Progress in the Spatial Modelling of Food Insecurity in Australia: A Foodbank Australia White Paper

Prepared for The Art of More on behalf of Foodbank Australia

Institute for Sustainable Futures

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THE ART OF MORE

FOOD BANK

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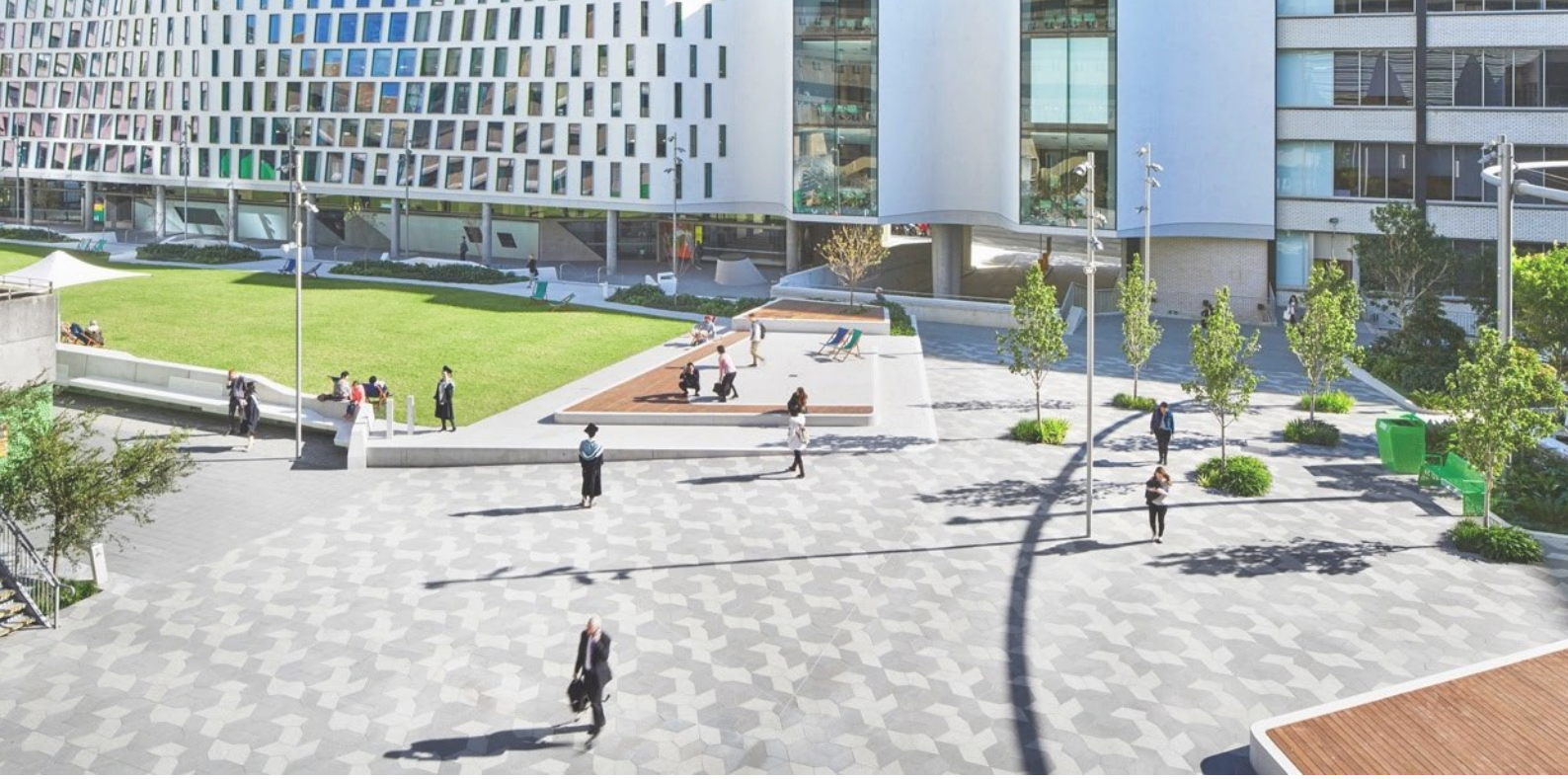

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The Institute for Sustainable Futures (ISF) is an interdisciplinary research and consulting organisation at the University of Technology Sydney. ISF has been setting global benchmarks since 1997 in helping governments, organisations, businesses and communities achieve change towards sustainable futures. We utilise a unique combination of skills and perspectives to offer long term sustainable solutions that protect and enhance the environment, human wellbeing and social equity.

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Executive Summary

Foodbank Australia is the largest provider of vital foodstuffs to charities around Australia, distributing 241,000 meals a day to 2,600 charities.

This white paper forms part of Foodbank Australia's goal of improving the food security position in Australia, and has four aims:

1. To provide a brief review of the concept of food insecurity as it applies to high-income countries, and the tools used to evaluate food insecurity with a focus on Australian research.
2. To document the progress made in Foodbank's efforts to develop a geospatial model of food insecurity to improve its service delivery.
3. To provide independent peer-review and analysis of Foodbank's methodology; and,
4. To guide the ongoing enhancement of the Foodbank's spatial model of food insecurity.

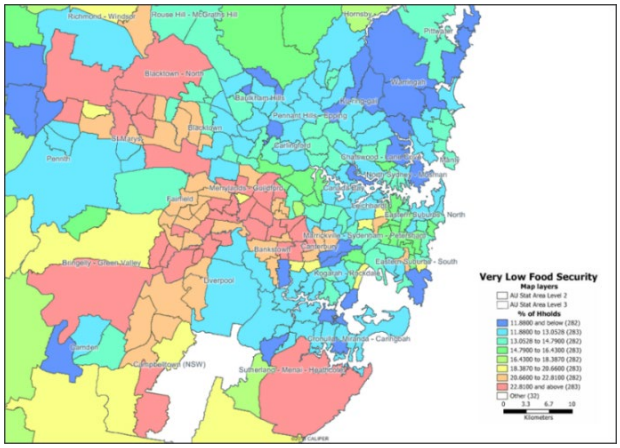
The paper seeks to unpack Foodbank's efforts to apply spatial and data science to its distribution data to identify patterns in food insecurity across a range of operational scales.

The review found that:

- Globally, the FAO identifies four pillars of food and nutrition security as: food access: food availability, food use, and food stability (HLPE 2020);
- In high income countries, most tools used for food insecurity assessment have been developed in the USA and are considered subjective often relying on recollections of participants, limited in scope, failed to assess food insecurity comprehensively (concentrating on access) and needed further development (Ashby 2016);
- In Australia, McKay et al (2019) reported that most studies suffered from small sample size, low response rates, poor participant retention, an inability to achieve interview saturation and a lack of longitudinal analysis.

The available literature indicates that the application of spatial and data science methods to food insecurity, while not new, remains a highly developmental area. A recent Web of Science search (7/9/2021) found no references at all for the combination of geographic information systems AND food insecurity. In terms of the spatial model of food insecurity, the paper describes the ideas and methods to draw on Foodbank distribution data and supplementary data from other sources to advance an understanding of Foodbank's national operating environment. This approach, especially the identification of *areas* of relative food insecurity, is new to Australia. An example of the visualisation of model outputs for Sydney is shown below.

Visualisation of food insecurity in Greater Sydney area.



Although it remains a work in progress, the model:

1. Identifies food insecurity across Australia, and thus provides insights into how Foodbank can meet the demand for food relief.
2. Identifies key demographic drivers of food insecurity at the small area level.
3. Estimates the number of people who suffer food insecurity over a 12-month period across Australia.
4. Identifies geographic regions across Australia which are oversupplied or undersupplied by Foodbank.
5. Aids understanding of the key variables or indicators driving demand for food relief.
6. Contributes to the progressive and developmental *science* of food insecurity in Australia by creating a genuine spatial model and dashboard environment that can be used to adaptively explore food insecurity patterns and trends across the country.

An expert review of the modelling methodology indicated that, as with all modelling, assumptions and statistical techniques can be improved. Specifically, clarification on whether the focus is on individual or household analysis, the application and method of sample weighting, the method of construction of the 'Hunger Segments', and small area estimates of demand driven food insecurity are areas for improvement and clarification and can be developed upon when more information comes to hand.

The methodology developed to model food insecurity represents a pioneering approach in a complex environment in which the available data was very mixed in both quantity and quality. The intention was, and remains, to refine and develop this innovative modelling approach as new and improved data sets become available and, also, based on input from expert informants as to how best to improve the accuracy, utility and sensitivity of the modelling. This report makes a series of general recommendations to guide the improvement of Foodbank's modelling of food insecurity. Nevertheless, Foodbank's efforts represent a significant achievement to understand and address food insecurity in an Australian context and are a major improvement on existing approaches.

Contents

Introduction

Foodbank Australia is the largest provider of vital foodstuffs to charities around Australia, distributing 241,000 meals a day to 2,600 charities. These relief activities are critical for supporting individuals and communities requiring food assistance in their daily lives, as well as providing rapid emergency responses to natural disasters. The COVID-19 economic shocks and associated government response measures have made Foodbank services even more critical.

This white paper forms part of Foodbank Australia's efforts to improve the food security position in Australia, during and following the COVID-19 pandemic by developing both the knowledge and application bases available in this space.

Within this context, this white paper has four aims:

1. To provide a brief review of the concept of food insecurity as it applies to high-income countries, and the tools used to evaluate food insecurity with a focus on Australian research.
2. To document the progress made in Foodbank's efforts to develop a geospatial model of food insecurity to improve its service delivery.
3. To provide independent peer-review and analysis of Foodbank's methodology; and,
4. To guide the ongoing enhancement of the Foodbank's spatial model of food insecurity.

