sample characteristics are presented. Then, the factor and cluster solutions are described and consumer subgroups are identified. Lastly, the results of the spatial analysis are shown through the SIM configurations, overall patterns of visitation, and visitation patterns disaggregated by consumer subgroups.

## *4.1 Sample Characteristics*

The questionnaire response rate, demographic characteristics, and consumption behaviours of respondents were fairly representative of the general sample, according to ABS Census 2011 data. The questionnaire response rate (as seen in Table 5) was higher than anticipated, at around 18%, with 864 responses collected in the period of data collection (see also *Appendix J: Response Rate*). At least 10% of responses collected contained incomplete data, which were removed from the sample for the cluster analysis. A 100% geocoding match rate was achieved, as all addresses in the sample frame were already geocoded.

**Table 5: Questionnaire response rate.**

| | ***n*** | **%** |
|---|---|---|
| **Mailed** | 5,000 | |
| **Returned to Sender (RTS)** | 407 | 8.1 |
| **Returned Mail** | 823 | 95.3 |
| **Returned Online** | 41 | 4.8 |
| **Total returned** | 864 | |
| **Lower-bound response rate (includes RTS)** | | 17.3 |
| **Upper-bound response rate (excludes RTS)** | | 18.8 |

### 4.1.1 Demographic Characteristics

Sociodemographic results from the questionnaire are shown in Table 6, and compared to actual population statistics obtained from the ABS Census 2011 (see *Appendix J: Response Rate*). There was a higher female than male response to the questionnaire, with 64.3% of the total sample female (*n* = 556), 33.9% male (*n* = 293), 0.1% identifying as ‘other’ (*n* = 1), and 1.6% not answering the question (*n* = 14). Previous research shows that women do more shopping than men (Roberts and Wortzel, 1979; DeVault, 1994; Cockburn-Wootten *et al.*, 2008); but, because the cover letter invited the person who does the most shopping in the household to respond, it is unclear if this gendered response results from males being less frequent grocery shoppers, or from a non-response bias.

In addition, the mean and median age (53), average weekly household income ($1,250 - $1,999), and modal level of education (university degree) were higher than the population average across the study area (see Table 6). Car ownership and household characteristics were close to their census counterparts, with larger families and newer residents slightly underrepresented. There was also an underrepresentation of labourers, machinery operators, and technicians and trade workers by over 6% compared to the population average. Unemployed, retired and self-employed individuals were overrepresented in the sample, while students were underrepresented. This bias is hypothesised to be potentially due to the removal of buildings not considered households in the sample frame, such as student residences.

Lastly, the average standard serving of vegetables consumed on a daily basis by respondents (mean = 3) was below recommended Australian Dietary Guidelines (5 - 6 servings). However, servings of fruit (mean = 2) and lean meat (mean = 1) met these guidelines. This indicates that, on average, households in the sample are not consuming the most healthy diet.

**Table 6: Respondent demographics compared to the general population in the study area.**

| Questionnaire Question | | *n** | Respondents (%) | Census 2011 - North Canberra** | % |
|---|---|---|---|---|---|
| **1** | **Household residence time (in months)** | | | | |
| | 0 – 11 | 75 | 8.7 | *12,182* | *35.8* |
| | 12 – 47 | 211 | 24.4 | *8,023* | *23.5* |
| | 48+ | 514 | 59.4 | *13,863* | *40.7* |
| **5** | **Number of people in household** | | | | |
| | ***Adults*** | | | | |
| | 1 | 242 | 28.0 | *5,661* | *28.2* |
| | 2 | 501 | 57.9 | *6,637* | *33.0* |
| | 3 | 86 | 9.9 | *2,996* | *14.9* |
| | 4 | 23 | 2.7 | *2,210* | *11.0* |
| | 5+ | 7 | 0.8 | *1,066* | *5.3* |
| | Missing data | 6 | 0.7 | *1,526* | *7.6* |
| | ***Children*** | | | | |
| | 0 | 667 | 77.1 | *15,049* | *74.9* |
| | 1 | 71 | 8.2 | *2,389* | *11.9* |
| | 2 | 98 | 11.3 | *1,926* | *9.6* |
| | 3 | 20 | 2.3 | *603* | *3.0* |
| | 4 | 1 | 0.1 | *100* | *0.5* |
| | 5+ | 1 | 0.1 | *29* | *0.1* |
| | Missing data | 7 | 0.8 | - | - |
| **6** | **Age** | | | | |
| | 18 - 29 | 71 | 8.2 | *10,368* | *30.4* |
| | 30 - 39 | 142 | 16.4 | *6,949* | *20.4* |
| | 40 - 49 | 139 | 16.1 | *5,503* | *16.2* |
| | 50 - 59 | 162 | 18.7 | *4,740* | *13.9* |
| | 60 + | 323 | 37.3 | *6,510* | *19.1* |
| | Missing data | 17 | 2.0 | - | - |
| **7** | **Gender** | | | | |
| | Female | 556 | 64.3 | *17,346* | *50.9* |
| | Male | 293 | 33.9 | *16,722* | *49.1* |
| | Other | 1 | 0.1 | - | - |
| | Missing data | 14 | 1.6 | - | - |
| **8** | **Car Ownership & Access** | | | | |
| | Yes | 750 | 86.7 | *15,132* | *79.1* |
| | No | 52 | 6.0 | *2,529* | *13.2* |
| | No Ownership, but Access | 57 | 6.6 | - | - |
| | Missing data | 5 | 0.6 | *1,480* | *7.7* |
| **9** | **Education** | | | | |
| | Primary | 8 | 0.9 | *787* | *2.3* |
| | Secondary | 86 | 9.9 | *8,406* | *24.7* |
| | Technical | 76 | 8.8 | *5,186* | *15.2* |
| | University | 688 | 79.5 | *17,275* | *50.7* |
| | Missing data | 6 | 0.7 | *2,414* | *7.1* |
| **10** | **Employment** | | | | |
| | Full-time | 347 | 40.1 | *12,425* | *36.5* |
| | Retired | 275 | 31.8 | *6,622* | *19.4* |
| | Part-time | 121 | 14.0 | *3,094* | *9.1* |
| | Self Employed | 56 | 6.5 | *1,837* | *5.4* |
| | Unemployed | 23 | 2.7 | *515* | *1.5* |
| | Student | 22 | 2.5 | *6,347* | *18.6* |
| | Other | 20 | 2.3 | *3,228* | *9.5* |
| **11** | **Occupation** | | | | |
| | Managers | 80 | 9.2 | *3,873* | *11.4* |
| | Professionals | 238 | 27.5 | *9,417* | *27.6* |

| | | | | | |
|---|---|---|---|---|---|
| | Technicians and Trade Workers | 9 | 1.0 | *1,538* | *4.5* |
| | Community and Personal Service Workers | 20 | 2.3 | *1,700* | *5.0* |
| | Clerical and Administrative Workers | 169 | 19.5 | *3,724* | *10.9* |
| | Sales Workers | 10 | 1.2 | *986* | *2.9* |
| | Machinery Operators and Drivers | 2 | 0.2 | *250* | *0.7* |
| | Labourers | 1 | 0.1 | *791* | *2.3* |
| | Not in labour force (retired/students) | 306 | 35.4 | *11,789* | *34.6* |
| | Missing data | 30 | 3.5 | - | - |
| **12** | **Household Income** | | | | |
| | <$199 | 8 | 0.9 | *535* | *2.8* |
| | $200 - 399 | 30 | 3.5 | *1,860* | *9.7* |
| | $400 - 799 | 88 | 10.2 | *2,663* | *13.9* |
| | $800 - $1,249 | 145 | 16.8 | *2,887* | *15.1* |
| | $1,250 - $1,999 | 218 | 25.2 | *4,660* | *24.3* |
| | > $2,000 | 330 | 38.2 | *3,209* | *16.8* |
| | Missing data | 45 | 5.2 | *3,327* | *17.4* |

Notes:
* *n* = number of respondents. Calculated with all (864) responses, before incomplete questionnaires were removed
** Calculated in TableBuilder Pro ABS 2011 Census, see *Appendix K: 2011 Census Variables* for the specific cross-tabulations used to extract census counts. As some questions are about households and others are about individuals, the totals of the counts listed in this column varies between variables.

### 4.1.2 Consumer Behaviour

The questionnaire measured visitation and expenditure of respondents at major food retailers in North Canberra and the surrounding region. A summary of consumer behaviours for all respondents is summarised in Table 7 (exact figures can be found in *Appendix L: Respondent Visitation and Expenditure*). A graphical representation of visitation and expenditure at each retailer is shown in Figure 13. There was a fair amount of diversity among retailers, both in terms of frequency of visitation, the number of visits per respondent and the amount at the retailer. Unsurprisingly, one of the largest retailers, Costco, had the largest average amount spent per respondent, for all the respondents that visited the retailer. However, the total number of visits in a fortnight to Costco was low; which indicates that even though Costco is not the most frequented retailer, most respondents who visit Costco spend a large amount in one visit. In comparison, Dickson Woolworths, had the highest number of respondents visit, with most visiting at least twice in the fortnight. It also had the second largest amount spent on average per respondent overall. This indicates that respondents who visit this retailer frequent the retailer more often and spend less than if they were visiting Costco. However, retailers outside of the study area were visited less often than retailers inside of the study area due to their greater distance from consumer households. Ainslie IGA received the highest number of all visits, but had a lower number of respondents visit overall. This implies that respondents who visited the independent store, visited multiple times in the fortnight.

**Table 7: Summary of average consumption behaviours per respondent in a fortnight (calculated using all respondents).**

| | μ | σ | TOTAL |
|---|---|---|---|
| **Number of visits to all retailers** | 246 | 298 | 8,372 |
| **Number of retailers visited per respondent** | 7 | 9 | 33 |
| **Amount spent at each retailer visited** | $82.40 | $39.94 | $319,043.12 |

Note: μ = Mean. σ = Standard deviation. $ = Australian Dollars (AUD).

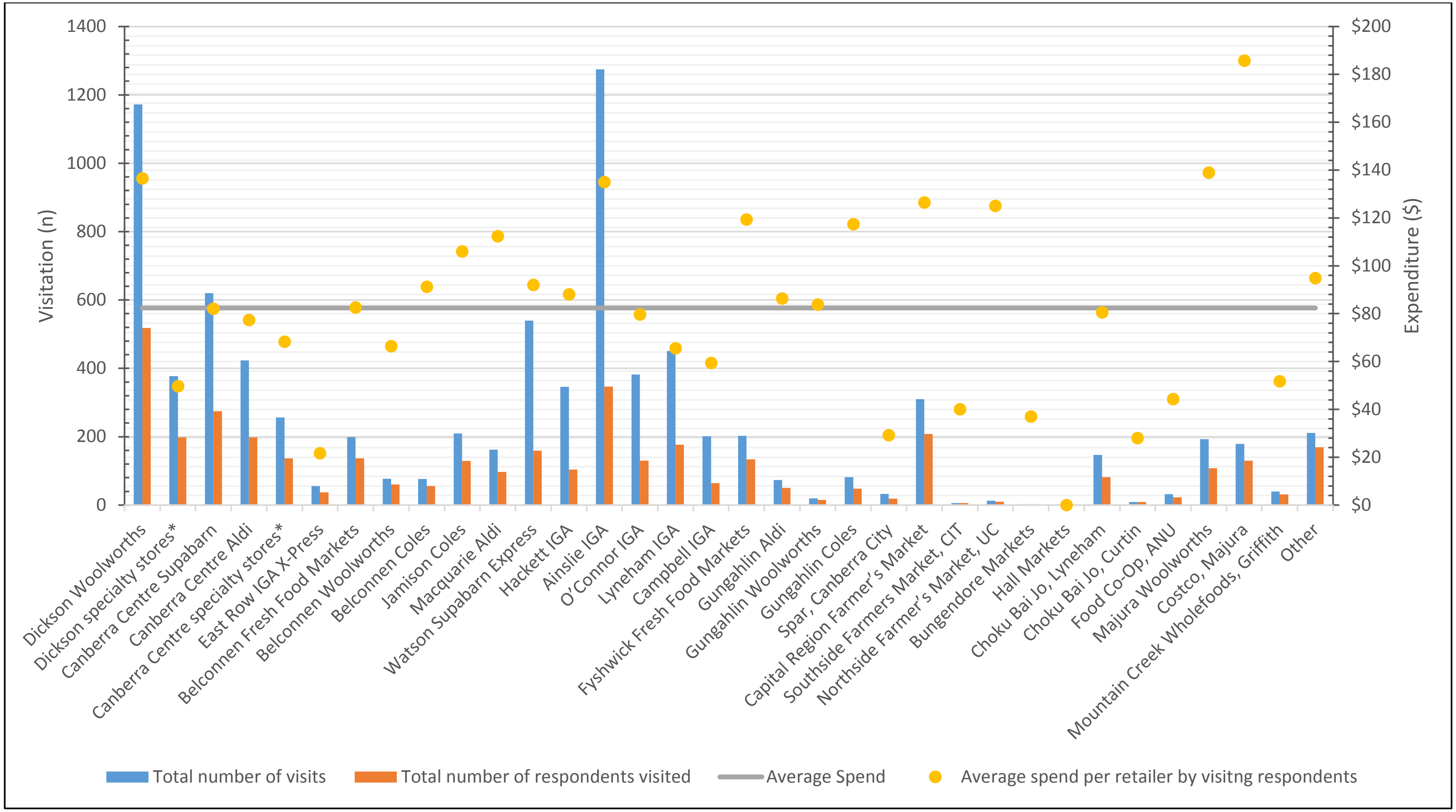



**Figure 13: Fortnightly visitation and expenditure for each major food retailer in North Canberra and surrounding region.**

## 4.2 Factor and Cluster Solutions

### 4.2.1 Exploratory Factors

Four factors were identified through the two exploratory factor analyses, performed on 17 variables in the whole sample (*n* = 864). Each factor was named as follows:

*Factor 1:* *Care* – based on the high importance of the following social, political, and ecological food choice motivations: $V_4$ Produced in an animal friendly way, $V_5$ Traded in a fair way, $V_7$ Purchased from a community I want to support, $V_8$ Produced in an environmentally friendly way.

*Factor 2:* *Convenience* – based on the high importance of the following convenient food choice motivations: $V_1$ Easy to prepare, $V_{11}$ Ready to be cooked very quickly.

*Factor 3:* *Cost* – based on the high importance of economic food choice motivations: $V_2$ Not expensive, $V_6$ Good value for money.

*Factor 4:* *SES* – based on $V_{14}$ Education, $V_{15}$ Household Equivalised Income.

The variables were selected from all FCQ questions (see *Appendix M: Food Choice Motivations*) and all SES variables (see 3.4.2 Factor Analysis). Conceptual and statistical assumptions of the factor analysis were tested, and all measures of intercorrelation were found to be within an acceptable range (see *Appendix N: Additional Factor Results*; Hair et al., 2006). Three factors were considered sufficient to extract from the FCQ variables, and one factor was considered sufficient to extract from the SES variables. This was determined by taking the majority of the outcomes from the Scree plot test, Eigen values, parallel analysis, optimal coordinates, and acceleration factor. Further information on the goodness of fit of the factor solutions is presented in Appendix N. Factors were transformed to an oblique solution using the 'oblimin' function (Bernaards and Jennrich, 2005). Out of the four identified factors in the data, factor 1 accounted for most of the variance. For the final rotated factor loadings see Table 8 and Table 9.

**Table 8: Rotated factor loadings for the FCQ variables.** Factors were transformed to an oblique solution using the oblimin function from the *GPArotation* package (Bernaards and Jennrich, 2005; Revelle, 2014). Significant factor loadings (±0.5) are highlighted in bold text.

| | | ***Care*** 1 | ***Convenience*** 2 | ***Cost*** 3 |
|---|---|---|---|---|
| **Variables** | $V_1$ Q14_EASY | -0.01 | **0.57** | 0.14 |
| | $V_2$ Q14_EXPE | -0.03 | 0.01 | **0.87** |
| | $V_3$ Q14_CHILD | 0 | 0.10 | 0.16 |
| | $V_4$ Q14_ANIMAL | **0.80** | 0.04 | 0.01 |
| | $V_5$ Q14_FAIR | **0.85** | 0.02 | 0.02 |
| | $V_6$ Q14_VALUE | 0.13 | -0.04 | **0.53** |
| | $V_7$ Q14_COMM | **0.67** | -0.02 | -0.05 |
| | $V_8$ Q14_ENV | **0.86** | -0.06 | 0.02 |
| | $V_9$ Q14_USUAL | 0.04 | 0.26 | 0.06 |
| | $V_{10}$ Q14_ENJOY | 0.19 | 0.11 | -0.08 |
| | $V_{11}$ Q14_QUICK | 0.00 | **0.87** | -0.03 |
| | $V_{12}$ Q14_POLIT | **0.50** | 0.04 | -0.07 |
| **Variance** | **Sums of Squared Loadings** | 2.85 | 1.2 | 1.12 |
| | **Proportion Variance** | 0.24 | 0.1 | 0.09 |
| | **Cumulative Variance** | 0.24 | 0.34 | 0.43 |
| | **Proportion Explained** | 0.55 | 0.23 | 0.22 |
| | **Cumulative Portion** | 0.55 | 0.78 | 1 |

**Table 9: Rotated factor loadings for the SES variables.** Factors were transformed to an oblique solution using the oblimin function from the *GPArotation* package (Bernaards and Jennrich, 2005; Revelle, 2014). Factor loadings considered to meet the minimal level for interpretation of structure (±0.30) are highlighted in bold text.

| | | ***SES*** 4 |
|---|---|---|
| **Variables** | $V_{13}$ Q11_BLUE_COLLAR | -0.24 |
| | $V_{14}$ Q9_EDU_U_DUMMY | **0.42** |
| | $V_{15}$ Q12_HH_EQU_INC | **0.46** |
| | $V_{16}$ Q10_UNEMPL_DUMMY | -0.06 |
| | $V_{17}$ Q8_NOCAR_DUMMY | -0.17 |
| **Variance** | **Sums of Squared Loadings** | 0.48 |
| | **Proportion Variance** | 0.1 |

### 4.2.2 Clusters Solutions for Consumer Subgroups

The initial complete-linkage hierarchical cluster analysis identified five clusters in the dataset. Five branches were identified through a visual inspection of the associated dendrogram. Although two clusters may also have been a plausible solution, five clusters were identified as the optimal number according to the majority of indices tested (as seen in Figure 14). Clusters were named as consumer subgroups with the following titles: 'Concerned' (A), 'Expedient' (B), 'Dispassionate' (C), 'Calculating' (D), and 'Frugal' (E). Applying the k-means after conducting the hierarchical analysis resulted in an improved fit of the data to these five clusters (see Figure 15 and Figure 16). Figure 15 shows the reallocation of individual respondents between clusters when the k-means re-analysis was run. Figure 16 shows the silhouette indices for both cluster solutions, where negative scores indicate poor clustering. It is clear that fewer respondents receive a negative silhouette index score in the k-means cluster solution, compared to the hierarchical cluster solution.

Significant differences exist between all variables (see Table 10), indicating that the k-means clustering solution discriminates well between the five clusters (for further statistical details refer to *Appendix O: Additional Cluster Results)*. The clusters were named through the visual analysis of the clusters in two-dimensions (see Table 11 and Figure 17), and interpreted using the highest factor score for each cluster.

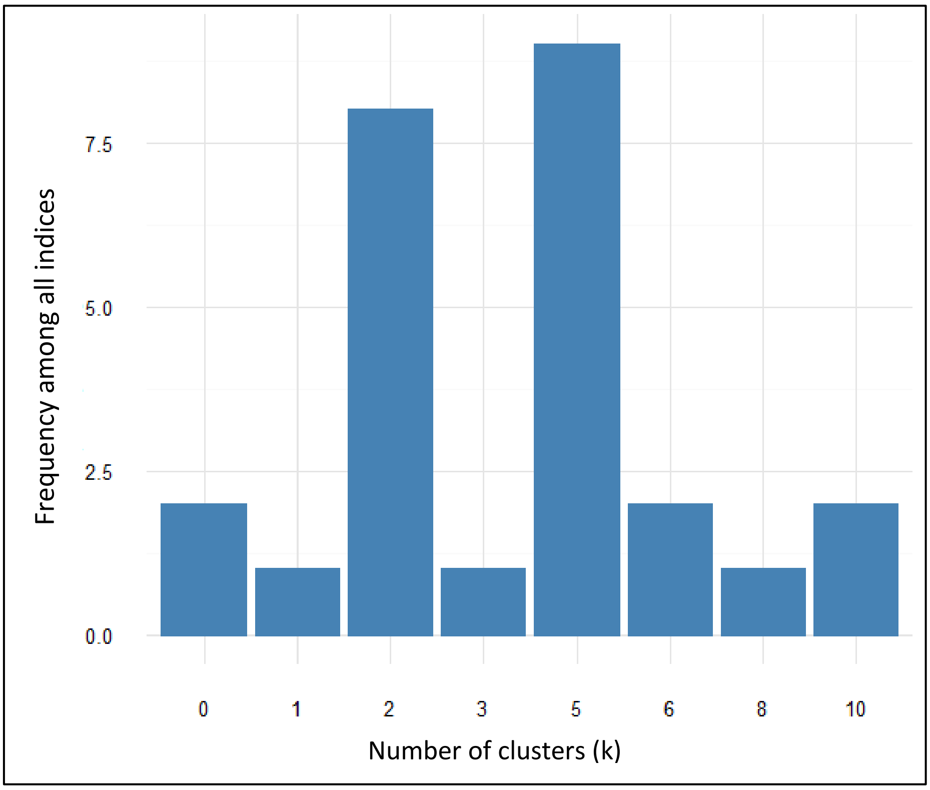



**Figure 14: Optimal number of clusters (k = 5) based on all indices tested.** Clusters numbers with a frequency below one (<1) were removed from the x-axis.

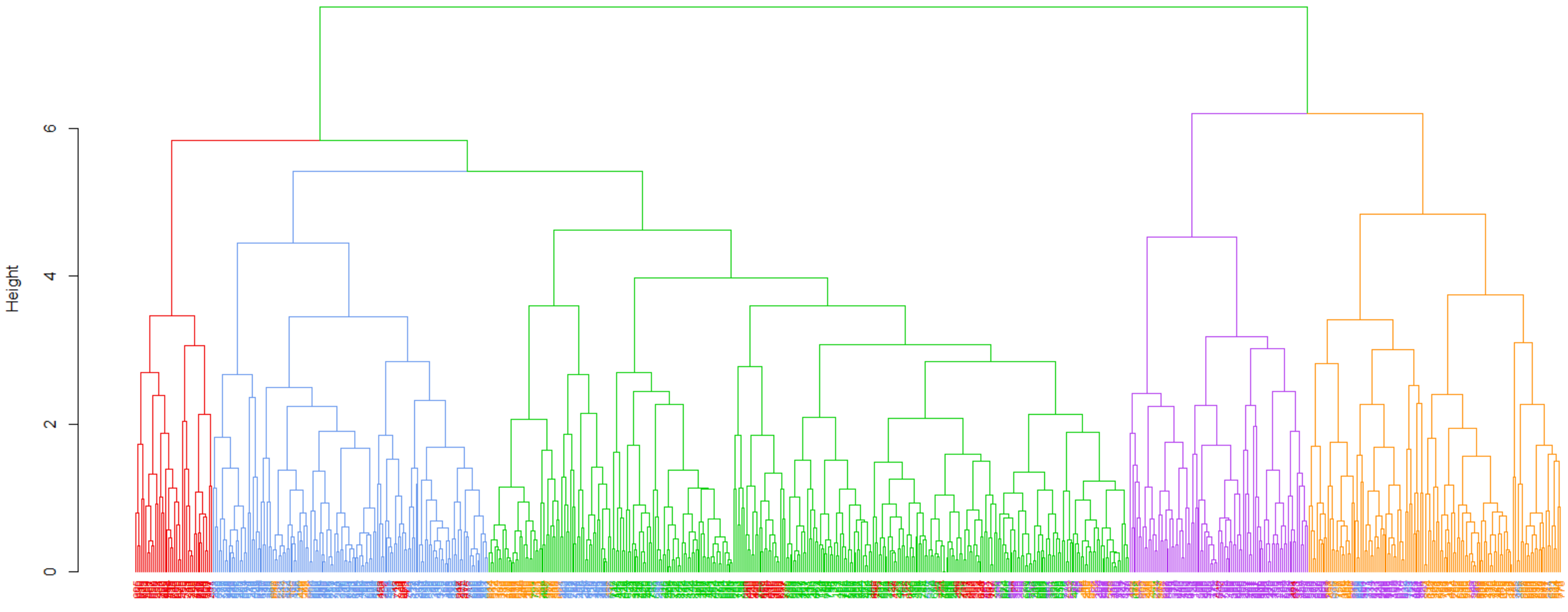



**Figure 15: Cluster solution dengrodram (k = 5).** Coloured branches represent the hierarchical cluster groups. Coloured bars along the bottom of the x-axis highlight points where the k-means analysis improved fit. Respondents who were reallocated to a different cluster when the k-means algorithm was run are indicated by bars of a different colour to the branch above.

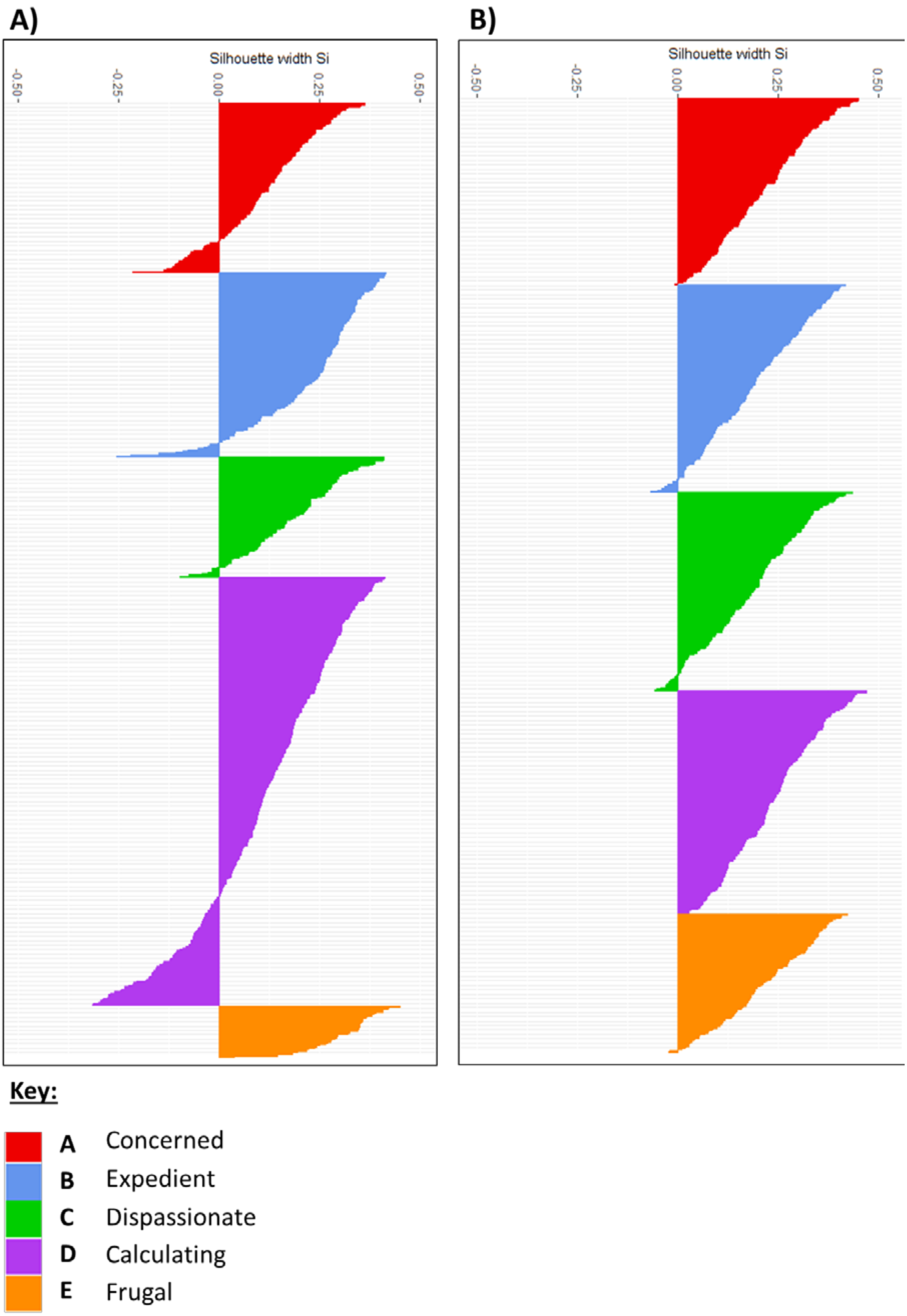



**Figure 16: Comparison of hierarchical cluster (A) and k-means (B) silhouette plots.** Negative values highlight the number of points that would fit better in another cluster. The average silhouette width improved by = 0.06 with use of the k-means cluster analysis.

**Table 10: Cluster means from k-means cluster solution.**

| Factor | | Clusters 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|---|
| 1 | *Care* | 0.90 | -0.17 | -0.89 | 0.74 | -0.87 |
| 2 | *Convenience* | 0.38 | 1.20 | -0.23 | -0.81 | -0.68 |
| 3 | *Cost* | -0.80 | 0.63 | -1.00 | 0.38 | 0.94 |
| 4 | *SES* | 0.13 | -0.12 | 0.12 | 0.03 | -0.21 |

**Table 11: Identified cluster solutions and subgroup names.**

| Cluster | Subgroup Name | Number of Respondents (n) | Highest Factor Score | Retailers Hypothetically Most Attractive |
|---|---|---|---|---|
| **A** | *Concerned* | 144 | *Care* | Alternative retailers – AFN |
| **B** | *Expedient* | 161 | *Convenience* | Most convenient retailers and processed foods – IGA or Woolworths (either for ease or one-stop-shopping) |
| **C** | *Dispassionate* | 154 | None significant, uninvolved | Closest retailers – IGA |
| **D** | *Calculating* | 173 | *Care* and *Cost* | Alternative retailers – AFN |
| **E** | *Frugal* | 107 | *Cost* | Largest retailers – Woolworths or Costco |

Cluster solutions were generally well separated for the factors of C*ost*, *Convenience,* and *Care*, but highly overlapping along the *SES* axis. There was relatively little socio-economic variation between clusters (see Table 12, Figure 17, and *Appendix P: Demographic Characteristics of Consumer Subgroups*). As such, socio-economic status was not a useful variable for identifying homogenous groups of consumers. Food choice motivations varied for respondents across the full range of SES, indicating that household income and education do not dictate food choice motivations in the study area. On average, every cluster had respondents located in the top income bracket, except for the *Frugal* (E) cluster, where consumers only reached the second highest bracket. In addition, the *Frugal* respondents reported spending the least amount of money at all retailers. The *Concerned* (A) respondents reported spending the largest amount of money per fortnight on average, while *Calculating* (D) respondents had the highest number of visits to retailers (Table 13). This indicates that respondents that consider social, political, and ecological values as important food choice motivations visit more retailers and spend more than the average consumer (see also *Appendix Q: Consumption Characteristics of Consumer Subgroups*).

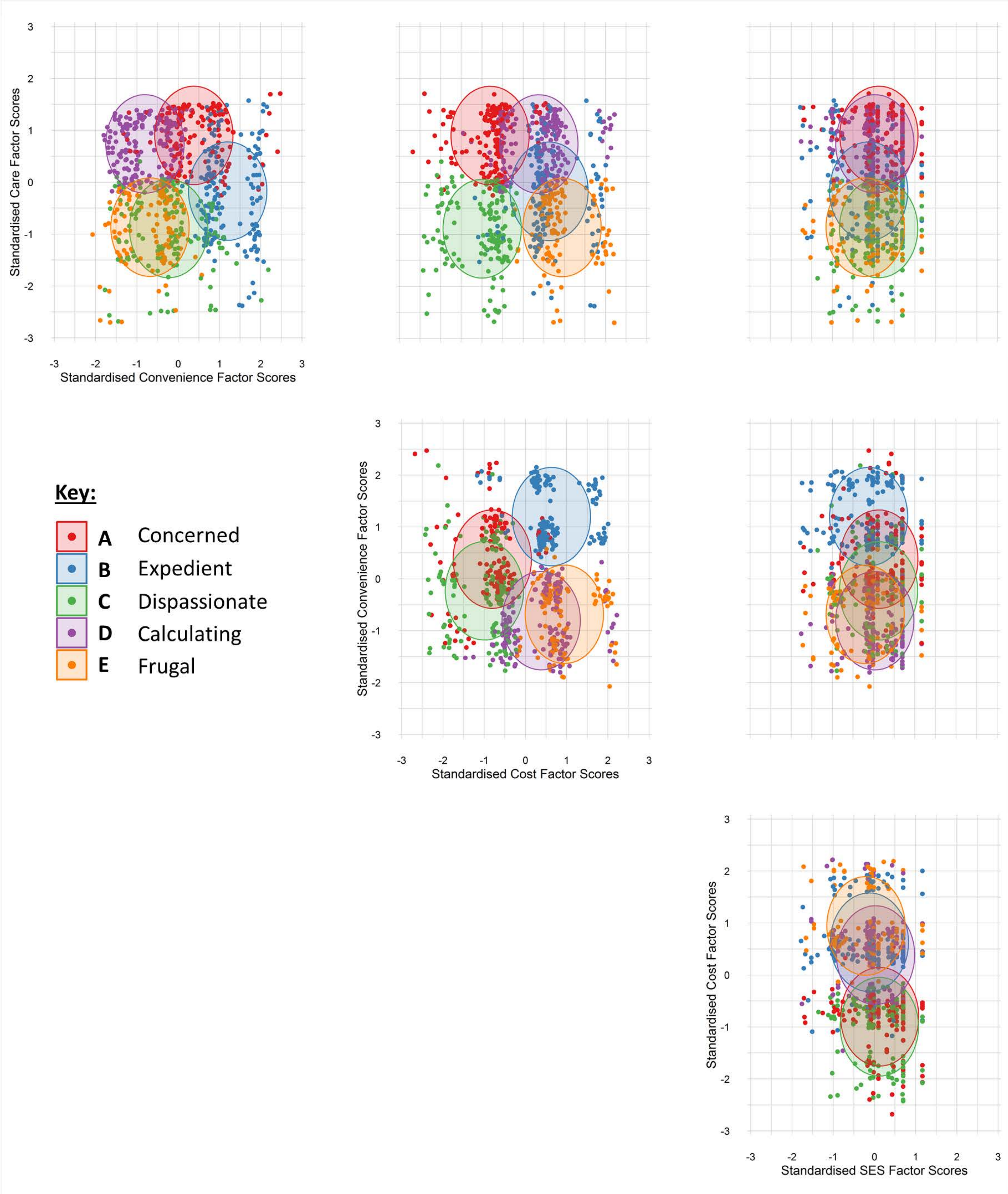



**Figure 17: Scatterplots of the cluster solutions in two-dimensions.** Ellipses were estimated using a multivariate t-distribution (Fox and Weisberg, 2010). The overlap of cluster ellipses for the factor of *SES*, in comparison to the separation of ellipses for the factors of *Care, Cost* and *Convenience*, suggests that the attitudinal factors are more important for understanding differences in consumer behaviours in North Canberra.

**Table 12: Cluster subgroup demographics.**

| Question | | Cluster Concerned A | Expedient B | Dispassionate C | Calculating D | Frugal E |
|---|---|---|---|---|---|---|
| **1** | **Household residence time (in months)** | | | | | |
| | 0 - 11 | 22 (15%) | 34 (21%) | 20 (13%) | 18 (10%) | 21 (20%) |
| | 12 - 47 | 33 (23%) | 40 (25%) | 36 (23%) | 56 (32%) | 32 (30%) |
| | 48+ | 89 (62%) | 87 (54%) | 98 (64%) | 99 (57%) | 54 (50%) |
| **5** | **Number of people in household** | | | | | |
| | **Adults** | | | | | |
| | 1 | 42 (29%) | 60 (37%) | 39 (25%) | 34 (20%) | 27 (25%) |
| | 2 | 78 (54%) | 80 (50%) | 98 (64%) | 119 (69%) | 58 (54%) |
| | 3 | 19 (13%) | 14 (9%) | 13 (8%) | 17 (10%) | 14 (13%) |
| | 4 | 4 (3%) | 6 (4%) | 3 (2%) | 3 (2%) | 5 (5%) |
| | 5+ | 1 (1%) | 1 (1%) | 1 (1%) | 0 (0%) | 3 (3%) |
| | **Children** | | | | | |
| | 0 | 108 (75%) | 123 (76%) | 127 (82%) | 127 (73%) | 82 (77%) |
| | 1 | 14 (10%) | 13 (8%) | 10 (6%) | 18 (10%) | 10 (9%) |
| | 2 | 21 (15%) | 18 (11%) | 14 (9%) | 23 (13%) | 11 (10%) |
| | 3 | 0 (0%) | 7 (4%) | 3 (2%) | 4 (2%) | 4 (4%) |
| | 4 | 0 (0%) | 0 (0%) | 0 (0%) | 1 (1%) | 0 (0%) |
| | 5+ | 1 (1%) | 0 (0%) | 0 (0%) | 0 (0%) | 0 (0%) |
| **6** | **Age** | | | | | |
| | 18 – 29 | 8 (6%) | 17 (11%) | 13 (8%) | 9 (5%) | 17 (16%) |
| | 30 – 39 | 27 (19%) | 31 (19%) | 27 (18%) | 25 (14%) | 26 (24%) |
| | 40 – 49 | 31 (22%) | 30 (19%) | 22 (14%) | 32 (18%) | 9 (8%) |
| | 50 – 59 | 40 (28%) | 31 (19%) | 31 (20%) | 34 (20%) | 15 (14%) |
| | 60 + | 37 (26%) | 49 (30%) | 60 (39%) | 70 (40%) | 40 (37%) |
| **7** | **Gender** | | | | | |
| | Female | 104 (72%) | 112 (70%) | 84 (55%) | 122 (71%) | 62 (58%) |
| | Male | 39 (27%) | 49 (30%) | 70 (45%) | 51 (29%) | 44 (41%) |
| | Other | 0 (0%) | 0 (0%) | 0 (0%) | 0 (0%) | 1 (1%) |
| **8** | **Car Ownership & Access** | | | | | |
| | Yes | 133 (92%) | 137 (89%) | 137 (89%) | 155 (90%) | 92 (86%) |
| | No | 3 (2%) | 18 (11%) | 9 (6%) | 6 (3%) | 4 (4%) |
| | No Ownership, but Access | 8 (6%) | 6 (4%) | 8 (5%) | 12 (7%) | 11 (11%) |
| **9** | **Education** | | | | | |
| | Primary | 1 (1%) | 0 (0%) | 0 (0%) | 1 (1%) | 2 (2%) |
| | Secondary | 10 (7%) | 17 (11%) | 13 (8%) | 8 (5%) | 14 (13%) |
| | Technical | 10 (7%) | 15 (9%) | 9 (6%) | 13 (8%) | 13 (12%) |
| | University | 123 (85%) | 129 (80%) | 132 (86%) | 148 (86%) | 78 (73%) |
| **10** | **Employment** | | | | | |
| | Full-time | 82 (57%) | 83 (52%) | 61 (40%) | 56 (32%) | 44 (41%) |
| | Retired | 22 (15%) | 39 (24%) | 56 (36%) | 62 (36%) | 34 (32%) |
| | Part-time | 24 (17%) | 24 (15%) | 14 (9%) | 31 (18%) | 17 (16%) |
| | Self Employed | 10 (7%) | 8 (5%) | 15 (10%) | 12 (7%) | 6 (6%) |
| | Unemployed | 2 (1%) | 1 (1%) | 3 (2%) | 2 (1%) | 1 (1%) |

| | | | | | | |
|---|---|---|---|---|---|---|
| | Student | 3 (2%) | 6 (4%) | 2 (1%) | 1 (1%) | 4 (4%) |
| **11** | **Occupation** | | | | | |
| | Managers | 23 (16%) | 15 (9%) | 14 (9%) | 15 (9%) | 10 (9%) |
| | Professionals | 52 (36%) | 47 (27%) | 42 (27%) | 57 (33%) | 25 (23%) |
| | Technicians and Trade Workers | 0 (0%) | 3 (2%) | 2 (1%) | 1 (1%) | 3 (3%) |
| | Community and Personal Service Workers | 3 (2%) | 7 (4%) | 0 (0%) | 5 (3%) | 4 (4%) |
| | Clerical and Administrative Workers | 35 (24%) | 42 (26%) | 33 (21%) | 25 (14%) | 20 (19%) |
| | Sales Workers | 5 (3%) | 1 (1%) | 1 (1%) | 0 (0%) | 3 (3%) |
| | Machinery Operators and Drivers | 0 (0%) | 1 (1%) | 1 (1%) | 0 (0%) | 0 (0%) |
| | Labourers | 0 (0%) | 0 (0%) | 0 (0%) | 0 (0%) | 1 (1%) |
| | Not in labour force (retired/students) | 26 (18%) | 45 (28%) | 61 (40%) | 70 (40%) | 41 (38%) |
| **12** | **Household Income** | | | | | |
| | <$199 | 0 (0%) | 0 (0%) | 0 (0%) | 4 (2%) | 1 (1%) |
| | $200 – 399 | 1 (1%) | 7 (4%) | 3 (2%) | 9 (5%) | 1 (1%) |
| | $400 – 799 | 9 (6%) | 19 (12%) | 12 (8%) | 15 (9%) | 17 (16%) |
| | $800 - $1,249 | 25 (17%) | 31 (19%) | 30 (19%) | 26 (15%) | 19 (18%) |
| | $1,250 - $1,999 | 34 (24%) | 51 (32%) | 31 (20%) | 49 (49%) | 36 (34%) |
| | > $2,000 | 75 (52%) | 53 (33%) | 78 (51%) | 70 (40%) | 33 (31%) |

Note: *n* for each cluster was calculated after incomplete questionnaires were removed

**Table 13: Summary of consumer subgroup behaviours.**

| **Sample mean (and standard deviation)** | **Concerned A** | **Expedient B** | **Dispassionate C** | **Calculating D** | **Frugal E** |
|---|---|---|---|---|---|
| **Number of visits to retailers** | 45 (64) | 40 (49) | 43 (55) | 53 (73) | 29 (36) |
| **Number of retailers visited** | 19 (21) | 20 (21) | 17 (18) | 20 (21) | 13 (14) |
| **Amount spent in total** | $1,920.17 ($2,719.67) | $1,564.17 ($2,431.11) | $1,581.23 ($2,110.32) | $1,773.90 ($2,361.37) | $1,026.59 ($1,648.26) |
| **Amount spent per retailer visited** | $56.48 ($78.81) | $46.00 ($70.44) | $46.51 ($61.15) | $52.71 ($68.42) | $30.19 ($47.76) |

Note: Calculations based on data collected over a fortnight, averaged by respondent for each subgroup. µ = Mean. σ = Standard deviation. Standard deviation in parentheses.

## 4.3 Spatial Analysis

### 4.3.1 Spatial Interaction Model Configurations and Overall Patterns of Visitation

The SIM explained the aggregate respondent-to-retailer visitation patterns to a reasonable degree (see Table 14 and Figure 18). Rather than improving model fit, disaggregation by consumer subgroups reduced model fit. Overall, consumer behaviour was most accurately described when all respondents were analysed together, with 63% of the variance explained in SA1–retailer visitation matrices (for more retailer-based results see *Appendix R: Calibrated Attractiveness Results*). Overall, larger retailers such as Costco and Majura Woolworths, which are located outside of the study area, were the most attractive. Inside of the study area, Dickson Woolworths was the most attractive retailer for all consumers, and had one of the most extensive spatial catchments (see Figure 19). In comparison, smaller retailers, and those participating in the AFN, had more confined spatial catchments than larger retailers. The calibrated catchments for each retailer varied spatially in parallel to the attractiveness measurements. The maps in Figure 19 show the probability of a consumer visiting a specific retailer on their next visit to any retailer in the next 14 days.

**Table 14: Spatial Interaction Model parameter estimates.**

| Subgroup | All Consumers | Concerned A | Expedient B | Dispassionate C | Calculating D | Frugal E |
|---|---|---|---|---|---|---|
| **Distance Decay (*β*)** | 1.55 (1.52, 1.58) | 1.62 (1.55, 1.69) | 1.39 (1.32, 1.45) | 1.59 (1.52, 1.66) | 1.56 (1.5, 1.62) | 1.39 (1.31, 1.47) |
| **Floor Area α** | 0.11 (0.09, 0.13) | 0.07 (0.03, 0.11) | 0.14 (0.1, 0.18) | 0.14 (0.1, 0.18) | 0.07 (0.03, 0.07) | 0.13 (0.09, 0.18) |
| **Business-District Area α** | 0.04 (0.02, 0.05) | 0.11 (0.07, 0.14) | -0.02 (-0.05, 0.01) | 0.07 (0.03, 0.1) | 0.06 (0.03, 0.09) | -0.03 (-0.07, 0.01) |
| **AFN α** | -0.86 (-0.97, -0.74) | -0.63 (-0.88, -0.37) | -0.88 (-1.13, -0.63) | -1.02 (-1.27, -0.77) | -0.7 (-0.93, -0.47) | -1.23 (-1.56, -0.91) |
| ***γ*** | 1.01 (0.96, 1.06) | 0.9 (0.81, 0.99) | 0.93 (0.84, 1.03) | 0.75 (0.67, 0.84) | 1.05 (0.97, 1.13) | 1 (0.87, 1.13) |
| ***k*** | 9.88 (9.64, 10.12) | 12.89 (12.44, 13.33) | 9.25 (8.88, 9.61) | 11.84 (11.32, 12.36) | 10.21 (9.84, 10.58) | 8.52 (8.02, 9.03) |
| $R^2$ | 0.63 | 0.56 | 0.46 | 0.39 | 0.5 | 0.3 |
| **SRMSE** | 1.67 | 2.33 | 2.28 | 2.51 | 2.3 | 2.76 |
| **RNWP** | 0.85 | 1.08 | 1.15 | 1.17 | 1.06 | 1.23 |
| ***n* respondents** | 739 | 144 | 161 | 154 | 173 | 107 |

Notes: Ninety-five percent (95%) confidence intervals for parameter estimates are indicated in parentheses. SRMSE = standardised root mean square error. RNWP = relative number of wrong predictions. k, γ , α, and β = empirically estimated parameters. α = refers to variables of attractiveness.

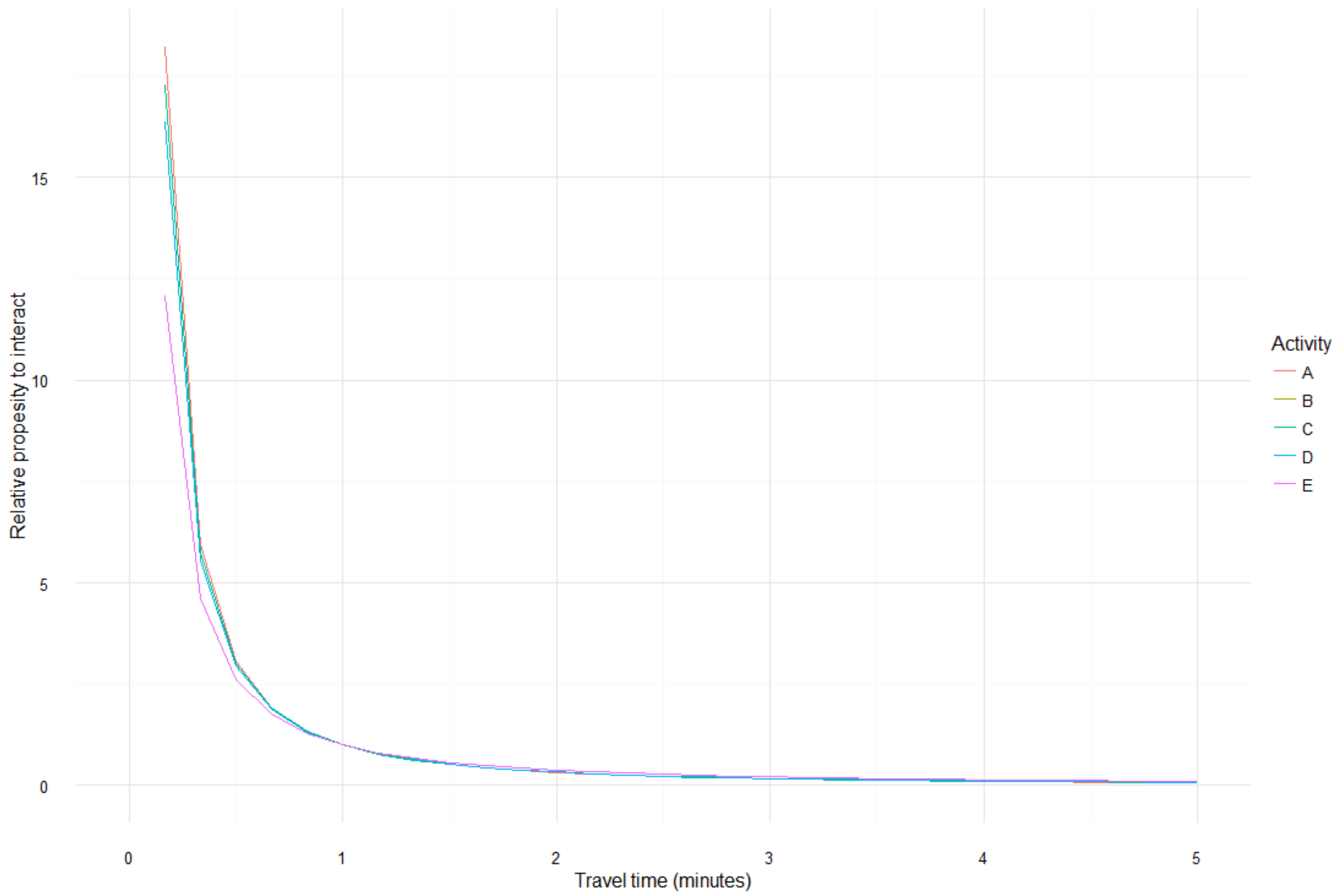



**Figure 18: Distance decay of each consumer subgroup.** A = 1.62, B = 1.39, C = 1.59, D = 1.56, E = 1.39. There is little variance between consumer groups.

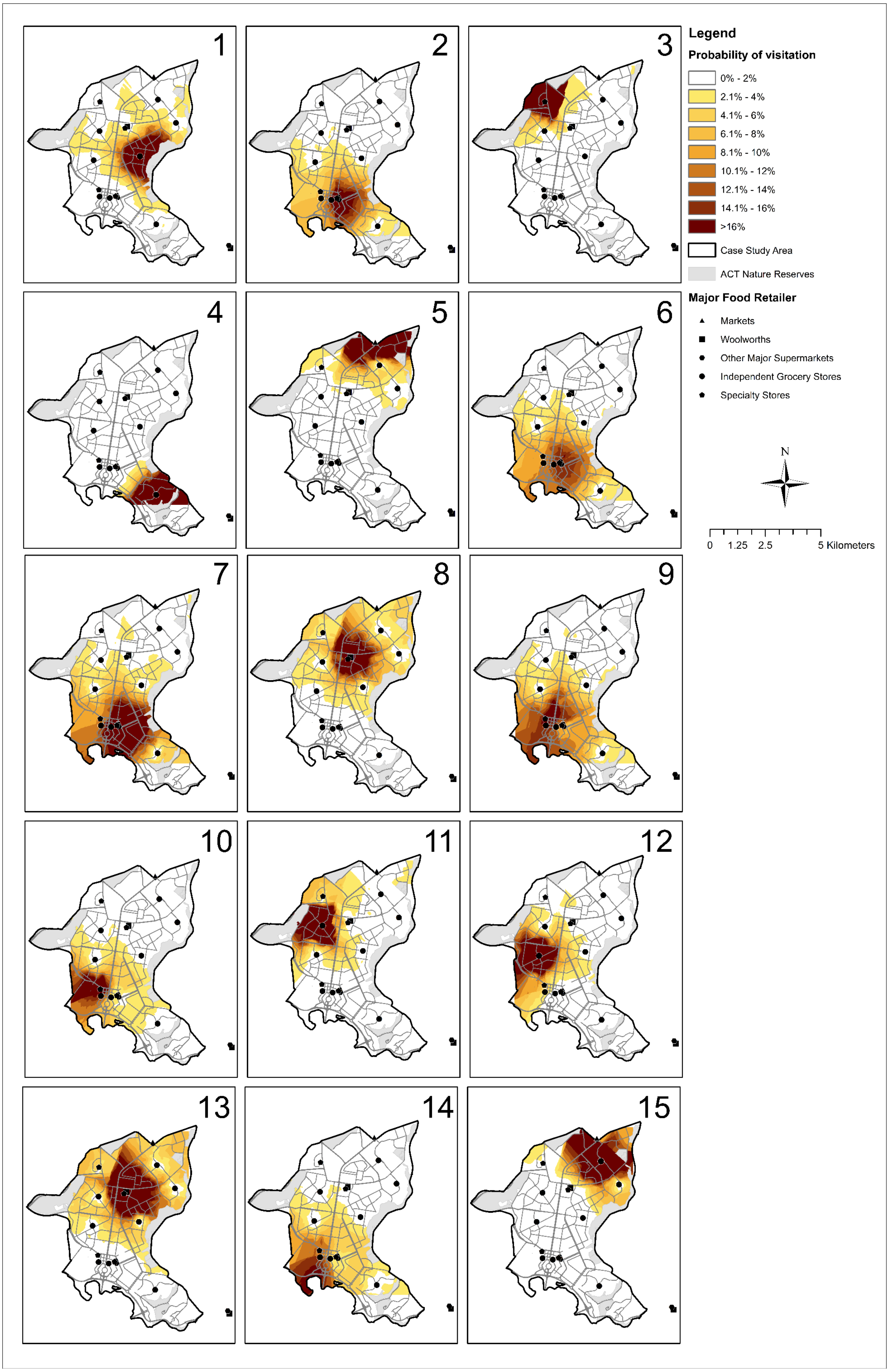



**Figure 19: Calibrated catchments for all retailers.** Retailers listed in alphabetical order. Retailers include: 1 = Ainslie IGA, 2 = Canberra Centre Aldi, 3 = Choku Bai Jo, 4 = Campbell IGA, 5 = Capital Region Farmers Market EPIC, 6 = Canberra Centre Specialty Stores, 7 = Canberra Supabarn, 8 = Dickson Specialty Stores, 9 = East Row IGA, 10 = Food Co-Op ANU, 11 = Lyneham IGA, 12 = O'Conner IGA, 13 = Dickson Woolworths, 14 = Spar City West, 15 = Watson Supabarn.

### 4.2.2 Comparison of Consumer Subgroups

In terms of parameter variables, such as retailer attractiveness, there were differences in consumer subgroups. Travel time was least important for *Expedient* (B) and *Frugal* (E) consumers, indicating that those consumers had a willingness to travel further to shop. In terms of proximity measurements, the relative importance of distance was fairly similar across all subgroups, but *Concerned* (A), *Dispassionate* (C), and *Calculating* (D) consumers were likely to travel for a slightly longer time than *Frugal* (E) and *Expedient* (B) consumers. However, retailer size was the most important variable for predicting of visitation for the *Expedient*, *Dispassionate,* and *Frugal* consumers. *Concerned* consumers were more likely to visit retailers located in settings with a larger business-district areas, indicating a preference for retailers in store agglomerations. AFNs were most attractive for C*oncerned* consumers and least attractive for *Frugal* consumers.

However, despite the differences in parameter estimates, when measured retailer catchments were mapped for the consumer subgroups, little spatial variation was evident. Spatial visitation behaviour among consumer subgroups for all retailers was remarkably similar (for maps of all retailers see *Appendix S: Retailer Spatial Catchments*). Among retailers, Dickson Woolworths had the largest and most intense catchment for every subgroup (Figure 20), indicating that all respondents have a greater probability of visiting this retailer, except in the case that the household is within close proximity of another retailer. For example, Choku Bai Jo in North Lyneham had a highly localised catchment to its surrounding region (see Figure 21), but the size of the spatial catchment were unchanged for each consumer subgroup. This indicates that consumers from varying attitudinal groups are likely to visit closer retailers, regardless of their known attractiveness.

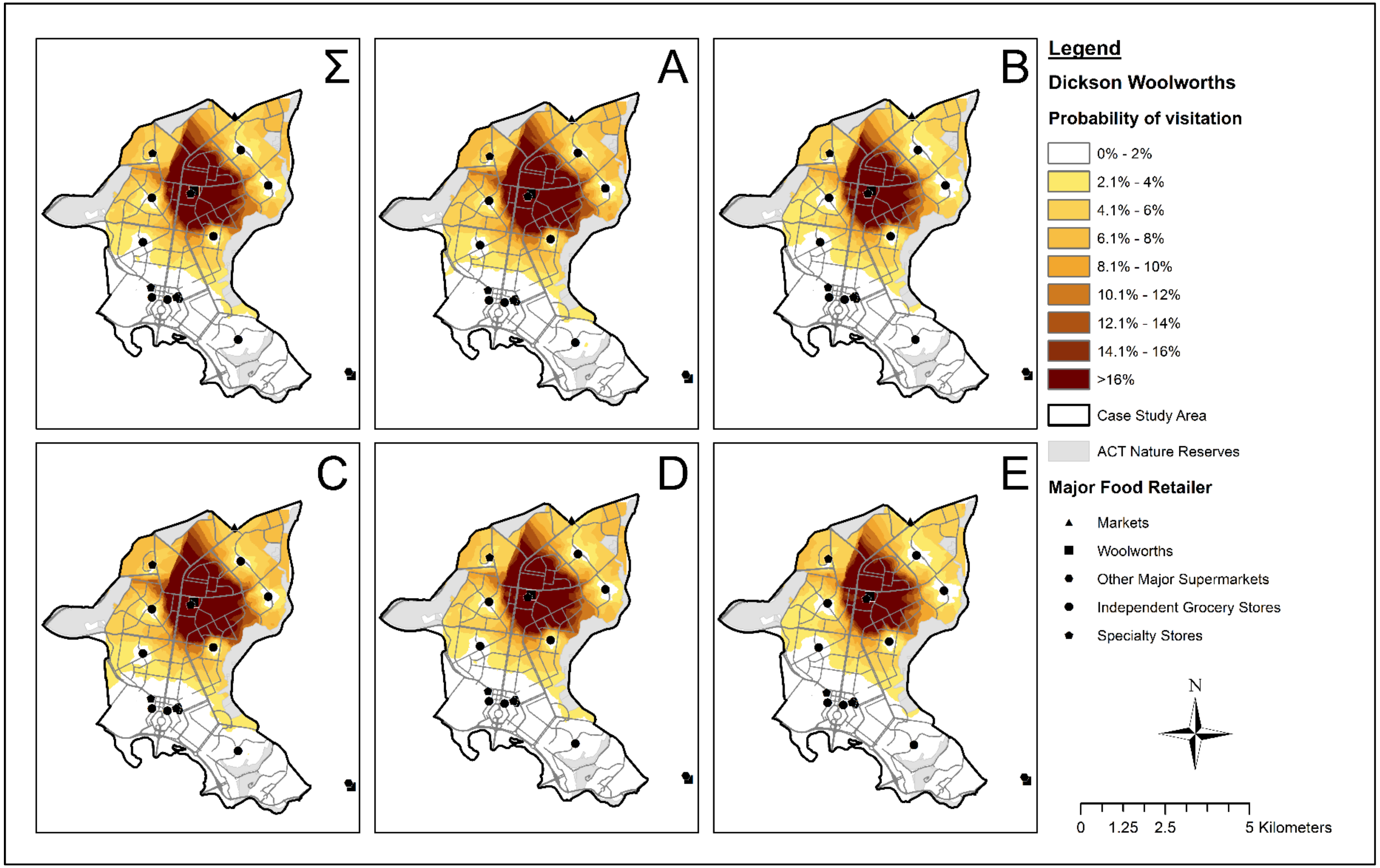



**Figure 20: Calibrated catchment of Dickson Woolworths, disaggregated by consumer subgroup.** Σ = All consumers, A = Concerned, B = Expedient, C = Dispassionate, D = Calculating, E = Frugal. This is an example of an extensive spatial catchment.

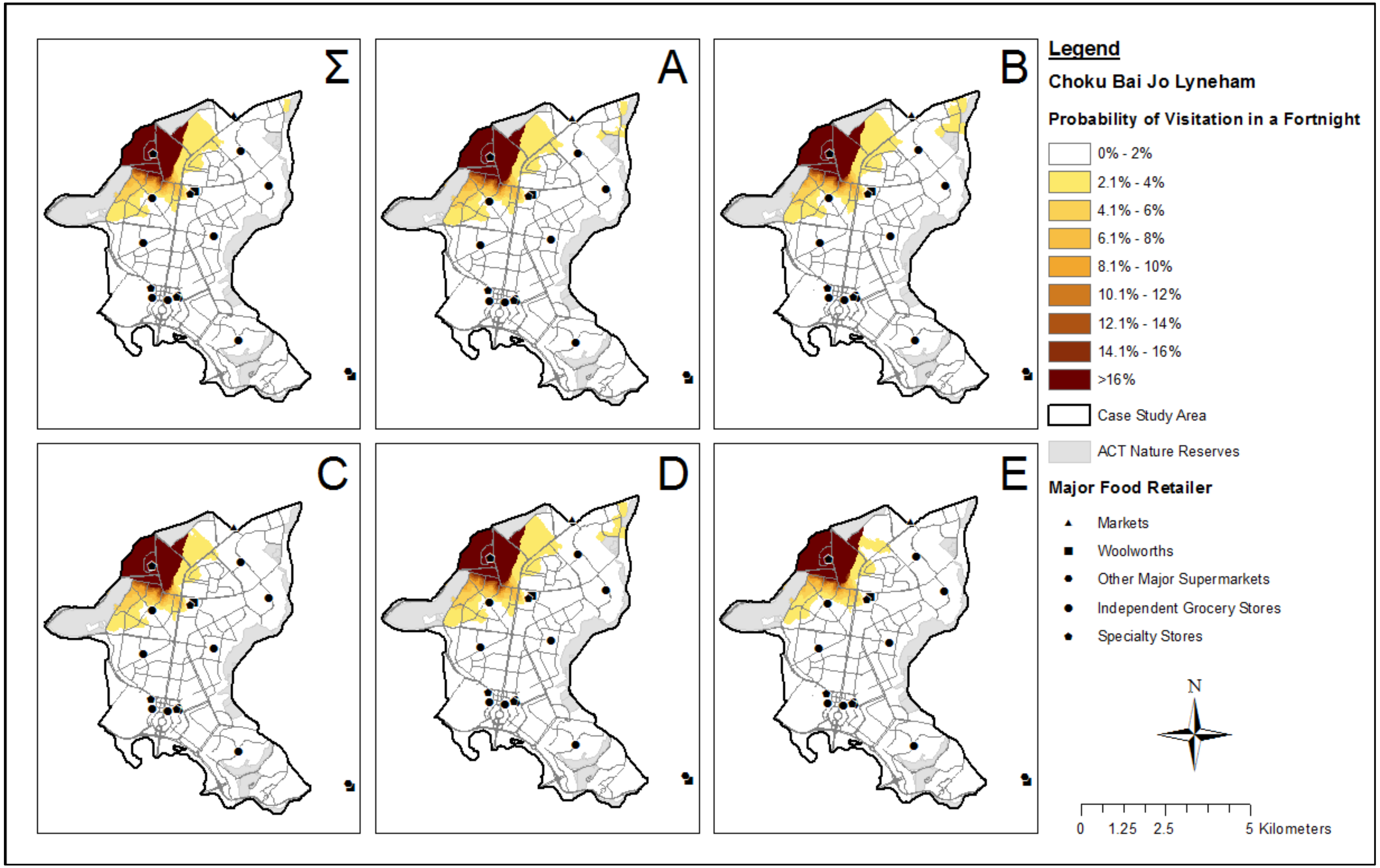



**Figure 21: Calibrated catchment of Choku Bai Jo North Lyneham, disaggregated by consumer subgroup.** Σ = All consumers, A = Concerned, B = Expedient, C = Dispassionate, D = Calculating, E = Frugal. This is an example of a confined spatial catchment.

## 4.4 Summary

The survey had a satisfactory response rate (>18%), yielding 864 valid responses. Compared to the ABS Census 2011 data, the sample collected was somewhat older, contained more women, and were more highly educated than the general population in the study area. Consumer subgroups were statistically identified through the consideration of four factors in the data: *Cost* (1), *Convenience* (2), and *Care* (3), and *SES* (4). Five clusters were identified, and named: *Concerned* (A), *Expedient* (B), *Dispassionate* (C), *Calculating* (D), and *Frugal* (E). Motivations toward food choices was an important determinate for separation between respondents. Socio-economic status played almost no role in the separation of consumer groups. In addition, the spatial pattern of their visitation to retailers in the study area was surprisingly uniform. Aggregate community-retailer visitation patterns showed that although larger retailers were favoured, proximity was also important. Consumers from varying attitudinal groups exhibited similar visitation behaviour, and are likely to visit closer retailers regardless of their size or participation in an AFN. The implications of these results are discussed in the following chapter.

# Chapter 5: Discussion

This chapter provides an interpretation of the main findings of this thesis featured in the previous chapter in relation to the research question: *To what extent do attitudes towards food influence spatial patterns of food access and consumer visitation to major food retailers?* Firstly, this includes an evaluation of the key results and unexpected findings, and a comparison of the statistically defined consumer subgroups to relevant food desert literature and sociological theory. Secondly, the implications of the research are described in terms of the benefits of sophisticated methods involving a calibrated disaggregated SIM for future policy and avenues for further research.

## *5.1 Interpretation of Key Results*

The key findings from the analysis were, largely, the limited influence of SES in identifying homogenous consumer groups in North Canberra (see Figure 18); and the comparatively uniform spatial patterns of consumer subgroup visitation to retailers (see Figure 21). It was hypothesised that consumer attitudes would have had a strong influence over spatial patterns of visitation to major food retailers in the study area. For example, it was imagined that consumers with a strong '*Care*' factor, would be more likely to visit a retailer in the AFN (see Table 11). In addition, it was thought that spatial catchments for consumers with a strong '*Care*' factor, would be larger in geographic extent for alternative retailers, such as Choku Bai Jo. However, it was found that there was little spatial variation evident between the consumer subgroups for visitation of all retailers. Consumers from all subgroups exhibited similar visitation behaviour, and were likely to visit and the closest retailer, regardless of their attitude, or retailer-attractiveness attributes.

These findings were unexpected because they challenge widely-held assumptions about SES and behaviour that underpin food deserts (for example, see: Charreire *et al.*, 2010; Desjardins, 2010; Leete *et al.*, 2011; Jiao *et al.*, 2012). This thesis found that households of lower SES were evident in all consumer subgroups (see Figure 18). This challenges the notion of the 'trickle effect' of consumption, which speculates that households of lower SES do not have access to products consumed by households of higher SES (Trigg, 2001; Walmsley, 2011; Bertrand and Morse, 2013; Klein and Murcott, 2014; Metheny and Beaudry, 2015). It is theorised in sociological literature that lower SES households emulate the consumption behaviours of higher SES households to achieve upward socio-economic mobility (Veblen and Banta, 2009). The food desert discourse follows similar logic, through the assumption that the retailers are unevenly distributed to favour those consumers of higher SES (O'Dwyer and Coveney, 2006).

However, this thesis suggests that the trickle effect is not evident in North Canberra, as consumers of all subgroups and SES have access to retailers.

As discussed in *Chapter 2: Literature Review*, a key dimension of spatially and GIS-based food access research is SES (for example, see: O'Dwyer and Coveney, 2006; Sharkey and Horel, 2008; Smoyer-Tomic *et al.*, 2008; Adams *et al.*, 2010; Desjardins, 2010; Walker *et al.*, 2011; Jiao *et al.*, 2012; Wang *et al.*, 2016). The emphasis on SES is thought to occur due to the prevalence of two research agendas in the discourse, social equity and health, which overlook the role of preference in favour of allocation and affordability. However, as Ericksen (2008) describes, food access is comprised of all three variables: allocation, affordability, and preference. Preference has been investigated through typologies of consumers since the 1950s (Stone, 1954; Williams *et al.*, 1978; Lesser and Hughes, 1986; Dagevos, 2005), but these have rarely been explored spatially. Research by Davegos (2005) suggests a neat framework for understanding consumer preferences, but this lacked spatially-explicit evidence of those behaviours. The results of this thesis contradict Davegos' consumer subgroups, as his typology was too simple to explain the number of statistically defined consumer subgroups. Yet his ideas should not be fully discredited, as food and social class have a long history of influence over consumption behaviour (Calnan, 1990; Toivonen, 1997; Hupkens *et al.*, 2000; Darmon and Drewnowski, 2008; Wills *et al.*, 2011). As (Mennell, 1996:17) states, "People have always used food in their attempts to climb the social ladder…." However, it is possible that the spatial assumptions about preferences have escalated the actual influence of SES in the discourse. This problem is known as 'deprivation amplification' in the field of behavioural nutrition (Macintyre, 2007). This thesis found that SES is not a significant determinant of spatial retailer visitation patterns in North Canberra. This implies that SES and the food desert metaphor are not applicable in every context.

## 5.2 Implications of the Research

The key results of this thesis have two important implications for research and regulation. Firstly, because these results challenge existing notions of SES in food deserts, it is questionable that the conventional definition of food deserts should be used as framework for determine food access. For example, according to Fine and Leopold (1993), the use of SES variables in food research can only explain 'horizontal' variance in consumption behaviours, such as advertising and retailing (Mansvelt, 2005). Fine and Leopold argue for the need to incorporate 'vertical' factors, such commodity chains and historical contexts, into this framework in order to understand the social and spatial factors influencing consumption. Secondly, this highlights the need for greater use of sophisticated, empirically-defined spatial models, that can explain underlying contextual variables and behavioural trends, in addition to all three key variables of food access (as defined by Ericksen, 2008).

### 5.2.1 Looking Past the Food Desert Discourse

The definition of food deserts is not spatially-explicit enough to explain patterns of consumer behaviour found in this thesis. Most food desert literature assumes a relationship between SES and spatial behaviour, where SES is considered a key variable, along with arbitrary geographic distance measures of 'proximity' to retailers (Desjardins, 2010: 88). This thesis found that it is overly-simplistic to reduce spatial notions of food access into a single metaphor constructed of only two variables. For example, although attitudes separated consumers into distinct subgroups, attitudes did not have a strong influence over spatial patterns of visitation to retailers at an SA1-level (see Figure 20 and 21). The surprising uniformity of visitation patterns by each consumer subgroup to multiple retailers suggested the presence of an attitude-behaviour gap (for literature on the 'attitude-behaviour gap' see Young *et al.*, 2010; and De Barcellos *et al.*, 2011). Examples of the attitude-behaviour gap where clear when the *Concerned* (A) consumers had the same probability catchment for a large commercial retailer (Woolworths Dickson), and for a local grocer (Choku Bai Jo North Lyneham) as the *Dispassionate* (C) consumers. This result would not have been explored if simplistic 'buffers' or arbitrary distances to model access were used. Thus, food access studies require more sophisticated methods of modelling social variables, such as attitude, to create outputs better aligned to actual behaviours.

The food environment of North Canberra is highly complex, and more representative of a food jungle, not a food desert. A food jungle is an emerging term used to describe an area with adequate access to retailers by households of all SES (for examples of the term's use, see: Balingasa and Balingasa, 1999; Flaherty *et al.*, 2012; Nestle, 2016). The word 'jungle' metaphorically describes the abundance of retailers, as well as the underlying complexities of access that support the UGCoP (Chen and Kwan, 2015; Kwan, 2012b; 2012b). The term explicitly incorporates contextual uncertainties, contrary to the standard definition of a food desert (Charreire *et al.*, 2010; Chen and Kwan, 2015). Yet, the underlying nature a food jungle is one where consumers may still have unhealthy diets. As Macintyre (2007) claims, "…supermarkets provide access to a range of foods at relatively low prices, so access to a supermarket could facilitate the bulk buying of high energy nutrient poor foods and therefore be health damaging." High levels of access to food at the neighbourhood-level does not necessarily equate to healthy patterns of consumption (LiveLighter, 2016).

### 5.2.2 Food Retailers as Chameleons

The statistically measured differences in attitudes between consumers was irrelevant for discerning behaviour at this level of analysis, which implies that consumers are likely to be acting upon their attitudinal values within stores, at a sub-catchment level. This is possible, as retailers are known to fragment their market share, and act as ‘chameleons’ (Kennedy, 2013). Kennedy (2013) describes retail chameleons as suppliers of diverse food product options, which cater to all consumers needs, and provide consumers with the opportunity to act upon their attitudinal desires. Burn-Callander (2013) argues that, “…businesses are increasingly becoming chameleons, changing their business models to adapt to the changing needs of the customer.” This is likely to be occurring in the study area, because retailers such as Woolworths use marketing and advertising to create the impression that their products let consumers fulfil their attitudinal desires within the retailer (Palmer, 2015). Woolworths Limited (2012) claim that they are a changing business that strives to ‘work harder for customers’ who have a range of opinions and choices. An example of this are the ‘ethically’ marketed products, such as free-range eggs, which target consumers concerned with animal welfare (Mannix, 2016). The *Concerned* (A) consumer can feel like they are buying food that aligns to their ‘ethically’ social, ecological or political values, without having to interact with the local AFN. Meanwhile, the store still stocks cheaper cage free eggs, available to the *Dispassionate* (C) and *Frugal* (E) consumers. In addition, it has been argued that even supporting a supermarket chain such as Woolworths is unethical due to their high investment in pubs and poker machines (Palmer, 2015; Livingstone, 2016).

This behaviour implies that retailers do not want to exclusively appeal to one type of consumer. For example, Woolworths may provide consumers with an in-store environment that can be obesogenic for some, and healthy for others, based on their purchases inside of the store. This can be seen as a form of social engineering. A dominant theory on the types of retailers most successful at social engineering is the ‘Big Middle’ category (Levy *et al.*, 2005). Big Middle retailers offer innovative products and low prices, attracting consumers of all subgroups and segments for the wide array of products, and promise of value for money (Levy *et al.*, 2005). This concept implies that retailers are intentionally shaping behaviours through attitudes in order to gain profit, regardless of the product sold. Hence, changing consumption to include healthier and more culturally appropriate foods is not a matter of creating more markets, or ‘ethical’ stores within more neighbourhoods. In fact, the findings of this thesis suggest evidence for the opposite action, a change food products at the source and removal of unhealthy options from inside of stores.

### 5.2.3 Implications for Policy

In general, the findings from this research on spatial patterns of consumer attitudes and visitation in North Canberra could form the basis of evidence-based policy formation and evaluation. There has been wide public and academic debate around the need for evidence-based policies (Banks, 2009), especially in the field of public health (for example, see: Lin and Gibson, 2003; Brownson *et al.*, 2009; Blumberg *et al.*, 2010; Cartwright and Hardie, 2012). However, there are relatively few examples of what constitutes evidence (Rycroft-Malone *et al.*, 2004). This thesis presents a specific means of generating evidence for policy-making and reformation of the food system. These results points toward the in-store environment as having the greatest impact on consumption behaviours. However, how this is implemented can be debated. An example of an in-store regulation to reduce consumption of unhealthy foods is a sugar tax. Taxes on processed high kilojoule foods and drinks, such as confectionary and soft-drinks, enforced in Mexico (Escobar *et al.*, 2013; Barquera *et al.*, 2013), the United Kingdom (Mytton *et al.*, 2012; Briggs *et al.*, 2013) and Berkeley, California (Brockett and Rose, 2014; Pomeranz, 2014; Falbe *et al.*, 2016; Somji *et al.*, 2016) have proven that there is a successful public policy case for regulating sugar consumption (Brownell and Frieden, 2009). Other examples include the regulation of adverting within aisles and store arrangement (LiveLighter, 2016), use of loyalty card data (Newing *et al.*, 2015), and regulation of 'vertical' consumption factors, such as production and distribution chains (Fine and Leopold, 1993). Nonetheless, the results in this thesis clearly point to an aspect of the food system for intervention, namely individual choice behaviours enacted at the store level.

## 5.3 Critical Evaluation of the Methods

The use of a calibrated disaggregated SIM, as demonstrated in this thesis, has demonstrated its utility as a sophisticated method for modelling the socio-spatial nature of food access, and other spatially-contextual social problems. A SIM is an effective way to estimate, visualise and communicate retail catchments (Doran and Young, 2010), that are more representative of human behaviours than previously applied methods. This study is the first that the author is aware of that examines the spatial behaviour of different consumer subgroups, with respect to food retailers and attitudes, using statistically defined subgroups and a calibrated SIM.

The benefits of a data-driven approach to calibration and disaggregation of a SIM are the incorporation of reported spatial behaviour, directly addressing the contextual uncertainty that much of previous research merely sidesteps by means of strong assumptions about visitation behaviour (Kwan, 2012b; Suárez-Vega *et al.*, 2014; Chen and Kwan, 2015). As this approach is empirically-based and not solely predictive, it has clear benefits for policy-making and regulation as described above. As discussed in *Chapter 2.3*, most food desert research commonly makes strong but poorly articulated assumptions about distance measurements, and preferences, which can both be addressed with recourse to reported behavioural data in a SIM (Markham *et al.*, 2013). For food access, calibration is also an effective way to model all three key dimensions of access: allocation, affordability, and preference (Ericksen, 2008) in a spatially-explicit manner. This approach could also be employed for research focused on only one of these variables, such as reviewing the validity of previous work on food deserts.

However, this method is subject to a number of limitations. The main limitations to this method are associated with the high degree of specificity involved. For example, the use of a data-driven approach to determine consumer subgroups can be a subjective process (Hair *et al.*, 2006). Different statistical methods for clustering data could create slightly different consumer subgroups depending on the technique employed. Yet, the benefit to statistically defining clusters is that the results have a closer relationship to characteristics of the study area and the sample (Charreire *et al.*, 2010) in comparison to theoretical approaches to defining subgroups, such as consumer typologies (for example Williams *et al.*, 1978; Westbrook and Black, 1985; Lesser and Hughes, 1986; Dagevos, 2005; Baum *et al.*, 2006). In addition, SIMs are limited by the embedded spatial and temporal assumptions in the sample frame, the collected data, and the mathematical form of the model (Longley *et al.*, 2001). This means that spatial catchment outputs are usually constrained by geographic issues, such as the Modifiable Area Unit Problem (MAUP; see Cromley and McLafferty, 2011). In the case of the MAUP, slightly different results may be achieved if geographic boundaries were of a different configuration. The Ecological Fallacy (see Golledge and Stimson, 1997) should also be considered to an extent, considering that the spatial behaviour of individuals is rarely identical to the calibrated average behaviour of their consumer subgroups as a whole (for example, this issue is described more broadly in: Walmsley and Lewis, 2014:128).

The use of a precise national dataset for the sample frame is a cost effective method for ensuring a high level of rigour and quality in the output data. The G-NAF is a current spatial dataset of accurately geocoded addresses and is available publicly (PMC, 2016). Access to the G-NAF means that predicting and calibrating retailer catchments at a fine-grained household-level is far more cost effective than traditional, manually geocoded methods (for example, see: Doran *et al.*, 2007; Markham *et al.*, 2014). With respect to geocoding survey responses, use of the G-NAF eliminates the time-consuming process of address-match geocoding (Cromley and McLafferty, 2011), which commonly has a wide variety of errors (Zandbergen, 2009; Hart and Zandbergen, 2013; Ganguly *et al.*, 2015). One limitation to the G-NAF is the exclusion of interstate visitors and mobile populations (Markham *et al.*, 2013). Markham *et al.,* (2013) suggests that this could be addressed through venue-exit surveys, run in collaboration among retailers and researchers. However, as Chambers *et al.* (1971) argues, when using research techniques, economic costs need to be balanced against scope and accuracy. In this context, the additional costs of a venue-exit survey would need to be compared to the ease and accuracy of using the G-NAF. Furthermore, permission to conduct venue-exit surveys can be problematic (Doran and Young, 2013).

The use of the G-NAF resulted in a large sample ($n$ = 864), and a relatively high response rate (>18%). In this study, potential bias was evident towards older and highly educated women, compared to the general population (Table 6). However, the response rate exceeded the expected rate (above 14.5% as seen in Markham *et al.*, 2013); and should also be noted that all surveys have some form of bias (Oppenheim, 2000). Where survey methods have been used in previous food access research, samples are usually more representative of older and highly educated women (for example, see: Walker *et al.*, 2010a [mean = 45 years old]; Walker *et al.*, 2012 [mean = 47 years old, 56% female]; Caspi *et al.*, 2012 [80.6% female]; Machín *et al.*, 2014 [57% female]; Lee *et al.*, 2015 [83% with a post-school qualification]). In general the G-NAF was found to be a very effective vehicle for generating a spatially-referenced survey with representative results (see Chapter 4.1.1). The G-NAF could be used as a sampling frame for other social issues that require geocoded surveying, such as transport (Troped *et al.*, 2001), health (Krieger *et al.*, 1997; Summerhayes *et al.*, 2006), and social equity and community governance (Taylor *et al.*, 2014).

## 5.4 Avenues of Future Research

Future research could successfully replicate the methods used in this thesis to investigate food accessibility in different geographic contexts. There is opportunity to apply these methods in areas previously defined as food deserts (for example, see: Burns and Inglis, 2007 for Casey, in Melbourne; Coveney and O'Dwyer, 2009 for Adelaide, in South Australia; Lê *et al.*, 2015 for Dorset, in Tasmania), to investigate food access and consumer attitudes through use of the G-NAF and a calibrated SIM. To pose this as a future research question: *would a calibrated SIM applied in the 'classic' food deserts above, confirm or refute the findings of previous research?* It is speculated that use of these methods would have mixed results, dependent on the geographic location and the type retailers in the area. It is hypothesised that there may be a bias in levels of access closer to city centres. It could be possible that as households get further away from the city centre, levels of access to retailers decline considerably. In addition, it is possible that areas with all four types of food system domains as described by Anderson (2015:550, see Figure 7), would have higher levels of access and a higher likelihood of spatial catchments characteristic of a food jungle, and not a food desert. Yet, if 'classic' food desert areas are found to be more characteristic of a food jungles, with retail chameleons, this would indicate that retailers are the key point in the supply chain to determine access and consumption behaviours. The implications of this would be a significant basis for evidence-based policy regarding retail-consumer interventions and regulatory responses. An example of this would be the possibility for local councils to subsidise rental and housing affordability around retailers that contain healthier and alternative food options.