While the application of spatial and data science methods to food insecurity is not new, it remains an emerging area of research dominated by recent developments and applications (e.g. Feeding America's *Hunger in America 2014* report). This paper seeks to unpack Foodbank's distribution data to identify patterns in food insecurity across a range of operational scales from national to the small area level.

The methodology described here represents a pioneering attempt at modelling a complex environment in which the available data was very mixed in both quantity and quality. The intention is to refine and develop this modelling approach to accommodate the availability of new and improved data sets and, based on expert review, determine how best to improve the accuracy, utility and sensitivity of the modelling. This is, therefore, an ongoing and developmental process in which the aim is to inform Foodbank's approach to data management for improved service outcomes, logistics management and planning activities.

The emphasis of the model is on 'everyday' food insecurity across Australia and not event-specific food insecurity (e.g. caused by natural disasters). Furthermore, the Breakfast for Schools program is not included in this whitepaper analysis and will be addressed separately.

Overview of the Science of Food Insecurity

The Food Insecurity Landscape

Globally, food insecurity from the immediate loss of employment or movement restrictions have been a common impact of COVID-19 (Bene et al 2021). The impacts of recent extreme weather events (e.g. bushfires in eastern Australia) and of the COVID-19 pandemic have demonstrated the vulnerability of food systems and food security risks. Combinations of natural, social and economic shocks in one region can potentially lead to price spikes and supply changes experienced at the global scale (Hamilton et al 2020). Aside from disruptions to food production and supply, system shocks contribute to food insecurity through impacts on social vulnerability including reduced employment and income (ABS 2021), housing stress (Baker et al 2020) and declining mental health (WHO 2020); all social indicators linked to food insecurity (Fang 2021; Kent et al 2020; McKell Institute 2020). These underlying vulnerabilities mean that food safety nets are essential for responding to the potential spikes in food security from environmental and socio-economic shocks.

During the initial year of COVID-19 impacts in 2020, 28% of Australians experiencing food insecurity had never experienced it before. Despite an estimated 4%[1] of the Australian population facing food insecurity, monitoring and measuring different dimensions of food insecurity, its spatial distribution and how underlying socio-economic factors intersect with food insecurity is not consistently analysed (Bowden 2020: pg. 6). Measurements of food insecurity have largely focused on one metric – access to food. This single-dimensional focus misses some of the wider aspects of food security that are globally recognised as essential for human development. Documenting how food relief services in Australia, such as Foodbank, are contributing to different pillars of food security is an important area of analysis that can increase awareness of food insecurity in the country.

Foodbank and broader food delivery services can make contributions to immediate food needs of vulnerable populations, yet measuring their impact is complex. For example, research into breakfast clubs in the UK found that only two studies looked at actual experiences of food insecurity, but did not use any specific food security metrics to see any changes (Lambie-Mumford and Sims 2018). In analysing 80 studies of home-delivery services, Godfryd et al (2015) found that the most commonly reported outcomes were on nutritional status based upon self-reported dietary intake, but many project analyses are descriptive and do not measure specific food security outcomes. In a review of food banks, which examined only nine studies, Simmet et al (2017) found that the food bags provided had varying levels of nutritional quality, and that nutritious food including milk, vitamins A and C, and calcium were low in food bank services. None of the studies were nationally representative and only a few studies controlled for the household composition of the recipients of food bags.

Feeding America operates the USA's largest food relief network comprising 200 food banks and 60,000 food pantries delivering a range of programs like school-based food pantries, emergency disaster relief, and 'Kids' Café'. Feeding America defines food insecurity according to the USDA's measure of lack of access, at times, to enough food for an active, healthy life for all household members and limited or uncertain availability of nutritionally adequate foods. Hunger in America 2014 is the most recent in a series of reports providing comprehensive demographic profiles of people seeking food assistance through the charitable sector and an in-depth analysis of the partner agencies in the Feeding America network that provide this assistance (Feeding America 2021a). This report aimed to provide national estimates of the total number of clients served through the Feeding America network and food bank level estimates of the total number of clients served. Data were collected through a survey of the agencies partnering with food banks in the Feeding America network (agency survey) and of adults 18 years or older who received food from meal programs and households that received food from grocery programs operated in partnership with the Feeding America food banks (client survey) (Montaquila and Weinfield, 2014). Hunger in America 2014 has been combined with a range of other data (public and private, local and national) to produce a range of supplementary reports and

[1] This figure was based on the 2011/2013 Australian Health Survey is contested (e.g. McKechnie et al 2018) and varies considerably among population segments (McKay and Dunn 2015).

visualisations, such as Map the Meal Gap (Feeding America 2021b) to improve the understanding of food insecurity and food costs at the local level, most recently in response to COVID-19.

Global approaches to food insecurity

Defining food insecurity

Food insecurity occurs when individuals and households are unable to acquire adequate food to meet their nutritional needs. In highly urbanised societies like Australia, food insecurity is largely driven by a combination of socio-economic and structural conditions. Food and nutrition security are defined as a situation that exists when all people always have access to safe and nutritious food to meet their dietary needs (FAO 2020). Four major pillars contribute to the concept of food and nutrition security (HLPE 2020):

1. Food access: the capacity to acquire and consume a nutritious diet,
2. Food availability: the supply of food within a community affecting food security of individuals, households or an entire population,
3. Food use: the appropriate use of food based on knowledge of basic nutrition and care.
4. Food stability: the stable supply of healthy foods to the right areas.

Much global food insecurity analysis and research is focused on developing nations. This is unsurprising, given there has been a strong 'feed the developing world' narrative embedded in United Nations framings of food security since the end of World War II. Developing countries are also home to most of the world's population, and highly populous regions such as Southeast Asia have the world's highest rates of child stunting and malnutrition and generally poor food security outcomes. Global food insecurity has been steadily growing since 2014, and COVID-19 is estimated to have added 83-132 million people to the total number of undernourished in the world.

Burchi and de Munro (2016) synthesised global approaches to measuring food and nutrition security. Traditional approaches to food and nutrition security focus on the core availability of food, a traditional measure dating back to Thomas Malthus' projections of population collapse due to lack of available food. In this measure, food security is a matter of per capita food availability. This notion was common in post-WW2 framings of food insecurity led by large aid programs from the United States and Europe towards the Global South. Food availability analysis tends to be used at a national level using food balance sheets, or by looking at the total productivity of a nation's agricultural sector. These metrics are problematic as they *assume* that if food is available, then people will be food secure. A separate metric is one focused on incomes at a micro-level. This approach to measuring food insecurity relates to the income available to buy food that is nutritious. If the incomes are insufficient, then the person or family is perceived to be food insecure. A challenge of this metric is the fact that people may have incomes, but still spend them on unhealthy foods. If this takes place, people have 'access' to food, but it is not meeting the nutritional requirements of food as per the FAO definitions.

The two approaches above fail to capture the underlying determinants that lead to pervasive food insecurities, notably the socio-cultural and underlying societal norms. The seminal approaches focused on entitlements (Sen 1982) and livelihoods (Scoones 2009) have become common lines of enquiry to understand the structural conditions that can enable food and nutrition security. These approaches look beyond the individual, and shift the narrative towards the accessibility of food as enabled by the state of markets. Assets and exposure to external vulnerabilities – such as disasters or COVID-19 – are dimensions of the livelihoods-based approaches to food insecurity.

Measuring food insecurity in high-income countries

Food insecurity assessments are conducted regularly in several high-income countries including the United States and Canada. There are a limited number of tools for measuring food insecurity. Ashby et al (2016) found most tools were developed in the USA and had been applied to a range of age groups and cultures. For example, some tools targeted children in a household (Cornell Child Food Security Measure), others

individuals (Radimer/Cornell tool) or households (e.g. Girard Four Point Tool). The complexity of the instruments varied, ranging from two (e.g. Townsend Food Behaviour Checklist) to nine questions (Cornell Child Food Security Measure). All the eight multi-item tools identified by Ashby et al (2016) relied on a survey or questionnaire. All these tools assessed food access and two partially assessed utilisation and stability dimensions of food insecurity. None assessed food availability. These tools were considered subjective often relying on recollections of hunger or food insufficiency over periods ranging from weeks to years, limited in scope, failed to assess food insecurity comprehensively and needed further development to cover all dimensions of food insecurity as defined by the FAO.

Ashby's review deliberately excluded perhaps the most influential food insecurity survey instrument, the United States Department of Agriculture's (USDA) Food Insecurity Survey. Table 1 lists a selection of the food insecurity measurement instruments developed since Ashby's review with the USDA survey and some of its variations for comparison. These tools fall into two categories: those based on empirical data collection through surveys or questionnaires, and those that draw data from public data sets, such as national census collections. The former tends to address aspects of food insecurity directly, while the latter selects proxy indicators supported with evidence from research.