This approach may also further justify the use of a calibrated SIM for analysis of other social issues. Calibration of a SIM could also incorporate more specific factors regarding retailer choice, such as marketing and advertising of the retailer, and quality of products and services to better understand consumer choices (Zainuddin and Mohd, 2014). In addition, integration of mixed-methods, such as GPS tracking, georeferenced photos, and food and travel diaries are particularly useful for realistically capturing the complexities of transportation methods (Walker, 2010a: 882), and individual food choices at an in-store level (Shannon, 2015).These methods are also useful for gaining insights into temporal differences in individual accessibility (Kwan, 1998; Kim and Kwan, 2003; Kwan, 2004; Shaw *et al.*, 2008), and the 'funnelling' nature of consumer behaviours (Golledge and Timmermans, 1990). This study was unable to incorporate these methods due to financial and temporal constraints, but presents an opportunity to research it further. Data collected in this thesis also holds the opportunity for future comparison-based studies regarding consumer attitude and consumption behaviours. Furthermore, the methods of this thesis have the potential to be used for the fine-scale and rigorous spatial examination of other social issues, such as community planning and gambling behaviours (as suggested in Doran and Young, 2010). Data collected in this thesis also holds the potential for use in decision-support of food access planning in North Canberra.

## 5.5 Summary

The key results of this thesis have two important implications for research and regulation. Firstly, they challenge existing notions of SES in food deserts. The definition of food deserts does not adequately explain the patterns of consumer behaviour found in this thesis. Spatial patterns of consumer subgroup visitation to retailers in the study area were comparatively uniform, suggesting that North Canberra was characteristic of a 'food jungle', not a food desert. The statistically measured differences in attitudes between consumers was irrelevant for discerning behaviour at this level of analysis, which implies that consumers are likely acting upon their attitudinal values within stores, at a sub-catchment level. This suggests the presence of retail 'chameleons', that appeal to multiple types of consumers in the area. These results point to the need for the regulation of in-store purchases, and could form the basis of evidence-based policy for food access. The use of a calibrated disaggregated SIM, as demonstrated in this thesis, has considerable potential to be used as a widespread method for modelling the socio-spatial nature of food access, and other spatially-contextual social problems. The use of a national dataset for the sample frame, such as the G-NAF, is a cost effective method for ensuring a high level of rigour and quality in the output data. Future research could successfully replicate the methods used in this thesis to investigate findings of food access in different geographic contexts. Data collected in this thesis also holds the potential for further analysis food jungles and retail chameleons.

# Chapter 6: Conclusion

Food access is a complex topic, full of implicit socio-spatial assumptions about behaviour. A common, but spatially-problematic concept that characterises social and spatial variables of access, is that of a 'food desert'. Geographic information systems (GIS) have been commonly used to model food access and food deserts, but few examples have incorporated the spatial intricacies of contemporary modelling techniques. In addition, few examples of GIS research have captured the complexities of consumer behaviour, such as individual attitudes towards food. The calibrated SIM used in this thesis showed a promising approach forward for creating outputs more closely aligned to actual consumer behaviours, and addressing aspects of food access previously overlooked.

This study collected empirical data to calibrate a SIM on consumer attitudes and visitation behaviour in the area of North Canberra. Four factors were found to statistically separate the data. These factors included: *Cost* (1), *Convenience* (2), and *Care* (3), and *SES* (4). These were used to statistically define five consumer subgroups, named: *Concerned* (A), *Expedient* (B), *Dispassionate* (C), *Calculating* (D), and *Frugal* (E). SES played almost no role in the separation of these consumer subgroups, which indicated that SES was not an significant variable in the measurement of food access in North Canberra. This result also challenged the implicit assumptions about SES and behaviour in the food desert discourse, and highlighted the need for greater use of sophisticated, empirically defined models, that can explain underlying behavioural trends. This also implies that food desert modelling which encompasses variables of allocation and affordability, but not preference, are missing a key component of the food system that influences consumer behaviours.

However, although attitude played a strong role in the statistical definition of consumer subgroups, it had little impact on the spatial pattern of visitation. The differences in attitudes between consumers was irrelevant for discerning behaviour at this level of analysis. This implied that consumers are either ignoring their attitudinal values, or acting upon them within stores, at a sub-catchment level. Thus, regulation and food access policies should be targeted at stores, and the influence of products, advertising, and choice behaviour interventions. Further research could be conducted on these topics improve understandings of consumer attitudes and food access.

In addition, the socio-spatial modelling methods used in this thesis could be applied to other geographic contexts to further investigate the social and spatial properties of food access. This study has demonstrated the benefits of a SIM for assessing other areas, including those previously labelled as food deserts, for the presence or absence of food jungles and retail chameleons. The successful use of a national geocoded address file dataset in this thesis also opens up the possibility for further research of this kind into other characteristics of consumerism, and social issues, such as transport, crime, and gambling. It is anticipated that the conclusions in this thesis will provide decision-support for food access planning in North Canberra into the future.

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# Appendix A: Metadata

Every dataset used in this thesis had associated metadata, summarised Table 15, 16, 17 and 18 below. A graphical explanation of the Australian Statistical Geographic Standard (ASGS) ABS data structures can be found in Figure 22.

**Table 15: PSMA G-NAF metadata**

| Field | Value |
|---|---|
| Title | PSMA Geocoded National Address File (G-NAF) |
| Type | Dataset |
| Language | English |
| Licence | Other (Open) |
| Data Status | Active |
| Update Frequency | Quarterly |
| Landing Page | https://data.gov.au/dataset/19432f89-dc3a-4ef3-b943-5326ef1dbecc |
| Date Published | 2016-02-22 |
| Date Updated | 2016-02-29 |
| Contact Point | Department of the Prime Minister and Cabinet<br>Phone: 02 6271 5111; Email: data@pmc.gov.au |
| Temporal Coverage | 2016-02-26 |
| Geospatial Coverage | "type": "Polygon", "coordinates": [[112.0, -44.0], [154.0, -44.0], [154.0, -9.0], [112.0, -9.0], [112.0, -44.0]] |
| Jurisdiction | Commonwealth of Australia |
| Data Portal | data.gov.au |
| Publisher/Agency | Department of the Prime Minister and Cabinet |
| Geospatial Topics | Transportation, Location |

**Table 16: ABS Mesh Block metadata**

<table>
<tr><th>Field</th><th>Value</th></tr>
<tr><td>Description</td><td>ABS Mesh Block</td></tr>
<tr><td>Geographic Extent</td><td>“Geographic Australia; including the external territories of Cocos (Keeling) Islands & Christmas Island but excluding all other external territories” (ABS, 2011).</td></tr>
<tr><td>File Attributes</td><td><table>
<tr><th>Field</th><th>Data type</th><th>Characters</th></tr>
<tr><td>Mesh Block ID</td><td>Numeric</td><td>11</td></tr>
<tr><td>Dwellings</td><td>Numeric</td><td>3</td></tr>
<tr><td>Persons usually resident</td><td>Numeric</td><td>5</td></tr>
</table></td></tr>
<tr><td>Data Currency</td><td>Data is current for Census Night, 9 August 2011</td></tr>
<tr><td>Dataset Status</td><td>Completed dataset</td></tr>
<tr><td>Maintenance and Update Frequency</td><td>No updates planned</td></tr>
<tr><td>Stored Data Format</td><td>Digital spreadsheet files</td></tr>
<tr><td>Available Format Type</td><td>Excel 2003 files (.xls)<br>CSV files (.csv)</td></tr>
<tr><td>Access Constraints</td><td>Copyright Commonwealth of Australia administered by the ABS</td></tr>
</table>

| | |
|---|---|
| Data quality | “Due to the small size of Mesh Blocks, data is confidentialised and is only released for basic dwelling counts and number of persons usually resident. Each state contains a single Mesh Block ID for No Usual Address. These have the following coding structure: <State Code>0000009499 For example, the NSW Mesh Block code for No Usual Address is 10000009499” (ABS, 2011). |
| Lineage | Mesh Block boundaries were created using PSMA and ABS datasets, and zoning information from state planning agencies. |

**Table 17: ABS SA1 metadata**

<table>
<tr><th>Field</th><th>Value</th></tr>
<tr><td>Title</td><td>Statistical Area Level 1 (SA1)</td></tr>
<tr><td>Custodian</td><td>Australian Bureau of Statistics (ABS)</td></tr>
<tr><td>Description</td><td>Digital Boundaries</td></tr>
<tr><td>File Attributes</td><td><table><tr><th>Field</th><th>Data type</th><th>Characters</th></tr><tr><td>Main code</td><td>Character</td><td>11</td></tr><tr><td>7 Digit Code</td><td>Character</td><td>28</td></tr></table></td></tr>
<tr><td>Data Currency</td><td>12 July 2016</td></tr>
<tr><td>Dataset Status</td><td>Completed dataset</td></tr>
<tr><td>Maintenance and Update Frequency</td><td>No updates planned</td></tr>
<tr><td>Stored Data Format</td><td>Digital boundary vector files</td></tr>
</table>

**Table 18: OpenStreetMap metadata**

| Field | Value |
|---|---|
| Title | OpenStreetMap |
| Language | English |
| Licence | Other (Open) |
| Data Status | Active |
| Custodian | © OpenStreetMap contributors |
| Landing Page | openstreetmap.org |
| Description | OpenStreetMap distributes free geographic data and is built by a community of contributors. Contributors use aerial imagery, GPS devices, and field maps to verify accuracy. |
| Stored Data Format | Online |

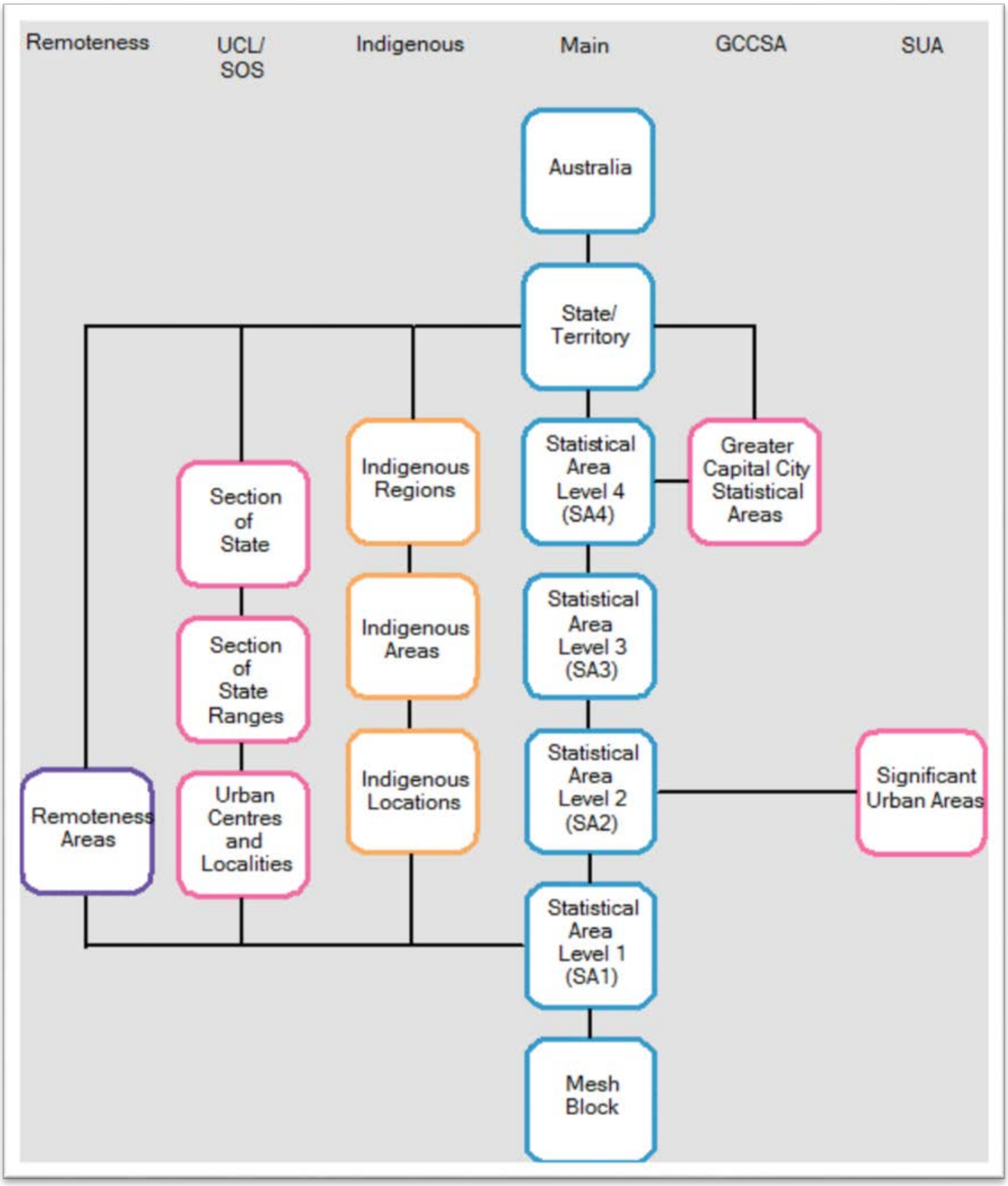


**Figure 22: Australian Statistical Geographic Standard (ASGS) ABS data structures (ABS, 2011).**

# Appendix B: Survey Material

All questionnaire material used to survey the random set of respondents in North Canberra is outlined in the following sections B.1 to B.4 below.

## B.1 Questionnaire Cover Letter

Australian National University

5088975

Canberra Food Study

4878 019
To the Resident
7/60 Boldrewood Street
TURNER ACT 2612

Dear Turner Resident,

This letter invites you to complete a **short questionnaire** (5 – 7 minutes) for the Canberra Food Study, a research project at The Australian National University.

The key aim is to learn more about the urban food system, and food purchasing behaviours of Canberrans. We would greatly appreciate a few minutes of your time to complete the enclosed questionnaire (front and back) and mail it to us within **a fortnight** in the enclosed reply-paid envelope.

If you have more than one person in your household, the **best person to fill it out is the adult who is most likely to do your grocery shopping each week**.

All information provided is **confidential**.

If you would like more information on the study please see the participant information sheet for more details.

Thank you on behalf of myself and my supervisors,

Brittany Dahl

Primary Investigator
Fenner School of Environment and Society, The Australian National University
Email: u5349586@anu.edu.au

Please return the questionnaire in the return mail envelope provided

## B.2 Participant Information Sheet

Australian National University

Canberra Food Study: Participant Information Sheet

Researcher:
Brittany Dahl, Fenner School of Environment and Society, The Australian National University

Project Title:
Role of store proximity in food purchasing behaviours

Project Description
This project aims to map the trade areas of stores and food outlets in Canberra, based on the food purchasing behaviours of different local consumers. This study aims to highlight differences in travel distance and outlet-choice, and inform policy for improving our urban food landscape.

Participants
In order to determine the food purchasing behaviours of consumers, questionnaires will be sent to selected households in Canberra.

Use of Data and Feedback
Results of this study will be published in a thesis, a scientific journal article and may be used for future research in the area of geographic information science. A summary of the research can be found on the website: https://canberrafoodstudy.wordpress.com/

Project Funding:
External funding will be provided by the project supervisor Dr. Bruce Doran. Bruce's contact details can be found at the end of this sheet.

Participant Involvement:
Voluntary Participation and Withdrawal:
Participation in this project is **voluntary,** and you may wish to decline to take part or withdraw from the project by not returning the questionnaire. Withdrawal is not possible once the survey has been returned as no names are collected. You may also refuse to answer any questions, and these empty responses will not be used in the research project.

Participation Requirements
To participate, please remove the questionnaire when completed and send back in the return mail envelope provided. Completing the questionnaire is estimated to take 5 –7 minutes of your time.

Risks
Most people find participating in research studies like this a positive experience. However, if you have any concerns or complaints about this research, you may contact the researcher or ethics manager using the contact details found at the end of this sheet.

Benefits
It is anticipated that this study will provide a better understanding of the spatial dynamics of the local food system and highlight areas of future improvement. This research is also anticipated to provide insights into the use of new modelling techniques, which may be further developed into the future.

Australian National University

## Confidentiality:

Confidentially during data collection and the publication of results will be protected as the law allows. Individuals will have no attribution or means of identification in the published materials. In addition, the only persons with access to the questionnaire data will be the primary investigator (Brittany Dahl) and project supervisor (Dr. Bruce Doran). In collecting your personal information within this research, the ANU must comply with the Privacy Act 1988. The ANU Privacy Policy is available at https://policies.anu.edu.au/ppl/document/ANUP_010007 and it contains information about how a person can:

- Access or seek correction to their personal information;
- Complain about a breach of an Australian Privacy Principle by ANU, and how ANU will handle the complaint.

## Data Storage:

All data will be stored and securely backed-up at the ANU. Data will be stored under password protection for one year after collection and one year following publications arising from the research. At the end of the storage period the data will be archived, and potentially used for future research projects in this field.

## Queries and Concerns:

More information?

If you have any questions or queries about any aspect of this study, please contact Brittany Dahl (02 6125 3250), or the project supervisor Bruce Doran (02 6125 0746). Our contact details appear below:

Brittany Dahl
Fenner School of Environment and Society
ANU College of Medicine, Biology & Environment
Geography Building #48a
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Acton ACT 2601
T: +61 2 61253250
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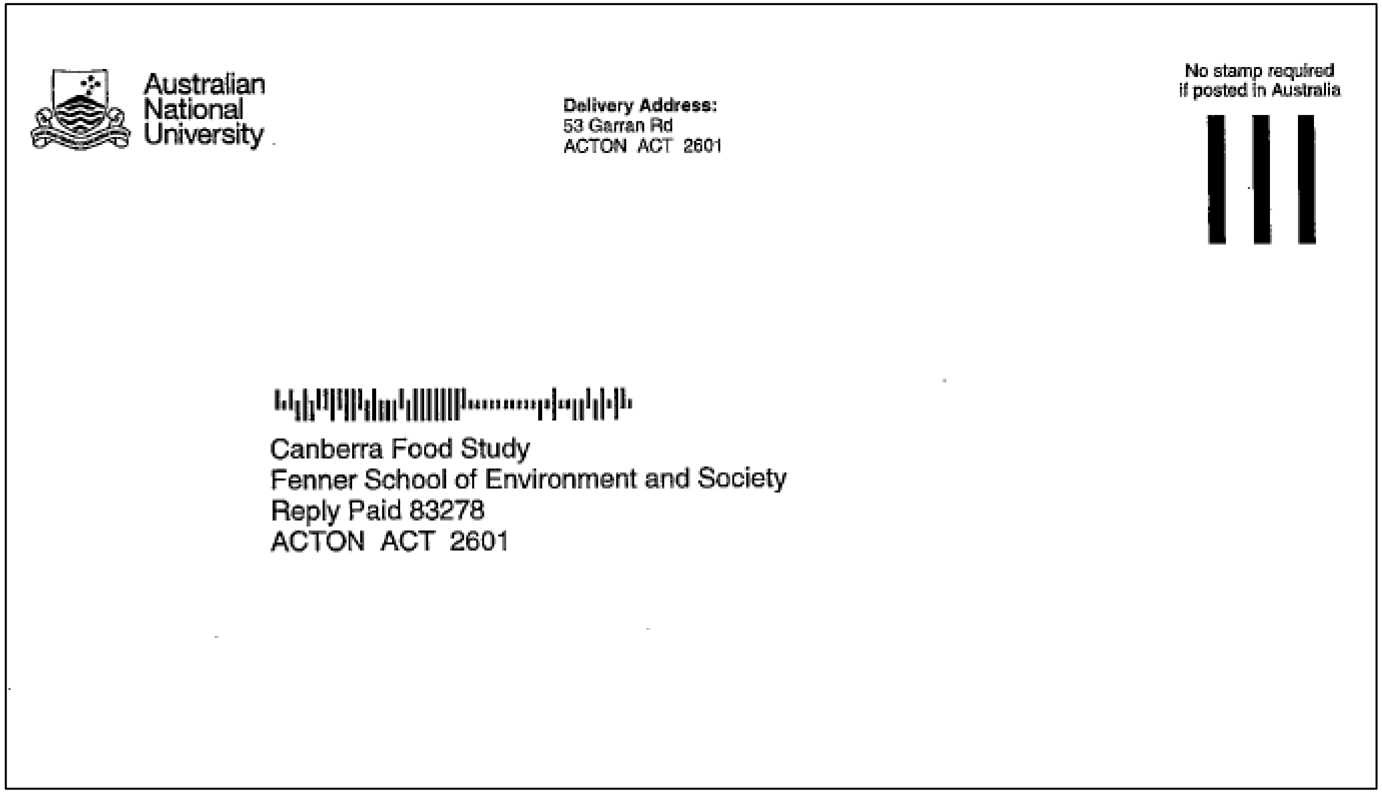
Dr Bruce Doran
Senior Lecturer in Geographic Information Systems
Fenner School of Environment and Society
ANU College of Medicine, Biology & Environment
Geography Building #48a
The Australian National University
Acton ACT 2601
T: +61 2 61253663
Email: Bruce.Doran@anu.edu.au

## Ethics Committee Clearance:

The ethical aspects of this research have been approved by the ANU Human Research Ethics Committee (Protocol 2016/078). If you have any concerns or complaints about how this research has been conducted, please contact:

Ethics Manager
The ANU Human Research Ethics Committee
The Australian National University
Telephone: +61 2 6125 3427
Email: Human.Ethics.Officer@anu.edu.au

## B.3 Reply-paid Envelope



Australian National University

**Delivery Address:**
53 Garran Rd
ACTON ACT 2601

No stamp required
if posted in Australia

Canberra Food Study
Fenner School of Environment and Society
Reply Paid 83278
ACTON ACT 2601

## B.4 Questionnaire

G-NAF Number

**1.** How long have you lived at your current Suburb address?

Years ________________ Months _______________

**2.** In the **last 14 days**, approximately how many times did you visit the following food and retail outlets? (Write the **number of visits** in **each** box. If you did not visit an outlet, please leave the box blank)

| | | |
|---|---|---|
| ☐ Dickson Woolworths | ☐ Watson Supabarn Express | ☐ Capital Region Farmer's Market, Exhibition Park (EPIC) |
| ☐ Dickson specialty stores* | ☐ Hackett IGA | ☐ Southside Farmers Market, CIT |
| ☐ Canberra Centre Supabarn | ☐ Ainslie IGA | ☐ Northside Farmer's Market, UC |
| ☐ Canberra Centre Aldi | ☐ O'Connor IGA | ☐ Bungendore Markets |
| ☐ Canberra Centre specialty stores* | ☐ Lyneham IGA | ☐ Hall Markets |
| ☐ East Row IGA X-Press | ☐ Campbell IGA | ☐ Choku Bai Jo, North Lyneham |
| ☐ Belconnen Fresh Food Markets | ☐ Fyshwick Fresh Food Markets | ☐ Choku Bai Jo, Curtin |
| ☐ Belconnen Woolworths | ☐ Gungahlin Aldi | ☐ Food Co-Op, ANU |
| ☐ Belconnen Coles | ☐ Gungahlin Woolworths | ☐ Majura Woolworths |
| ☐ Jamison Coles | ☐ Gungahlin Coles | ☐ Costco, Majura |
| ☐ Macquarie Aldi | ☐ Spar, Canberra City | ☐ Mountain Creek Wholefoods, Griffith |

☐ Other ____________________________________________________________

* Specialty stores are individual retailers that focus on a particular product, such as butchers or green grocers

**3.** In the **last 14 days**, how much money did you spend on food and groceries at different outlets?

$ __________ was spent at ________________________________________ store or outlet
$ __________ was spent at ________________________________________ store or outlet
$ __________ was spent at ________________________________________ store or outlet
$ __________ was spent at ________________________________________ store or outlet
$ __________ was spent at ________________________________________ store or outlet
$ __________ was spent at ________________________________________ store or outlet

**4.** In the **last 14 days**, approximately, how many people did you regularly shop for?

_________ **adults** (aged 16 years or more), _________ **children** (below the age of 16 years)

**5.** How **many** people usually live in your household, including you?

_________ **adults** (aged 16 or more), _________ **children** (below the age of 16 years)

PLEASE TURN OVER

**6.** Which year were you born?

___________________

**7.** Do you identify as: (please tick ✓ one)

❍ Male ❍ Female ❍ Other

**8.** Do you have ownership or access to a car? (please tick ✓ one)

❍ I have access to my own car ❍ I have access to a car, but not my own ❍ I have no access to a car

**9.** What is the highest level of education you have completed?

❍ Primary ❍ Secondary ❍ Technical ❍ University

**10.** What is your main employment status?

❍ Full Time employee ❍ Part time employee ❍ Self employed
❍ Student ❍ Retired / pensioner ❍ Unemployed

**11.** What is your usual main occupation?*

_______________________________________

*Please give a full title. For example: Childcare Aid, Maths Teacher, Pastry Cook. For public servants, provide official designation.

**12.** How much income does your **household** usually receive per week (before tax)?

❍ <$199 ❍ $400 - $799 ❍ $1,250 – $1,999
❍ $200 - $399 ❍ $800 - $1,249 ❍ > $2,000

**13.** On a **daily** basis, how many standard servings of the selected food groups do you consume?

_________ **vegetables** (a single serving is 75g, or ½ cup of cooked broccoli, carrots, or peas)
_________ **fruit** (a single serving is 150g, or one medium apple, banana, or orange)
_________ **lean meat** (a single serving is 65g cooked beef, or 80g poultry)

**14.** On a **daily** basis, it is important to me that the food I eat is: **(tick ✓ one circle only per row)**

| | Not at all important | A little important | Moderately important | Very important |
|---|---|---|---|---|
| Easy to prepare | ❍ | ❍ | ❍ | ❍ |
| Not expensive | ❍ | ❍ | ❍ | ❍ |
| Like the food I ate as a child | ❍ | ❍ | ❍ | ❍ |
| Produced in an animal friendly way | ❍ | ❍ | ❍ | ❍ |
| Traded in a fair way | ❍ | ❍ | ❍ | ❍ |
| Good value for money | ❍ | ❍ | ❍ | ❍ |
| Purchased from a community I want to support | ❍ | ❍ | ❍ | ❍ |
| Produced in an environmentally friendly way | ❍ | ❍ | ❍ | ❍ |
| What I usually eat | ❍ | ❍ | ❍ | ❍ |
| Purchased from a store that I enjoy spending time in | ❍ | ❍ | ❍ | ❍ |
| Ready to be cooked very quickly | ❍ | ❍ | ❍ | ❍ |
| Comes from a country I approve of politically | ❍ | ❍ | ❍ | ❍ |

**THANK YOU FOR YOUR PARTICIPATION**

# Appendix C: Ethics Approval

The research carried out in this thesis received approval by the chair of the ANU Human Ethics Committee on the 11th of April 2016 (see the associated email below).

Human Ethics Protocol 2016/078 Inbox x

**aries@anu.edu.au**
to u5349586, human.ethics.o., Bruce.Doran

THIS IS A SYSTEM-GENERATED E-MAIL. PLEASE DO NOT REPLY. SEE BELOW FOR E-MAIL CONTACT DETAILS.

Dear Ms Brittany Dahl,

Protocol: 2016/078
Role of store proximity in food purchasing behaviour

I am pleased to advise you that your Human Ethics application received approval by the Chair of the ANU HREC on 11/04/2016.

For your information:

1. Under the NHMRC/AVCC National Statement on Ethical Conduct in Human Research we are required to follow up research that we have approved. Once a year (or sooner for short projects) we shall request a brief report on any ethical issues which may have arisen during your research or whether it proceeded according to the plan outlined in the above protocol.

2. Please notify the committee of any changes to your protocol in the course of your research, and when you complete or cease working on the project.

3. Please notify the Committee immediately if any unforeseen events occur that might affect continued ethical acceptability of the research work.

4. Please advise the HREC if you receive any complaints about the research work.

5. The validity of the current approval is five years' maximum from the date shown approved. For longer projects you are required to seek renewed approval from the Committee.

All the best with your research,

Human Ethics Officer
Research Integrity & Compliance
Research Services Division
Level 2, Birch Building 36
Science Road, ANU
The Australian National University
Acton ACT 2601

T: 6125-3427
E: human.ethics.officer@anu.edu.au
W: https://services.anu.edu.au/research-support/ethics-integrity

# Appendix D: Coding Guidelines

An independent coder was given guidelines to strive for consistency between coders, and additional information to familiarise with the dataset (see Table 18, 19 and 20).

### Table 19: Coding instructions

| Question | Instruction |
|---|---|
| G-NAF ID | Find the G-NAF ID from the top of the questionnaire in the Excel database |
| Q 1 | Input the years and months as separate numbers |
| Q 2 | Type in the number for each of the retailers visited. Any 'X' are counted as '1'. Do not insert blanks as '0'. Leave all blanks, they are to be filled in as 'N/A' during data processing |
| Q 3 | Type in $ for each retailer visited |
| Q 4 | Input the adults and children as separate numbers |
| Q 5 | Input the adults and children as separate numbers |
| Q 6 | Type in the number |
| Q 7 | Type in the associated abbreviation |
| Q 8 | Type in the associated abbreviation |
| Q 9 | Type in the associated abbreviation |
| Q 10 | Type in the associated abbreviation |
| Q 11 | Type in the written occupation. This will be coded to ABS standards during data processing. |
| Q 12 | Type in the associated abbreviation |
| Q 13 | Type in the associated abbreviation |
| Q 14 | Type in the associated abbreviation |

| **In addition:** | |
|---|---|
| - | Note time and date response was received (written on front of envelope) |
| - | Note time and date of entry, and add your name |

### Table 20: Coding abbreviations

| Question Number | Variable | |
|---|---|---|
| **Q 1** | Length of Time in Years and Months | |
| **Q 2** | Number of Visits (#) to retailers | |
| | **Abbreviation** | **Stores** |
| | **DW** | Dickson Woolworths |
| | **DSS** | Dickson specialty stores |
| | **CSUP** | Canberra Centre Supabarn |
| | **CA** | Canberra Centre Aldi |
| | **CSS** | Canberra Centre specialty stores |
| | **ER_IGA** | East Row IGA X-Press |
| | **BFFM** | Belconnen Fresh Food Markets |
| | **BW** | Belconnen Woolworths |
| | **BC** | Belconnen Coles |
| | **JC** | Jamison Coles |
| | **MA** | Macquarie Aldi |
| | **WS** | Watson Supabarn Express |
| | **HIGA** | Hackett IGA |
| | **AIGA** | Ainslie IGA |
| | **OIGA** | O'Connor IGA |

| | | |
|---|---|---|
| | **LIGA** | Lyneham IGA |
| | **CIGA** | Campbell IGA |
| | **FFFM** | Fyshwick Fresh Food Markets |
| | **GA** | Gungahlin Aldi |
| | **GW** | Gungahlin Woolworths |
| | **GC** | Gungahlin Coles |
| | **SCC** | Spar, Canberra City |
| | **CRFM** | Capital Region Farmer's Market, Exhibition Park (EPIC) |
| | **SFM** | Southside Farmers Market, CIT |
| | **NFM** | Northside Farmer's Market, UC |
| | **BUFM** | Southern Harvest Farmers Market in Bungendore |
| | **HM** | Hall Markets |
| | **CBJNL** | Choku Bai Jo, North Lyneham |
| | **CBJC** | Choku Bai Jo, Curtin |
| | **FCOP** | The Food Co-Op, ANU |
| | **MW** | Majura Woolworths |
| | **C** | Costco, Majura |
| | **MCWG** | Mountain Creek Wholefoods, Griffith |
| | | Other |
| **Q 3** | Expenditure at Retailer ($) – same as above | |
| **Q 4** | Number of People (Adults and Children) | |
| **Q 5** | Number of People (Adults and Children) | |
| **Q 6** | Year of Birth | |
| **Q 7** | Gender | |
| | **Abbreviation** | **Gender** |
| | **M** | Male |
| | **F** | Female |
| | **O** | Other |
| **Q 8** | Car Accessibility | |
| | **Abbreviation** | **Car Access** |
| | **Y** | I have access to my own car |
| | **O** | I have access to a car, but not my own |
| | **N** | I have no access to a car |
| **Q 9** | Education Level | |
| | **Abbreviation** | **Education** |
| | **P** | Primary |
| | **S** | Secondary |
| | **T** | Technical |
| | **U** | University |
| **Q 10** | Employment Level | |
| | **Abbreviation** | **Employment** |
| | **F** | Full Time Employee |
| | **P** | Part Time Employee |
| | **SE** | Self Employed |
| | **ST** | Student |
| | **R** | Retired / Pensioner |
| | **U** | Unemployed |
| **Q 11** | Occupation (written in text) | |
| **Q 12** | Household Income Bracket | |
| | **Abbreviation** | **Income** |
| | **1** | <$199 |
| | **2** | $200 - 399 |
| | **3** | $400 - 799 |

| | | |
|---|---|---|
| | 4 | \$800 - \$1,249 |
| | 5 | \$1,250 - \$1,999 |
| | 6 | > \$2,000 |
| **Q 13** | Serving Size (number) | |
| **Q 14** | Food Choice Motivation | |

| Abbreviation | Food Choice Variable |
|---|---|
| **Q14_EASY** | Easy to prepare |
| **Q14_EXPE** | Not expensive |
| **Q14_CHILD** | Like the food I ate as a child |
| **Q14_ANIMAL** | Produced in an animal friendly way |
| **Q14_FAIR** | Traded in a fair way |
| **Q14_VALUE** | Good value for money |
| **Q14_COMM** | Purchased from a community I want to support |
| **Q14_ENV** | Produced in an environmentally friendly way |
| **Q14_USUAL** | What I usually eat |
| **Q14_ENJOY** | Purchased from a store that I enjoy spending time in |
| **Q14_QUICK** | Ready to be cooked very quickly |
| **Q14_POLIT** | Comes from a country I approve of politically |

**Likert Scale:**

| 1 | 2 | 3 | 4 |
|---|---|---|---|
| Not at all important | A little important | Moderately important | Very important |

**Table 21: Description of survey questions and associated literature sources.**

| Question Descriptions | Literature Source | Use |
|---|---|---|
| **Retailer Visitation** Respondents were asked about their visitation behaviours to major food retailers in the study area (Q2). The design of this question was based on previous research using G-NAF surveys. | Markham *et al.* (2013) | Variable to be used for understanding the visitation behaviour of the respondents, and generating a origin-destination matrix. |
| **Food Expenditure** Respondents were asked about the amount spend at visited major food retailers (Q3). The design of this question was based on previous research using G-NAF surveys. | Markham *et al.* (2013) | Variable to be used for understanding the purchasing behaviour of the respondents. |
| **Food Choice Motivations** The importance of typical food characteristics was determined through a shortened and modified Food Choice Questionnaire (Q14). | Steptoe *et al.* (1995) Fotopoulos *et al.* (2009) Lindeman and Väänänen (2000) | Variables to be used in the hybrid factor-cluster analysis. |
| **Nutrition** Respondents were asked about their average consumption of vegetables, fruit, and lean meat (Q13). | Townsend *et al.* (2003) Thompson and Subar (2008) | Variable to be used for understanding consumption behaviour, and for further research. |
| **Socio-demographics** Questions were used to determine household characteristics (length of stay at household, number of people in household number of people regularly shopped for; Q1, Q4, Q5), year of birth (Q6), gender (Q7), income (Q12), education (Q9), occupation (Q11), employment (Q10), and car access and ownership (Q8). | Caspi *et al.* (2012) ABS (2013) Dubowitz *et al.* (2015) | Variables to be used in the hybrid factor-cluster analysis. |

# Appendix E: Manually Geocoded Food Retailers

Co-ordinate pairs were collected for each Major Food Retailer in the study area (see Table 21).

**Table 22: List of geocoded major food retailers (sourced manually and from Martin, 2009).**

| Description | Centre Area | Suburb | Floor Area ($m^2$) | Centre Type | X | Y |
|---|---|---|---|---|---|---|
| GROCERIES | ANU | Acton | 56 | Other centre | 149.1166 | -35.2845 |
| FOOD CO-OP | ANU | Acton | n/a | Other centre | 149.1251 | -35.276 |
| SUPERMARKET IGA | Ainslie | Ainslie | 1200 | Local Centre | 149.1451 | -35.2621 |
| SUPERMARKET WOOLWORTHS | Belconnen | Belconnen | 4820 | Town Centre | 149.0646 | -35.2386 |
| SUPERMARKET COLES | Belconnen | Belconnen | 3460 | Town Centre | 149.0641 | -35.2379 |
| FARMER'S MARKET | University of Canberra | Belconnen | n/a | Other centre | 149.085 | -35.2374 |
| FRESH FOOD MARKETS | Belconnen | Belconnen | n/a | Town Centre | 149.0653 | -35.2459 |
| SUPERMARKET 5 STAR | Braddon | Braddon | 130 | Local Centre | 149.1327 | -35.2641 |
| SUPERMARKET IGA X-PRESS | Campbell | Campbell | 280 | Local Centre | 149.1539 | -35.2896 |
| SUPERMARKET SUPABARN | Civic | City | 3700 | Town Centre | 149.134 | -35.2782 |
| SUPERMARKET IGA X-PRESS | Civic - East Row | City | 401 | Town Centre | 149.1306 | -35.2793 |
| ASIAN GROCERIES | Civic | City | 44 | Town Centre | 149.1254 | -35.2769 |
| SPECIALTY STORES | Civic | City | 176 | Town Centre | 149.1334 | -35.2785 |
| ALDI | Civic | City | 50 | Town Centre | 149.1344 | -35.2791 |
| SUPERMARKET SPAR | Civic - West | City | 472 | Town Centre | 149.1255 | -35.2788 |
| CHOKU BAI JO | Curtin | Curtin | n/a | Group Centre | 149.0821 | -35.3249 |
| SUPERMARKET WOOLWORTHS | Dickson | Dickson | 3055 | Group Centre | 149.1385 | -35.2501 |
| ASIAN GROCERIES | Dickson | Dickson | 94 | GC (Service Trades) | 149.1368 | -35.2516 |
| ASIAN GROCERIES | Dickson | Dickson | 40 | GC (Service Trades) | 149.1363 | -35.2504 |
| SPECIALTY STORES | Dickson | Dickson | 170 | GC (Service Trades) | 149.1374 | -35.2507 |
| FRESH FOOD MARKETS | Fyshwick | Fyshwick | n/a | Industrial area | 149.1547 | -35.3243 |
| MOUNTAIN CREEK WHOLEFOODS | Griffith | Griffith | n/a | Local Centre | 149.1424 | -35.3279 |
| SUPERMARKET WOOLWORTHS | Gungahlin Core | Gungahlin | 4583 | Town Centre | 149.1339 | -35.1847 |

| | | | | | | |
|---|---|---|---|---|---|---|
| SUPERMARKET COLES | Gungahlin | Gungahlin | 3706 | Town Centre | 149.1358 | -35.1863 |
| ALDI | Gungahlin | Gungahlin | 1326 | Town Centre | 149.1357 | -35.1854 |
| SUPERMARKET IGA | Hackett | Hackett | 887 | Local Centre | 149.1626 | -35.2482 |
| SUPERMARKET IGA | Lyneham | Lyneham | 559 | Local Centre | 149.1248 | -35.2522 |
| CHOKU BAI JO | North Lyneham | Lyneham | n/a | Local Centre | 149.1247 | -35.2402 |
| SUPERMARKET COLES | Jamison | Macquarie | 4350 | Group Centre | 149.0712 | -35.2528 |
| ALDI | Jamison | Macquarie | 1360 | Group Centre | 149.0707 | -35.2528 |
| COSTCO | Majura | Majura | n/a | Industrial area | 149.1901 | -35.2975 |
| SUPERMARKET WOOLWORTHS | Majura | Majura | n/a | Industrial area | 149.191 | -35.2986 |
| FARMER'S MARKET | Exhibition Park | Mitchell | n/a | Other centre | 149.1511 | -35.2296 |
| SUPERMARKET IGA | O'Connor | O'Connor | 385 | Local Centre | 149.1222 | -35.2641 |
| FARMER'S MARKET | CIT | Phillip | n/a | Other centre | 149.0966 | -35.3488 |
| SUPERMARKET SUPERBARN EXPRESS | Watson | Watson | 338 | Local Centre | 149.1534 | -35.2389 |

# Appendix F: R Commands

```
# Script Name: Honours Thesis Data Analysis in R
# Author: Brittany Dahl
# Email: u5349586@anu.edu.au
# Version: 0.3
# Date: 18.09.2016
# Acknowledgements: The production of this code was supported by
   Francis Markham. Part 2 adapted from "spintr" (spatial interaction
   models in r), copyright Francis Markham. For package citations see
   Appendix I.
# Notes: This script was created for the statistical analysis of data
   collected for the Honours Thesis of Brittany Dahl, with the help and
   support of Francis Markham.


###### PART 1 - Statistical Modelling ######

#### PREPARATION #### [Step 1]
# Set up project in Rstudio. Set up workspace.
setwd("C:/UserData/dahlb/Rstudio/Exploratory Data Analysis")

# Download and Install Packages (listed in order of use)
install.packages("ggplot2")
install.packages("car")
install.packages("Hmisc")
install.packages("psych")
install.packages("nFactors")
install.packages("clustrd")
install.packages("GPArotation")
install.packages("NbClust")
install.packages("factoextra")
install.packages("cluster")
install.packages("RColorBrewer")

# Load Packages
library(ggplot2)
library(car)
library(Hmisc)
library(psych)
library(nFactors)
library(clustrd)
library(GPArotation)
library(NbClust)
library(factoextra)
library(cluster)
library(RColorBrewer)

# Load Raw Data
survey2 <- read.csv("data.4.7.csv")

# View Raw Data
View(survey2)
summary(survey2)
describe(survey2) # This outlines: n, nmiss, unique, mean,
 5,10,25,50,75,90,95th percentiles
                   # and the 5 lowest and 5 highest scores

#### EXPLORATORY ANALYSIS #### [Step 2]
# Inspect Attitudinal Data - plot each of the FCQ responses against
 each other for comparison.

ggplot(data=survey2, aes(x=Q14_EXPE, y=Q14_EASY)) +
  geom_jitter(width=0.5, height=0.5) + stat_smooth(method="lm",
 colour="blue") +
  stat_smooth(method="loess", colour="red")

ggplot(data=survey2, aes(x=Q14_EXPE, y=Q14_QUICK)) +
  geom_jitter(width=0.5, height=0.5) + stat_smooth(method="lm")

ggplot(data=survey2, aes(x=Q14_EXPE, y=Q14_USUAL)) +
```

```
  geom_jitter(width=0.5, height=0.5) + stat_smooth(method="lm")

ggplot(data=survey2, aes(x=Q14_EASY, y=Q14_USUAL)) +
  geom_jitter(width=0.5, height=0.5) + stat_smooth(method="lm")

ggplot(data=survey2, aes(x=Q14_EASY, y=Q14_QUICK)) +
  geom_jitter(width=0.5, height=0.5) + stat_smooth(method="lm")

ggplot(data=survey2, aes(x=Q14_ANIMAL, y=Q14_ENV)) +
  geom_jitter(width=0.5, height=0.5) + stat_smooth(method="lm")

ggplot(data=survey2, aes(x=Q14_COMM, y=Q14_ENJOY)) +
  geom_jitter(width=0.5, height=0.5) + stat_smooth(method="lm")

ggplot(data=survey2, aes(x=Q14_ENV, y=Q14_ENJOY)) +
  geom_jitter(width=0.5, height=0.5) + stat_smooth(method="lm")

ggplot(data=survey2, aes(x=Q14_ENV, y=Q14_FAIR)) +
  geom_jitter(width=0.5, height=0.5) + stat_smooth(method="lm")

ggplot(data=survey2, aes(x=Q14_FAIR, y=Q14_VALUE)) +
  geom_jitter(width=0.5, height=0.5) + stat_smooth(method="lm")

ggplot(data=survey2, aes(x=Q14_EXPE, y=Q14_VALUE)) +
  geom_jitter(width=0.5, height=0.5) + stat_smooth(method="lm")

ggplot(data=survey2, aes(x=Q14_EASY, y=Q14_VALUE)) +
  geom_jitter(width=0.5, height=0.5) + stat_smooth(method="lm")

ggplot(data=survey2, aes(x=Q14_COMM, y=Q14_ENV)) +
  geom_jitter(width=0.5, height=0.5) + stat_smooth(method="lm")

ggplot(data=survey2, aes(x=Q14_COMM, y=Q14_ANIMAL)) +
  geom_jitter(width=0.5, height=0.5) + stat_smooth(method="lm")

ggplot(data=survey2, aes(x=Q14_ENV, y=Q14_POLIT)) +
  geom_jitter(width=0.5, height=0.5) + stat_smooth(method="lm")

ggplot(data=survey2, aes(x=Q14_ANIMAL, y=Q14_POLIT)) +
  geom_jitter(width=0.5, height=0.5) + stat_smooth(method="lm")

ggplot(data=survey2, aes(x=Q14_EASY, y=Q14_CHILD)) +
  geom_jitter(width=0.5, height=0.5) + stat_smooth(method="lm")

ggplot(data=survey2, aes(x=Q14_EXPE, y=Q14_CHILD)) +
  geom_jitter(width=0.5, height=0.5) + stat_smooth(method="lm")

# Visually Inspect - all attitudinal variables using Scatterplot
 Matrices from the Car Package
scatterplot.matrix(~Q14_EASY+Q14_EXPE+Q14_CHILD+Q14_ANIMAL+Q14_FAIR+Q1
 4_VALUE+Q14_COMM+
                     Q14_ENV+Q14_USUAL+Q14_ENJOY+Q14_QUICK+Q14_POLIT,
 data=survey2, main="Attitudes to Food")
    # Result: Best Correlations - 1. ENV, ANIMAL, COMM AND POLIT. ALSO
 FAIR. - 2. EASY, EXPE, QUICK, AND VALUE.

# Save FCQ Variables
survey2_Q14 <- survey2[,names(survey2)[grep("Q14_", names(survey2))]]
write.csv(cor(survey2_Q14, use = "pairwise.complete.obs"),
 "quick_correlation_matrix.csv")


#### FACTOR ANALYSIS #### [Step 3]

#### 3.1 PREPARE VARIABLES ####
# No changes to the FCQ variables
# Changes needed for the SES variables.

## SES Variables: 1, 2, 3, 4, & 5 ##

# 1. Car access (no access to car as a dummy variable)
survey2$Q8_NOCAR_DUMMY <- ifelse(survey2$Q8_CAR == "N", 1, 0)
```

```
survey2$Q8_NOCAR_DUMMY <- ifelse(survey2$Q8_CAR == "", NA,
 survey2$Q8_NOCAR_DUMMY)

# Check results
table(survey2$Q8_CAR, survey2$Q8_NOCAR_DUMMY)

# 2. Unemployment (as a dummy variable)
survey2$Q10_UNEMPL_DUMMY <- ifelse(survey2$Q10_EMPL == "U", 1, 0)
survey2$Q10_UNEMPL_DUMMY <- ifelse(survey2$Q10_EMPL == "", NA,
 survey2$Q10_UNEMPL_DUMMY)

# Check Results
table(survey2$Q10_EMPL, survey2$Q10_UNEMPL_DUMMY)
summary(survey2$Q10_EMPL)
summary(survey2$Q10_UNEMPL_DUMMY)

# 3. Income
# Change questionnaire income groups into income mid-points
survey2$Q12_INC_MID <- ifelse(survey2$Q12_INC == 1, 100,
 survey2$Q12_INC)
survey2$Q12_INC_MID <- ifelse(survey2$Q12_INC == 2, 300,
 survey2$Q12_INC_MID)
survey2$Q12_INC_MID <- ifelse(survey2$Q12_INC == 3, 600,
 survey2$Q12_INC_MID)
survey2$Q12_INC_MID <- ifelse(survey2$Q12_INC == 4, 1025,
 survey2$Q12_INC_MID)
survey2$Q12_INC_MID <- ifelse(survey2$Q12_INC == 5, 1625,
 survey2$Q12_INC_MID)
survey2$Q12_INC_MID <- ifelse(survey2$Q12_INC == 6, (1.42 * 2000) /
 (1.42 - 1), survey2$Q12_INC_MID)

# For income group 6 (only unbracketed group): Following Measham and
 Fleming (2015) in Aust. Geographer, use a pareto distribution
 following the 70/30 rule to impute a mean for this bracket (hence the
 a = 1.42 parameter), right_mean.2000 <- (1.42 * 2000) / (1.42 - 1)

# Check results
table(survey2$Q12_INC, survey2$Q12_INC_MID)

# Calculate Equivalised Household Income (EHI)

# STEP 1 - Calculate Household Size:
  # Equivalised household income is derived by calculating an
 equivalence factor according to the 'modified OECD' equivalence
 scale, and then dividing income by the factor. The equivalence factor
 is built up by allocating points to each person in a household (1
 point to the first adult, 0.5 points to each additional person who is
 15 years and over, and 0.3 to each child under the age of 15) and
 then summing the equivalence points of all household members.
 #http://www.abs.gov.au/ausstats/abs@.nsf/0/A390E2529EC00DFECA25720A00
 76F6C6?opendocument

# Remove 0 adult households
survey2$Q5_ADULT <- ifelse(survey2$Q5_ADULT == 0, NA,
 survey2$Q5_ADULT)

# Household size
survey2$Q5_HOUSE_EQUIV <- (survey2$Q5_ADULT * 0.5 + 0.5) +
 (survey2$Q5_CHILD * 0.3)

# STEP 2 - Combine with income to make EHI:
survey2$Q12_HH_EQU_INC <- survey2$Q12_INC_MID / survey2$Q5_HOUSE_EQUIV
summary(survey2$Q12_HH_EQU_INC)

# 4. Education
survey2$Q9_EDU_U_DUMMY <- ifelse(survey2$Q9_EDU == "U", 1, 0)
survey2$Q9_EDU_U_DUMMY[survey2$Q9_EDU == ""] <- NA

# 5. Occupation

# Identify working class occupations
summary(survey2$Occup_Code)
```

```
survey2$Q11_blue_collar <- ifelse((survey2$Occup_Code %/% 100000) %in%
 c(3, 4, 6, 7, 8), 1, 0)
survey2$Q11_blue_collar <- ifelse(is.na(survey2$Occup_Code), NA,
 survey2$Q11_blue_collar)


#### 3.2 MEASURE INTERCORRELATION ####

# Save SES and FCQ variables as 'factor analysis variables' (fav)
survey2_fav <- survey2[,c("Q11_blue_collar", "Q9_EDU_U_DUMMY",
 "Q12_HH_EQU_INC", "Q10_UNEMPL_DUMMY", "Q8_NOCAR_DUMMY",
                          names(survey2)[grep("Q14_",
 names(survey2))])]
survey2$fav_na <- apply(is.na(survey2_fav), 1, any)     # Remove N/As

# Calculate Bartlett test of sphericity
r <- cor(survey2_fav, use = "pairwise.complete.obs")
cortest.bartlett(r, n = nrow(survey2_fav))

# Calculate Measure of Sampling Adequacy (KMO index)
KMO(r)

### 3.3 [TEST] PRINCIPLE COMPONENT ANALYSIS ####
# Use to look at both variables (FCQ and SES)

survey2_pca <- prcomp(na.omit(survey2_fav),
                      center = TRUE,
                      scale. = TRUE)
summary(survey2_pca)
print(survey2_pca)

# Determine Number of Factors to Extract:
ev <- eigen(r) # Get eigenvalues
ap <- parallel(subject=nrow(survey2_fav),var=ncol(survey2_fav),
               rep=100,cent=.05)
nS <- nScree(x=ev$values, aparallel=ap$eigen$qevpea)
plotnScree(nS)
    # Results:
      # Scree plot suggestions 3 or 5 factors
      # Eigen value method suggestions 5 factors
           # Proportions of variance up to 60% (Hair et al.
      recommendation) was 6 factors
      # Parallel analysis gives 4. This seems to be the best method
      according to: Kaplan, D. (2004).
ncomp <- 4   # 4 was chosen as most appropriate


## ROTATION ##
  # Choose orthogonal rotation so variables are uncorrelated.
  # This makes it easier to interpret, and helpful for the next step
 of cluster analysis, because multicollinearity is a problem for
 cluster analysis.
  # VARIMAX was used as Hair et al. suggested it gives clearer
 separation and consistency (Kaiser) than competing orthogonal
 rotating methods.

rawLoadings     <- survey2_pca$rotation[,1:ncomp] %*%
 diag(survey2_pca$sdev, ncomp, ncomp)
rotatedLoadings <- varimax(rawLoadings)$loadings
invLoadings     <- t(pracma::pinv(rotatedLoadings))
scores          <- as.data.frame(scale(survey2_fav) %*% invLoadings)
names(scores) <- c("care", "convenience", "affordability.ses",
 "tradition")
print(scores)                   # Scores computed via rotated loadings

# PLOT ROTATED VARIABLES
ggplot(data=scores, aes(x=care, y=convenience)) +
  geom_jitter(width=0.5, height=0.5) + stat_smooth(method="lm",
 colour="blue") +
  stat_smooth(method="loess", colour="red")
```

```
### 3.4 [TEST] CLUSTER ANALYSIS ###
  # REDUCED K-MEANS
  survey2_fav_clus.rkm <- ReducedKM(na.omit(survey2_fav), 4,6, nstart
 = 100, smartStart = FALSE)
  str(survey2_fav_clus)
  (survey2_fav_clus.rkm.rotatedLoadings <-
 varimax(survey2_fav_clus.rkm$attcoord)$loadings)
  survey2_fav_clus.fkm <- FactorialKM(na.omit(survey2_fav), 4, ncomp,
 nstart = 100, smartStart = FALSE)
    # Results did not find good cluster solutions – try with separate
 variables and alternative approach!


#### 3.5 SEPERATE FACTOR ANALYSIS (for FCQ & SES) ####
survey2_ses <- survey2[!survey2$fav_na,c("Q11_blue_collar",
 "Q9_EDU_U_DUMMY", "Q12_HH_EQU_INC", "Q10_UNEMPL_DUMMY",
 "Q8_NOCAR_DUMMY")]
survey2_fcq <- survey2[!survey2$fav_na,names(survey2)[grep("Q14_",
 names(survey2))]]

## 1. FCQ ##
# Determine Number of Factors to Extract
r <- cor(na.omit(survey2_fcq))
ev <- eigen(r) # Get eigenvalues
ap <- parallel(subject=nrow(survey2_fcq),var=ncol(survey2_fcq),
               rep=100,cent=.05)
nS <- nScree(x=ev$values, aparallel=ap$eigen$qevpea)
plotnScree(nS)
ncomp1 <- 3

# FCQ Factor Analysis with rotation
survey2_fa_fcq <- fa(na.omit(survey2_fcq), nfactors = 3, rotate =
 "oblimin", scores="tenBerge",  max.iter = 5000)
print(survey2_fa_fcq)


## 2. SES ##
# Determine Number of Factors to Extract
r <- cor(na.omit(survey2_ses))
ev <- eigen(r) # Get eigenvalues
ap <- parallel(subject=nrow(survey2_ses),var=ncol(survey2_ses),
               rep=100,cent=.05)
nS <- nScree(x=ev$values, aparallel=ap$eigen$qevpea)
plotnScree(nS)
ncomp2 <- 1

# SES Factor Analysis with rotation
survey2_fa_ses <- fa(na.omit(survey2_ses), nfactors = 1, rotate =
 "oblimin", scores="tenBerge",  max.iter = 5000)
print(survey2_fa_ses)

#### 3.6 RESULTS ####
# Save factor scores back into original data set

# Identify omitted NA rows
survey3 <- survey2[!survey2$fav_na,]

# Extract SES factor scores into new data frame
survey2_ses_scores <- data.frame(survey2_fa_ses$scores)
names(survey2_ses_scores) <- "FA_SES"

# Repeat for FCQ
survey2_fcq_scores <- as.data.frame(survey2_fa_fcq$scores)
names(survey2_fcq_scores) <- c("Q14_FA_CARE", "Q14_FA_CONV",
 "Q14_FA_COST")

# Attach to the full data frame
survey3 <- cbind(survey3, survey2_ses_scores, survey2_fcq_scores)

# Prepare Data for clustering
survey3_clus <- survey3[,c("FA_SES", "Q14_FA_CARE", "Q14_FA_CONV",
 "Q14_FA_COST")]
```

```
  # No need to standardise variables (as you would normally) because
 factor scores have a mean of 0 and standard deviation of 1 already


#### CLUSTER ANALYSIS #### [Step 4]

# Multiple clustering methods were tested to determine that the
 "complete" and "Euclidean" distance were most appropriate for this
 analysis

# Establish optimal number of clusters
# Compute the number of clusters:
nb <- NbClust(survey3_clus, distance = "euclidean", min.nc = 2,
              max.nc = 10, method = "complete", index ="all")

# Visualize the result
fviz_nbclust(nb) + theme_minimal() # using complete and Euclidean, 5
 clusters is best


### 4.1 HYBRID APPROACH ###

# Hierarchical clustering for 5 clusters, with complete and Euclidean
res.hc <- eclust(survey3_clus, "hclust", k = 5,
                 hc_method = "complete", graph = TRUE)
# Plot Dendrogram
fviz_dend(res.hc, rect = TRUE, show_labels = FALSE)
grp <- res.hc$cluster

# Compute cluster centers
clus.centers <- aggregate(survey3_clus, list(grp), mean)
clus.centers

# Remove the first column
clus.centers <- clus.centers[, -1]
clus.centers

# Use cluster centres in k-means clustering (combination approach)
km.res2 <- eclust(survey3_clus, "kmeans", k = clus.centers, graph =
 TRUE)
fviz_silhouette(km.res2)
km.res2

# Create silhouette coefficient of observations
sil <- silhouette(km.res2$cluster, dist(survey3_clus))
head(sil[, 1:3], 10)

# Silhouette plot
plot(sil, main ="Silhouette plot - K-means", col=
 c("red","blue","green","purple","orange"), border=NA)

# Compare results of hybrid approach:
  # res.hc$cluster: Initial clusters defined using hierarchical
 clustering
  # km.res2$cluster: Final clusters defined using k-means
table(km.res2$cluster, res.hc$cluster)

# k-means group number of each observation
km.res2$cluster

# Visualise k-means clusters
fviz_cluster(km.res2, geom = "point", frame.type = "norm")+
  scale_color_brewer(palette = "Set2")+
  scale_fill_brewer(palette = "Set2") +
  theme_minimal()

# Visualise differences in dendrogram
fviz_dend(res.hc, k = 5,
          k_colors = c("blue", "green3", "red", "black", "yellow"),
          label_cols =  km.res2$cluster[res.hc$order], cex = 0.6)

# Save results from hybrid analysis
```

```
survey3$cluster <- factor(letters[km.res2$cluster])
x <- km.res2$cluster
write.csv(survey3, file= "hybridcluster.csv")



### 4.2 CLUSTER RESULTS ###

# Display final hybrid clusters:
# Plot 4 dimensional results in 2 dimensions using ggplot2, comparing
 each factor against each other
  # Key:
    # n = Factor x Factor

    # p = Convenience x Care
    # Q = SES x Cost
    # R = SES x Care
    # S = Cost x Convenience
    # U = SES x Convenience
    # V = cost x Care

# Plot as polygons    #
 http://docs.ggplot2.org/current/stat_ellipse.html
p <- ggplot(data=survey3, aes(x=Q14_FA_CONV, y=Q14_FA_CARE,
 colour=cluster, fill=cluster)) +
  geom_point() +
  stat_ellipse(geom = "polygon", alpha=0.2) +
  scale_x_continuous(limits=c(-2.8, 2.8), name="Standardised
 Convenience Factor Scores") +
  scale_y_continuous(limits=c(-2.8, 2.8), name="Standardised Care
 Factor Scores") +
  scale_fill_brewer(palette = "Set1") +
  scale_colour_brewer(palette = "Set1") +
  theme_minimal()
print(p)
ggsave(filename = "care_conv_scatter1.png", width = 5, height = 5,
 units = "cm", dpi = 600, scale = 2.5)

Q <- ggplot(data=survey3, aes(x=FA_SES, y=Q14_FA_COST, colour=cluster,
 fill=cluster)) +
  geom_point() +
  stat_ellipse(geom = "polygon", alpha=0.2) +
  scale_x_continuous(limits=c(-2.8, 2.8), name="Standardised SES
 Factor Scores") +
  scale_y_continuous(limits=c(-2.8, 2.8), name="Standardised Cost
 Factor Scores") +
  scale_fill_brewer(palette = "Set1") +
  scale_colour_brewer(palette = "Set1") +
  theme_minimal()
print(Q)
ggsave(filename = "ses_cost_scatter1.png", width = 5, height = 5,
 units = "cm", dpi = 600, scale = 2.5)

R <- ggplot(data=survey3, aes(x=FA_SES, y=Q14_FA_CARE, colour=cluster,
 fill=cluster)) +
  geom_point() +
  stat_ellipse(geom = "polygon", alpha=0.2) +
  scale_x_continuous(limits=c(-2.8, 2.8), name="Standardised SES
 Factor Scores") +
  scale_y_continuous(limits=c(-2.8, 2.8), name="Standardised Care
 Factor Scores") +
  scale_fill_brewer(palette = "Set1") +
  scale_colour_brewer(palette = "Set1") +
  theme_minimal()
print(R)
ggsave(filename = "care_ses_scatter1.png", width = 5, height = 5,
 units = "cm", dpi = 600, scale = 2.5)

S <-ggplot(data=survey3, aes(x=Q14_FA_COST, y=Q14_FA_CONV,
 colour=cluster, fill=cluster)) +
  geom_point() +
  stat_ellipse(geom = "polygon", alpha=0.2) +
```

```
  scale_x_continuous(limits=c(-2.8, 2.8), name="Standardised Cost
 Factor Scores") +
  scale_y_continuous(limits=c(-2.8, 2.8), name="Standardised
 Convenience Factor Scores") +
  scale_fill_brewer(palette = "Set1") +
  scale_colour_brewer(palette = "Set1") +
  theme_minimal()
print(S)
ggsave(filename = "cost_conv_scatter1.png", width = 5, height = 5,
 units = "cm", dpi = 600, scale = 2.5)

U <-ggplot(data=survey3, aes(x=FA_SES, y=Q14_FA_CONV, colour=cluster,
 fill=cluster)) +
  geom_point() +
  stat_ellipse(geom = "polygon", alpha=0.2) +
  scale_x_continuous(limits=c(-2.8, 2.8), name="Standardised SES
 Factor Scores") +
  scale_y_continuous(limits=c(-2.8, 2.8), name="Standardised
 Convenience Factor Scores") +
  scale_fill_brewer(palette = "Set1") +
  scale_colour_brewer(palette = "Set1") +
  theme_minimal()
print(U)
ggsave(filename = "ses_conv_scatter1.png", width = 5, height = 5,
 units = "cm", dpi = 600, scale = 2.5)

V <-ggplot(data=survey3, aes(x=Q14_FA_COST, y=Q14_FA_CARE,
 colour=cluster, fill=cluster)) +
  geom_point() +
  stat_ellipse(geom = "polygon", alpha=0.2) +
  scale_x_continuous(limits=c(-2.8, 2.8), name="Standardised Cost
 Factor Scores") +
  scale_y_continuous(limits=c(-2.8, 2.8), name="Standardised Care
 Factor Scores") +
  scale_fill_brewer(palette = "Set1") +
  scale_colour_brewer(palette = "Set1") +
  theme_minimal()
print(V)
ggsave(filename = "care_cost_scatter1.png", width = 5, height = 5,
 units = "cm", dpi = 600, scale = 2.5)


#Plot as Euclidian ellipses #
 http://docs.ggplot2.org/current/stat_ellipse.html
p <- ggplot(data=survey3, aes(x=Q14_FA_CONV, y=Q14_FA_CARE,
 colour=cluster, fill=cluster)) +
  geom_point() +
  stat_ellipse(type = "euclid", geom = "polygon", alpha=0.2) +
  scale_x_continuous(limits=c(-2.8, 2.8), name="Standardised
 Convenience Factor Scores") +
  scale_y_continuous(limits=c(-2.8, 2.8), name="Standardised Care
 Factor Scores") +
  scale_fill_brewer(palette = "Set1") +
  scale_colour_brewer(palette = "Set1") +
  theme_minimal()
print(p)
ggsave(filename = "care_conv_scatter.png", width = 5, height = 5,
 units = "cm", dpi = 600, scale = 2.5)

Q <- ggplot(data=survey3, aes(x=FA_SES, y=Q14_FA_COST, colour=cluster,
 fill=cluster)) +
  geom_point() +
  stat_ellipse(type = "euclid", geom = "polygon", alpha=0.2) +
  scale_x_continuous(limits=c(-2.8, 2.8), name="Standardised SES
 Factor Scores") +
  scale_y_continuous(limits=c(-2.8, 2.8), name="Standardised Cost
 Factor Scores") +
  scale_fill_brewer(palette = "Set1") +
  scale_colour_brewer(palette = "Set1") +
  theme_minimal()
print(Q)
```

```
ggsave(filename = "ses_cost_scatter.png", width = 5, height = 5, units
 = "cm", dpi = 600, scale = 2.5)

R <- ggplot(data=survey3, aes(x=FA_SES, y=Q14_FA_CARE, colour=cluster,
 fill=cluster)) +
  geom_point() +
  stat_ellipse(type = "euclid", geom = "polygon", alpha=0.2) +
  scale_x_continuous(limits=c(-2.8, 2.8), name="Standardised SES
 Factor Scores") +
  scale_y_continuous(limits=c(-2.8, 2.8), name="Standardised Care
 Factor Scores") +
  scale_fill_brewer(palette = "Set1") +
  scale_colour_brewer(palette = "Set1") +
  theme_minimal()
print(R)
ggsave(filename = "care_ses_scatter.png", width = 5, height = 5, units
 = "cm", dpi = 600, scale = 2.5)

S <-ggplot(data=survey3, aes(x=Q14_FA_COST, y=Q14_FA_CONV,
 colour=cluster, fill=cluster)) +
  geom_point() +
  stat_ellipse(type = "euclid", geom = "polygon", alpha=0.2) +
  scale_x_continuous(limits=c(-2.8, 2.8), name="Standardised Cost
 Factor Scores") +
  scale_y_continuous(limits=c(-2.8, 2.8), name="Standardised
 Convenience Factor Scores") +
  scale_fill_brewer(palette = "Set1") +
  scale_colour_brewer(palette = "Set1") +
  theme_minimal()
print(S)
ggsave(filename = "cost_conv_scatter.png", width = 5, height = 5,
 units = "cm", dpi = 600, scale = 2.5)

U <-ggplot(data=survey3, aes(x=FA_SES, y=Q14_FA_CONV, colour=cluster,
 fill=cluster)) +
  geom_point() +
  stat_ellipse(type = "euclid", geom = "polygon", alpha=0.2) +
  scale_x_continuous(limits=c(-2.8, 2.8), name="Standardised SES
 Factor Scores") +
  scale_y_continuous(limits=c(-2.8, 2.8), name="Standardised
 Convenience  Factor Scores") +
  scale_fill_brewer(palette = "Set1") +
  scale_colour_brewer(palette = "Set1") +
  theme_minimal()
print(U)
ggsave(filename = "ses_conv_scatter.png", width = 5, height = 5, units
 = "cm", dpi = 600, scale = 2.5)

V <-ggplot(data=survey3, aes(x=Q14_FA_COST, y=Q14_FA_CARE,
 colour=cluster, fill=cluster)) +
  geom_point() +
  stat_ellipse(type = "euclid", geom = "polygon", alpha=0.2) +
  scale_x_continuous(limits=c(-2.8, 2.8), name="Standardised Cost
 Factor Scores") +
  scale_y_continuous(limits=c(-2.8, 2.8), name="Standardised Care
 Factor Scores") +
  scale_fill_brewer(palette = "Set1") +
  scale_colour_brewer(palette = "Set1") +
  theme_minimal()
print(V)
ggsave(filename = "care_cost_scatter.png", width = 5, height = 5,
 units = "cm", dpi = 600, scale = 2.5)


###### PART 2 - Spatial Modelling ######

#### PREPARATION #### [Step 5]

# Download and Install Packages
install.packages("tidyr")
install.packages("rgdal")
install.packages("dplyr")
```

```
# Load Packages
library(tidyr)
library(rgdal)
library(dplyr)

# Load Packages Downloaded and Installed Previously in Part 1
library(ggplot2)
library(Hmisc)

# Load Data
Cluster  <- read.csv("hybridcluster.csv")
SA1 <- readOGR("C:\\UserData\\dahlb\\GIS", "ACT_SA1_SEIFA")

# Define cluster data as spatial data
clusterpoints <- SpatialPoints(cbind(Cluster$LONG, Cluster$LAT),
 proj4string = CRS("+proj=longlat +ellps=GRS80 +no_defs"))
plot(clusterpoints)

# Spatial overlay
clus.SA1 <- clusterpoints %over% SA1
head(clus.SA1)
nrow(clus.SA1)

Cluster$SA1 <- clus.SA1$SA1_7DIG11
summary(Cluster)
table(Cluster$SA1)


#### DATA MANIPULATION #### [Step 6]
  # Clusters Labelled: A, B, C, D, E

# Sort data into columns – run loop once for each cluster
read.esri.od <- function(filename){
  ftype <- substring(filename, nchar(filename)-2)
  if (ftype == “dbf”){
    network.od <- read.dbf(filename, as.is=T)
  } else if (ftype %in% c(“csv”, “txt”)){
    network.od <- read.csv(filename)
  } else {
    stop(paste(“Unrecognised file type”, filename))
  }
  dist_fieldname <- names(network.od)[grep(“^Total_”,
 names(network.od))][1]
  network.od.idlist <- strsplit(as.character(network.od$Name),” – “)
  out <- data.frame(OriginID = sapply(network.od.idlist,
 function(x)(x[1])),
                    DestID = sapply(network.od.idlist,
 function(x)(x[2])),
                    Netdist = network.od[,dist_fieldname])

  out <- out[order(out$DestID, out$OriginID),]
  out
}


#Load in Major Food Retailers as “outlets”
outlets <-  readOGR(“C:\\UserData\\dahlb\\GIS”, “Outlets”)@data
summary(outlets)
outlets$ID <- factor(as.character(outlets$ID))

# Outlet names
outlets$shortname <- c(“Q2_DW”, “DSS”, “CSUP”, “CA”, “CSS”, “ER_IGA”,
 “BFFM”, “BW”, “BC”, “JC”, “MA”, “WS”, “HIGA”, “AIGA”, “OIGA”, “LIGA”,
 “CIGA”, “FFFM”, “GA”, “GW”, “GC”, “SCC”, “CRFM”, “SFM”, “NFM”,
 “BUFM”, “HM”, “CBJNL”, “CBJC”, “FCOP”, “MW”, “C”, “MCWG”)

# Convert the visit matrix from wide to tall
victims <- gather(data = Cluster[,c(“GNAF_N”, “SA1”, “cluster”,
 outlets$shortname)], shortname, visits, Q2_DW:MCWG)

# Join outlet data to visit matrix
```

```
outlets.slim <- outlets[,c("ID", "Area", "BDA", "PAFN", "shortname")]

# Convert shortnames to characters (not factors)
visit.mtx$shortname <- as.character(visit.mtx$shortname)
outlets.slim$shortname <- as.character(outlets.slim$shortname)

# Join
visit.mtx.2 <- merge(visit.mtx, outlets.slim, by="shortname", all.x =
 TRUE, all.y = FALSE)

# Read in and join travel time data
ODM  <- read.esri.od("C:\\UserData\\dahlb\\GIS\\ODMatrix.txt")

# Convert join columns to common data type
ODM$OriginID <- as.integer(as.character(ODM$OriginID))
ODM$DestID <- as.integer(as.character(ODM$DestID))
visit.mtx.2$GNAF_N <- as.integer(as.character(visit.mtx.2$GNAF_N))
visit.mtx.2$ID <- as.integer(as.character(visit.mtx.2$ID))
visit.mtx.3 <- merge(visit.mtx.2, ODM, by.x=c("GNAF_N", "ID"),
 by.y=c("OriginID", "DestID"), all.x=TRUE, all.y=FALSE)

# Aggregate to SA1:
# Group by SA1
sa1.mtx <- group_by(visit.mtx.3, SA1, ID) %>%
  summarise(visits=sum(visits),
            t_time=median(Netdist),
            n_respondents=length(unique(GNAF_N))) %>%
  arrange(ID, SA1) %>% # Must be sorted first by destination then by
 origin!!!
  as.data.frame


# Assemble attractiveness and propulsiveness variables

## Attractiveness variables:
# Must be sorted by destination ID but not include destination ID as a
 column
outlets.attract <-  arrange(outlets.slim, ID) %>%
  mutate(
    PAFN = as.integer(PAFN == "Y") + 1 #,
    # Area = log(Area),
    # BDA = log(BDA)
  ) %>%
  select(Area, BDA, PAFN)
sa1s.respondents <- group_by(Cluster, SA1) %>%
  summarise(n=n()) %>%
  as.data.frame %>%
  arrange(SA1) %>%
  select(n)

source("sprintr.R")
m.huff <- estimate.huff.model(sa1.mtx[,c("SA1", "ID", "t_time")],
                   negative.pow, 1.0, outlets.attract, rep(0,
                   ncol(outlets.attract)), sa1s.respondents, rep(1,
                   ncol(sa1s.respondents)), sa1.mtx[,"visits"])

summary(m.huff)


# Generate data to plot distance decay curves
distance.decay.predictions <- data.frame(Travel_time=seq(from=10/60,
 to=60, by=10/60))
distance.decay.predictions$Food <-
 negative.pow(distance.decay.predictions$Travel_time, 1.55)
distance.decay.predictions$Poker_machines <-
 negative.pow(distance.decay.predictions$Travel_time, 1.02)

# Example: Compare distance decay curves of food to poker machines
 (work by Francis Markham)
distance.decay.predictions <-
  gather(data = distance.decay.predictions, Activity, ddecay,
 Food:Poker_machines)
```

```
ggplot(data=distance.decay.predictions, aes(y=ddecay, x=Travel_time,
 colour=Activity)) +
  geom_line() +
  scale_x_continuous(name="Travel time (mins)", limits=c(0, 5)) +
  scale_y_continuous(name="Relative propensity to interact") +
  theme_minimal()


#### CALCULATE ATTRACTIVENESS FOR OUTLETS #### [Step 7]
outlets$Attractiveness <- outlets$Area^0.11 * outlets$BDA^0.04 *
 (((outlets$PAFN == "Y") + 1)^(-0.86))
summary(outlets$Attractiveness)

# Calculate attractiveness for each cluster

# Cluster A
outlets$AAttractivenessA <- outlets$Area^0.07 * outlets$BDA^0.11 *
 (((outlets$PAFN == "Y") + 1)^(-0.63))

# Cluster B
outlets$BAttractivenessB <- outlets$Area^0.14 * outlets$BDA^-0.02 *
 (((outlets$PAFN == "Y") + 1)^(-0.88))

# Cluster C
outlets$CAttractivenessC <- outlets$Area^0.14 * outlets$BDA^0.07 *
 (((outlets$PAFN == "Y") + 1)^(-1.02))

# Cluster D
outlets$DAttractivenessD <- outlets$Area^0.07 * outlets$BDA^0.06 *
 (((outlets$PAFN == "Y") + 1)^(-0.70))

# Cluster B
outlets$EAttractivenessE <- outlets$Area^0.13 * outlets$BDA^-0.03 *
 (((outlets$PAFN == "Y") + 1)^(-1.23))

# Write to csv file
write.csv(outlets, "outlet_attract.csv")


#### REVIEW RESULTS ##### [Step 8]

Hclus <- read.csv("hybridcluster.csv")   # All clusters
Aclus <- read.csv("ClusterA.csv")
summary(Aclus)
Bclus <- read.csv("ClusterB.csv")
summary(Bclus)
Cclus <- read.csv("ClusterC.csv")
summary(Cclus)
Dclus <- read.csv("ClusterD.csv")
summary(Dclus)
Eclus <- read.csv("ClusterE.csv")
summary(Eclus)

describe(Aclus)
describe(Bclus)
describe(Cclus)
describe(Dclus)
describe(Eclus)

# Attractiveness Values for each Cluster now ready for ArcMap & Python
 Script
```

# Appendix G: Installed R Packages

```
# Citations for packages used in “Honours Thesis Data Analysis in R”

> citation()
To cite R in publications use:
R Core Team (2016). R: A language and environment for statistical comp
uting. R Foundation for Statistical Computing, Vienna, Austria. URL: h
ttps://www.R-project.org/.

> citation("ggplot2")
To cite ggplot2 in publications, please use:
H. Wickham. ggplot2: Elegant Graphics for Data Analysis. Springer-Verl
ag New York, 2009.

> citation("car")
To cite the car package in publications use:
John Fox and Sanford Weisberg (2011). An R Companion to Applied Regres
sion, Second Edition. Thousand Oaks CA: Sage. URL:
http://socserv.socsci.mcmaster.ca/jfox/Books/Companion

> citation("Hmisc")
To cite package ‘Hmisc’ in publications use:
Frank E Harrell Jr, with contributions from Charles Dupont and many ot
hers. (2016). Hmisc: Harrell Miscellaneous. R package version 3.17-4.
https://CRAN.R-project.org/package=Hmisc

> citation("psych")
To cite the psych package in publications use:
Revelle, W. (2016) psych: Procedures for Personality and Psychological
Research, Northwestern University, Evanston, Illinois, USA, https://CR
AN.R-project.org/package=psych Version = 1.6.9.

> citation("nFactors")
To cite package 'nFactors' in publications use:
Raiche, G. (2010). nFactors: an R package for parallel analysis and no
n graphical solutions to the Cattell scree test.R package version  2.3
.3.

> citation("clustrd")
To cite package ‘clustrd’ in publications use:
Angelos Markos, Alfonso Iodice D' Enza and Michel Van de Velden (2013)
.clustrd: Methods for joint dimension reduction and clustering. R pack
age version 0.1.2. https://CRAN.R-project.org/package=clustrd

> citation("GPArotation")
To cite package 'GPArotation' in publications use:
Bernaards, Coen A. and Jennrich, Robert I. (2005) Gradient Projection
Algorithms and Software for Arbitrary Rotation Criteria in Factor Anal
ysis, Educational and Psychological Measurement: 65, 676-696. <http://
www.stat.ucla.edu/research/gpa>

> citation("NbClust")
To cite NbClust in publications use:
Malika Charrad, Nadia Ghazzali, Veronique Boiteau, Azam Niknafs(2014).
NbClust: An R Package for Determining the Relevant Number of Clusters
in a Data Set. Journal of Statistical Software, 61(6), 1-36. URL http:
//www.jstatsoft.org/v61/i06/.

> citation("factoextra")
To cite package ‘factoextra’ in publications use:
```

```
Alboukadel Kassambara and Fabian Mundt (2016). factoextra: Extract and
Visualize the Results of Multivariate Data Analyses. R package version
1.0.3. http://www.sthda.com/english/rpkgs/factoextra

> citation("cluster")
To cite the R package 'cluster' in publications use:
Maechler, M., Rousseeuw, P., Struyf, A., Hubert, M., Hornik,
K.(2016).  cluster: Cluster Analysis Basics and Extensions. R package
version 2.0.4.

> citation("RColorBrewer")
To cite package ‘RColorBrewer’ in publications use:
Erich Neuwirth (2014). RColorBrewer: ColorBrewer Palettes. R package v
ersion 1.1-2. https://CRAN.R-project.org/package=RColorBrewer

> citation("tidyr")
To cite package ‘tidyr’ in publications use:
Hadley Wickham (2016). tidyr: Easily Tidy Data with `spread()` and `ga
ther()` Functions. R package version 0.5.1. https://CRAN.R-project.org
/package=tidyr

> citation("rgdal")
To cite package ‘rgdal’ in publications use:
Roger Bivand, Tim Keitt and Barry Rowlingson (2016). rgdal: Bindings f
or the Geospatial Data Abstraction Library. R package version 1.1-10.
https://CRAN.R-project.org/package=rgdal

> citation("dplyr")
To cite package ‘dplyr’ in publications use:
Hadley Wickham and Romain Francois (2016). dplyr: A Grammar of Data Ma
nipulation. R package version 0.5.0. https://CRAN.R-project.org/packag
e=dplyr
```