Table 1 Selected recent food insecurity measurement instruments used in high income countries

Measurement Instrument	Year	Country	Type	Description
Radimer/Cornell Food Insecurity Questionnaire	1990	US	Survey	Estimates the prevalence of hunger and food insecurity in a population. Forerunner to USDA Food Insecurity Survey.
Health Canada - Household Food Security Survey Module	2007	Canada	Survey	18–question, standardized and validated scale of food insecurity severity of households -measures inadequate or insecure access due to financial constraints. Adapted from USDA Survey.
USDA - Food Insecurity Survey	2021	US	Annual survey	40,000 US households. Food insecurity - households were, at times, unable to acquire adequate food for one or more household members because the households had insufficient money and other resources for food.
USDA - Food Insufficiency Survey	2021	US	Survey	Supplement to Food Insecurity Survey. Single question asking whether a household generally has enough to eat. Food insufficiency closer to very low food security than to overall food insecurity. Linked to household well-being.
Cambridge Biomedical Research Centre -24-hour diet recall questionnaire	2021	UK	Survey	24-hour dietary recalls measuring a person's food and beverage consumption during the preceding 24 hours. Self-reported – potentially subject to recall bias.
FAO - Food Insecurity Indicators	2021	Global	Indicator-based (secondary data)	Core set of food security indicators to informed by expert judgment and the availability of data with enough coverage to enable comparisons across regions and over time. Indicators are classified along the four dimensions of food security -- availability, access, utilization and stability.
Urban Institute - Health Reform Monitoring Survey	2021	US	Semi-annual survey	USDA survey based. Provides data on health insurance coverage, access to and use of health care, health care affordability, and self-reported health status.
Curtin University - Food Stress Index-Food Basket Recommendation	2021	Australia	Indicator-based	Developed to assist effective food relief in Western Australia: the Food Stress Index (similar to rental stress, predicts the likelihood of household food insecurity by geographic location) and a basic and nutritious Food Basket Recommendation (that quantifies the types and amounts of food to meet dietary recommendations for different family types). Designed for organisations and their clients involved in emergency food assistance and/or disaster preparedness. Applied to COVID-19 pandemic restrictions and Australian bushfires.

An example of an empirical assessment is the USDA Food Insecurity Survey, which evolved from a questionnaire designed by Cornell University researchers (Radimer et al 1990), and has been adapted for use in other countries (e.g. Canada). Subsets of questions from this survey have been used to focus on specific aspects of food insecurity (e.g. food insufficiency). Although widely used, the USDA survey is not above criticism with claims that it focuses on affordability; other dimensions of access, utilization, stability and health are not as well captured. This aligns with common critique of other approaches to measuring food insecurity, which tend to focus on only one or a few pillars of food security.

Alternative empirical approaches to the USDA survey include self-reported dietary recall methods such as the UK's 24-hour dietary recall questionnaire (Cambridge Biomedical Research Centre), which measures a

person's recollection of their recent consumption of food and beverages. However, these types of studies are often criticised because of the potential for results to be skewed through participant recall bias.

Comprehensive indicator-based methods using secondary data are less common in high-income countries. At global scale, the FAO has developed an expert-derived, core set of 42 food security indicators to enable comparison of regions over time. The indicators relate to the four dimensions of the FAO's food security model: availability, access, utilisation, and stability. While indicators have been presented geospatially, the focus of the mapping is generally on low-income nations.

Food insecurity - Australian experience

Australia is a global food exporter, and as a nation it is food secure. However, conservative estimates suggest that in Australia more than of 5% of the population experience food insecurity with 40% of those at a severe level (Burns, 2004; Temple, 2008). Foodbank's Hunger Report 2019, the most recent and comprehensive study of food insecurity in Australia, estimates 21% of Australians have suffered from food insecurity. Despite this prevalence, in contrast to the USA, Australia does not have a universally accepted scale or agreed definition for food insecurity (McKell Institute 2020)

In Australia, the Australian Bureau of Statistics (ABS) periodically reports food insecurity-related statistics through the National Nutrition and Physical Activity Survey (NNPAS) component of the Australian Health Survey (AHS) (ABS 2015). The NNPAS was last updated in 2011-2012. It includes information on household demographics, Socio-Economic Indexes for Areas (SEIFA), education qualifications, occupation, industry, country of birth, general dietary information, physical measures, selected long-term medical conditions, smoker status, physical activity and sedentary behaviour, pedometer steps and dietary intake (ABS 2015). In addition to these proxy indicators, this survey directly addresses food insecurity by asking adult respondents if there was any time in the last 12 months that they, or members of their household, had run out of food and could not afford to buy more. Respondents who answered yes were asked if they, or members of their household, had gone without food. ABS places caveats on the interpretation of these data including: the likelihood of under-reporting, the potential for individual rather than household level responses, and the lack of information about frequency of occurrence of food insecurity or nutritional aspects of food. Food insecurity among Aboriginal and Torres Straight Islanders is also assessed through the inclusion of the NNPAS questions in the National Aboriginal and Torres Strait Islander Health Survey (NATSIHS) and National Aboriginal and Torres Strait Islander Nutrition and Physical Activity Survey (NATSINPAS) (ABS 2015).

McKay et al (2019) reviewed the use of food insecurity measures in Australia. They found that twenty-two studies used a limited, single-item measure to examine food security status; 11 used the United States Department of Agriculture (USDA) Household Food Security Survey Module (HFSSM); two used the Radimer/Cornell instrument; one used the Household Food and Nutrition Security Survey (HFNSS); while the remainder used a less rigorous or unidentified method. McKay reported that most Australian studies suffered from small sample size, low response rates, poor participant retention, an inability to achieve interview saturation, and a lack of longitudinal analysis.

Recent research in North Queensland (McKell Institute 2020) illustrated the geospatial variation that can occur in food insecurity at sub-national scales. This research constructed a Food Insecurity Index for federal electorates based on five proxy variables drawn from ABS Census data and known to be associated with food insecurity: 1. Unemployment rates in the electorate; 2. The proportion of the population who are sole parents working part time; 3. Rates of Disability/Needing assistance for core activities; 4. Proportion of the population who are Aboriginal or Torres Strait Islander; and, 5. Proportion of low-income earners in the electorate. Of the six federal electorates comprising Central and North Queensland, all are in the top 15 for likelihood of food insecurity (of 30 federal electorates in Queensland) and the three most northern, Leichhardt, Kennedy and Herbert, showed the highest indicators for food insecurity. Similar levels of variability are likely to occur in other Australian jurisdictions, particularly those with high levels of exposure to natural hazards, such as droughts, bushfires, flooding and cyclones.

Kent et al (2020) reported on the prevalence and socio-demographic associations of food insecurity in Tasmania, Australia, during the COVID-19 pandemic. They used a cross-sectional survey that incorporated questions from the U.S. Household Food Security Survey, and fifteen demographic and COVID-related

income questions. The prevalence of food insecurity appeared to have increased during the COVID-19 pandemic among economically vulnerable households and people who lost income.

Pollard et al (2021) assessed the combination of a Food Stress Index (like rental stress, predicts the likelihood of household food insecurity by geographic location) and a basic and nutritious Food Basket Recommendation (that quantifies the types and amounts of food to meet dietary recommendations for different family types) to assist agencies involved in the distribution of food assistance and disaster preparedness. Qualitative interviews with service providers demonstrated the intrinsic value of such tools in the provision of emergency food relief under both normal circumstances and in times of increased need, such as the COVID-19 pandemic.

Selection of indicators

Collation of the proxy-indicators of food insecurity used in selected assessment tools from 2004 to 2021 suggests limited consistency among the seven studies (Table 2). These studies varied from city- to national-scale and were drawn from US, European and Australian research. Some studies assessed food insecurity through an empirical survey method (e.g. Furness 2004), others (e.g. The McKell Institute 2020) used secondary data sources. Proxy-indicators fell into four broad categories: demographic, socio-cultural, economic/financial, and health. In total, approximately 21 indicators were used in these studies. Most, but not all, included basic demographic data of respondents: age, gender, household size and the presence of children. All sought to link various aspects of social status to food insecurity such as education level, marital status, security of residency. Race and ethnicity also featured, with the Australian studies focused on linking food insecurity to Aboriginal and Torres Strait Islander heritage and immigration status. Among the economic indicators, employment and/or income appeared frequently. Three studies linked the need for public assistance or government support payments to food insecurity. Housing status and car ownership were household financial indicators included in the city-scale assessment (Bartfield and Wang 2007). Inclusion of health indicators (chronic illness, mental health, disability) appeared more recently in studies post-2014, which may reflect the findings of research linking dimensions of health to social vulnerability generally. One recent study (Kent 2020), specifically sought to link COVID-related economic impacts to food insecurity.

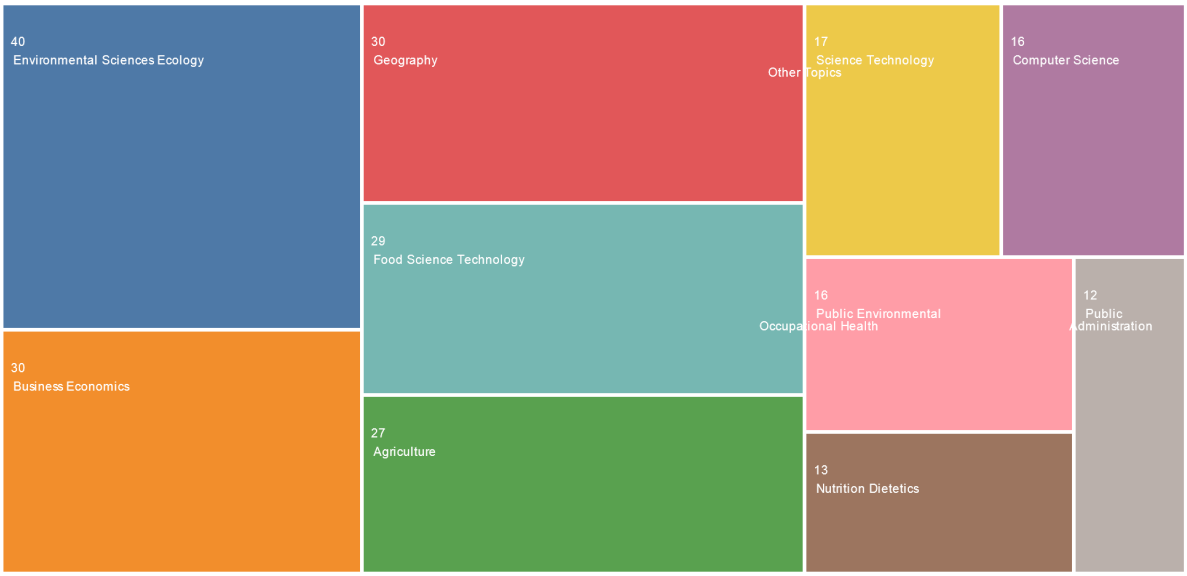
Table 2 Collation and comparison of indicators from selected food insecurity assessments.

		Study						
		Furness (2004)	Bartfield & Wang (2006)	Bates et al (2007)	Alvares & Amaral (2014)	Kent (2020)	McKell Institute (2020)	Moretti et al (2021)
	Indicator / **Scale**	US regional	US city	UK national	Portugal national	Australia state	Australia regional	UK national
Demo-graphic	Age			■	■	■		■
	Gender			■	■	■		
	Household status		■	■		■		■
	Children	■	■	■				
Socio-cultural	Social grade							■
	Race/Ethnicity	■				■	■	■
	Education		■		■	■		
	Relationship status				■	■		
	Homelessness	■						
	Residency status			■		■		
Economic	Employment status		■	■	■		■	
	Income	■	■	■	■	■		
	Public assistance	■				■	■	
	Remoteness/rurality					■		
	Disadvantage index							■
	Housing		■					
	Car ownership		■					
	COVID-impacted					■		
Health	Chronic illness				■			■
	Disability					■	■	■
	Mental health				■			

Summary of Modelling Methodology

This section of the whitepaper outlines the key ideas and methods utilised in developing this modelling process of everyday food insecurity in its first major iteration. As noted elsewhere in this paper, food insecurity is a major societal issue not only in Australia but internationally. The available literature indicates that the application of spatial and data science methods to food insecurity, while not new, remains a highly developmental area especially in the context of understanding everyday food insecurity in society. A recent Web of Science search (7/9/2021) found no references at all for the combination of geographic information systems AND food insecurity. The combination of food insecurity and GIS (a common acronym for geographic information systems and software) produced a mere 73 results and 53 of these were published in or after 2017. So, while there is a long 'tail' to this literature going back to the early 1990's, it is dominated by recent developments and applications. In addition, two main disciplinary, and overlapping, fields are responsible for the bulk of this literature (Figure 1).

Figure 1 Visualisation of the main disciplinary fields containing food insecurity and GIS



Perhaps not surprisingly a related search on data visualisation AND food insecurity produced only eight (8) results. All of these had been published during or since 2013, with the majority (7) yet again published since 2017. The data suggest that the specific application of spatial and data visualisation methods in the food insecurity research and application space remains very niche currently. Given the weighting towards the last five years or so, this may yet indicate a rising interest in and application of these techniques by food security researchers and practitioners.

Looking to more industry-focused applications of spatial data science in the food insecurity sector also suggests that there is a rising level of interest in GIS and related data analysis and visualisation. And, if anything, the COVID-19 pandemic has added urgency to these applications. Examples include work from ESRI, the world's largest GIS software company, on COVID and non-COVID applications of their software (including dashboards) to enhance responses to food insecurity and the often-problematic issues of supply chain and logistics management associated with not-for-profit responses (Bauman, 2020; Lehman, 2021).

Objectives

The objectives in Foodbank undertaking this exercise were several. At the centre of the modelling exercise was the intention to utilise Foodbank data and supplementary data from other sources to develop an understanding of Foodbank's national operating environment and to improve understanding of national patterns and trends in food insecurity. This represents a planning function and strategy that is both present and future oriented, with the aim to explore patterns in what is happening now and what may be needed in the future. Complicating this to some degree was the advent of the COVID-19 pandemic and the impact it

has had on the Australian population as well as on particular population groups and communities. The focus was, more broadly, on being able to understand longitudinal patterns of food insecurity and the resulting shifts in the demand or food, and the role that Foodbank plays before, during and following specific events, including crises. Specific objectives included the following:

1. To develop a model which identifies food insecurity across Australia, and thus provides insights as to how Foodbank can meet the demand for food relief.
2. To identify key demographic drivers of food insecurity at the small area level.
3. Estimate the number of people who suffer food insecurity over a 12-month period across Australia.
4. To identify geographic regions across Australia which are oversupplied or undersupplied by Foodbank.
5. To understand what key variables or indicators drive demand for food relief.

The focus of these objectives was to unpack the data to identify patterns in food insecurity and Foodbank distribution patterns that could accommodate the national scale down to the small area level. These objectives shaped the way in which the model was developed and the visualisation format of the modelled outputs. Central to achieving these objectives was developing an approach that could be accessed across the organisation, informing Board-level strategy decisions down to daily operational decisions and actions.

The Modelling Process

This model has developed to understand what key variables drive demand for food relief and identify Australians that are more vulnerable to food insecurity and to use that model to inform Foodbank's organisational strategy and response to changes in the food security status of individuals and communities with whom it works.

The focus has been initially on "everyday" food insecurity[2] as it is more of a constant and more reliable to predict than food insecurity associated with crisis and disaster events which can have a distorting effect on the general picture of food insecurity experienced at the population level due to their unpredictability and episodic nature. It has enabled the focus to be on key factors such as understanding where demand exists, to what degree, and where and how the current supply caters to that pattern of demand.

The process for developing this understanding was to:

- Identify a geographic 'footprint' for supply of everyday food relief through Foodbank agencies, currently the major provider of such services across Australia
- Utilise the Vulnerable Australia model to analyse that footprint using more than 70 data sources to determine the quantifiable degree to which specific attributes are predictive of demand and changes in demand patterns over time (and in response to external factors like COVID-19).
- Segment these communities where the relationships between community attributes and food insecurity were homogeneous
- Define 10 key community segments and the extent to which they experience food insecurity
- Apply these segments to each community in the total population, calculating demand for food relief for each of these geographies and the degree of coverage being achieved by Foodbank.

A basic summary of the modelling process and its development is provided below so that anyone new to this work can quickly appraise themselves of the approach followed the main data elements included in that development process. The steps in this brief framework are then provided in more detail as this section progresses.

Table 3 briefly summarises the model development process and each key step taken in producing the final model. This provides any reader with a short overview of the broad process by which the model has been developed. This is also the process reviewed by Professor James Brown from UTS. Recommended changes are enhancements are likely to be reflected in future iterations of the modelling process as this is a

[2] "everyday" food insecurity is defined as that food insecurity that is not caused by crisis or disaster events.

developmental piece of work intended to inform and enhance the scientific understanding of and response to food insecurity across Australia.

Table 3 Key initial steps in the model development process

Step	Description
Stage 1	
1	Geo-coded food distribution agencies and the volumes of food that they are supplied with by Foodbank
2	Identified agencies that supply significantly larger volumes than the mean and reduced their influence in order to normalize the supply pattern.
3	Distributed food allocated to a small area level by applying a gravity model within a range of 5km from each agency to each SA1.
Stage 2	
4	Overlaid the population for each SA1 to determine kgs of food per person and then aggregated to SA2 geography
5	Decision Tree analysis (CHAID) to identify the key variables that drive demand at the SA1 level and then aggregated those indicators to the SA2 level
6	Developed the segmentation model using K-Means cluster analysis
7	Developed a two-step demand model calculating Foodbank's influence, aggregating demand for each segment and verifying demand based on existing consumer surveys
8	Quantified the number of food insecure people by leveraging the food recipient surveys from 2018, 2019 and 2020
9	Identified gaps between demand and supply by estimating difference between demand and supply patterns at the SA2 level