# Appendix H: Python Script

```
"""
Script Name: Honours Thesis Spatial Interaction Modelling in Python
Author: Edited by Brittany Dahl, original script by Drew Flater,
 edited previously by Zac Hatfield-Dodds
Email: u5349586@anu.edu.au
Version: 3.0
Date: 18.09.2016
Acknowledgements:

Created: “HuffModel.py” 2007-04-13 by Drew Flater
Fixed: 2015-03-18 by Zac Hatfield-Dodds (Fixed network distance and
refactor everything)
Edited: 2016-09-18 by Brittany Dahl (Fixed to display probability
surface as an output)
Usage: Creating probability-based trade areas for retail stores
Notes: This script was edited for the Honours Thesis of Brittany Dahl.
Originally downloaded from:
https://www.arcgis.com/home/item.html?id=f4769668fc3f486a992955ce55cac
a18
"""

# Import system modules
import sys, arcgisscripting, os, re

# Create the Geoprocessor object
gp = arcgisscripting.create(93)

# Set overwrite
gp.overwriteoutput = 1

def AddPrintMessage(msg, severity):
    """Prints a message in the ArcGIS console with appropriate
severity."""
    print(msg)
    if severity == 0:
        gp.AddMessage(msg)
    elif severity == 1:
        gp.AddWarning(msg)
    elif severity == 2:
        gp.AddError(msg)

# Script parameters...
stores = gp.getparameterastext(0)
store_name = gp.getparameterastext(1)
store_attr = gp.getparameterastext(2)
outfolder = gp.getparameterastext(3)
fc_name = gp.getparameterastext(4)
studyarea = gp.getparameterastext(5)
blockgroups = gp.getparameterastext(6)
sales = gp.getparameterastext(7)
distances = gp.getparameterastext(8).lower() == 'true' # actually a
boolean
streets = gp.getparameterastext(9)
x = gp.getparameterastext(10)
marketareas = gp.getparameterastext(11)
potential_st = gp.getparameterastext(12)
surfaces = gp.getparameterastext(13).lower() == 'true' # actually a
boolean
distanceconstraint = gp.getparameterastext(14)
neighborconstraint = gp.getparameterastext(15)

# If using geographic constraints, set variable True
if distanceconstraint != "" or neighborconstraint > 0:
    constraints = True
else:
    constraints = False

# Make sure ArcInfo license is available
if gp.productinfo().lower() not in ['arcinfo', 'arcserver']:
```

```
    gp.adderror("An ArcInfo or ArcServer license is required to run 
this tool.")
    sys.exit()

# Establish 'step' progressor settings
gp.SetProgressor("step", "Checking inputs against parameter 
requirements...", 0, 9, 1)

# Process: Make output file gdb
gp.createfilegdb(outfolder, "output.gdb")
outputgdb = outfolder + "\\output.gdb" + os.sep
gp.SetProgressorPosition()

# Set parameter as text in lines 623-624
outfc = outputgdb + fc_name
outmarkets = outputgdb + "Surface_Markets"
outpotential = outputgdb + "potential_stores"

# Check to make sure user has the necessary extensions...
if distances:
    try:
        gp.CheckOutExtension("Network")
    except:
        gp.adderror("Network Analyst extension is not licensed. 
Uncheck the 'Use Street-Network Travel Times' option to use Straight-
Line Distances.")
        sys.exit()
    if streets == "":
        gp.adderror("ERROR 000735: Input analysis network: Value is 
required.")
        gp.adderror("If the 'Use Street-Network Travel Times' option 
is checked (TRUE), a valid Street Network Dataset must be provided.")
        sys.exit()
    else:
        desc = gp.describe(streets)
        if desc.datatype not in ["NetworkDataset", 
"NetworkDatasetLayer"]:
            gp.adderror("If the 'Use Street-Network Travel Times' 
option is checked (TRUE), a valid Street Network Dataset must be 
provided.")
            sys.exit()

if surfaces:
    try:
        gp.CheckOutExtension("Spatial")
    except:
        gp.adderror("Spatial Analyst extension is not licensed. 
Surfaces cannot be interpolated. Uncheck the 'Generate Probability 
Surfaces' option to process the model without generating surfaces.")
        sys.exit()

# Check to make sure there are a sufficient number of stores for 
modelling (>1)
numstoresondisk = gp.getcount_management(stores).getoutput(0)
if gp.exists(potential_st):
    numpotentialstores = 
gp.getcount_management(potential_st).getoutput(0)
else:
    numpotentialstores = 0
if int(numstoresondisk) + int(numpotentialstores) < 2:
    gp.adderror("There are an insufficient number of stores to perform 
modelling. There must be at least two total records between the Store 
Locations dataset and the Potential Stores feature set.")
    sys.exit()

# Check to make sure there are no duplicate field values in the Store 
Name Field
sNameList = []
cur = gp.SearchCursor(stores)
row = cur.Next()
while row:
    sName = row.GetValue(store_name)
```

```
    if sName in sNameList:
        gp.adderror("Field values in field '" + str(store_name) + "' 
are not unique. Use a different field.")
        sys.exit()
    sNameList.append(sName)
    row = cur.Next()
del cur, row

# Check to make sure all input parameters are in a common projected 
coordinate system
if blockgroups == "":
    desccs_st = gp.describe(stores)
    sr_st = desccs_st.spatialreference
    desccs_sa = gp.describe(studyarea)
    sr_sa = desccs_sa.spatialreference
    if sr_st.projectionname == sr_sa.projectionname:
        pass
    else:
        gp.adderror("The store and study area feature classes must be 
in the same projected coordinate system.")
        sys.exit()
    del desccs_st, desccs_sa
else:
    desccs_st = gp.describe(stores)
    sr_st = desccs_st.spatialreference
    desccs_bg = gp.describe(blockgroups)
    sr_bg = desccs_bg.spatialreference
    desccs_sa = gp.describe(studyarea)
    sr_sa = desccs_sa.spatialreference
    if sr_st.projectionname == sr_bg.projectionname and 
sr_st.projectionname == sr_sa.projectionname:
        pass
    else:
        gp.adderror("The stores, origin locations, and study area 
feature classes must be in the same projected coordinate system.")
        sys.exit()
    del desccs_st, desccs_sa, desccs_bg

# Warn that stores with an attribute value of 0 or less will be 
dropped from analysis
desc = gp.describe(stores)
OIDfield = desc.OIDFieldName

cur = gp.SearchCursor(stores)
row = cur.Next()
while row:
    attr_val = row.GetValue(store_attr)
    OID_val = row.GetValue(OIDfield)
    if attr_val <= 0:
        gp.addwarning("Feature " + str(OID_val) + " in dataset: " + 
str(stores) + " has an attractiveness value of less than or equal to 
zero. This store location will be excluded from modelling.")
    row = cur.Next()
del desc, row, cur

# Process: Convert Store locations to points and replace non-
alphanumeric characters in store names with underscore...
gp.select(stores, r"in_memory\st", store_attr + " > 0")
gp.SetProgressorPosition()
fields = gp.listfields(r"in_memory\st", "*")
for field in fields:
    if not field.required and not field.name in [str(store_name), 
str(store_attr)]:
        gp.deletefield(r"in_memory\st", field.name)
del fields
gp.SetProgressorPosition()

# If the potential stores feature set contains features, append them 
to the stores feature class
if int(numpotentialstores) > 0:
```

```
    # If the potential stores feature set has NAME and ATTRACTIVENESS
fields, append them to the stores feature class
    fields = gp.listfields(potential_st, "*")
    name_field = 0
    attr_field = 0

    for field in fields:
        if field.name == "NAME":
            name_field = 1
        if field.name == "ATTRACTIVENESS":
            attr_field = 1
    del fields
    if name_field + attr_field == 2:

        # Make permanent copy of features in Potential Stores feature
set
        gp.copyfeatures(potential_st, outputgdb + "potential_stores")

        # Make sure text in potential stores fields fits in the Stores
feature class fields
        fields = gp.listfields(r"in_memory\st")
        for field in fields:
            if field.name == store_name:
                maxlength = field.length
        del fields
        cur = gp.updatecursor(outputgdb + "potential_stores", "", "",
"NAME")
        row = cur.next()
        while row:
            name_orig = row.GetValue("NAME")
            name_new = name_orig.ljust(maxlength)[:maxlength]
            if len(name_orig) > maxlength:
                set_name = row.setvalue("NAME", name_new)
            else:
                set_name = row.setvalue("NAME", name_orig)

            cur.Updaterow(row)
            row = cur.next()
        del cur, row

        # Create field mappings for appending potential stores to
Stores
        fieldmappings = gp.CreateObject("FieldMappings")
        fieldmappings.AddTable(outputgdb + "potential_stores")
        fieldmappings.AddTable(r"in_memory\st")

        # Map the "NAME" field from the potential stores feature set
to the store_name field in st
        fieldmap =
fieldmappings.GetFieldMap(fieldmappings.FindFieldMapIndex(store_name))
        fieldmap.AddInputField(outputgdb + "potential_stores", "NAME")
        if store_name.lower() != "name":

fieldmappings.ReplaceFieldMap(fieldmappings.FindFieldMapIndex(store_na
me), fieldmap)

fieldmappings.RemoveFieldMap(fieldmappings.FindFieldMapIndex("NAME"))

        # Map the "ATTRACTIVENESS" field from the potential stores
feature set to the store_attr field in st
        fieldmap =
fieldmappings.GetFieldMap(fieldmappings.FindFieldMapIndex(store_attr))
        fieldmap.AddInputField(outputgdb + "potential_stores",
"ATTRACTIVENESS")
        if store_attr.lower() != "attractiveness":

fieldmappings.ReplaceFieldMap(fieldmappings.FindFieldMapIndex(store_at
tr), fieldmap)

fieldmappings.RemoveFieldMap(fieldmappings.FindFieldMapIndex("ATTRACTI
VENESS"))
```

```
        gp.append(outputgdb + "potential_stores", r"in_memory\st",
"NO_TEST", fieldmappings)

        del fieldmappings
        gp.SetProgressorPosition()

    else:
        gp.addwarning("Your Potential Store Locations features class
or layer does not have fields NAME and/or ATTRACTIVENESS. These
features have been excluded from the model.")

# Truncate store names if they are too long (45 characters), or
substitute underline for non-supported characters
fields = gp.listfields(r"in_memory\st")
for field in fields:
    if field.name == store_name:
        maxlength = field.length
del fields

cur = gp.updatecursor(r"in_memory\st", "", "", store_name)
row = cur.next()
while row:
    name_orig = row.GetValue(store_name)
    name_num = name_orig.rjust(1)[:1]
    numlist = ['1', '2', '3', '4', '5', '6', '7', '8', '9', '0']
    if name_num in numlist:
        name_orig = "_" + name_orig
    #name_new = re.sub('[^a-zA-Z_0-9]', '_', str(name_orig))
    name_new = re.sub(r'[!"#$%&\'()*+,\-./:;<=>?@[\\\]^_`|~
\t\r\n\v\f]', '_', name_orig)
    if len(name_new) > maxlength:
        name_new = name_new.ljust(maxlength)[:maxlength]
    name_trunc = name_new.ljust(45)[:45]
    if len(name_new) >= 45:
        set_name = row.setvalue(store_name, name_trunc)
    else:
        set_name = row.setvalue(store_name, name_new)
    try:
        cur.Updaterow(row)
    except:
        gp.adderror("Rows in store layer contain bad records.  Problem
may have occurred if Potential stores were drawn with no NAME added.
Check the geoprocessing 'Results' tab to ensure that the Potential
Stores feature set has values in both the NAME and ATTRACTIVENESS
fields.")
        sys.exit()
    row = cur.next()
del cur, row
gp.SetProgressorPosition()

# If study area contains more than one polygon, dissolve it
numstudyarea = int(gp.getcount_management(studyarea).getoutput(0))
if numstudyarea > 1:
    gp.dissolve_management(studyarea, r"in_memory\studyarea")
    studyarea = r"in_memory\studyarea"
cur = gp.searchcursor(studyarea)
descunit = gp.describe(studyarea)
sr = descunit.spatialreference
row = cur.next()
area = 0

# Process: Calculate area of study area
while row:
    feat = row.shape
    area = feat.Area
    if sr.linearunitname == "Foot_US":
        if area / 5318313.2 > 500: # max number of points
            pointnum = 500
        elif area / 5318313.2 < 100: # min number of points
            pointnum = 100
        else:
            pointnum = area / 5318313.2
```

```
    elif sr.linearunitname == "Meter":
        if area / 494089.52 > 500: # max number of points
            pointnum = 500
        elif area / 494089.52 < 100: # min number of points
            pointnum = 100
        else:
            pointnum = area / 494089.52
    else:
        gp.adderror("Your study area feature class does not have a
projected coordinate system.  Please project your data or use another
data source.")
        sys.exit()
    row = cur.next()
del descunit, row, cur

# Process: Generate random origin points...
if blockgroups == "":
    gp.CreateRandomPoints_management("in_memory", "bgrandom",
studyarea, "", int(pointnum))
    gp.SetProgressorPosition()

    gp.merge_management(r"in_memory\st;in_memory\bgrandom",
r"in_memory\bg")
    gp.SetProgressorPosition()
    fields = gp.listfields(r"in_memory\bg", "*")
    for field in fields:
        if not field.required and field.name != "Shape":
            gp.deletefield_management(r"in_memory\bg", field.name)
    del fields
    gp.SetProgressorPosition()

# Process: Create centroid points from input origin locations
else:
    gp.FeatureToPoint_management(blockgroups, r"in_memory\bg",
"INSIDE")
    gp.SetProgressorPosition()

    # Process: clear attributes in block group points layer by
deleting
    fields = gp.listfields(r"in_memory\bg", "*")
    for field in fields:
        if not field.required and field.name != sales:
            gp.deletefield_management(r"in_memory\bg", field.name)
    del fields
    gp.SetProgressorPosition()

# Process: Add ID field for stores and block groups
gp.AddField_management(r"in_memory\st", "SID", "SHORT", "", "", "",
"", "NULLABLE", "NON_REQUIRED", "")
gp.AddField_management(r"in_memory\bg", "BID", "SHORT", "", "", "",
"", "NULLABLE", "NON_REQUIRED", "")
gp.SetProgressorPosition()

# Process: Calculate ID field for block groups
desc = gp.describe(r"in_memory\bg")
gp.CalculateField_management(r"in_memory\bg", "BID", "[" +
desc.OIDFieldName + "]")
del desc
gp.SetProgressorPosition()

# Process: Calculate ID field for stores
desc = gp.describe(r"in_memory\st")
gp.CalculateField_management(r"in_memory\st", "SID", "[" +
desc.OIDFieldName + "]")
del desc
gp.SetProgressorPosition()

gp.addmessage("Finished checking inputs against parameter
requirements.")

################################################################
```

```
if distances:
    gp.SetProgressor("default", "Calculating travel time impedance 
from Origin Locations to Store Destinations......", 0, 1, 1)

    # Figure out Network Dataset attributes for use in Making the OD 
Cost Matrix
    usetime = ""
    uselength = ""
    cost = ""
    useheirarchy = ""

    desc = gp.describe(streets)
    attributes = desc.attributes
    #attributes.reset() # a list has no reset() method
    attribute = attributes.pop(0)
    while attribute:
        if attribute.UsageType == "Cost":
            if attribute.Units in ["Days", "Hours", "Minutes", 
"Seconds"]:
                usetime = attribute.Name
            else:
                uselength = attribute.Name
        if attribute.UsageType == "Hierarchy":
            useheirarchy = "USE_HIERARCHY"
        try:
            attribute = attributes.pop(0)
        except IndexError:
            attribute = False

    if usetime != "":
        cost = usetime
    else:
        cost = uselength
    del desc

    # Process: Make OD Cost Matrix Layer...
    gp.MakeODCostMatrixLayer_na(streets, "OD", cost, 
distanceconstraint.split(" ")[0], neighborconstraint, cost, 
"NO_UTURNS", "", useheirarchy, "", "STRAIGHT_LINES")

    # Add Origin Locations to OD Matrix
    gp.addlocations_na("OD", "Origins", r"in_memory\bg", "Name BID 
#;CurbApproach # 0;TargetDestinationCount # #", "1000 Meters", "", "", 
"MATCH_TO_CLOSEST", "APPEND")

    # Add Destination Locations to OD Matrix
    gp.addlocations_na("OD", "Destinations", r"in_memory\st", "Name 
SID #;CurbApproach # 0;TargetDestinationCount # #", "1000 Meters", "", 
"", "MATCH_TO_CLOSEST", "APPEND")

    # Process: Solve Origin Destination matrix...
    gp.Solve_na("OD", "SKIP")
    gp.addmessage("Finished calculating travel time impedance from 
origin locations to stores.")
    gp.savetolayerfile_management("OD", outfolder + "\\ODafter.lyr")

# If Network Analyst is not available, calculate distances that are 
straight line
else:
    gp.SetProgressor("default", "Calculating straight-line distance 
from input locations to store destinations...", 0, 1, 1)
    gp.generateneartable(r"in_memory\bg", r"in_memory\st", 
r"in_memory\tbl", distanceconstraint, "", "", "ALL", 
neighborconstraint)
    gp.SetProgressorposition()
    gp.addmessage("Finished calculating straight-line distances from 
origin locations to stores.")

################################################################

# Set progressor for stage of process
numst = gp.getcount_management(r"in_memory\st").getoutput(0)
```

```
count = (5*int(numst)) + 2

# If Network Analyst is available, calculate model based on travel
time
if distances:
    if surfaces:
        gp.SetProgressor("step", "Calculating probabilities and
generating surfaces...", 0, count, 1)
    else:
        gp.SetProgressor("step", "Calculating probabilities...", 0,
count, 1)

    # Process: Make Table from OD lines...
    gp.CopyRows_management("OD\\Lines", outputgdb + "tbl")

    # Process: Delete fields
    gp.deletefield(outputgdb + "tbl", "Name;DestinationRank")
    gp.CopyRows(outputgdb + "tbl", r"in_memory\tbl")
    gp.delete(outputgdb + "tbl")
    gp.SetProgressorPosition()

    # Process: Delete in-memory OD matrix
    try:
        gp.delete_management("OD")
    except:
        pass

    # Make minimum travel time 0.1 minutes instead of 0 minutes (for
calculation)
    if blockgroups == "":
        cur = gp.updatecursor(r"in_memory\tbl", "Total_" + cost + " =
0")
        row = cur.next()
        while row:
            row.Total_Time = row.Total_Time + .1
            cur.Updaterow(row)
            row = cur.next()
        del cur, row

    # Process: Join store and origin attributes to OD table...
    gp.JoinField(r"in_memory\tbl", "OriginID", r"in_memory\bg", "BID",
"BID;" + str(sales))
    gp.SetProgressorPosition()
    gp.JoinField(r"in_memory\tbl", "DestinationID", r"in_memory\st",
"SID", "SID;" + str(store_attr) + ";" + str(store_name))
    gp.delete_management(r"in_memory\st")
    gp.SetProgressorPosition()

    # Process: Add and Calculate tt_x_att Field ...
    gp.AddField_management(r"in_memory\tbl", "tt_x_att", "FLOAT", "",
"", "", "", "NULLABLE", "NON_REQUIRED", "")
    if x == "":
        x = 2
    gp.CalculateField_management(r"in_memory\tbl", "tt_x_att", "(1/
([Total_" + cost + "]^" + str(x) + ")) * [" + str(store_attr) + "]")
    gp.SetProgressorPosition()

# If Network Analyst is not available, calculate model based on
straight line distance
else:
    if surfaces:
        gp.SetProgressor("step", "Calculating probabilities and
generating surfaces...", 0, count, 1)
    else:
        gp.SetProgressor("step", "Calculating probabilities...", 0,
count, 1)

    # Make minimum distance 0.1 instead of 0 (for calculation)
    if blockgroups == "":
        cur = gp.updatecursor(r"in_memory\tbl", "NEAR_DIST = 0")
        row = cur.next()
        while row:
```

```
            row.NEAR_DIST = row.NEAR_DIST + .1
            cur.Updaterow(row)
            row = cur.next()
        del cur, row
    gp.SetProgressorPosition()

    # Process: Join origin attributes to near_table...
    desc = gp.describe(r"in_memory\bg")
    gp.JoinField(r"in_memory\tbl", "IN_FID", r"in_memory\bg",
desc.OIDFieldName, "BID;" + str(sales))
    del desc
    gp.SetProgressorPosition()

    # Process: Join store attributes to near_table...
    desc = gp.describe(r"in_memory\st")
    gp.JoinField(r"in_memory\tbl", "NEAR_FID", r"in_memory\st",
desc.OIDFieldName, "SID;" + str(store_name) + ";" + str(store_attr))
    gp.delete_management(r"in_memory\st")
    del desc
    gp.SetProgressorPosition()

    # Process: Add and Calculate tt_x_att Field ...
    gp.AddField_management(r"in_memory\tbl", "tt_x_att", "FLOAT", "",
"", "", "", "NULLABLE", "NON_REQUIRED", "")
    if x == "":
        x = 2
    gp.CalculateField_management(r"in_memory\tbl", "tt_x_att", "(1/
([NEAR_DIST]^" + str(x) + ")) * [" + str(store_attr) + "]")
    gp.SetProgressorPosition()

#RESUME model calculations with tbl from EITHER OD Matrix or
Near_Table

# Process: Summary Statistics (SUM of tt_x_att grouped by unique
bg_stfid)...
gp.Statistics_analysis(r"in_memory\tbl", r"in_memory\sumstats_tbl",
"tt_x_att SUM", "BID")
gp.SetProgressorPosition()

# Process: Summary Statistics(make list of store names)
gp.Statistics_analysis(r"in_memory\tbl", r"in_memory\st_names",
str(store_name) + " FIRST", str(store_name))
gp.SetProgressorPosition()

# Create search cursor to export and perform operations on tables with
separate store names
cur = gp.SearchCursor(r"in_memory\st_names")
row = cur.Next()

while row:
    storename = row.GetValue(store_name)
    whereclause = str(store_name) + " = '" + storename + "'"
    tblname = storename + "_tbl"

    # Process: Make Table View of unique store names...
    gp.tabletotable(r"in_memory\tbl", "in_memory", tblname,
whereclause)
    gp.SetProgressorPosition()

    # Process: Join separate store tables to summary statistics table
    gp.joinfield("in_memory" + os.sep + tblname, "BID",
r"in_memory\sumstats_tbl", "BID", "SUM_tt_x_att")
    gp.SetProgressorPosition()

    # Process: Add and calculate probabilities in each store table
(probability of each block group going to store x) ...
    gp.AddField_management("in_memory" + os.sep + tblname, storename +
"_prob", "FLOAT", "", "", "", "", "NULLABLE", "NON_REQUIRED", "")
    gp.CalculateField_management("in_memory" + os.sep + tblname,
storename + "_prob", "[tt_x_att] / [SUM_tt_x_att]")
    gp.SetProgressorPosition()
```

```
    # Process: if sales projections are to be calculated, do so
    if sales == "":
        gp.joinfield(r"in_memory\bg", "BID", "in_memory" + os.sep +
tblname, "BID", storename + "_prob")

        # If using geographic constraints, make null values 0
        if constraints == True:
            gp.maketableview(r"in_memory\bg", "tbl_view", storename +
"_prob IS NULL")
            gp.calculatefield("tbl_view", str(storename) + "_prob", 0)
        gp.SetProgressorPosition()
    else:
        gp.AddField_management("in_memory" + os.sep + tblname,
storename + "_sales", "FLOAT", "", "", "", "", "NULLABLE",
"NON_REQUIRED", "")
        gp.CalculateField_management("in_memory" + os.sep + tblname,
storename + "_sales", "[" + storename + "_prob] * [" + str(sales)
+"]")
        gp.SetProgressorPosition()
        gp.joinfield(r"in_memory\bg", "BID", "in_memory" + os.sep +
tblname, "BID", storename + "_prob;" + storename + "_sales")

        # If using geographic constraints, make null values 0
        if constraints == True:
            gp.maketableview(r"in_memory\bg", "tbl_view", storename +
"_prob IS NULL")
            gp.calculatefield("tbl_view", storename + "_prob", 0)
            gp.maketableview(r"in_memory\bg", "tbl_view", storename +
"_sales IS NULL")
            gp.calculatefield("tbl_view", storename + "_sales", 0)
        gp.SetProgressorPosition()

    # Delete in memory table to free up memory
    gp.delete_management(r"in_memory" + os.sep + tblname)

    # Determine the expected mean distance between input origin
locations
    num1 = gp.getcount_management(r"in_memory\bg")
    num = int(num1.getoutput(0))
    expectedMeanDist = 1.0 / (2.0 * ((num / float(area))**0.5))

    # Process: Create surface from store probability values
(interpolate with Kriging)
    field = storename + "_prob"
    output = outputgdb + "kriging_" + storename
    props = "Spherical " + str(expectedMeanDist)
    gp.kriging_sa(r"in_memory\bg", field, output, props)
    gp.SingleOutputMapAlgebra_sa("Int([" + outputgdb + "kriging_" +
storename + "] * 100)", outputgdb + storename + "_ProbSurface", "#")
    gp.delete(outputgdb + "kriging_" + storename)
    gp.SetProgressorPosition()

    gp.extent = ""

    # Exit the while loop
    row = cur.Next()
del row, cur

# Delete in memory table to free up memory
gp.delete_management(r"in_memory\tbl")
gp.delete_management(r"in_memory\sumstats_tbl")
gp.delete_management(r"in_memory\st_names")

if surfaces:
    gp.addmessage("Finished calculating probabilities and generating
surfaces.")
else:
    gp.addmessage("Finished calculating probabilities.")

################################################################

# setting progress bar for creating output feature class
```

```
gp.SetProgressor("default", "Creating output feature class '" +
fc_name + "'...")

if blockgroups == "":
    gp.copyfeatures(r"in_memory\bg", outputgdb + str(fc_name))
    gp.delete_management(r"in_memory\bg")
else:
    gp.featureclasstofeatureclass(blockgroups, "in_memory", "origins")
    desc = gp.describe(blockgroups)
    shapetype = desc.Shapetype
    if shapetype == "Polygon":
        gp.spatialjoin(r"in_memory\origins", r"in_memory\bg",
outputgdb + str(fc_name), "", "", "", "CONTAINS")
    else:
        gp.spatialjoin(r"in_memory\origins", r"in_memory\bg",
outputgdb + str(fc_name), "", "", "", "INTERSECTS")
    gp.delete_management(r"in_memory\bg")
    del desc

# Process: delete fields in fc_name
deletefields = gp.listfields(outputgdb + str(fc_name), "*")
for field in deletefields:
    if field.name == "BID" or field.name == str(sales) + "_1" or
field.name == "Join_Count":
        gp.deletefield(outputgdb + str(fc_name), field.name)
del deletefields
'''
# Delete all in_memory data, since output has been written to gdb
gp.workspace = "in_memory"
fclist = gp.listfeatureclasses()
for fc in fclist:
    gp.delete_management(fc)
del fclist
'''
gp.addmessage("Finished creating output feature class '" + fc_name +
"'.")

################################################################

if marketareas.lower() == "surfaces" or marketareas.lower() == "both":
    # setting progress bar for creating market areas
    gp.SetProgressor("default", "Creating market areas from
probability surfaces...")

    # set workspace to retrieve all probability surfaces
    gp.workspace = outfolder + "\\output.gdb"

    # Create list of all probability surface rasters
    rasterList = gp.listrasters("*ProbSurface")
    rasterNames = ""
    rasterNameLength = -1

    # Length of the longest store name needed for length of
Highest_Prob field
    for raster in rasterList:
        rasterNames = rasterNames + raster + ";"
        length = len(str(raster))
        if length >= rasterNameLength:
            rasterNameLength = length
    del rasterList
    newRasterNames = rasterNames.ljust(-1)[:-1]

    #Perform Highest Position tool to determine which store has the
highest probability at each cell
    gp.highestposition(newRasterNames, outputgdb + "Surface_Markets")

    newRasterList = newRasterNames.split(";")

    #add field for indicating the store with the highest probability
    gp.addfield(outputgdb + "Surface_Markets", "Market", "TEXT", "",
"", rasterNameLength - 12)
```

```
    rows = gp.UpdateCursor(outputgdb + "Surface_Markets")
    row = rows.Next()

    while row:
        highestGrid = row.getvalue("VALUE")
        highestText = str(newRasterList[(int(highestGrid) - 1)])
        highestTextName = highestText.ljust(-12)[:-12]
        # Update Highest_Prob field with the name of the store
        row.SetValue("Market", highestTextName)
        rows.UpdateRow(row)
        row = rows.Next()
    del rows, row

if marketareas.lower() == "origins" or marketareas.lower() == "both":

    # setting progress bar for creating market areas
    gp.SetProgressor("default", "Creating market areas from
origins...")

    # set workspace to retrieve all probability surfaces
    gp.workspace = outfolder + os.sep + "output.gdb"

    # to determine the highest probability value
    fieldlist = gp.listfields(outputgdb + str(fc_name), "*prob")
    fieldNameLength = -1

    # Get the length of the longest store name
    for field in fieldlist:
        length = len(str(field))
        if length >= fieldNameLength:
            fieldNameLength = length

    #add field for indicating the store with the highest sales value
    gp.addfield(fc_name, "Market", "TEXT", "", "", fieldNameLength -
5)
    rows = gp.UpdateCursor(fc_name)
    row = rows.Next()

    while row:
        probValue = -9999.0
        probName = "NULL"

        # find the field with the highest probability value at that
origin location
        for field in fieldlist:
            prob = row.getvalue(field.name)
            if prob >= probValue:
                probValue = prob
                probName = field.name

        #update the Highest_Prob field with the store name that has
the highest probability at that origin location
        row.SetValue("Market", probName.ljust(-5)[:-5])
        rows.UpdateRow(row)
        row = rows.Next()
    del rows, row, fieldlist
if marketareas.lower() != "none":
    gp.addmessage("Finished creating market areas.")

################################################################

# Add the output feature class to display, and in modelbuilder
gp.setparameterastext(16, outfc)
gp.setparameterastext(17, outmarkets)
gp.setparameterastext(18, outpotential)

gp.addmessage(" -- Process Complete -- ")
```

# Appendix I: Technical Log

The creation of results in *Chapter 4: Results* required additional steps in ArcGIS (ArcMap and ArcCatalog, 10.4.1), as outlined in Table 22. Use of the Symbology Tool in ArcMap is illustrated in Figure 23.

**Table 23: ArcGIS technical notes**

| Description | Input | Function/Tool | Output |
|---|---|---|---|
| 1. DATA PREPARATION | | | |
| **Create road network dataset – using hierarchy and assumed speed limits to create travel time** | Road Centrelines | Create Network Dataset [in ArcCatalog] | Roads9_ND |
| **Re-project sample frame (G-NAF locations where questionnaire was sent) into Zone 55 Projection** | Sampleframe – taken from G-NAF, cut to North Canberra | Project – Data Management Toolbox | Sampleframe2 |
| **Cut SA3 to "North Canberra" study area** | SA3 [Cut to ACT] | Select by attributes in attribute table | Studyareap |
| **Re-project geocoded dataset of Major Food Retailers** | Geocoded from GPS locations in Google Maps [Abbreviations for each retailer used found under the term: Shortname] | Project – Data Management Toolbox | OutletAttr2 |
| **Add in calibrated data** | Attractiveness values – calculated for each consumer group in R | Add X-Y Data | Attractiveness<br>AAttractiveness<br>BAttractiveness<br>CAttractiveness<br>DAttractiveness<br>EAttractiveness |
| 2. SPATIAL INTERACTION MODELLING | | | |
| **Model 1 – All Consumers** | OutletAttr2<br>Attractiveness<br>Shortname<br>Studyareap<br>Roads9_ND<br>Sampleframe2 | Model builder -> Huff Model (Market Analysis Tools – Python Script) | CALL |
| **Model 2 – Subgroup A 'The Concerned Consumer'** | OutletAttr2<br>AAttractiveness<br>Shortname<br>Studyareap<br>Roads9_ND<br>Sampleframe2 | Model builder -> Huff Model (Market Analysis Tools – Python Script) | CA |
| **Model 3 – Subgroup B 'The Expedient Consumer'** | OutletAttr2<br>BAttractiveness<br>Shortname<br>Studyareap<br>Roads9_ND<br>Sampleframe2 | Model builder -> Huff Model (Market Analysis Tools – Python Script) | CB |
| **Model 4 – Subgroup C 'The Unconcerned Consumer'** | OutletAttr2<br>CAttractiveness<br>Shortname<br>Studyareap<br>Roads9_ND | Model builder -> Huff Model (Market Analysis Tools – Python Script) | CC |

| | | | |
|---|---|---|---|
| | Sampleframe2 | | |
| **Model 5 – Subgroup D 'The Calculating Consumer'** | OutletAttr2<br>DAttractiveness<br>Shortname<br>Studyareap<br>Roads9_ND<br>Sampleframe2 | Model builder -> Huff Model<br>(Market Analysis Tools – Python Script) | CD |
| **Model 6 – Subgroup E 'The Frugal Consumer'** | OutletAttr2<br>EAttractiveness<br>Shortname<br>Studyareap<br>Roads9_ND<br>Sampleframe2 | Model builder -> Huff Model<br>(Market Analysis Tools – Python Script) | CE |
| 3. SYMBOLOGY | | | |
| **Create base layers as symbology for each store on the All Consumer "CALL" file (PolyGeo and Danalif, 2013)** | 33 x CALL <retailername><br><br>Symbology:<br>Manual breaks of 2% (from 0% to >16%) with 8 intervals. Brown to yellow colour ramp. Labels in percentages with 1 decimal place | Properties > Symbology<br>Edit –<br><br>[Same classification ranges, colours and symbols for all inputs] | CALL<retailername>.lyr |
| **Edit symbology for each file of each consumer group using base layer** | 33 x CALL<retailername>.lyr x each consumer subgroup: CA, CB, CC, CD, & CE<br>(Total 165 outputs) | Model builder -> "DahlToolbox": "SymbologyModel" | <subgroup><retailername>.shp |
| 4. DISPLAY | | | |
| **View**<br>**Insert 5 new data frames – adjust to align to margins and fit to be same size. Zoom to case study area in each.** | Data frame for each subgroup x each store<br><br>Additional Features:<br>Legend<br>Scale<br>North Arrow<br>Neatline – around all frames<br>Lettering - to differentiate each data-frame | Export Map | <retailername>.png |

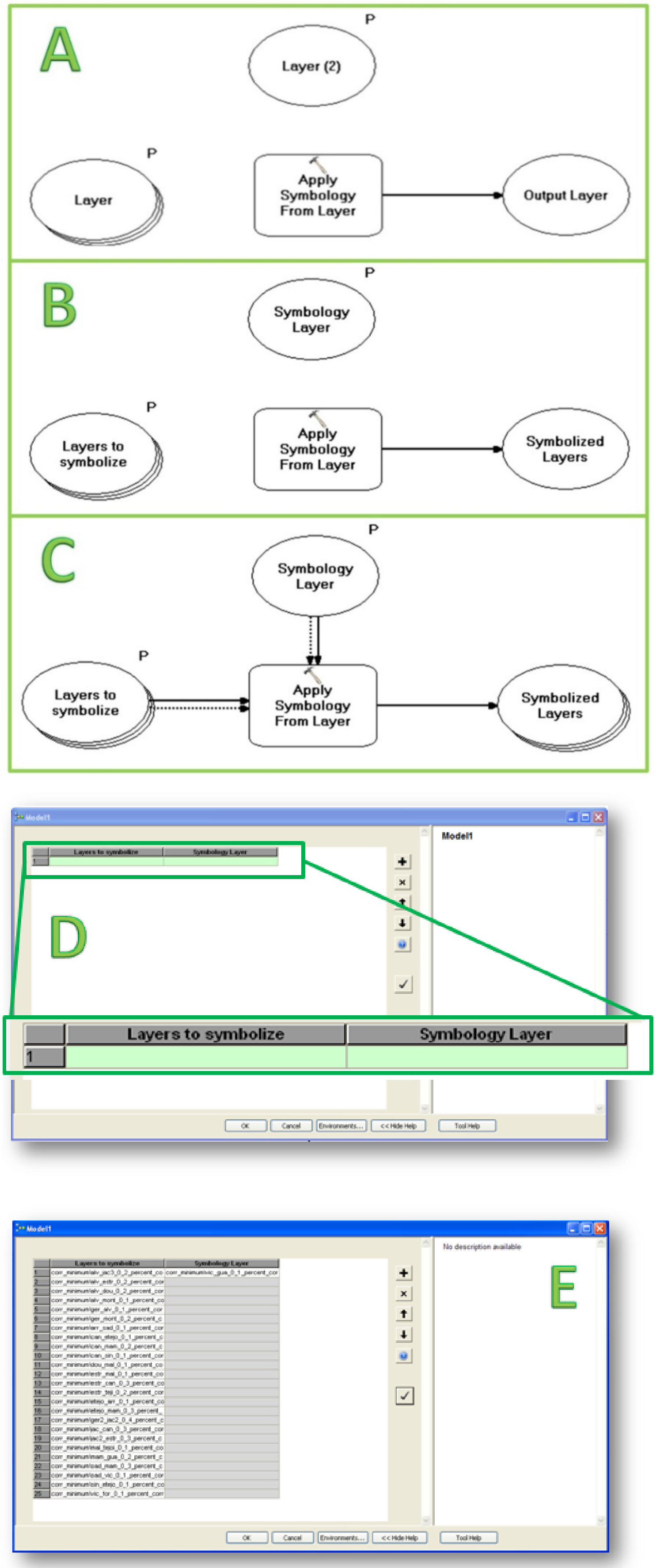



**Figure 23: Application of the Symbology Tool to multiple layers in ArcMap ModelBuilder (taken from PolyGeo and Danalif, 2013).**

# Appendix J: Response Rate

A large number of responses were received within a week of postage (see Figure 24). As expected, response rate declined as time progressed.

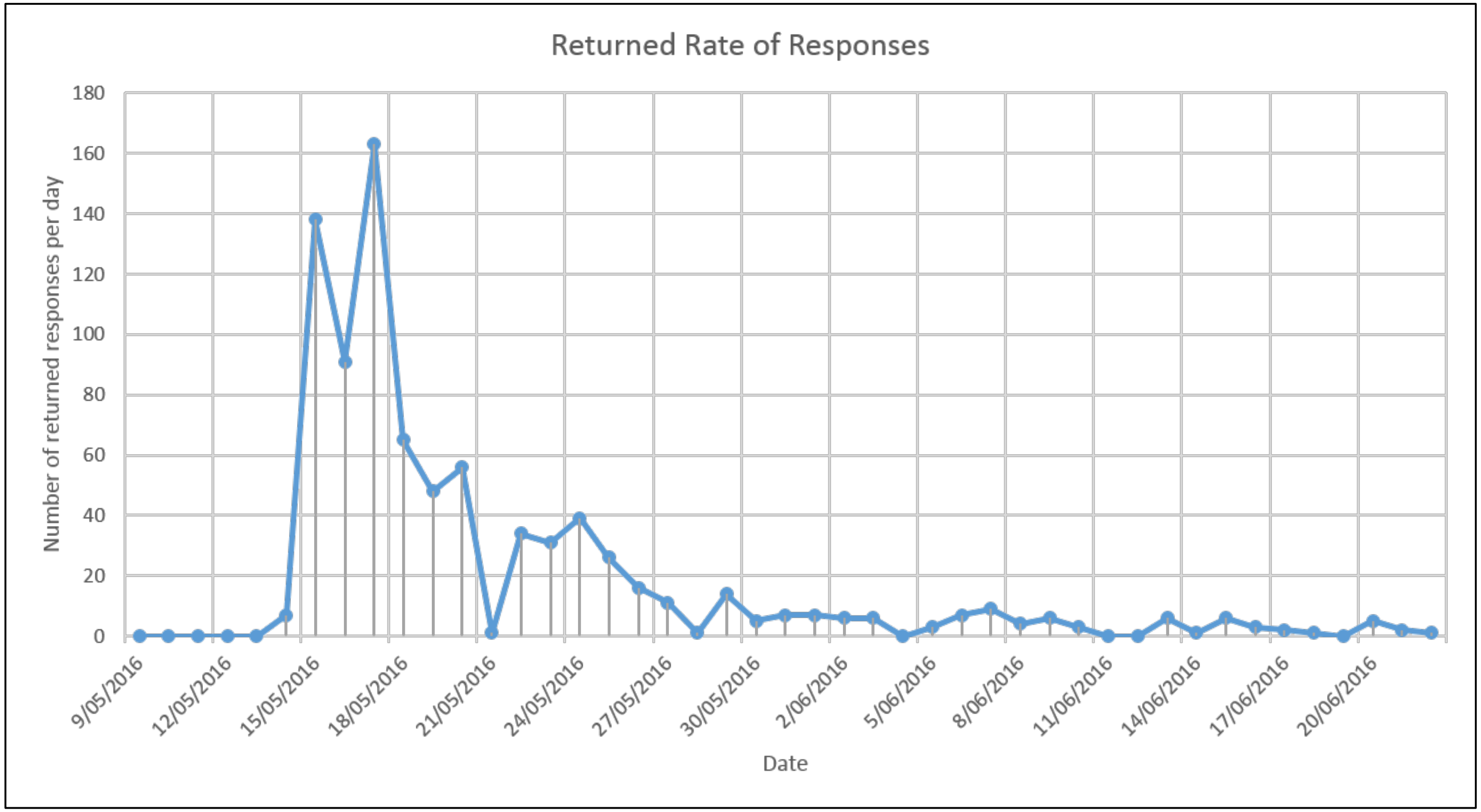



**Figure 24: Returned rate of mailed and online questionnaires.**

# Appendix K: 2011 Census Variables

Data was extracted from the 2011 Census using TableBuilder Pro, for the comparison of ten socio-economic and demographic variables (see Table 23).