Stage 3 Data Visualisation Output

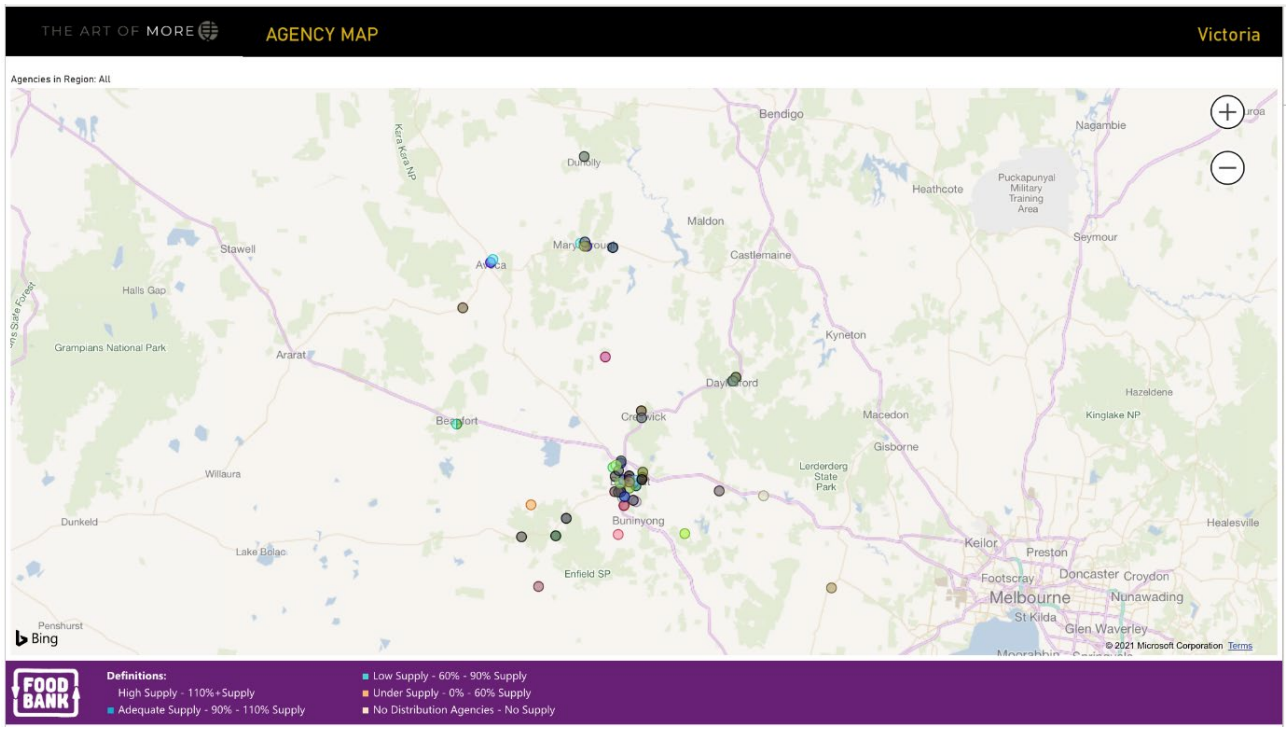
Taking advantage of developments in the data visualisation space, a Power BI dashboard was developed to allow for planning by identifying agency distribution, regions with anticipated food security needs and fulfilment of that need. The purpose of this is to make the complex modelling environment more accessible to the Foodbank user group and to allow interaction with the results so that strategic and tactical issues can be explored over time and space.

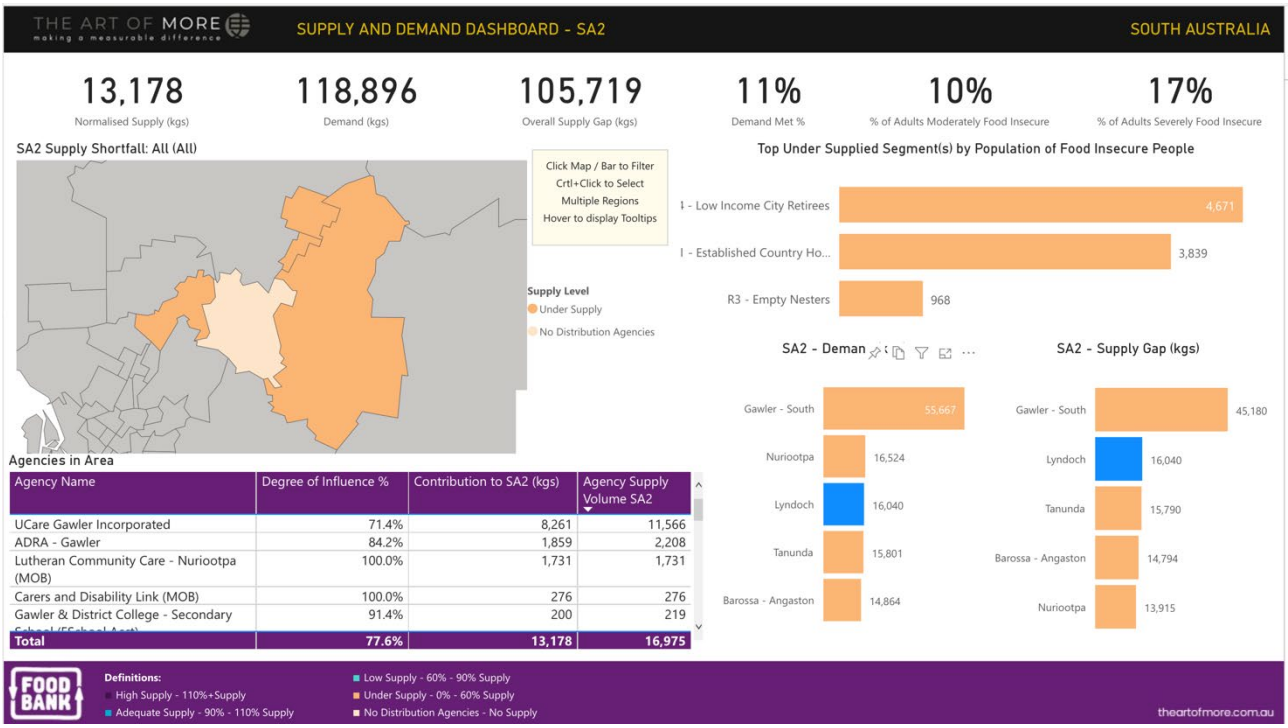
The key components of the dashboard are:

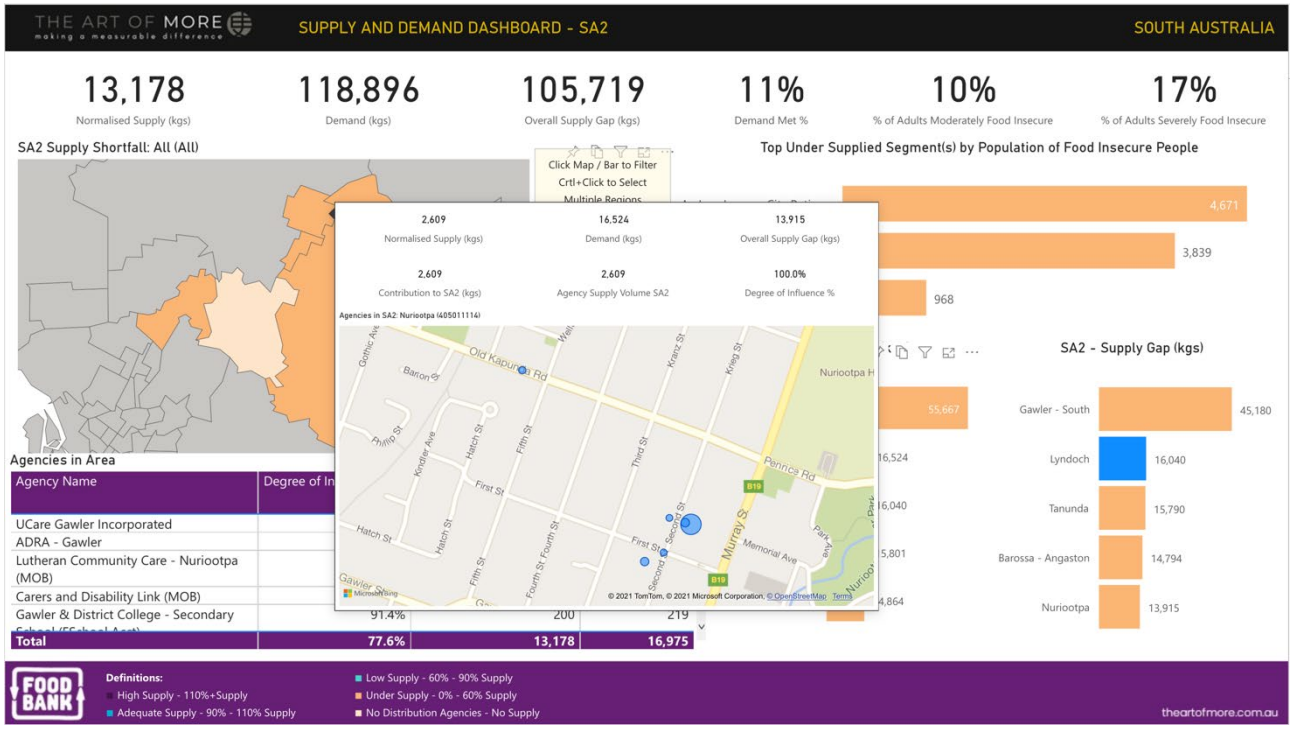
1. Agency network geocoded with financial year total food distribution volume (kgs) from 2018/19 to 2020/21. It was also populated by estimates of the population by USDA classification within 5kms of the agency location
2. SA2 geography sourced from 2016 Census.
3. The SA2s are populated with:
    - Estimated population broken down by adults and dependants x USDA classification.
    - Estimated volume of food distributed to the SA2
    - They are also tagged with the segment classifications
4. A matrix identifying the agency contribution to each SA2 i.e. the volume each agency possibly distributed to each SA2 (so it had the agency code, the SA2 id and the modelled volumes that went from that agency to that SA2 per annum 2018-19, 2019-20 and 2020-21.

5. A spatial hierarchy table for each SA2 with the SA2 code, SA2 name and SA3 Code and name, SA4 code and name and the GCCSA regions which include the definition of each capital and the balance of state. This is to allow for aggregation of summary data at various levels.
6. A separate spatial layer was presented at the LGA level. This was done because there's a lot of 'split' SA2's which do not fit perfectly into the LGA layer through aggregation.
7. Attributes at the LGA level include:
    - Population by USDA classification (adults and dependents)
    - LGA share of volume as a time series from 2018-19 to 2020-21
8. A spatial hierarchy table for each LGA identifying the SA4 and section of State or Territory (except for Queensland as noted).

Figure 2 Examples of the spatial visualisation option (upper) and the dashboard option (lower) developed for Foodbank.







Understanding the modelling process

The model was developed to understand where demand exists, to how and to what degree the current pattern of supply caters for that estimated demand. The current supply of food to agencies has been used as an initial basis from which to understand the key variables driving food demand and then to project that nationally (via a segmentation process) to identify demand and current supply and the resulting under or oversupply across Australia.

A variety of statistical and geographical concepts and techniques have been applied in developing this initial modelling process. It should be emphasised here that the process is developmental and aimed at improving the scientific understanding of food insecurity patterns across Australia with a view to initially improving the supply side of the equation, in terms of food availability at the right time and location. However, from a knowledge development perspective, there is also an intention in this work to better understand and intervene in the demand side of the food security equation by identifying those drivers and influencers of demand, including under the unique conditions generated by the COVID-19 pandemic which has destabilised ‘business as usual’ patterns in economic and food insecurity. Both sides of the food insecurity ‘equation’ are developmental because the modelling process has identified key areas for improvements in areas such as data quality, quantity and detail. This white paper is, therefore, a contribution to the food security knowledge base premised on the modelling done to date.

NORMALISING VOLUME PRIOR TO GRAVITY MODELLING

Some agencies deemed “outliers” (95 of a total 3786 agencies or 2.5%) were disproportionately large when compared to others. These are more likely to be secondary distribution warehouses, agency centres or centres used for transient food insecurity and if included could adversely bias the analysis of volume (and the demand drivers - see later).

Therefore, before applying a gravity model to existing agency volumes, these were normalised within two standard deviations of the mean volume of food deliveries across all food distribution agencies. This is a common statistical practice applied to limit the influence of outliers and, in effect, means that 2.5% of agencies have their volume reduced to fit within the volume bands of 97.5% of agencies before gravity modelling could be applied. The reason for this was that it was important to clearly understand the existing distribution footprint of Foodbank’s agencies and limit the influence of outliers from the data so as not to bias the analysis of volume distributions to populations. This process provided stability to the model before relating these volumes to the populations being serviced.

GRAVITY MODEL

The next step in this process was the development of a gravity model. Gravity models are used in various social sciences to predict and describe certain behaviours that mimic gravitational interaction as described in Isaac Newton's law of gravity. A gravity model provides an estimate of the volume of flows of, for example, goods, services, or people between two or more locations.

It was important to clearly map and quantify the actual geographic footprint of Foodbank's agencies, the density of agencies and the concentration of food volume. This was undertaken to see how volumes are distributed across the footprint. A 5km driving distance was used because, based on industry applications by the model developer, research into regular movements of people across a geographical region have shown that 80% to 90% of activity occurs within 5 kms of their dwelling (e.g. shopping centre studies, exit surveys, monitoring of mobile phones data). A gravity model allows Foodbank to distribute those volumes and the density of those volumes to populations more accurately by applying a rule that the further away from an agency a population is the less share of that volume could be attributed to that agency. This process allows for an unbiased view of which populations and demographic groups are within a quantifiable and reasonable geographic reach of accessing and receiving food relief.

DECISION TREE MODELLING

Decision tree modelling refers to a branch of machine learning that makes use of supervised learning algorithms (Tan et al, 2019). These approaches divide data sets into smaller units until those units can be usefully labelled. This derives from the machine learning concepts of data classification problems (e.g. differentiating between types of ground cover in satellite imagery or cancerous lumps in x-ray imagery and so on) and regression problems (Yse, 2019). These techniques can help analyse large volumes of similar types of data and reach faster outcomes for action or expert inquiry. The point here is that decision tree modelling has many useful applications in dealing with complex problems of the kind we encounter in the complex systems we see in society.

Chi-square automatic interaction detection (CHAID) is one such decision tree technique, based on adjusted significance testing (Bonferroni testing). CHAID can be used for prediction as well as classification, and for the detection of interactions between variables. One of the key benefits of CHAID analysis is that it permits multiple branching in the data splitting (classification) process so that any decision tree model can have, in effect, several branches suspended off a subordinate branch. In addition, CHAID analysis permits such decision trees to be adjusted based on new data additions or refinements to the parameters in the model. This is especially useful in managing the complexities associated with trying to understand the interactions between multiple variables in data sets drawn from complex environments.

WHY WAS THIS DECISION TREE MODELLING APPLIED?

Having identified the populations where food is being distributed, the relationship of key variables to food volumes needed to be determined. To undertake this, decision tree modelling was applied across thousands of variables as they related to now normalised supply. This allowed the quantifiable degree to which individual (single) and multiple combinations of variables are currently predictive of patterns in food demand to be determined. This allowed the weighting of the presence of variables in populations to calculate food demand and allowed a statistically sound view of the predictive nature of each individual, and multiple combinations of variables.

DETERMINING DEMAND PROFILES

Having now understood the statistical relationship of variables to food, a cluster analysis was developed of those populations being serviced to understand how many unique types of communities are in that population. Then this was tested against the entire population to determine if these could be applied. The intention was to identify unique segments of the population and their relationship to food insecurity, so a calculation of demand could be applied to each community in Australia that would be a statistically accurate representation of demand. This allowed a calculation of the relationship between unique communities and food volume and developed a picture of demand for food relief for each geographic community in Australia.

CALCULATING DEMAND

The identification of 10 unique community segments provided a robust view of volume demand by applying unique calculations to each segment type. The model then needed to ensure a robust understanding of demand. To do this the demand drivers in each segment were validated and their contribution to demand volume determined. This allowed the analysis to provide an accurate calculation of demand that was validated by multiple sources of data to ensure the integrity of demand forecasted by each level of geography utilised across Australia. The resulting segments were divided into two groupings, firstly regional segments and secondly urban metropolitan segments. This was done because the industry mix and socio-economic profiles in regional and metropolitan urban regions were different and distinct.

DETERMINING THE NUMBER OF FOOD INSECURE PEOPLE

Having now understood the demand by segment, the demand needed to be apportioned to people by reviewing frequency data from National Recipient Surveys (2018[3],2019, 2020) and applying those frequencies to each segment. Using an agreed measure of 0.555kgs per meal and an assumption that a respondent required 1 meal per reported incidence of food insecurity. This was weighted by identified frequency of need (i.e. daily, weekly etc. sourced from the survey) per segment and applied to quantify and estimate of the number of people in need by geographic area.

This was done to identify the number of food insecure people in each geography by applying survey respondent data to our geographic segments and apportioning that out to the populations of these segments. This allowed us to provide an estimate of food insecure people by geographic area in Australia and is represented as a percentage of population that experience food insecurity during a 12-month period.

A thorough understanding of people and communities enables a very specific view of the extent of vulnerability in each community or geographic area. This vulnerability needs to be related to food insecurity.

Leveraging supply data, enabled a better understanding of these relationships within specific geographic locations and how they vary. The relationships between food insecurity and vulnerability differed to the extent that 10 demand profiles were identified within the Australian population. However, total supply data alone is not predictive of demand. There are specific demographic and situational attributes and characteristics within each segment of vulnerable people and their relationship to food security, that were found to be predictive of food insecurity across the Australian community. These attributes were then leveraged to forecast food insecurity demand within each specific segment of Australia's vulnerable people within the Australian population. This enabled the forecasting of the kilograms required to alleviate food insecurity by each location.

Internal Data Source 1

The key internal data source utilised in this modelling process was Foodbank supply by month by individual agencies for the period FTD June 2019 and June 2021. Foodbank has supplied 6574 distinct food distribution agencies in the three years to 2020/21. Of these 2128 are schools supplied through the School Breakfast Program (SBP). Not all agencies received food across those three years with some entering or leaving Foodbank's distribution network. *(Please note that Queensland food distribution agencies were not included in the analysis and modelling due to difficulties in accessing reliable data)*.

The summary food distribution by volumes to these agencies was:

- 2018/19 2753 agencies were supplied a total volume of 21.64 million kgs of food.
- 2019/20 2973 agencies were supplied a total volume of 17.38 million kgs. A dramatic drop due (potentially) to Jobseeker and Youth Allowance increase as well as increases in other social support payments.

[3] 2018 Survey by McCrindle Research incorporates the USDA measure of frequency of need

- 2020/21 2762 agencies were supplied a total of 19.97million kgs of food an increase of 8% over the previous year. Also, 601 of these agencies had not been supplied food in the previous years.

The food distribution agency addresses were geocoded to latitude and longitude by Foodbank and then mapped using the geographic information systems (GIS) software package Maptitude (https://www.caliper.com/maptovu.htm). This included geocoding and mapping outlets by their food distribution volumes and supplied attributes tagged against the location for viewing (Figure 3). This process was undertaken for all Foodbank agencies across Australia, consequently this map is only an illustration of this process and what the results look like when mapped. The dots represent Foodbank partner food distribution agencies. It should be noted here, as mentioned elsewhere in this document, that the school-based food programs are not included in this whitepaper and will be reviewed as a later and separate exercise. In addition, this also excludes any disaster food relief delivery as the intention in this research has been to focus on everyday food insecurity in the community.