**Table 24: TableBuilder Pro variables from ABS 2011 Census**

| Questions | | Census database | Geographic area | Census subgroups | Census variables |
|---|---|---|---|---|---|
| **1** | **Household residence time (in months)** | 2011 Census - Counting Persons, Place of Usual Residence | Custom Geography - Local Government Areas (2011 Boundaries) (UR) -North Canberra suburbs | AGEP in range (18 - 115 years); RLNP = "not applicable" | UAI1P by UAI5P |
| **5** | **Number of people in household** | *(This is a bit of a problematic one, as the census only differentiates between children and adults in the families dataset, which isn't what we want because there can be multiple families in each household)* | | | |
| | ***Adults*** | 2011 Census - Counting Families, Place of Usual Residence | Custom Geography - Local Government Areas (2011 Boundaries) (UR) - North Canberra suburbs | DWTD = "Occupied private dwellings" | NPRD x CACF (noting that "not applicable" includes families with 0 children) |
| | ***Children*** | 2011 Census - Counting Families, Place of Usual Residence | Custom Geography - Local Government Areas (2011 Boundaries) (UR) - North Canberra suburbs | DWTD = "Occupied private dwellings" | CACF (noting that "not applicable" includes families with 0 children) |
| **6** | **Age** | 2011 Census - Counting Persons, Place of Usual Residence | Custom Geography - Local Government Areas (2011 Boundaries) (UR) - North Canberra suburbs | RLNP = "not applicable" | AGEP |
| **7** | **Gender** | 2011 Census - Counting Persons, Place of Usual Residence | Custom Geography - Local Government Areas (2011 Boundaries) (UR) - North Canberra suburbs | AGEP in range (18 - 115 years); RLNP = "not applicable" | SEXP |
| **8** | **Car Ownership & Access** | 2011 Census - Counting Dwellings, Place of Enumeration | Custom Geography - Local Government Areas (2011 Boundaries) (UR) - North Canberra suburbs | DWTD = "Occupied private dwellings" | VEHD |
| **9** | **Education** | 2011 Census - Counting Persons, Place of Usual Residence | Custom Geography - Local Government Areas (2011 Boundaries) (UR) - North Canberra suburbs | AGEP in range (18 - 115 years); RLNP = "not applicable" | HSCP x QALLP |
| **10** | **Employment** | 2011 Census - Counting Persons, Place of Usual Residence | Custom Geography - Local Government Areas (2011 Boundaries) (UR) - North Canberra suburbs | AGEP in range (18 - 115 years); RLNP = "not applicable" | LFSP x STUP x EMTP (Including owner managers of incorporated enterprises and owner managers of unincorporated enterprises) |

| | | | | | |
|---|---|---|---|---|---|
| 11 | **Occupation** | 2011 Census - Counting Persons, Place of Usual Residence | Custom Geography - Local Government Areas (2011 Boundaries) (UR) - North Canberra suburbs | AGEP in range (18 - 115 years); RLNP = "not applicable" | OCCP |
| 12 | **Income** | 2011 Census - Counting Dwellings, Place of Enumeration | Custom Geography - Local Government Areas (2011 Boundaries) (UR) - North Canberra suburbs | DWTD = "Occupied private dwellings" | HIND or HIED |

# Appendix L: Respondent Visitation and Expenditure

Respondents visitation and expenditure is explored in further detail in Table 24.

**Table 25: Respondent visitation and expenditure for all retailers.** The highest value for variable is highlighted in bold text.

| Major Food Retailers | Total number of visits (n visits) | Total number of respondents visiting | Average respondent spend per all retailers ($) | Average respondent spend per retailer visited ($) |
|---|---|---|---|---|
| **DW** | 1,172 | **518** | **74.54** | 136.45 |
| **DSS** | 377 | 198 | 7.47 | 49.68 |
| **CSUP** | 620 | 275 | 22.51 | 82.05 |
| **CA** | 423 | 198 | 15.47 | 77.26 |
| **CSS** | 256 | 137 | 5.45 | 68.20 |
| **ER_IGA** | 56 | 37 | 0.73 | 21.62 |
| **BFFM** | 199 | 137 | 9.08 | 82.54 |
| **BW** | 77 | 60 | 3.69 | 66.34 |
| **BC** | 76 | 56 | 4.75 | 91.21 |
| **JC** | 210 | 129 | 12.51 | 105.98 |
| **MA** | 162 | 97 | 9.75 | 112.36 |
| **WS** | 540 | 159 | 13.94 | 91.93 |
| **HIGA** | 346 | 104 | 9.17 | 87.98 |
| **AIGA** | **1,275** | 347 | 45.93 | 134.98 |
| **OIGA** | 382 | 130 | 10.31 | 79.57 |
| **LIGA** | 451 | 177 | 10.61 | 65.50 |
| **CIGA** | 201 | 64 | 3.71 | 59.39 |
| **FFFM** | 203 | 134 | 14.37 | 119.37 |
| **GA** | 73 | 50 | 3.40 | 86.33 |
| **GW** | 20 | 15 | 1.26 | 83.74 |
| **GC** | 82 | 48 | 5.30 | 117.39 |
| **SCC** | 33 | 19 | 0.34 | 29.16 |
| **CRFM** | 310 | 208 | 25.03 | 126.47 |
| **SFM** | 6 | 6 | 0.19 | 40.00 |
| **NFM** | 13 | 10 | 0.72 | 125.00 |
| **BUFM** | 2 | 2 | 0.04 | 37.00 |
| **HM** | 2 | 2 | 0.00 | 0.00 |
| **CBJNL** | 147 | 82 | 5.96 | 80.50 |
| **CBJC** | 9 | 9 | 0.26 | 28.00 |
| **FCOP** | 32 | 23 | 0.72 | 44.25 |
| **MW** | 193 | 108 | 13.98 | 138.85 |
| **C** | 179 | 130 | 22.57 | **185.76** |
| **MCWG** | 40 | 31 | 1.02 | 51.76 |
| **'Other'** | 211 | 169 | 14.49 | 94.83 |
| **TOTAL** | 8,378 | 3,869 | | |

# Appendix M: Food Choice Motivations

Out of the 12 FCQ questions, the majority of respondents reported that most of the food choice motivations were moderately important (see Table 25). The relationship between these variables is shown in Figure 25.

**Table 26: FCQ responses.** Highest values highlighted in bold text.

| Variable | "Motive" | "Importance Statement" | Not at all important 1 | A little important 2 | Moderately important 3 | Very important 4 |
|---|---|---|---|---|---|---|
| **$V_1$ Q14_EASY** | Convenience | Easy to prepare | 60 | 193 | **366** | 238 |
| **$V_2$ Q14_EXPE** | Price | Not expensive | 88 | 317 | **356** | 85 |
| **$V_3$ Q14_CHILD** | Familiarity | Like the food I ate as a child | **578** | 173 | 70 | 20 |
| **$V_4$ Q14_ANIMAL** | Ecological welfare | Produced in an animal friendly way | 69 | 196 | **263** | 311 |
| **$V_5$ Q14_FAIR** | Political Values | Traded in a fair way | 53 | 213 | **312** | 267 |
| **$V_6$ Q14_VALUE** | Price | Good value for money | 20 | 103 | **450** | 280 |
| **$V_7$ Q14_COMM** | Social Values | Purchased from a community I want to support | 101 | 240 | **332** | 175 |
| **$V_8$ Q14_ENV** | Ecological welfare | Produced in an environmentally friendly way | 38 | 181 | **330** | 297 |
| **$V_9$ Q14_USUAL** | Familiarity | What I usually eat | 139 | 241 | **354** | 112 |
| **$V_{10}$ Q14_ENJOY** | Social Values | Purchased from a store that I enjoy spending time in | 178 | 250 | **305** | 118 |
| **$V_{11}$ Q14_QUICK** | Convenience | Ready to be cooked very quickly | 231 | **321** | 209 | 87 |
| **$V_{12}$ Q14_POLIT** | Political Values | Comes from a country I approve of politically | **244** | 242 | 218 | 144 |

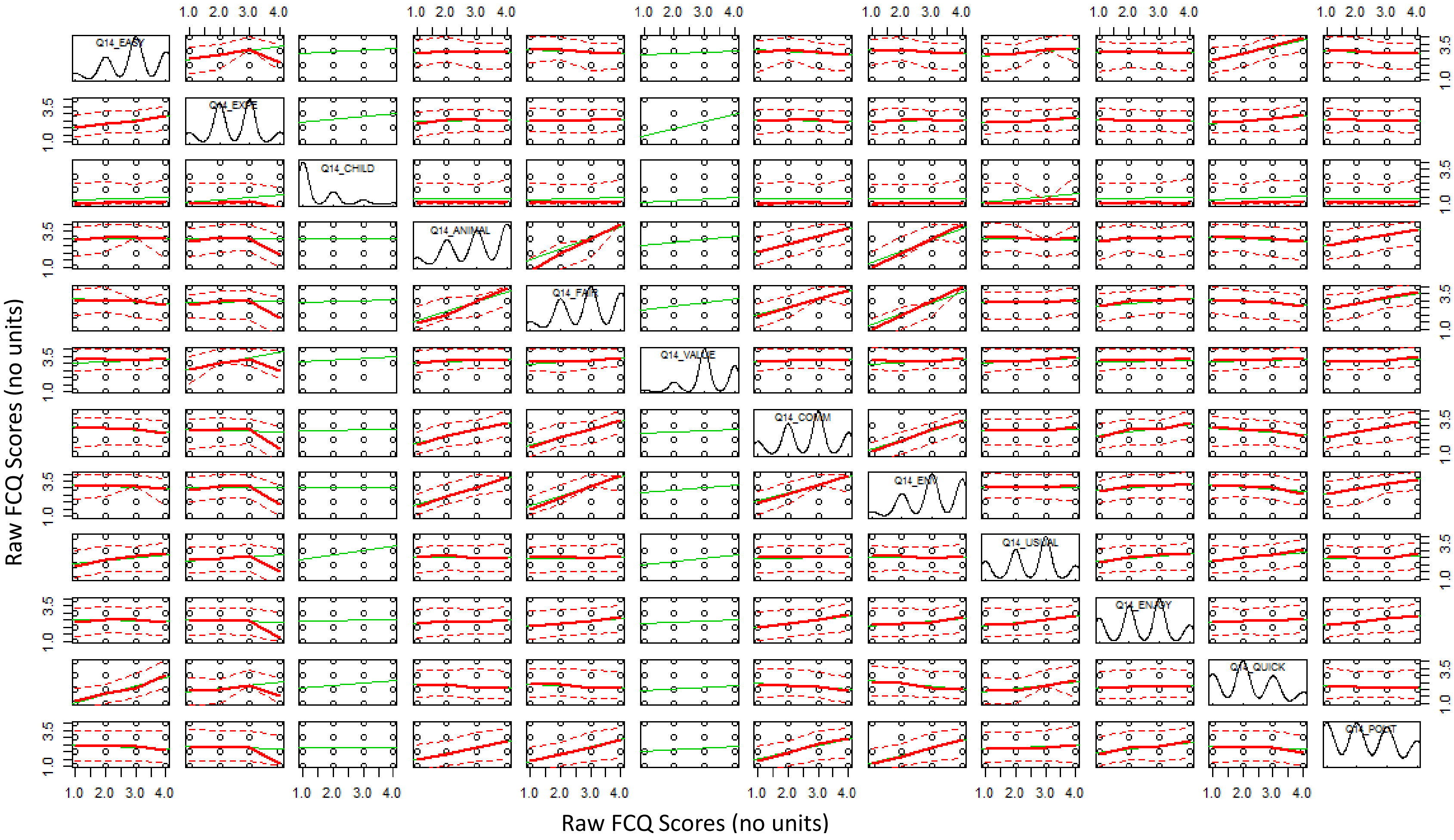



**Figure 25: Initial scatterplot matrix of all FCQ variables considered in the factor analysis.**

# Appendix N: Additional Factor Results

## N.1 Measures of Intercorrelation

Results of Bartlett's Test of Sphericity produced a very small p-value ($p < 0.00001$; Hair *et al.,* 2006; see Table 26), therefore it was appropriate to continue with the factor analysis. Overall MSA of 0.75 was acceptable (above the 0.50 cut-off range; Hair *et al.,* 2006; see Table 28). All variable-specific measures of MSA were also above 0.50; and as a result, no variables were excluded.

**Table 27: Bartlett's Test of Sphericity**

| | |
|---|---|
| **Chi squared** | 3138.453 |
| **p.value** | 0 |
| **Degrees of Freedom** | 136 |

**Table 28: Measure of Sampling Adequacy (MSA), using the Kaiser-Meyer-Olkin factor adequacy (KMO index).**

| **Variables:** | **MSA** |
|---|---|
| Q14_EASY | 0.59 |
| Q14_EXPE | 0.6 |
| Q14_CHILD | 0.62 |
| Q14_ANIMAL | 0.82 |
| Q14_FAIR | 0.82 |
| Q14_VALUE | 0.61 |
| Q14_COMM | 0.86 |
| Q14_ENV | 0.82 |
| Q14_USUAL | 0.65 |
| Q14_ENJOY | 0.69 |
| Q14_QUICK | 0.64 |
| Q14_POLIT | 0.9 |
| Q11_BLUE_COLLAR | 0.6 |
| Q9_EDU_U_DUMMY | 0.56 |
| Q12_HH_EQU_INC | 0.58 |
| Q10_UNEMPL_DUMMY | 0.53 |
| Q8_NOCAR_DUMMY | 0.8 |
| | |
| **Overall MSA** | **0.75** |

## N.2 Factor Selection Criteria

A number of methods were used to determine the optimal number of factors for the FCQ variables (see Figure 26), and the SES variables (see Figure 27). Additional statistical results are described in Table 28 and 29 below.

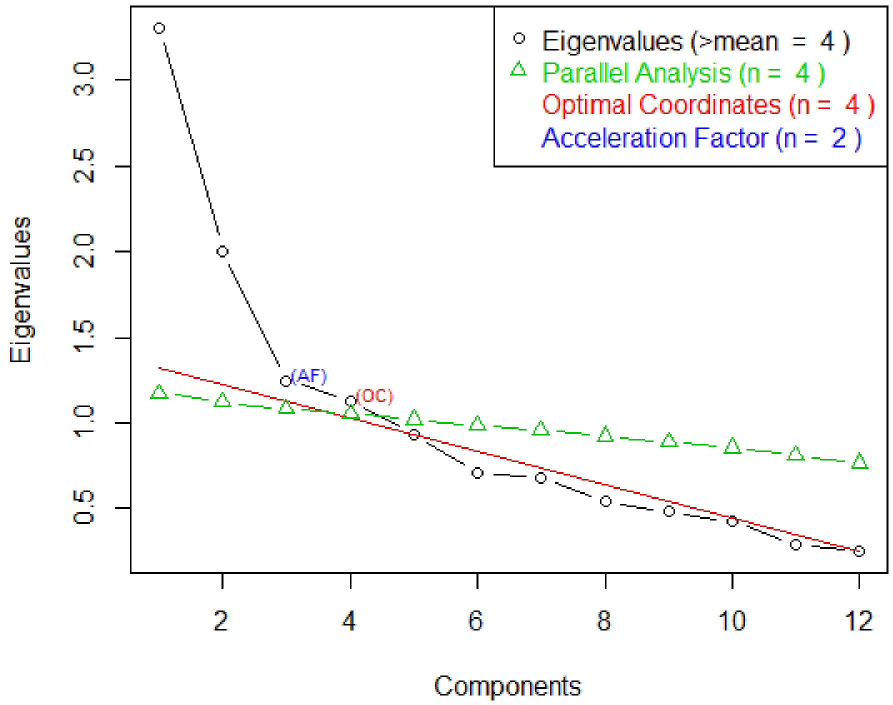



**Figure 26: FCQ Scree test**

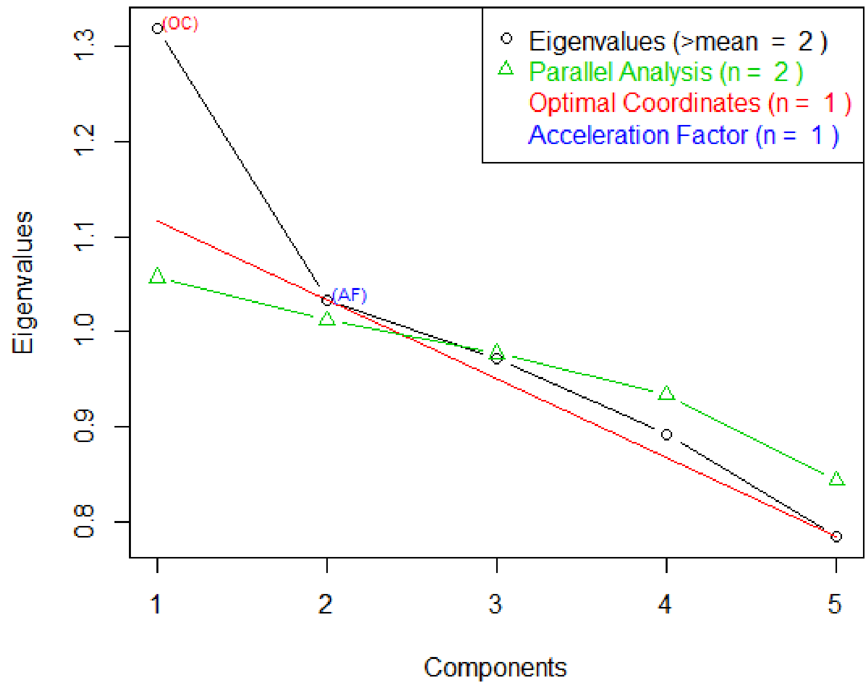



**Figure 27: SES Scree test**

### Table 29: Additional FCQ Factor Results

| Test of the hypothesis that 3 factors are sufficient. | Result | |
|---|---|---|
| Mean item complexity | 1.20 | |
| The degrees of freedom for the null model (objective function) | 66 (3.39) | |
| Chi Square | 2481.92 | |
| The degrees of freedom (df) for the model (objective function) | 33 (0.25) | |
| Root mean square of the residuals (RMSR) | 0.05 | |
| The df corrected root mean square of the residuals | 0.07 | |
| Harmonic number of observations | 739 | |
| Empirical chi square (with probability < 5e-27) | 206.67 | |
| The total number of observations | 739 | |
| MLE Chi Square (with probability < 7.8e-23) | 183.76 | |
| Tucker Lewis Index of factoring reliability | 0.875 | |
| RMSEA index (90 % confidence intervals are 0.068 - 0.09) | 0.079 | |
| BIC | -34.22 | |
| Fit based upon off diagonal values | 0.97 | |

| Measures of factor score adequacy | MR1 | MR3 | MR2 |
|---|---|---|---|
| **Correlation of scores with factors** | 0.95 | 0.89 | 0.89 |
| **Multiple R square of scores with factors** | 0.90 | 0.79 | 0.79 |
| **Minimum correlation of possible factor scores** | 0.79 | 0.57 | 0.57 |

### Table 30: Additional SES Factor Results

| Test of the hypothesis that 1 factor is sufficient. | Result |
|---|---|
| Mean item complexity | 1 |
| The degrees of freedom for the null model (objective function) | 10 (0.08) |
| Chi Square | 56.65 |
| The degrees of freedom (df) for the model (objective function) | 5 (0.01) |
| Root mean square of the residuals (RMSR) | 0.03 |
| The df corrected root mean square of the residuals | 0.04 |
| Harmonic number of observations | 739 |
| Empirical chi square (with probability < 0.082) | 9.77 |
| The total number of observations | 739 |
| MLE Chi Square (with probability < 0.32) | 5.9 |
| Tucker Lewis Index of factoring reliability | 0.961 |
| RMSEA index (90 % confidence intervals are 0 - 0.055) | 0.016 |
| BIC | -27.12 |
| Fit based upon off diagonal values | 0.92 |

| Measures of factor score adequacy | MR1 |
|---|---|
| **Correlation of scores with factors** | 0.61 |
| **Multiple R square of scores with factors** | 0.37 |

# Appendix O: Additional Cluster Results

The optimal number of clusters was selected based on 33 indicies, including the D-index (seen in Figure 28). Cluster centres and silhouette width were calculated using an initial hierarchical analysis, and then a k-means analysis. Cluster centres and silhouette width are described in further detail in Table 30 below. To assist with naming final cluster solutions, the subgroups were compared to existing consumer typologies (see Table 31).

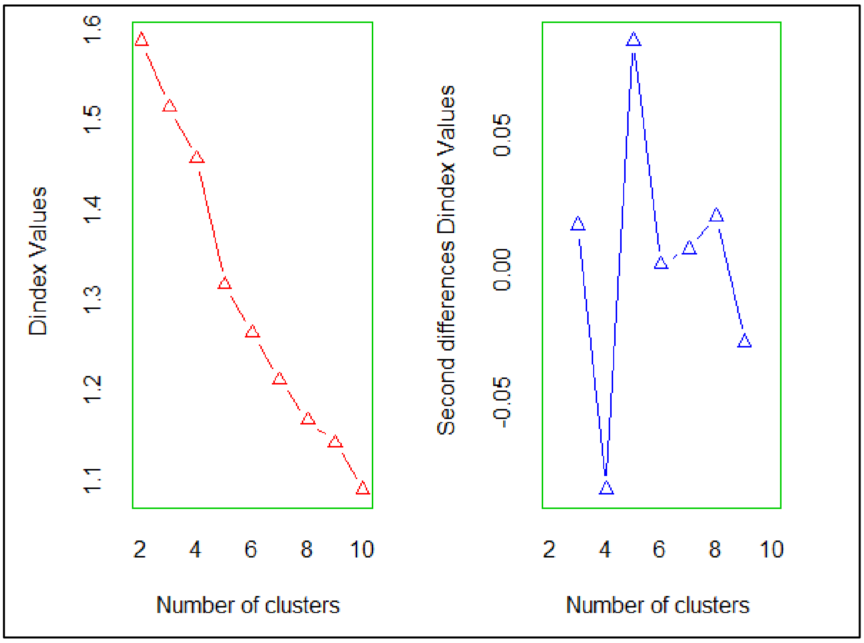



**Figure 28: D-Index results**

**Table 31: Additional Cluster Results**

| Cluster | Cluster Size (*n*) | Average Silhouette Width | SES | CARE | CONVENIENCE | COST |
|---|---|---|---|---|---|---|
| | | | Cluster Centres | | | |
| **A** | 144 | 0.21 | 0.27 | 0.11 | 0.84 | -0.95 |
| **B** | 161 | 0.18 | 0.10 | -0.29 | 1.01 | 0.76 |
| **C** | 154 | 0.18 | 0.05 | -0.80 | -0.68 | -1.17 |
| **D** | 173 | 0.24 | -0.16 | 0.48 | -0.47 | 0.23 |
| **E** | 107 | 0.22 | -0.04 | -1.40 | -0.91 | 1.18 |

**Table 32: Consumer subgroup similarities to food retailer-based consumer typologies.**

| Cluster | Subgroup Name | Similar Consumer Typologies: Stone (1954) | Williams *et al.,* (1978) | Lesser and Hughes (1986) | Dagevos (2005) |
|---|---|---|---|---|---|
| **A** | *Concerned* | “ethical” | “involved” | ~ “transitional” | “new” |
| **B** | *Expedient* | | “convenience” | “service” | “old” |
| **C** | *Dispassionate* | “apathetic” | “apathetic” | “inactive” | |
| **D** | *Calculating* | | | ~ “fringe” | “new” |
| **E** | *Frugal* | “economic” | “low-price” | “price” | “old” |

Note: ~ = Approximation based on description of clustering factors.

# Appendix P: Demographic Characteristics of Consumer Subgroups

The demographic characteristics of each consumer subgroup are explored in further detail below (see Figure 29 - 35).

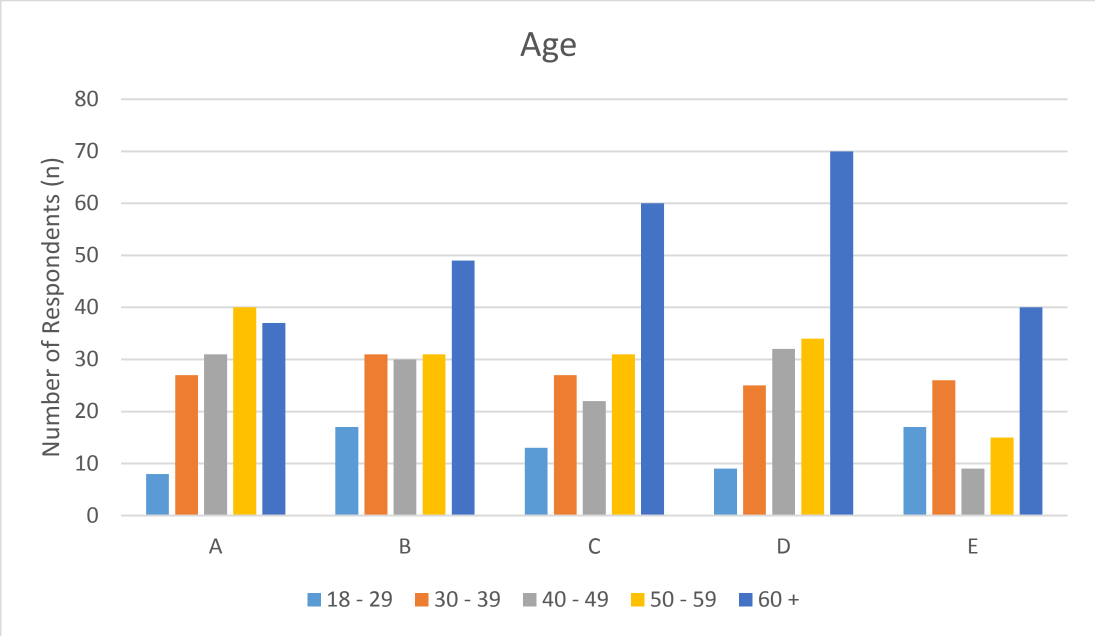



**Figure 29: Age characteristics**

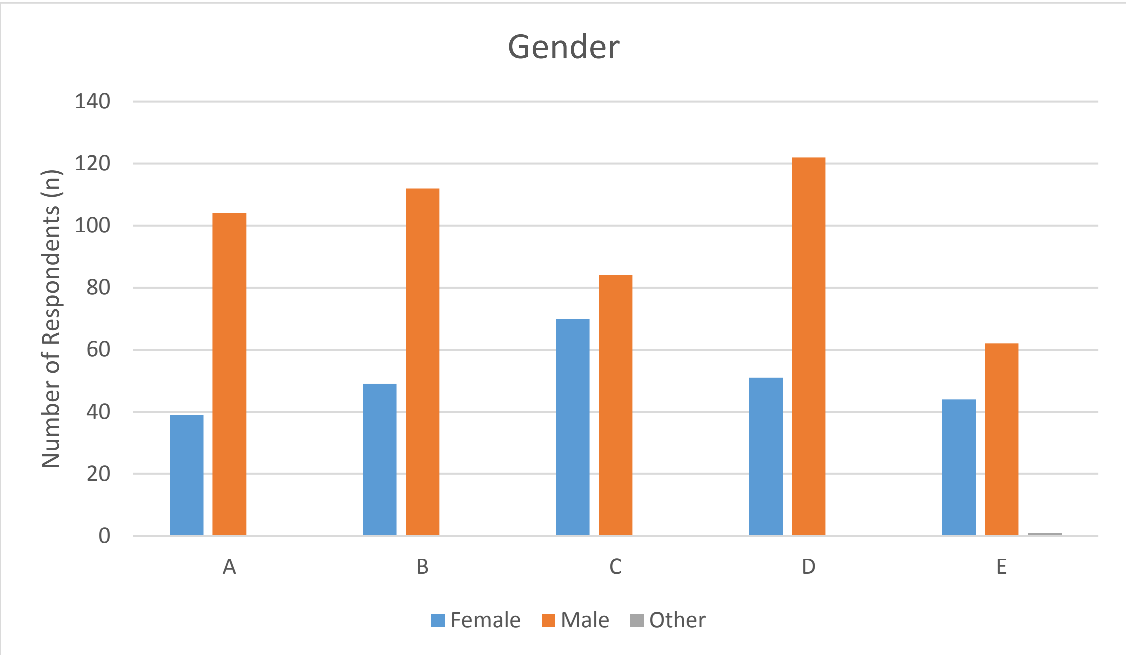



**Figure 30: Gender characteristics**

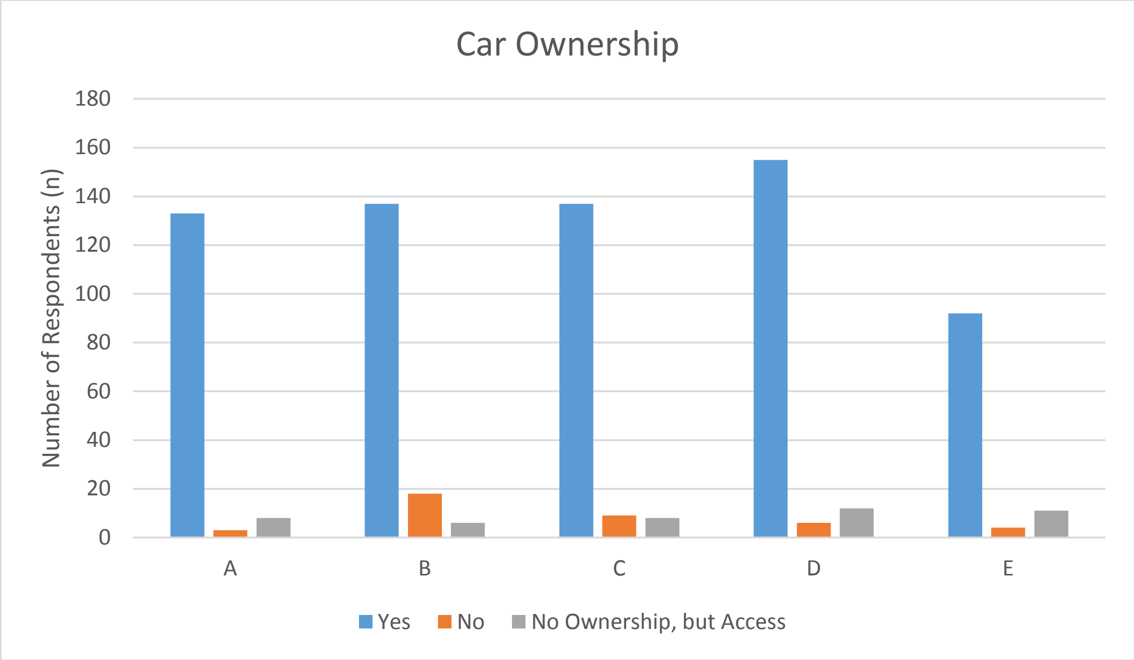



**Figure 31: Car ownership characteristics**

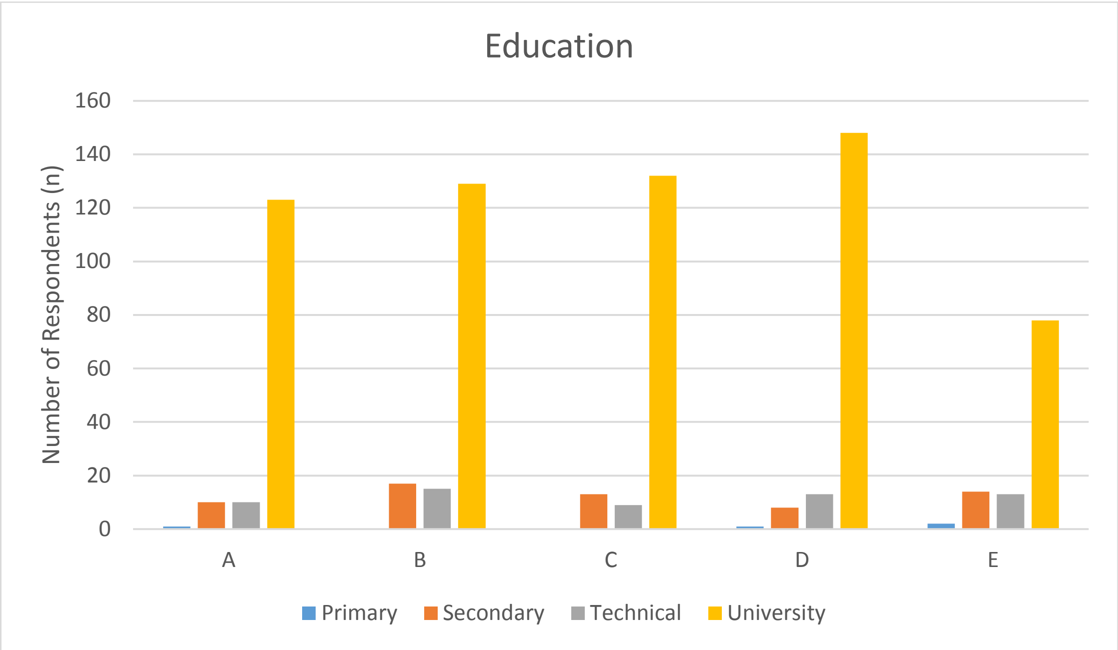



**Figure 32: Education characteristics**

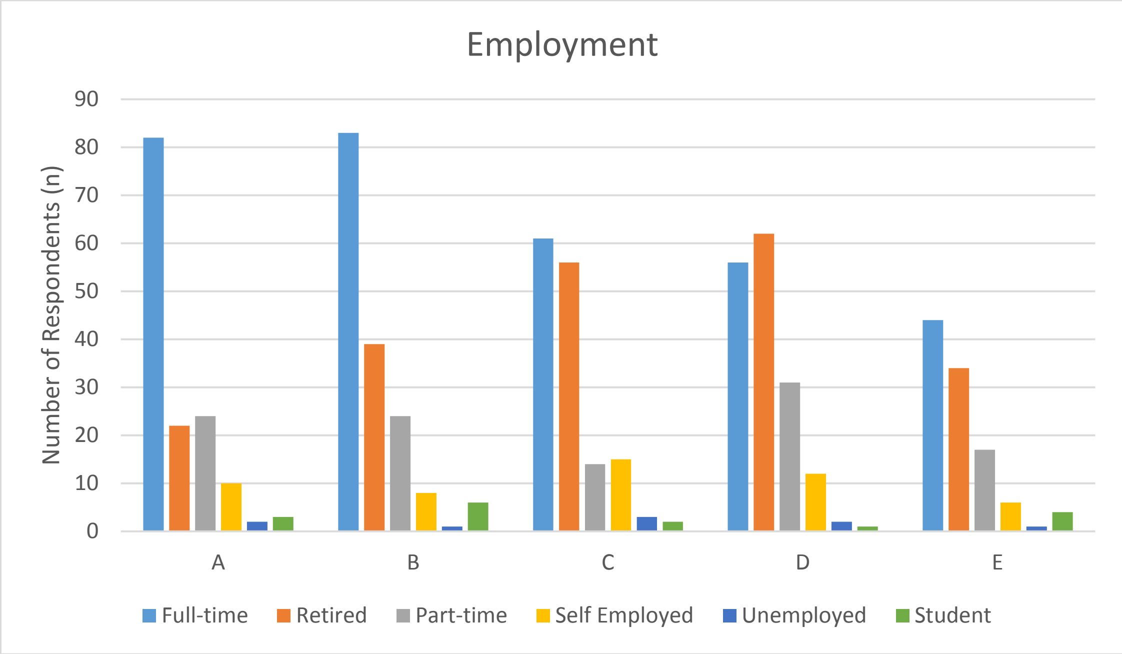



**Figure 33: Employment characteristics**

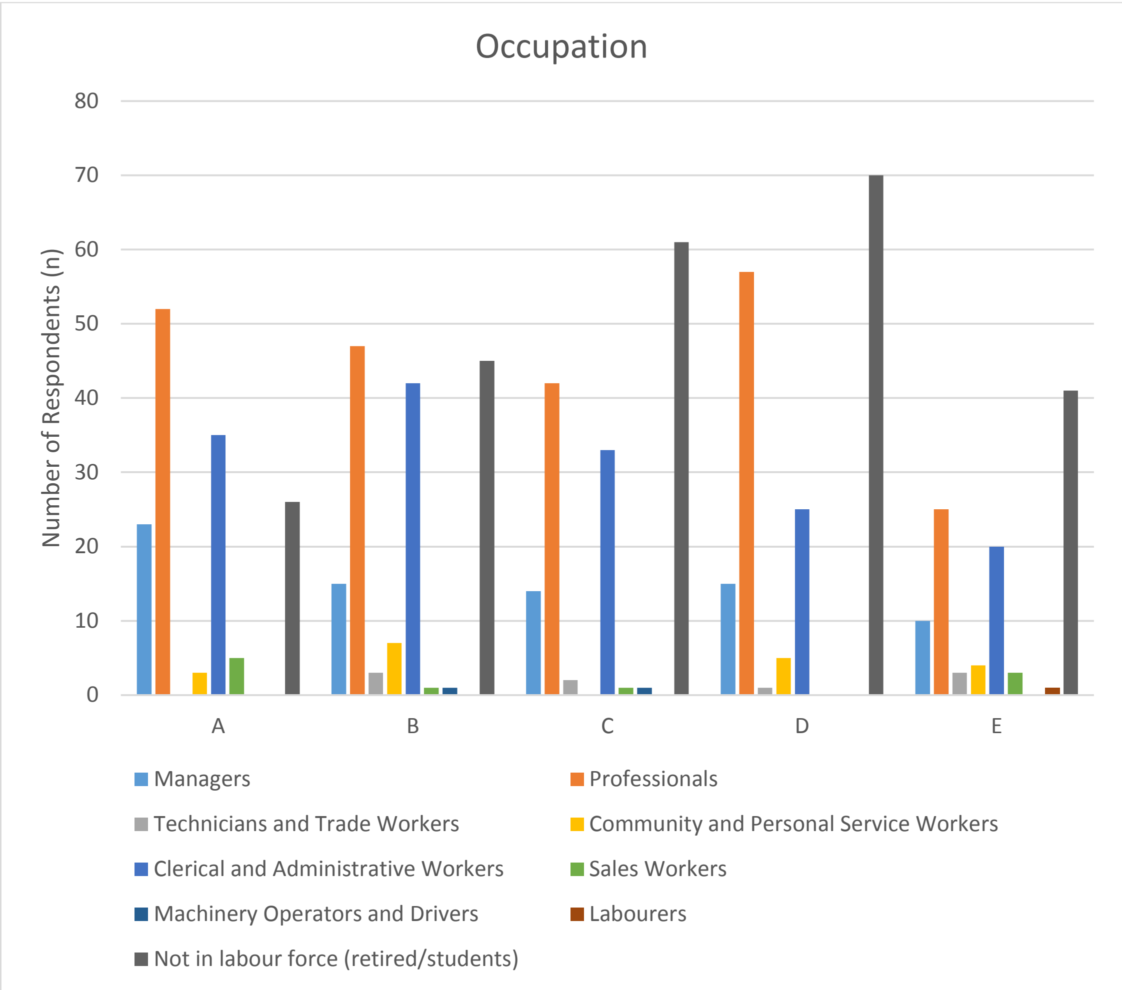



**Figure 34: Occupation characteristics**

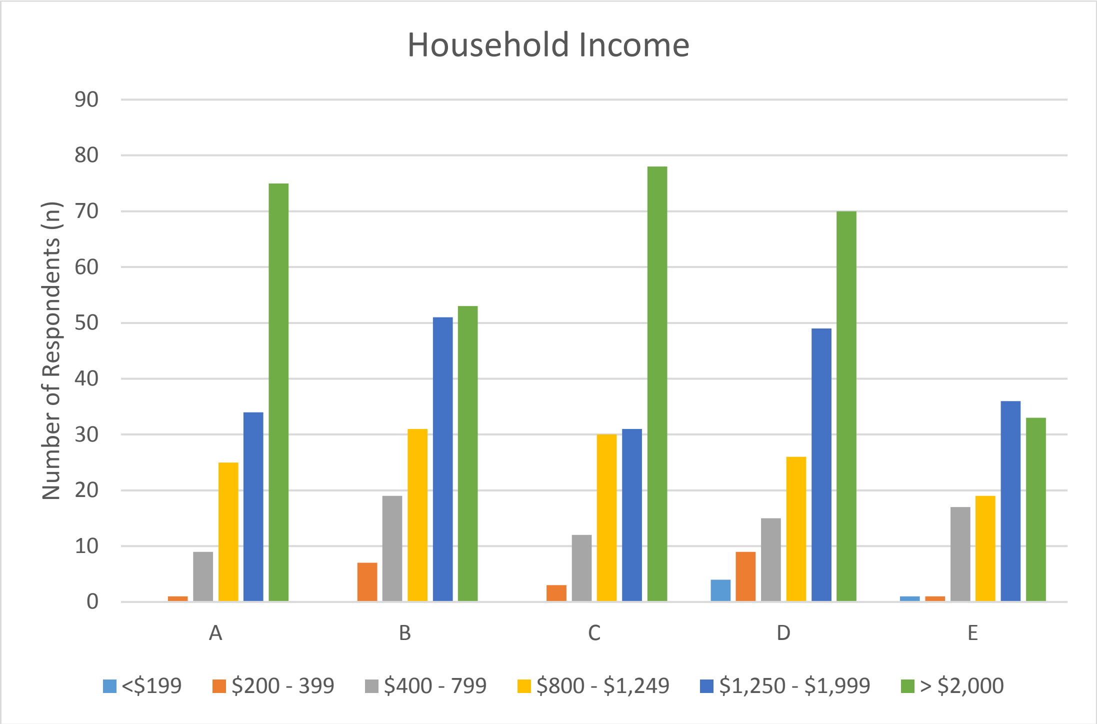



**Figure 35: Household income characteristics**

# Appendix Q: Consumption Characteristics of Consumer Subgroups

The consumption characteristics of each consumer subgroup are explored in further detail below (see Table 32 – 35, and Figure 36 - 48).