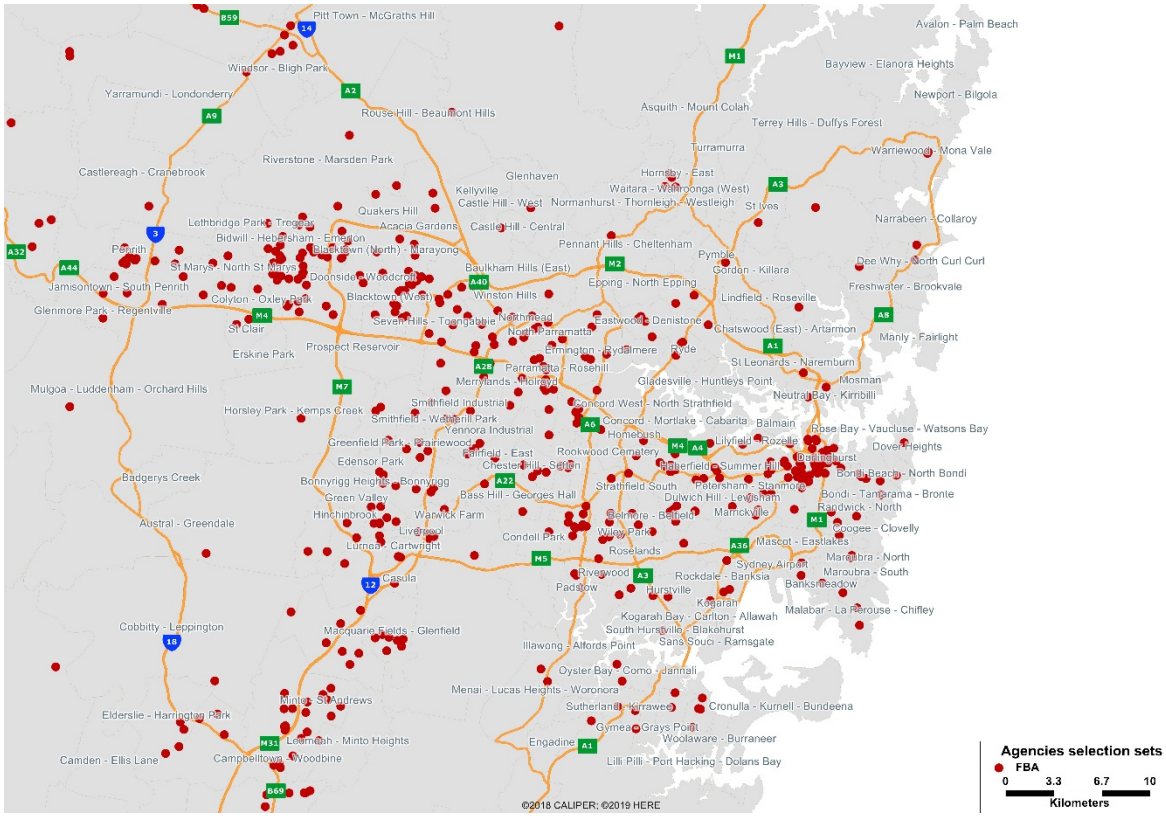


Figure 3 Location by Agency

The food volumes distributed were also mapped to location in map Figure 4. The purpose of this second map is that it gives the viewer an understanding of the relationship between agency locations and the volumes of food distributed within geographic areas. This second map obviously assists in visualising the scale of the food insecurity across geography. It also has the potential to help in analysing the relationships between distribution agencies and the social effects across space e.g. which areas are larger overall users of Foodbank services and their socio-economic characteristics versus, more simply, the distribution of available agencies. This data assists in developing a hierarchical model of food insecurity and related food distribution as well as other analytical options such as the relative performance of specific services relative to modelled community need. In other words, a spatially contextualised modelling approach informs the developmental science of identifying, monitoring and responding to food insecurity across space and time. This is especially relevant during the pandemic when many people have lost employment and are likely to be facing increased financial, housing and related stressors.

Figure 4 Location by food volumes (kgs)

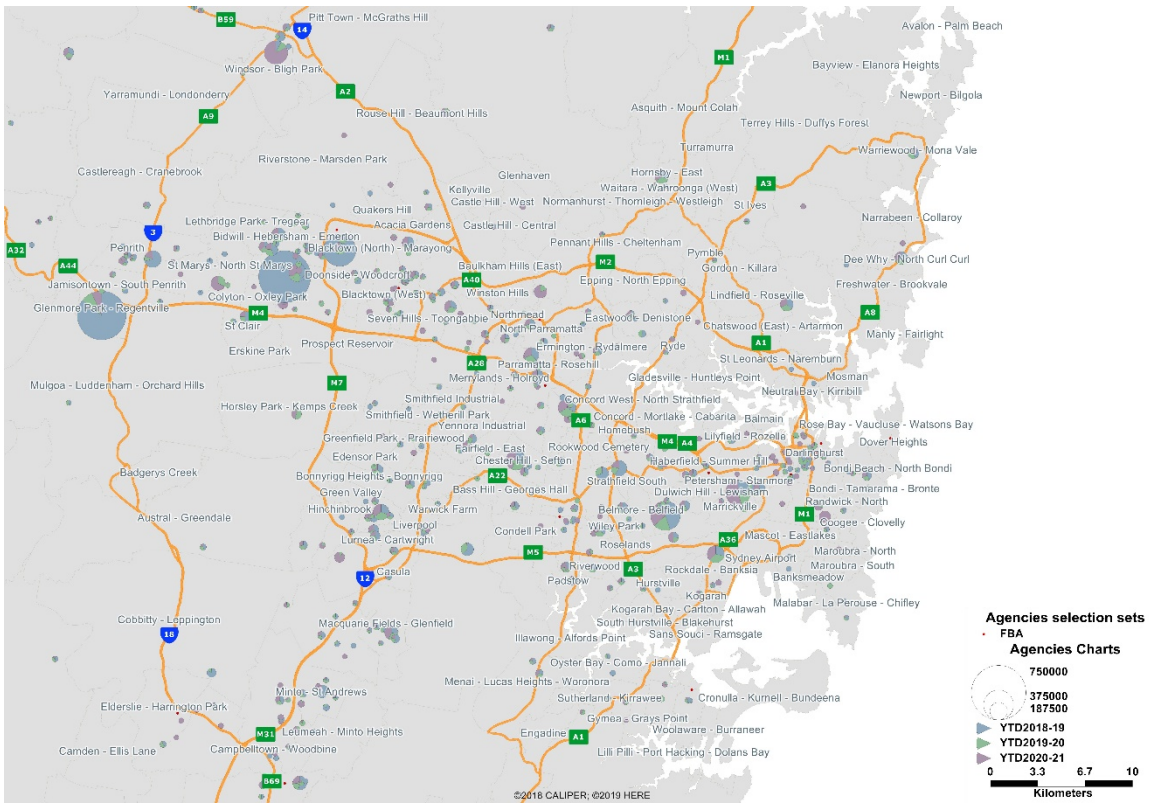


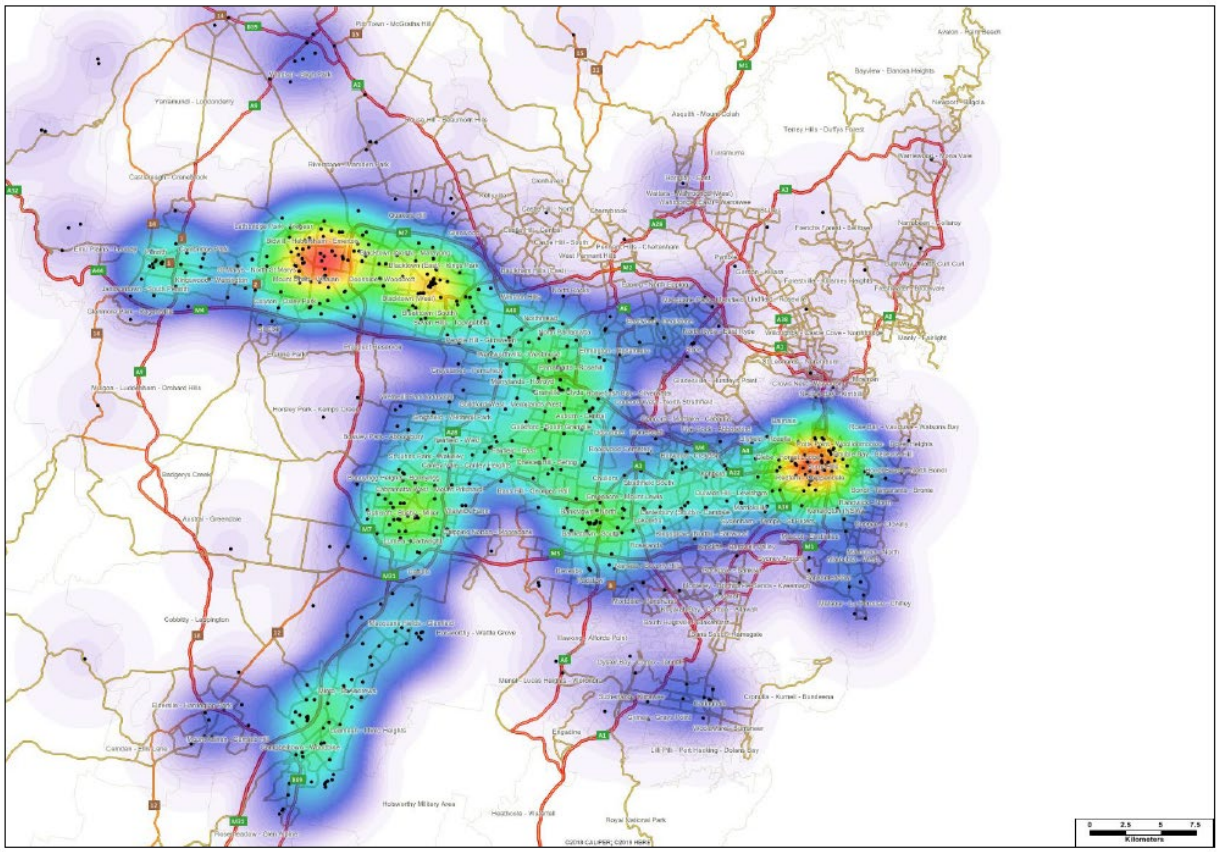
Figure 5 illustrates the spatial relationship between agency locations by distance in one-kilometre bands up to a maximum of five kilometres. This is based on the concept of travel time to services and the measurement of convenient travel to an agency as well as assisting in modelling the probable populations in need within set distances of the existing pattern of food distribution agencies. This step essentially indicates 'catchment areas' for each food distribution agency and the degree of overlap that exists between them where they are close by. This is important because not all agencies service the same types of groups or populations (beyond them being food insecure) and so the idea of 'overlap' is a constrained one rather than a general rule. This structural distance modelling underlies the density map that follows. The point here is that this scaffolded modelling process means that specific questions can be addressed at each stage and the steps assist in building the overall model at scale.