**Table 33: Subgroup visitation patterns to all major food retailers**

| Abbreviation | Major Food Retailers | A | B | C | D | E |
|---|---|---|---|---|---|---|
| **DW** | Dickson Woolworths | 158 | **232** | **226** | 232 | **172** |
| **DSS** | Dickson specialty stores* | 63 | 61 | 78 | 77 | 45 |
| **CSUP** | Canberra Centre Supabarn | 99 | 96 | 134 | 128 | 73 |
| **CA** | Canberra Centre Aldi | 46 | 78 | 61 | 91 | 87 |
| **CSS** | Canberra Centre specialty stores* | 47 | 35 | 43 | 66 | 31 |
| **ER_IGA** | East Row IGA X-Press | 11 | 7 | 10 | 17 | 9 |
| **BFFM** | Belconnen Fresh Food Markets | 43 | 33 | 28 | 39 | 23 |
| **BW** | Belconnen Woolworths | 7 | 25 | 12 | 8 | 7 |
| **BC** | Belconnen Coles | 13 | 19 | 13 | 13 | 11 |
| **JC** | Jamison Coles | 22 | 46 | 43 | 31 | 42 |
| **MA** | Macquarie Aldi | 15 | 36 | 30 | 27 | 31 |
| **WS** | Watson Supabarn Express | 103 | 92 | 91 | 113 | 56 |
| **HIGA** | Hackett IGA | 91 | 56 | 47 | 67 | 40 |
| **AIGA** | Ainslie IGA | **328** | 144 | 204 | **355** | 108 |
| **OIGA** | O'Connor IGA | 94 | 74 | 90 | 61 | 32 |
| **LIGA** | Lyneham IGA | 99 | 93 | 77 | 105 | 30 |
| **CIGA** | Campbell IGA | 28 | 25 | 39 | 40 | 26 |
| **FFFM** | Fyshwick Fresh Food Markets | 34 | 22 | 36 | 49 | 20 |
| **GA** | Gungahlin Aldi | 7 | 12 | 10 | 22 | 12 |
| **GW** | Gungahlin Woolworths | 2 | 11 | 0 | 5 | 1 |
| **GC** | Gungahlin Coles | 5 | 24 | 17 | 17 | 12 |
| **SCC** | Spar, Canberra City | 2 | 9 | 10 | 0 | 2 |
| **CRFM** | Capital Region Farmer's Market, Exhibition Park (EPIC) | 82 | 26 | 56 | 94 | 25 |
| **SFM** | Southside Farmers Market, CIT | 0 | 0 | 0 | 3 | 2 |
| **NFM** | Northside Farmer's Market, UC | 2 | 3 | 0 | 3 | 2 |
| **BUFM** | Bungendore Markets | 0 | 0 | 0 | 2 | 0 |
| **HM** | Hall Markets | 1 | 1 | 0 | 0 | 0 |
| **CBJNL** | Choku Bai Jo, Lyneham | 45 | 16 | 14 | 46 | 17 |
| **CBJC** | Choku Bai Jo, Curtin | 2 | 2 | 2 | 3 | 0 |
| **FCOP** | Food Co-Op, ANU | 17 | 3 | 1 | 9 | 0 |
| **MW** | Majura Woolworths | 23 | 33 | 49 | 36 | 18 |
| **C** | Costco, Majura | 31 | 33 | 34 | 30 | 34 |
| **MCWG** | Mountain Creek Wholefoods, Griffith | 20 | 2 | 7 | 9 | 1 |
| | **TOTAL** | 1541 | 1349 | 1462 | **1798** | 969 |

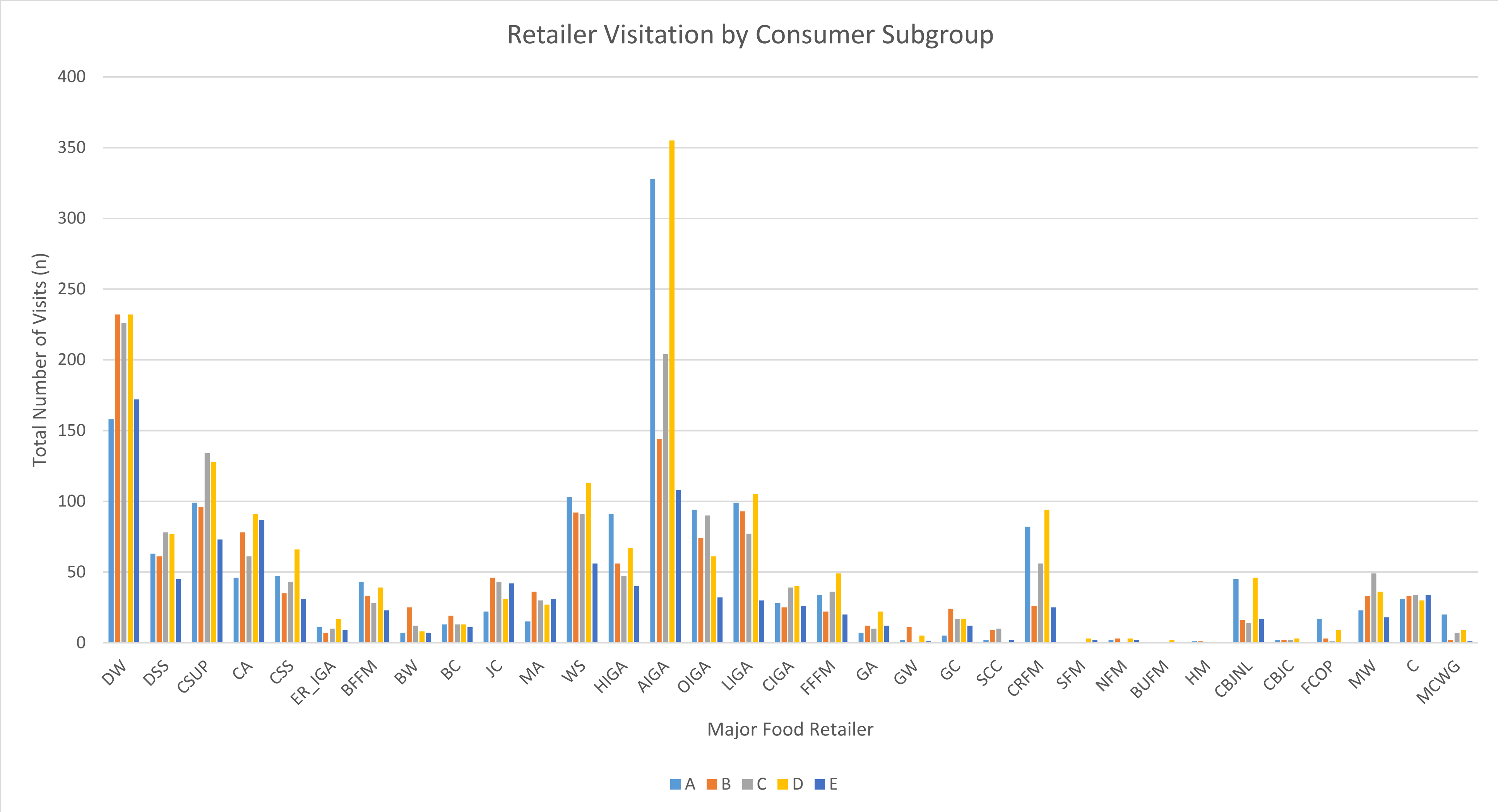



**Figure 36: Retailer visitation disaggregated by consumer subgroup.**

**Table 34: Total number of customers per retailer for each subgroup.** Highest number in bold text.

| Abbreviation | Major Food Retailers | A | B | C | D | E |
|---|---|---|---|---|---|---|
| **DW** | Dickson Woolworths | **82** | **104** | **82** | **88** | **65** |
| **DSS** | Dickson specialty stores* | 32 | 39 | 37 | 35 | 21 |
| **CSUP** | Canberra Centre Supabarn | 43 | 52 | 56 | 41 | 35 |
| **CA** | Canberra Centre Aldi | 27 | 38 | 24 | 37 | 33 |
| **CSS** | Canberra Centre specialty stores* | 20 | 20 | 23 | 28 | 15 |
| **ER_IGA** | East Row IGA X-Press | 7 | 6 | 5 | 7 | 7 |
| **BFFM** | Belconnen Fresh Food Markets | 28 | 25 | 19 | 22 | 17 |
| **BW** | Belconnen Woolworths | 5 | 22 | 8 | 5 | 6 |
| **BC** | Belconnen Coles | 9 | 14 | 9 | 9 | 7 |
| **JC** | Jamison Coles | 13 | 31 | 24 | 17 | 24 |
| **MA** | Macquarie Aldi | 8 | 19 | 16 | 19 | 15 |
| **WS** | Watson Supabarn Express | 30 | 30 | 19 | 30 | 21 |
| **HIGA** | Hackett IGA | 21 | 22 | 10 | 19 | 12 |
| **AIGA** | Ainslie IGA | 82 | 46 | 51 | 75 | 31 |
| **OIGA** | O'Connor IGA | 29 | 30 | 22 | 20 | 14 |
| **LIGA** | Lyneham IGA | 33 | 41 | 21 | 35 | 18 |
| **CIGA** | Campbell IGA | 6 | 10 | 12 | 13 | 8 |
| **FFFM** | Fyshwick Fresh Food Markets | 21 | 13 | 23 | 27 | 13 |
| **GA** | Gungahlin Aldi | 5 | 8 | 9 | 9 | 9 |
| **GW** | Gungahlin Woolworths | 2 | 7 | 0 | 2 | 1 |
| **GC** | Gungahlin Coles | 4 | 12 | 7 | 9 | 8 |
| **SCC** | Spar, Canberra City | 2 | 8 | 4 | 0 | 2 |
| **CRFM** | Capital Region Farmer's Market, Exhibition Park (EPIC) | 52 | 20 | 34 | 52 | 19 |
| **SFM** | Southside Farmers Market, CIT | 0 | 0 | 0 | 3 | 2 |
| **NFM** | Northside Farmer's Market, UC | 2 | 2 | 0 | 2 | 2 |
| **BUFM** | Bungendore Markets | 0 | 0 | 0 | 1 | 0 |
| **HM** | Hall Markets | 1 | 1 | 0 | 0 | 0 |
| **CBJNL** | Choku Bai Jo, Lyneham | 26 | 10 | 7 | 22 | 6 |
| **CBJC** | Choku Bai Jo, Curtin | 2 | 2 | 2 | 2 | 0 |
| **FCOP** | Food Co-Op, ANU | 10 | 2 | 1 | 7 | 0 |
| **MW** | Majura Woolworths | 13 | 20 | 19 | 14 | 14 |
| **C** | Costco, Majura | 24 | 20 | 24 | 18 | 26 |
| **MCWG** | Mountain Creek Wholefoods, Griffith | 14 | 2 | 5 | 7 | 1 |

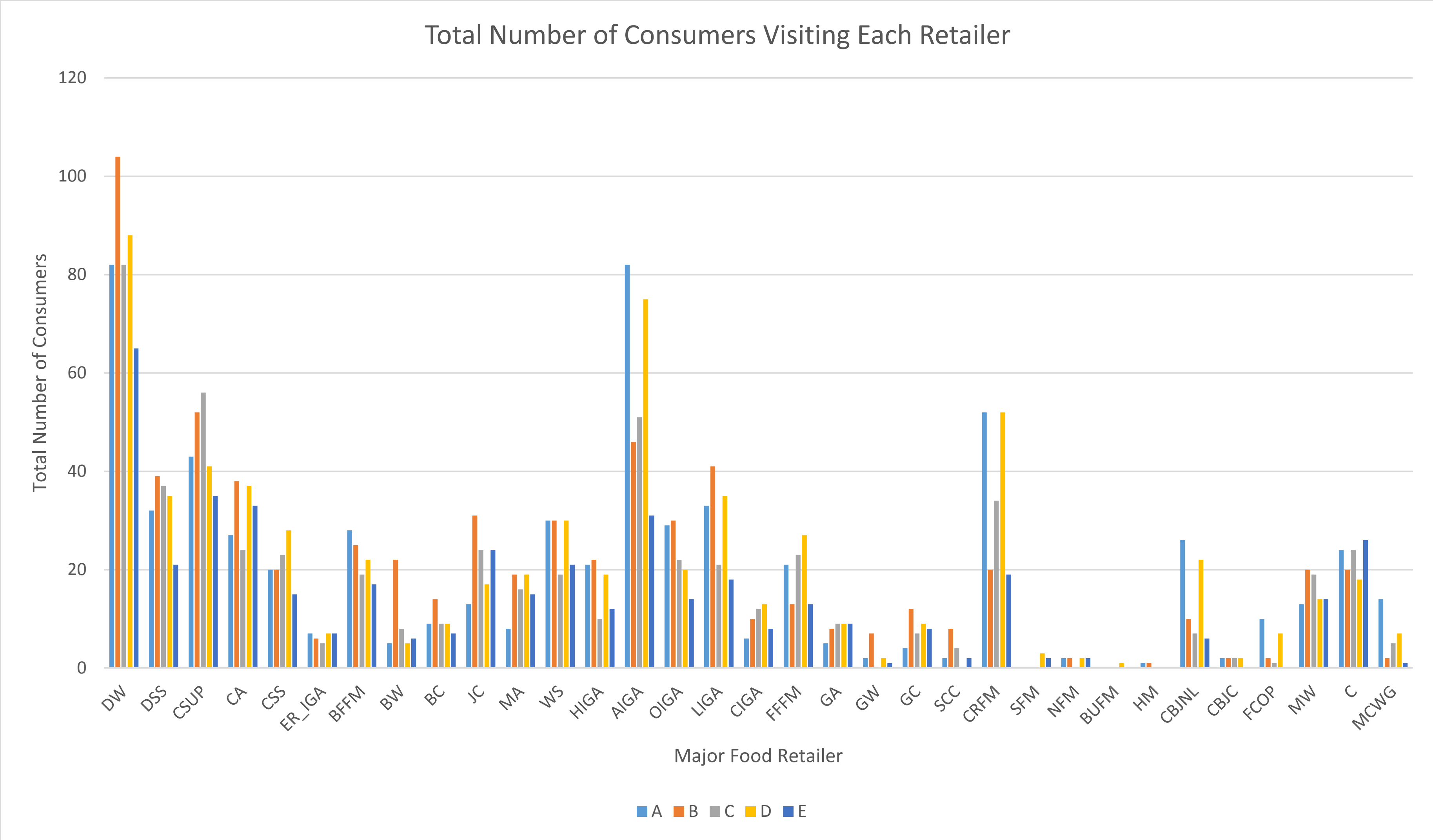



**Figure 37: Total number of customers visiting each retailer, disaggregated by consumer subgroup.**

**Table 35: Total recorded expenditure for each cluster subgroup.** Highest number in bold text.

| Abbreviation | Major Food Retailers | A | B | C | D | E |
|---|---|---|---|---|---|---|
| **DW** | Dickson Woolworths | 10,271.72 | **13,484.81** | **10,539.94** | **10,685.30** | **8,692.24** |
| **DSS** | Dickson specialty stores* | 888.00 | 1,390.88 | 1,649.35 | 919.00 | 468.34 |
| **CSUP** | Canberra Centre Supabarn | 3,249.91 | 3,959.13 | 4,794.00 | 3,114.00 | 1,261.55 |
| **CA** | Canberra Centre Aldi | 1,919.00 | 2,325.00 | 2,148.50 | 2,323.00 | 2,206.08 |
| **CSS** | Canberra Centre specialty stores* | 1,081.00 | 492.00 | 1,008.00 | 888.00 | 256.60 |
| **ER_IGA** | East Row IGA X-Press | 52.00 | 134.00 | 90.00 | 143.00 | 153.63 |
| **BFFM** | Belconnen Fresh Food Markets | 2,304.00 | 1,089.75 | 1,140.00 | 920.00 | 790.00 |
| **BW** | Belconnen Woolworths | 515.00 | 894.00 | 698.00 | 290.00 | 223.48 |
| **BC** | Belconnen Coles | 603.34 | 795.00 | 969.00 | 1,300.00 | 332.80 |
| **JC** | Jamison Coles | 1,548.00 | 2,616.00 | 2,310.36 | 1,359.67 | 1,733.06 |
| **MA** | Macquarie Aldi | 180.00 | 2,380.00 | 1,567.15 | 1,549.00 | 1,546.85 |
| **WS** | Watson Supabarn Express | 3,245.74 | 1,901.09 | 2,333.00 | 1,918.00 | 1,079.50 |
| **HIGA** | Hackett IGA | 2,042.29 | 1,285.00 | 593.20 | 1,929.00 | 654.40 |
| **AIGA** | Ainslie IGA | **11,570.75** | 4,520.00 | 5,726.18 | 8,004.10 | 2,454.58 |
| **OIGA** | O'Connor IGA | 2,155.79 | 888.50 | 1,536.00 | 2,822.00 | 514.00 |
| **LIGA** | Lyneham IGA | 2,474.87 | 1,556.25 | 950.50 | 1,608.00 | 882.00 |
| **CIGA** | Campbell IGA | 610.00 | 340.00 | 705.00 | 729.00 | 186.79 |
| **FFFM** | Fyshwick Fresh Food Markets | 2,531.29 | 570.00 | 2,456.13 | 3,396.00 | 1,001.00 |
| **GA** | Gungahlin Aldi | 530.36 | 516.00 | 432.00 | 500.00 | 425.00 |
| **GW** | Gungahlin Woolworths | 75.00 | 825.65 | 0.00 | 116.00 | 0.00 |
| **GC** | Gungahlin Coles | 213.00 | 1,221.00 | 1,048.00 | 758.00 | 643.38 |
| **SCC** | Spar, Canberra City | 20.00 | 65.50 | 30.00 | 0.00 | 0.00 |
| **CRFM** | Capital Region Farmer's Market | 6,322.00 | 1,755.00 | 3,372.00 | 6,579.00 | 1,100.00 |
| **SFM** | Southside Farmers Market, CIT | 0.00 | 0.00 | 45.00 | 45.00 | 70.00 |
| **NFM** | Northside Farmer's Market, UC | 75.00 | 0.00 | 0.00 | 400.00 | 0.00 |
| **BUFM** | Bungendore Markets | 0.00 | 0.00 | 0.00 | 37.00 | 0.00 |
| **HM** | Hall Markets | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| **CBJNL** | Choku Bai Jo, Lyneham | 2,029.17 | 392.00 | 385.00 | 1,569.00 | 305.00 |
| **CBJC** | Choku Bai Jo, Curtin | 40.00 | 38.00 | 58.00 | 53.00 | 0.00 |
| **FCOP** | Food Co-Op, ANU | 340.00 | 10.00 | 30.00 | 215.00 | 0.00 |
| **MW** | Majura Woolworths | 1,142.04 | 2,061.00 | 2,938.00 | 1,949.00 | 904.94 |
| **C** | Costco, Majura | 4,875.02 | 3,982.00 | 2,687.00 | 1,878.00 | 3,929.76 |
| **MCWG** | Mountain Creek Wholefoods, Griffith | 565.00 | 5.00 | 120.00 | 80.00 | 70.00 |
| | Other | 1,816.63 | 1,689.20 | 1,402.50 | 2,236.50 | 3,019.15 |
| | **Total** | **65,285.92** | 53,181.76 | 53,761.81 | 60,312.57 | 34,904.13 |

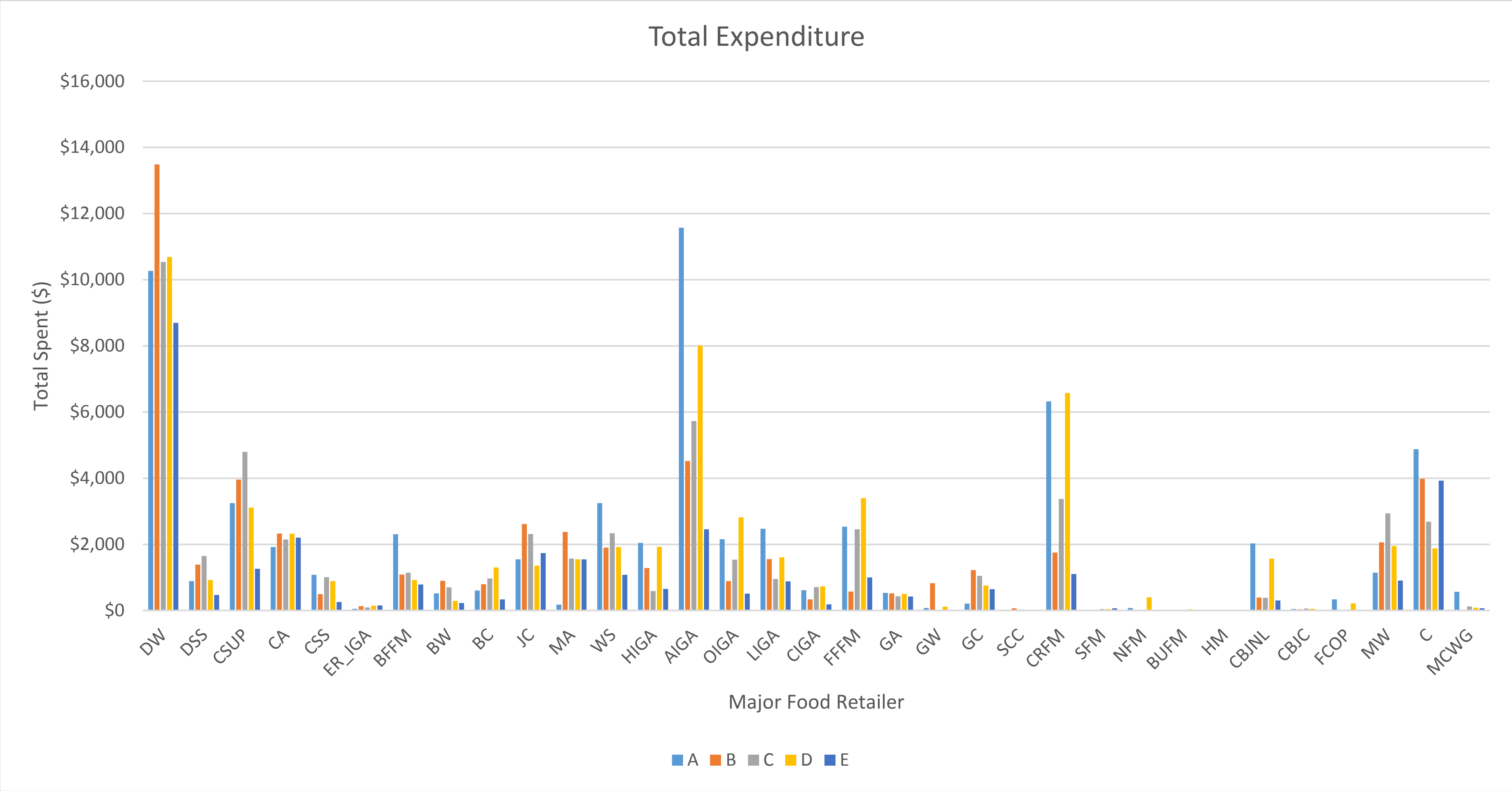



**Figure 38: Total recorded expenditure at each retailer disaggregated by consumer subgroup.**

**Table 36: FCQ subgroup responses.** Highest values for each cluster highlighted in bold text.

| | | **Not at all important 1** | | | | | **A little important 2** | | | | | **Moderately important 3** | | | | | **Very important 4** | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Question** | **FCQ Motive** | **A** | **B** | **C** | **D** | **E** | **A** | **B** | **C** | **D** | **E** | **A** | **B** | **C** | **D** | **E** | **A** | **B** | **C** | **D** | **E** |
| **Q14_EASY** | Convenience | 5 | 1 | 15 | 20 | 8 | 33 | 5 | 49 | 49 | 28 | 70 | 47 | 72 | 86 | 51 | 36 | **108** | **18** | 18 | 20 |
| **Q14_EXPE** | Price | 25 | 0 | 42 | 2 | 0 | **108** | 10 | **112** | 56 | 4 | 11 | **118** | 0 | **104** | **78** | 0 | 33 | 0 | 11 | 25 |
| **Q14_CHILD** | Familiarity | **111** | **94** | **121** | **125** | **69** | 21 | 43 | 22 | 34 | 26 | 9 | 20 | 10 | 10 | 10 | 3 | 4 | 1 | 4 | 2 |
| **Q14_ANIMAL** | Ecological welfare | 0 | 12 | 35 | 0 | 13 | 6 | 50 | 62 | 6 | 51 | 27 | 57 | 51 | 56 | 39 | **111** | 42 | 6 | 111 | 4 |
| **Q14_FAIR** | Political Values | 0 | 11 | 20 | 0 | 14 | 2 | 57 | 84 | 4 | 47 | 54 | 56 | 48 | 66 | 44 | 88 | 37 | 2 | 103 | 2 |
| **Q14_VALUE** | Price | 3 | 0 | 7 | 0 | 0 | 22 | 4 | 48 | 12 | 8 | **91** | 93 | **84** | 81 | 47 | 28 | 64 | 15 | 80 | **52** |
| **Q14_COMM** | Social Values | 2 | 19 | 42 | 2 | 20 | 23 | **58** | 58 | 16 | 51 | 56 | 71 | 45 | 86 | 34 | 63 | 13 | 9 | 69 | 2 |
| **Q14_ENV** | Ecological welfare | 0 | 6 | 16 | 0 | 8 | 2 | 50 | 64 | 0 | 40 | 43 | 73 | 72 | 48 | 58 | 99 | 32 | 2 | **125** | 1 |
| **Q14_USUAL** | Familiarity | 22 | 16 | 28 | 47 | 19 | 39 | 30 | 54 | 55 | 35 | 63 | 78 | 62 | 54 | 43 | 20 | 37 | 10 | 17 | 10 |
| **Q14_ENJOY** | Social Values | 9 | 32 | 40 | 33 | 30 | 52 | 48 | 42 | 53 | 29 | 50 | 57 | 57 | 65 | 39 | 33 | 24 | 15 | 22 | 9 |
| **Q14_QUICK** | Convenience | 11 | 0 | 43 | 104 | 39 | 73 | 1 | 75 | **68** | **65** | 50 | 99 | 33 | 1 | 3 | 10 | 61 | 3 | 0 | 0 |
| **Q14_POLIT** | Political Values | 18 | 50 | 62 | 28 | 56 | 31 | 53 | 55 | 38 | 32 | 50 | 38 | 28 | 63 | 17 | 45 | 20 | 9 | 44 | 2 |

# Appendix R: Calibrated Attractiveness Results

The characteristics of each retailer were collected to calibrate model attractiveness values. Collected data is summarised in Table 36 and Figure 39 below.

**Table 37: Retailer characteristics**

| Major Food Retailers (Shops, stores and markets) | Abbreviation | Suburb | Type | Floor Area (m²) | BDA (m²) | Presence in Study Area | Participation in AFN? |
|---|---|---|---|---|---|---|---|
| **Dickson Woolworths** | DW | Dickson | Large Supermarket | 3055 | 91602 | Y | N |
| **Dickson specialty stores** | DSS | Dickson | Small Retailers | 170 | 91602 | Y | N |
| **Canberra Centre Supabarn** | CSUP | City East | Large Supermarket | 3700 | 163851 | Y | N |
| **Canberra Centre Aldi** | CA | City East | Large Supermarket | 50 | 163851 | Y | N |
| **Canberra Centre specialty stores** | CSS | City East | Small Retailers | 176 | 163851 | Y | N |
| **East Row IGA X-Press** | ER_IGA | City West | Independent Supermarket | 401 | 25677 | Y | N |
| **Belconnen Fresh Food Markets** | BFFM | North Belconnen | Group of Small Retailers | 22808.00 | 22808 | N | N |
| **Belconnen Woolworths** | BW | North Belconnen | Large Supermarket | 4820 | 101252 | N | N |
| **Belconnen Coles** | BC | North Belconnen | Large Supermarket | 3460 | 101252 | N | N |
| **Jamison Coles** | JC | Macquarie | Large Supermarket | 4350 | 19920 | N | N |
| **Macquarie Aldi** | MA | Macquarie | Large Supermarket | 1360 | 19920 | N | N |
| **Watson Supabarn Express** | WS | Watson | Independent Supermarket | 338 | 338 | Y | N |
| **Hackett IGA** | HIGA | Hackett | Independent Supermarket | 887 | 887 | Y | N |
| **Ainslie IGA** | AIGA | Ainslie | Independent Supermarket | 1200 | 1200 | Y | N |
| **O'Connor IGA** | OIGA | O'Connor | Independent Supermarket | 385 | 385 | Y | N |
| **Lyneham IGA** | LIGA | Lyneham | Independent Supermarket | 559 | 559 | Y | N |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| **Campbell IGA** | CIGA | Campbell | Independent Supermarket | 280 | 280 | Y | N |
| **Fyshwick Fresh Food Markets** | FFFM | Fyshwick | Group of Small Retailers | 28477.00 | 28477 | N | N |
| **Gungahlin Aldi** | GA | Gungahlin | Large Supermarket | 1326 | 64716 | N | N |
| **Gungahlin Woolworths** | GW | Gungahlin | Large Supermarket | 4583 | 64716 | N | N |
| **Gungahlin Coles** | GC | Gungahlin | Independent Supermarket | 3706 | 64716 | N | N |
| **Spar, Canberra City** | SCC | City West | Independent Supermarket | 472 | 1698 | Y | N |
| **Capital Region Farmer's Market, Exhibition Park (EPIC)** | CRFM | Mitchell | Market | 11000 | 11000 | N | Y |
| **Southside Farmers Market, CIT** | SFM | Phillip | Market | 5030 | 5030 | N | Y |
| **Northside Farmer's Market, UC** | NFM | East Belconnen | Market | 906 | 906 | N | Y |
| **Southern Harvest Farmers Market in Bungendore** | BUFM | Bungendore | Market | 503 | 503 | N | Y |
| **Hall Markets** | HM | Hall | Market | 18765 | 18765 | N | Y |
| **Choku Bai Jo, North Lyneham** | CBJNL | Lyneham | Small Alternative Retailer | 4430 | 4430 | Y | Y |
| **Choku Bai Jo, Curtin** | CBJC | Curtin | Small Alternative Retailer | 9932 | 9932 | N | Y |
| **The Food Co-Op, ANU** | FCOP | Acton | Small Alternative Retailer | 9481 | 9481 | Y | Y |
| **Majura Woolworths** | MW | Majura | Independent Supermarket | 224510 | 224510 | N | N |
| **Costco, Majura** | C | Majura | Independent Supermarket | 224510 | 224510 | N | N |
| **Mountain Creek Wholefoods, Griffith** | MCWG | Griffith | Small Alternative Retailer | 4430 | 4430 | N | Y |

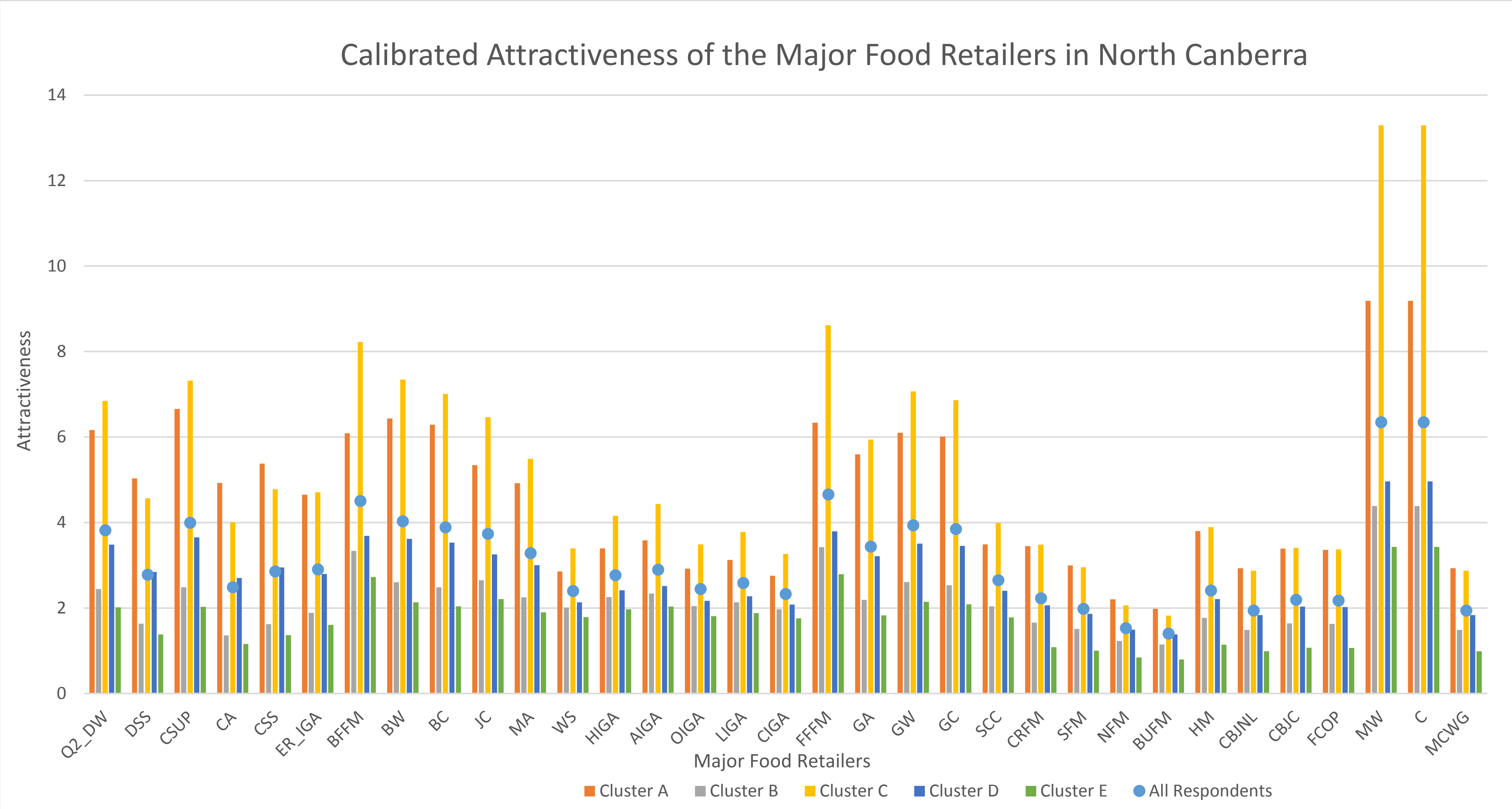



**Figure 39: Calibrated attractiveness of each retailer, disaggregated by consumer subgroup.** Cluster A = Concerned, B = Expedient, C = Dispassionate, D = Calculating, E = Frugal. For a list of retailer abbreviations, see Table 32.

# Appendix S: Retailer Spatial Catchments

Catchments of visitation were calculated for each retailer, and disaggregated by each consumer subgroup. Outputs for each retailer are shown in alphabetical order below (see Figure 40 – 51).

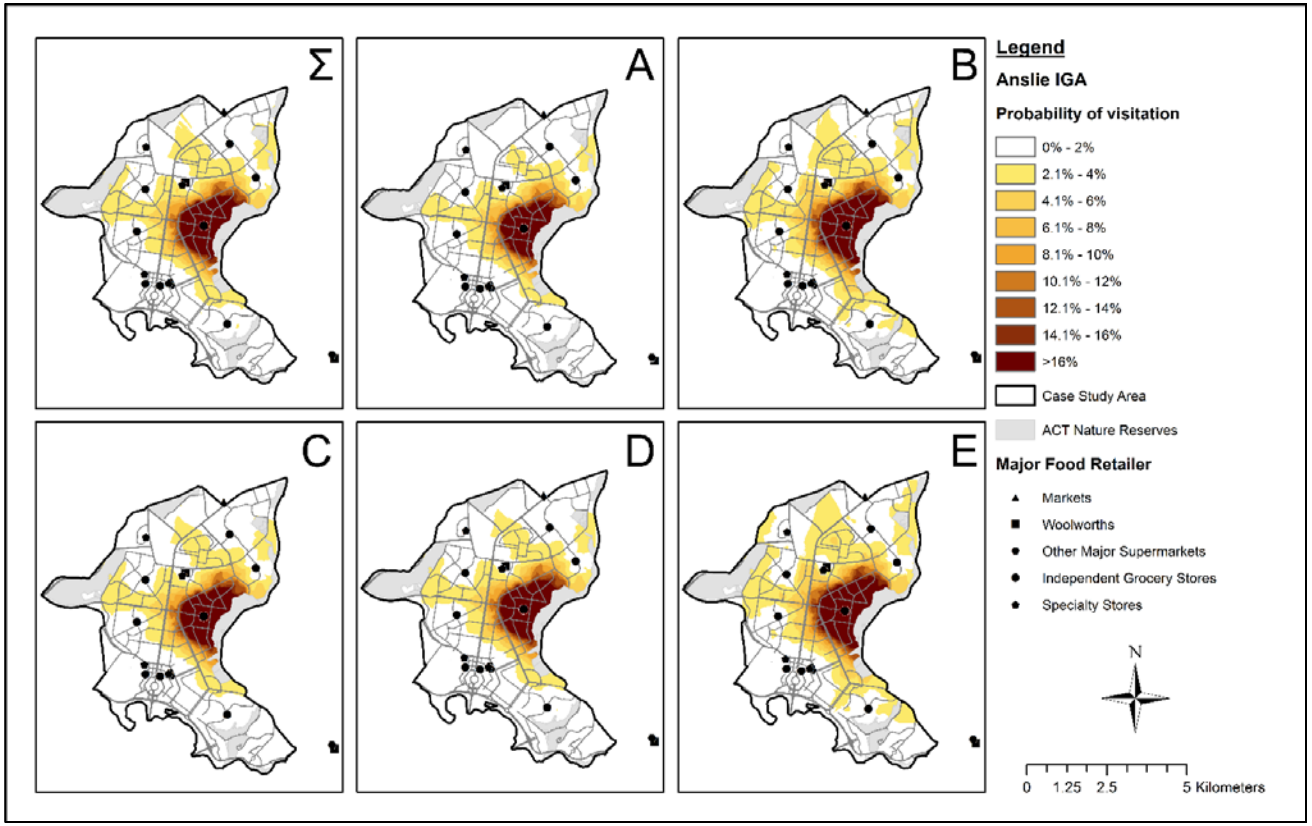



**Figure 40: Calibrated catchment of Ainslie IGA, disaggregated by consumer subgroup.** Σ = All consumers, A = Concerned, B = Expedient, C = Dispassionate, D = Calculating, E = Frugal.

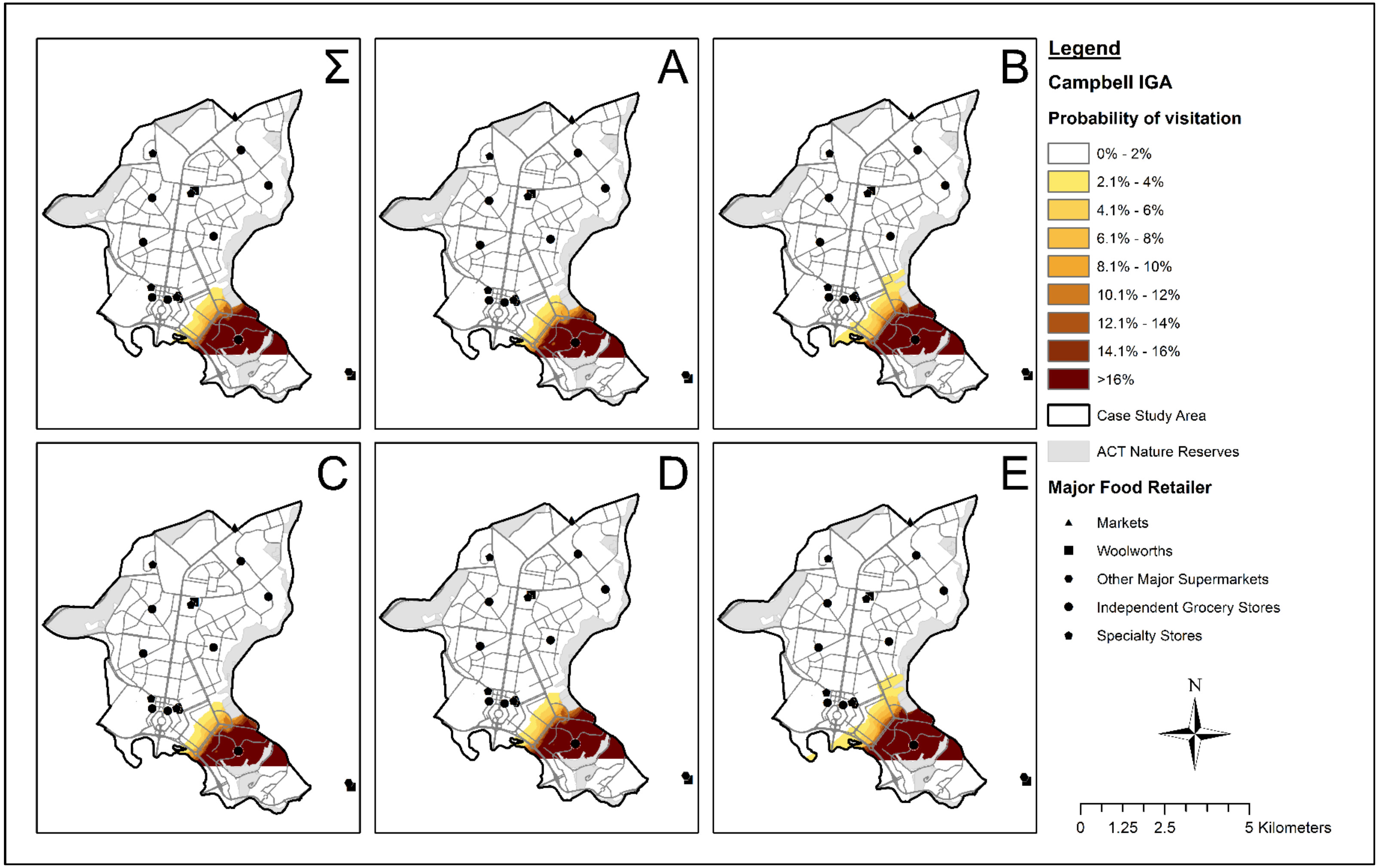



**Figure 41: Calibrated catchment of Campbell IGA, disaggregated by consumer subgroup.** Σ = All consumers, A = Concerned, B = Expedient, C = Dispassionate, D = Calculating, E = Frugal.

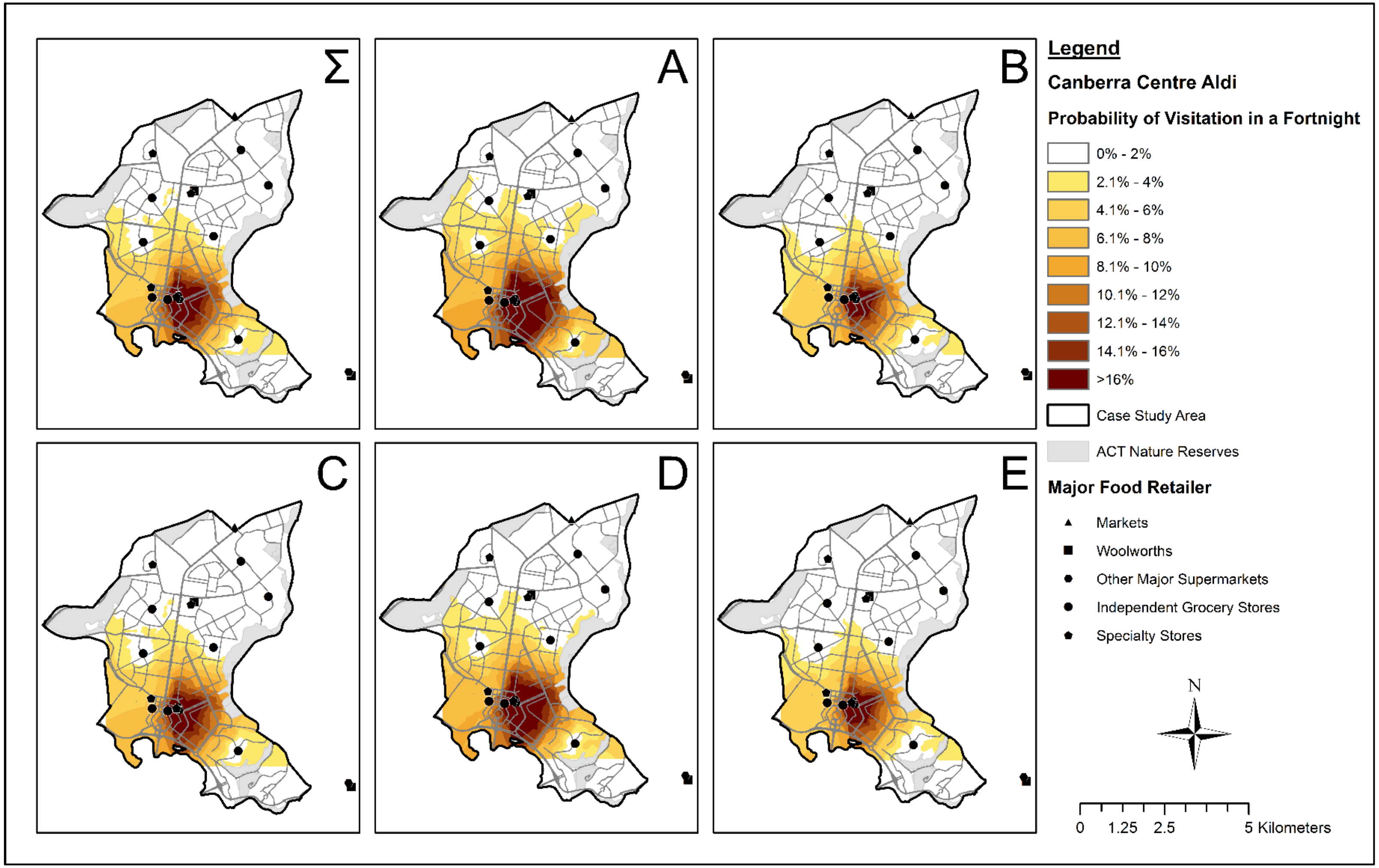



**Figure 42: Calibrated catchment of Canberra Centre Aldi, disaggregated by consumer subgroup.** Σ = All consumers, A = Concerned, B = Expedient, C = Dispassionate, D = Calculating, E = Frugal.

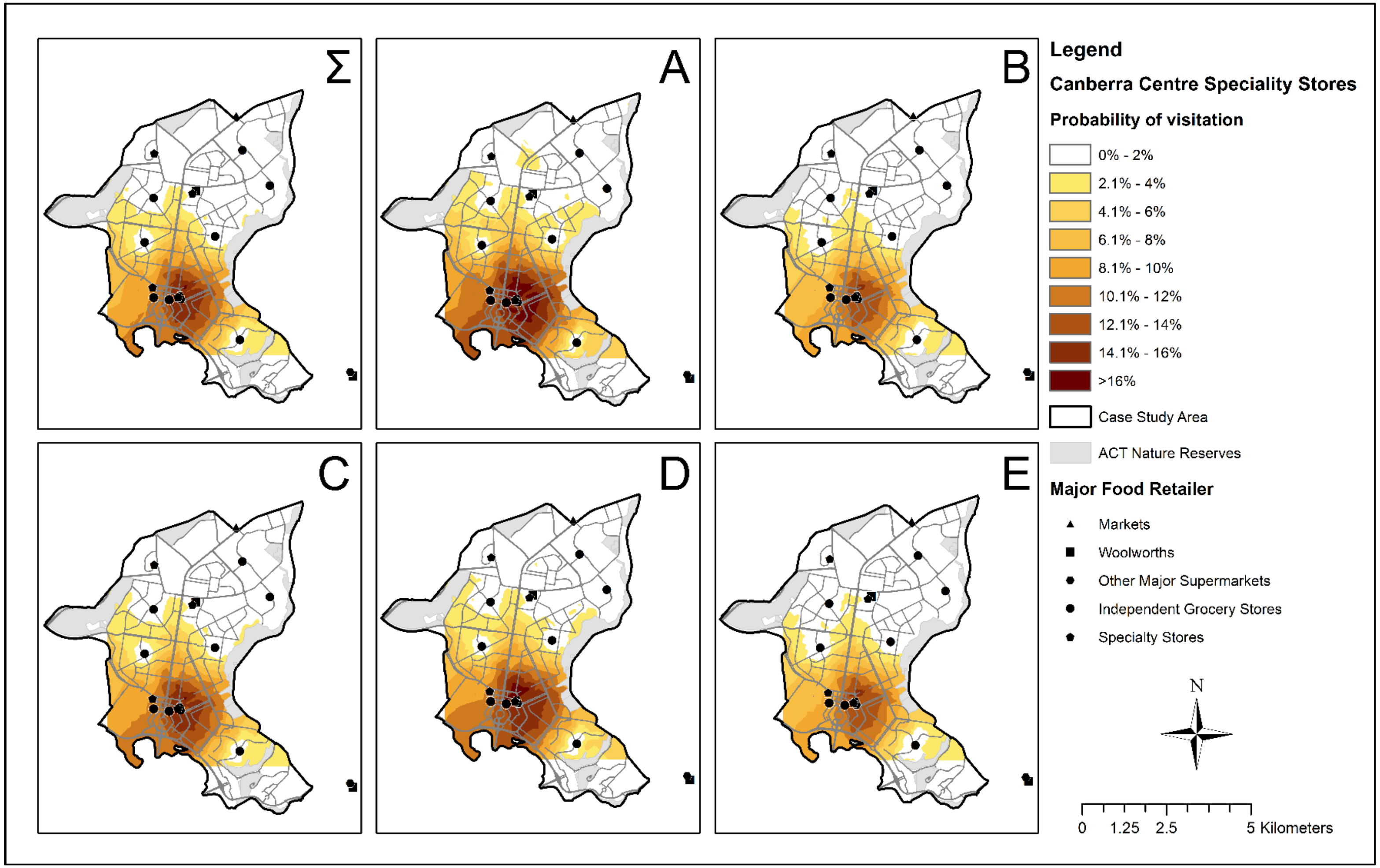



**Figure 43: Calibrated catchment of Canberra Centre Specialty Stores, disaggregated by consumer subgroup.** Σ = All consumers, A = Concerned, B = Expedient, C = Dispassionate, D = Calculating, E = Frugal.

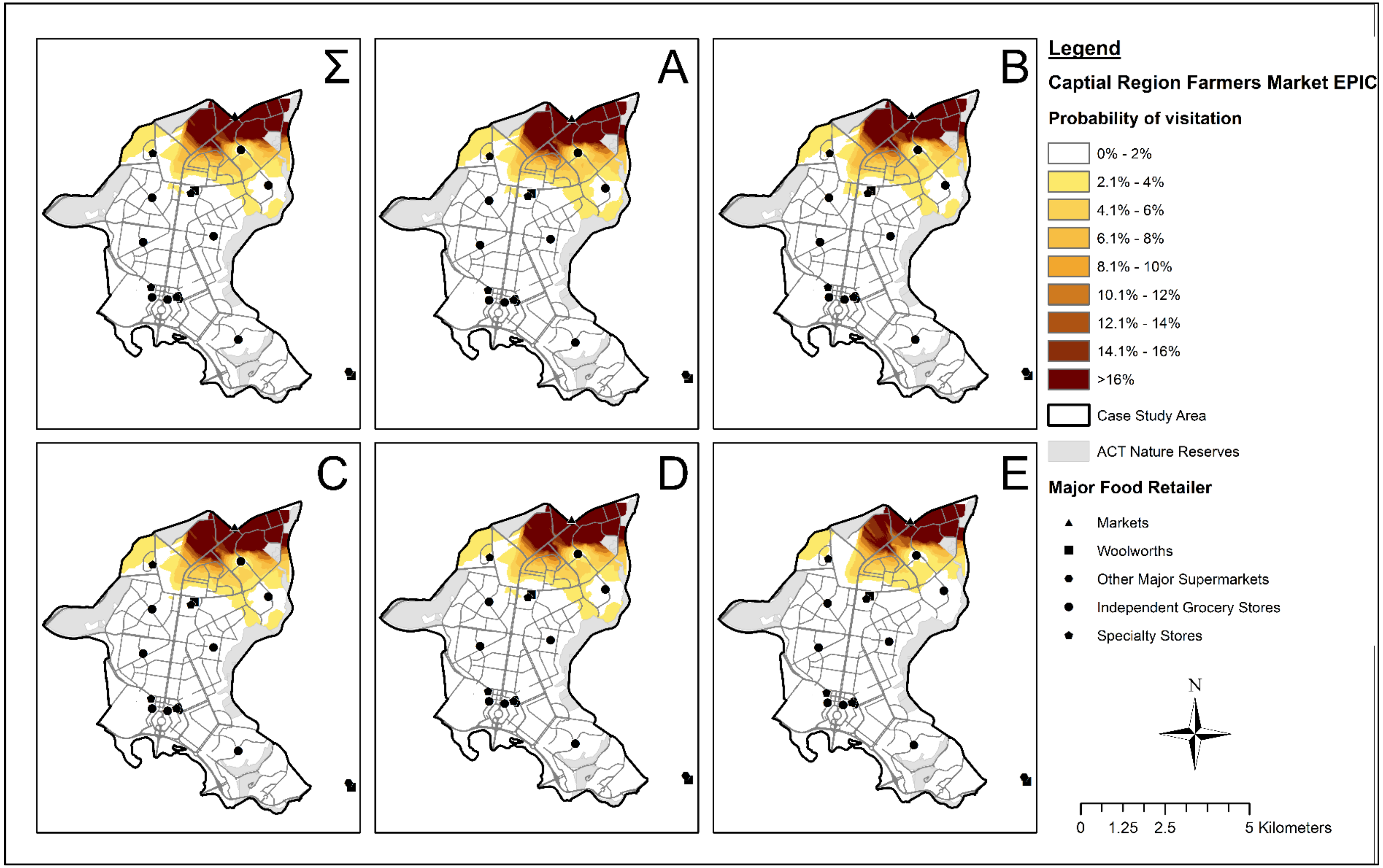



**Figure 44: Calibrated catchment of Capital Region Farmers Market EPIC, disaggregated by consumer subgroup.** Σ = All consumers, A = Concerned, B = Expedient, C = Dispassionate, D = Calculating, E = Frugal.

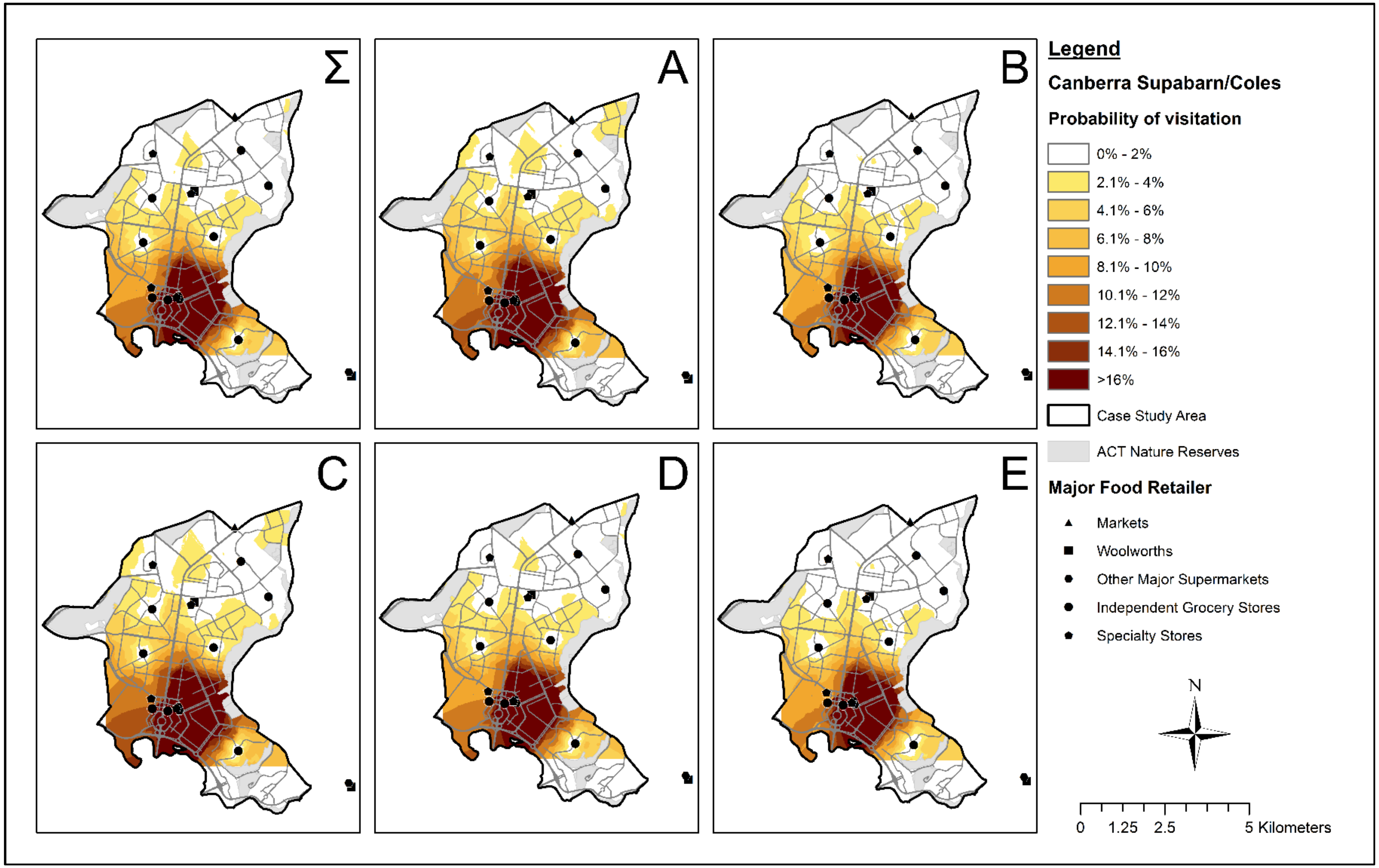



**Figure 45: Calibrated catchment of Canberra Centre Supabarn, disaggregated by consumer subgroup.** Σ = All consumers, A = Concerned, B = Expedient, C = Dispassionate, D = Calculating, E = Frugal.

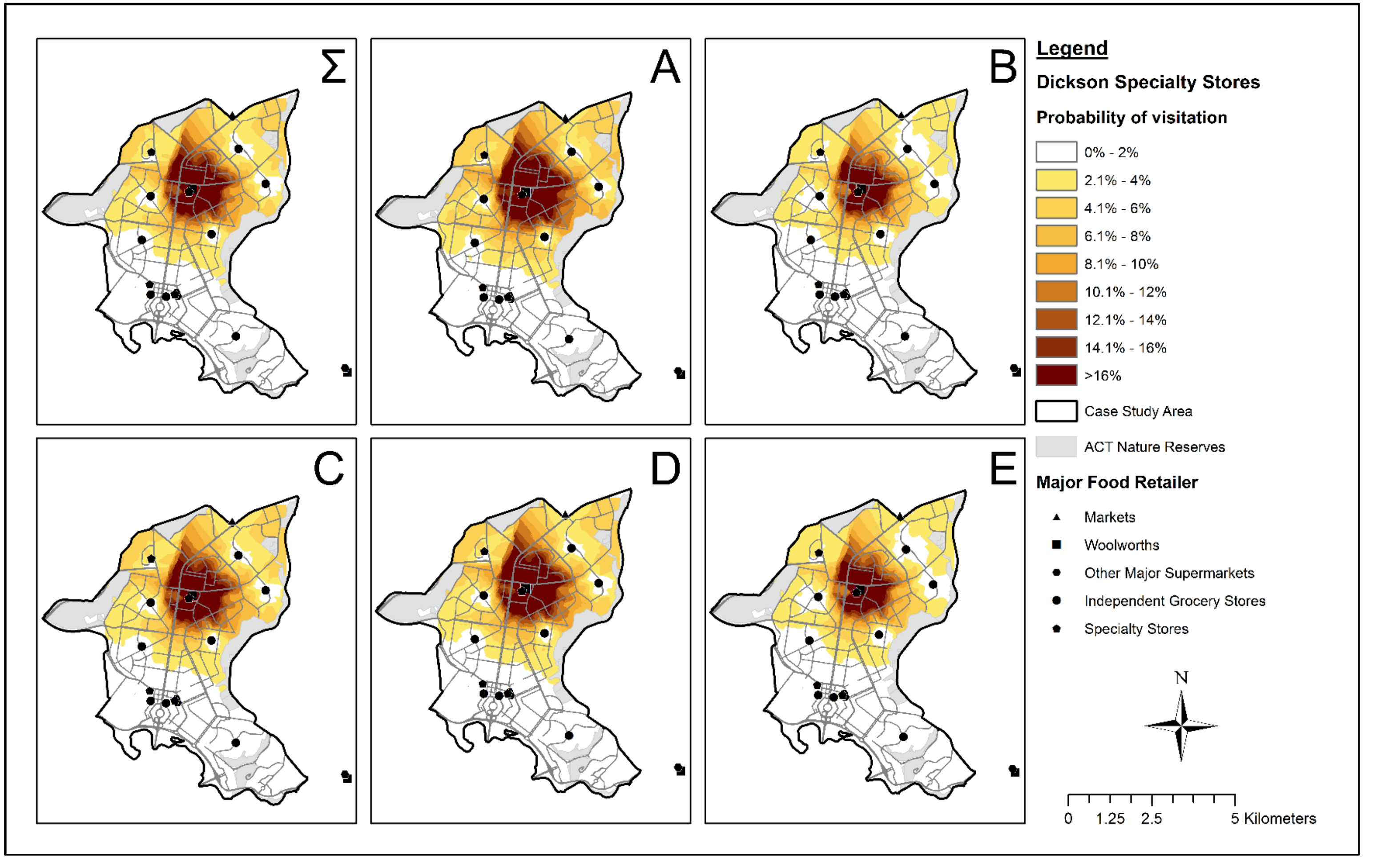



**Figure 46: Calibrated catchment of Dickson Speciality Stores, disaggregated by consumer subgroup.** Σ = All consumers, A = Concerned, B = Expedient, C = Dispassionate, D = Calculating, E = Frugal.

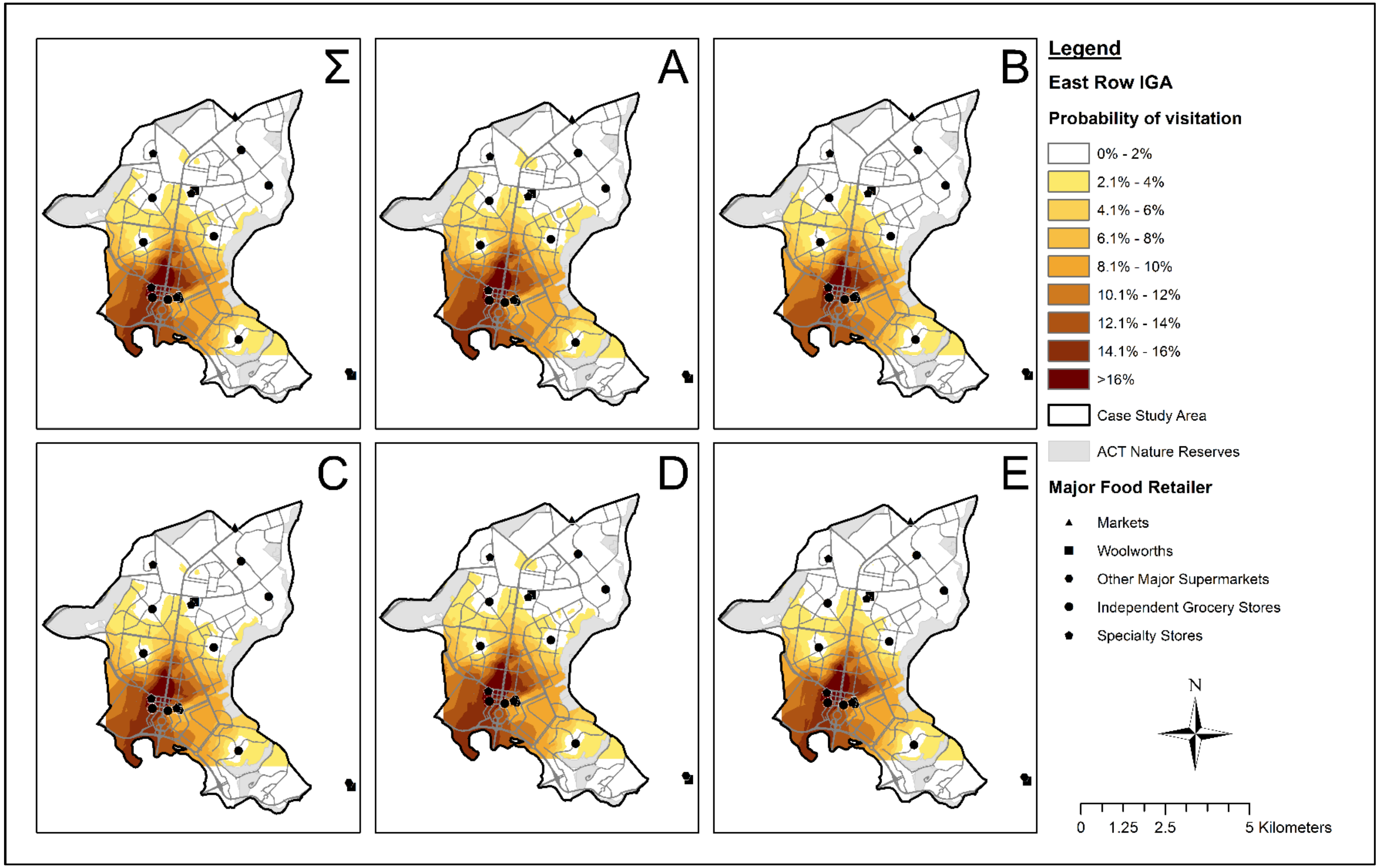



**Figure 47: Calibrated catchment of East Row IGA, disaggregated by consumer subgroup.** Σ = All consumers, A = Concerned, B = Expedient, C = Dispassionate, D = Calculating, E = Frugal.

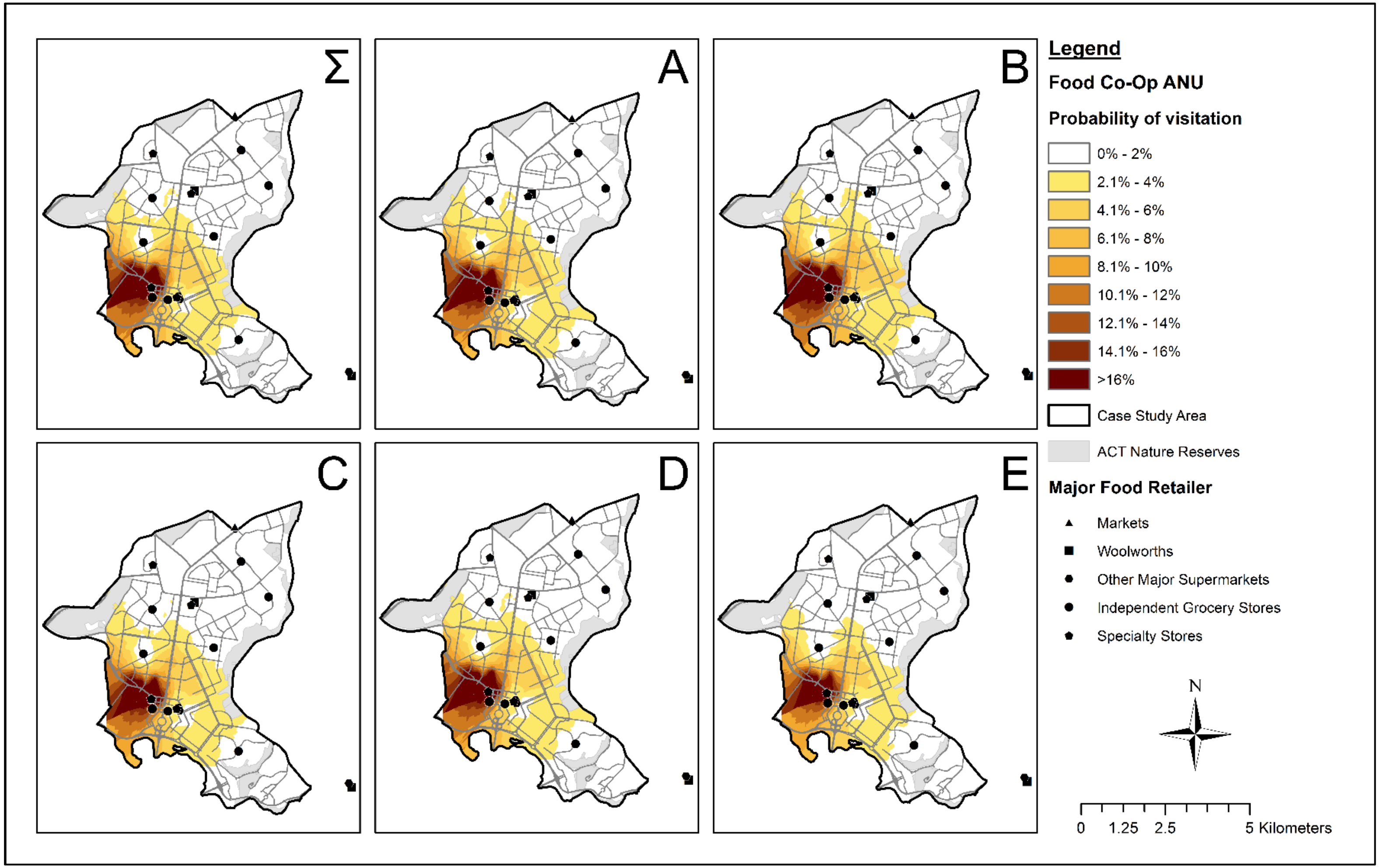



**Figure 48: Calibrated catchment of Food Co-Op ANU, disaggregated by consumer subgroup.** Σ = All consumers, A = Concerned, B = Expedient, C = Dispassionate, D = Calculating, E = Frugal.

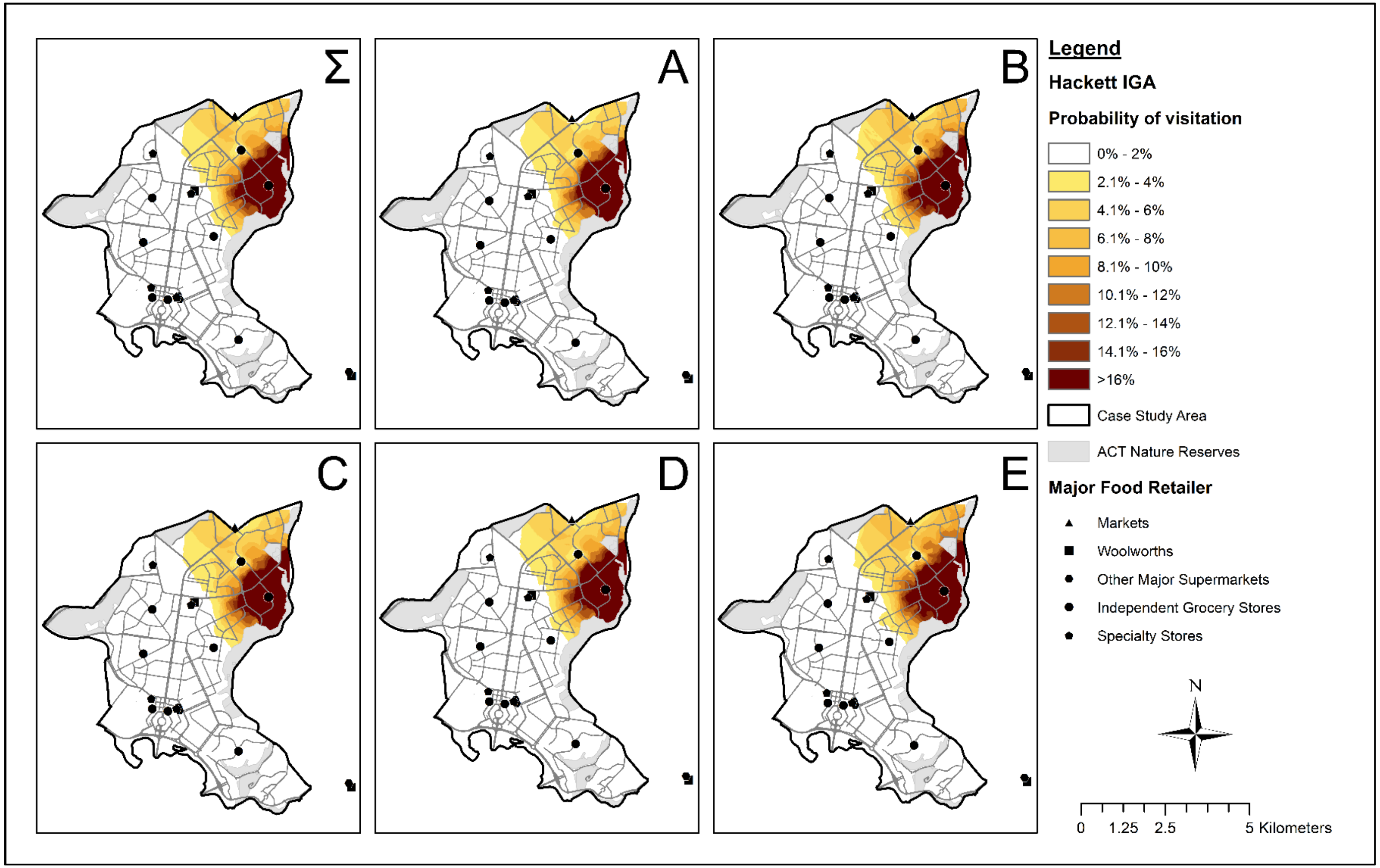



**Figure 49: Calibrated catchment of Hackett IGA, disaggregated by consumer subgroup.** Σ = All consumers, A = Concerned, B = Expedient, C = Dispassionate, D = Calculating, E = Frugal.

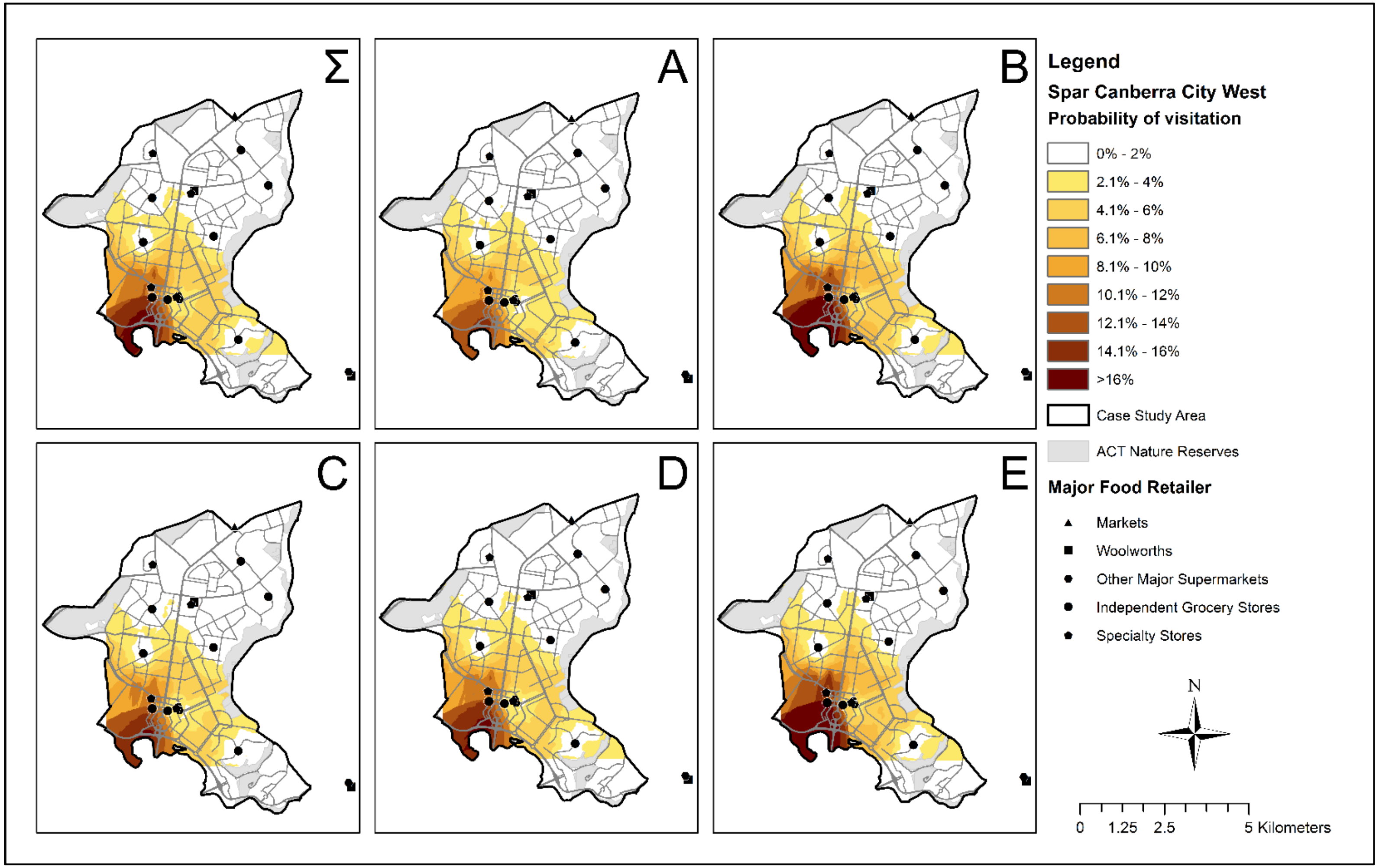



**Figure 50: Calibrated catchment of Spar, Canberra City, disaggregated by consumer subgroup.** Σ = All consumers, A = Concerned, B = Expedient, C = Dispassionate, D = Calculating, E = Frugal.

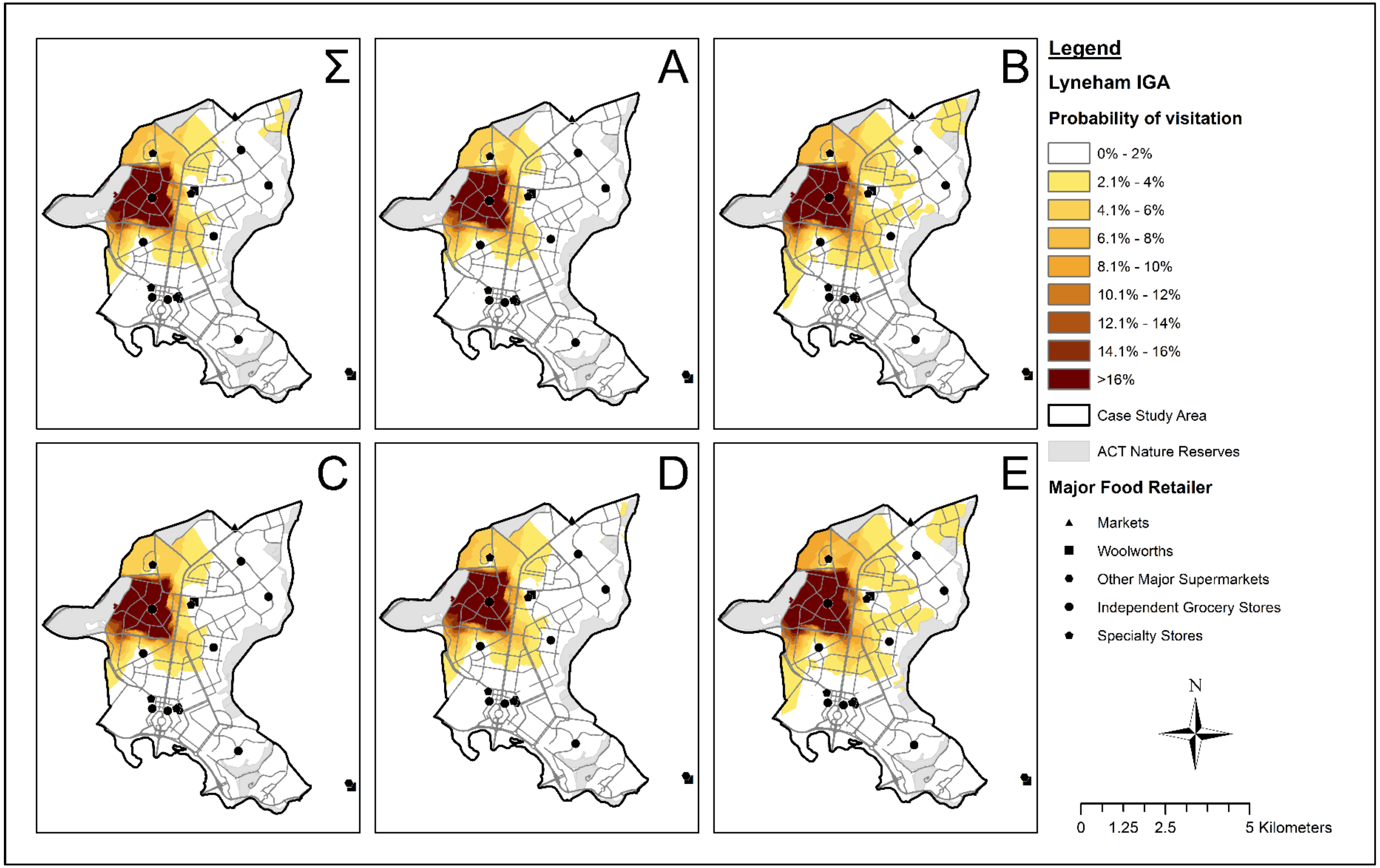



**Figure 51: Calibrated catchment of Lyneham IGA, disaggregated by consumer subgroup.** Σ = All consumers, A = Concerned, B = Expedient, C = Dispassionate, D = Calculating, E = Frugal