Figure 5 Spatial relationship between agency locations by distance in one-kilometre bands up to a maximum of five kilometres.

Agency Density Map by Distance Cohorts: Metropolitan Sydney

Figure 6 illustrates an application of a density function analysis (often referred to as heat mapping) to describing and analysing the distance relationships between agency providers across geographic space. This map of Sydney metropolitan is simply an example since the process was scaled for all of Australia. The graduation in colour range across blue, green, yellow and red shows the density of services in parts of Sydney visualised within the context of the whole urban environment. In addition, this is done quantitatively so that future changes in this pattern can be assessed and they can inform actions by Foodbank and its partner food distribution agencies for a variety of practical purposes including e.g. gap identification, new service location or relocation and so on.

Figure 6 Density function analysis of the distance relationships between agency providers across the Sydney metropolitan area.



External and Secondary Data Sources

The objective here was to interrogate a data library of variables contained in The Vulnerable Australia Model that could be attributed or projected to the small area level, i.e. either SA1 or SA2 to permit a more granular analysis and understanding of patterns of local food insecurity. The purpose of this data is to assist in quantifying the key triggers for food insecurity at a more localised level. The main 'trigger' categories identified in this stage of the analysis were:

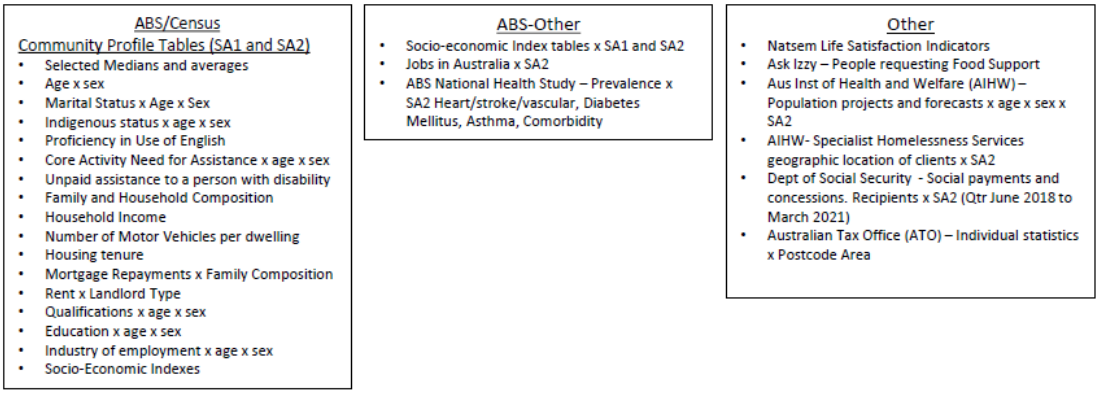
- Income and primary expenses (rent, mortgage etc.) leading to a reduction in discriminant or disposable income;
- Health and the probability of chronic disease – mainly because of progressive ageing;
- Health risk because of lifestyle (smoking, obesity, quality of diet, alcohol consumption);
- Family breakdowns;
- Family structure/composition;
- Single parent families;
- Access and availability of public housing;
- Housing tenure (own, renting etc.);
- Aboriginal/Torres Strait Islander communities;
- Employment status and employment risk/job security;
- Occupation and education/qualifications;
- Use of English language/ethnicity and;
- Remoteness/Location.

This data also included data sets from the Department of Social Security (DSS Payment Demographic Data) at the SA2 and LGA levels. The data sets utilised were from 2016 onwards. The reason for this was due to the use of the 2016 Census SA2 defintions (which replaced the 2011 SA2 definitions). The variables used in this step included:

- Job Keeper;
- Carer Allowance;
- Aged Pension;
- Disability Support Pension;
- Youth Allowance
- Aus Study;
- Pension Concessions.

These data sets underpin and inform the modelled data from Foodbank to correlate the statistical relationships between population characteristics, changes over time and the patterns of food insecurity and supply that Foodbank agencies are called upon to provide. The next step in stage one of the modelling process is summarised below (Figure 7) showing the key additional data sets accessed to build the utility of the model in contextualising external environmental factors. These include key data elements drawn from the 2016 Australian Census (with the 2021 Census data to come later), other Australian Bureau of Statistics data sets and, lastly, data sets drawn from other sources that have relevance to the food insecurity equation and its estimation.

Figure 7 Key data elements accessed to build the utility of the model in contextualising external environmental factors



Data Sources 2: The Foodbank Survey and Hunger Report

Foodbank also surveys the general population to quantify and qualify the proportion of the population that has suffered food insecurity on an annual basis. The survey was conducted by McCrindle, a market research company and is summarised in The Foodbank Hunger Report. This annual survey collects information about food insecurity in Australia, bringing together Foodbank's research, data, on-the ground information and observations. It aims at providing a snapshot of the prevalence and depth of the issue of food insecurity across Australia, as well as insights into the day-to-day experience for people living with this fundamental vulnerability. One of the issues in this latest report is COVID-19 which continued to impact the food security environment in Australia during the past 12 months. Much of the report is informed by a national survey conducted between 1 and 28 July 2021 involving more than 2,500 Australians, over 1,000 of whom had experienced food insecurity in the last 12 months. The detailed methodology of this survey is available in a separate report. A selection of this data was incorporated into the modelling process to inform the behavioural aspects of food insecurity and people's actions when faced with food insecurity. This work utilised the USDA Food Insecurity questions in its design and implementation.

The survey data was projected to the SA2 level using the AIHW's age by sex projections which were filtered by the geo-segments (identified elsewhere in this white paper). This process permits the model to be updated and calibrated on a quarterly basis because that is the frequency with which the key data components are updated.

Demographic Information

Food insecurity/insufficiency. The USDA Food insecurity survey questions and measures are used to quantify this measure including:

- frequency of access
- barriers to accessing food relief
- type of food relief
- additional unmet needs
- additional needs (pet food, baby care items, etc.)
- reliance on pensions and benefits
- emotional response to needing food relief
- emotional response from receiving assistance
- awareness of Foodbank services
- impact of COVID-19
- access to government assistance (prior to and during COVID-19).

The survey is conducted annually in two waves:

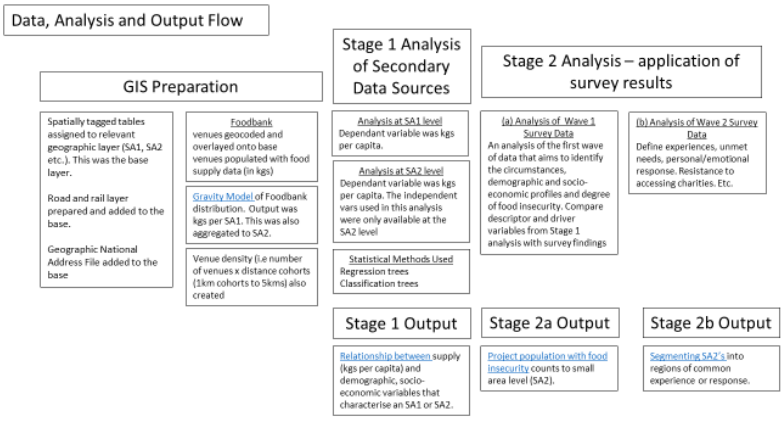
- Wave 1 identifies the proportion of and characteristics of people who suffer food insecurity from a sample size of 1731 people
- Wave 2 identifies the attitudes and behaviour of people who have experienced food insecurity from a sample of 1152 people.

There is access to three Foodbank surveys from 2018/19 to 2020/21. Sample sizes by wave and year are approximately the same.

Composite Modelling of Stages 1 and 2 Analysis

The analysis from the above steps in the modelling process were then developed into a second stage of analysis to provide a complete modelling approach to the issue of food insecurity and managing its effects through the network of Foodbank food distributors (with the Queensland data issue excepted). Figure 8 shows, this provides three levels of steps in the modelling and analysis phase; (1) an analysis of the relationships between current food distribution patterns and socio-demographic variables at the SA1 and SA2 levels; (20 projecting modelled food insecurity down to the SA geographic level, and; (3) providing a useful segmentation of need clusters and profiles across metropolitan and rural areas.

Figure 8 Three levels of steps in the modelling and analysis phase



Segmentation Model

The K-means cluster analysis method was used to develop “hunger segments” based on the demand drivers and calculating the relationship between unique segments, their demand drivers and food requirements at the SA2 level. The K-means clustering method is useful for reducing data complexity and building clusters of similar data observations. It is one of several clustering methods considered for analysis including factor analysis, hierarchical two-step analysis and latent class analysis. K-means was chosen because it’s commonly used and well known in research and so the method could be replicated. The underlying variables were all continuous data (% of DSS payments, % unemployed, mortgage repayments to household income etc.) and were standardized using Z-scores. This also allowed the modelers to check for correlations across multiple variables and run models based on different distance and centroid methods. It has the additional benefit that it is easier to interpret and communicate, and allows for the quick identification of outliers.

Gravity Model and Output

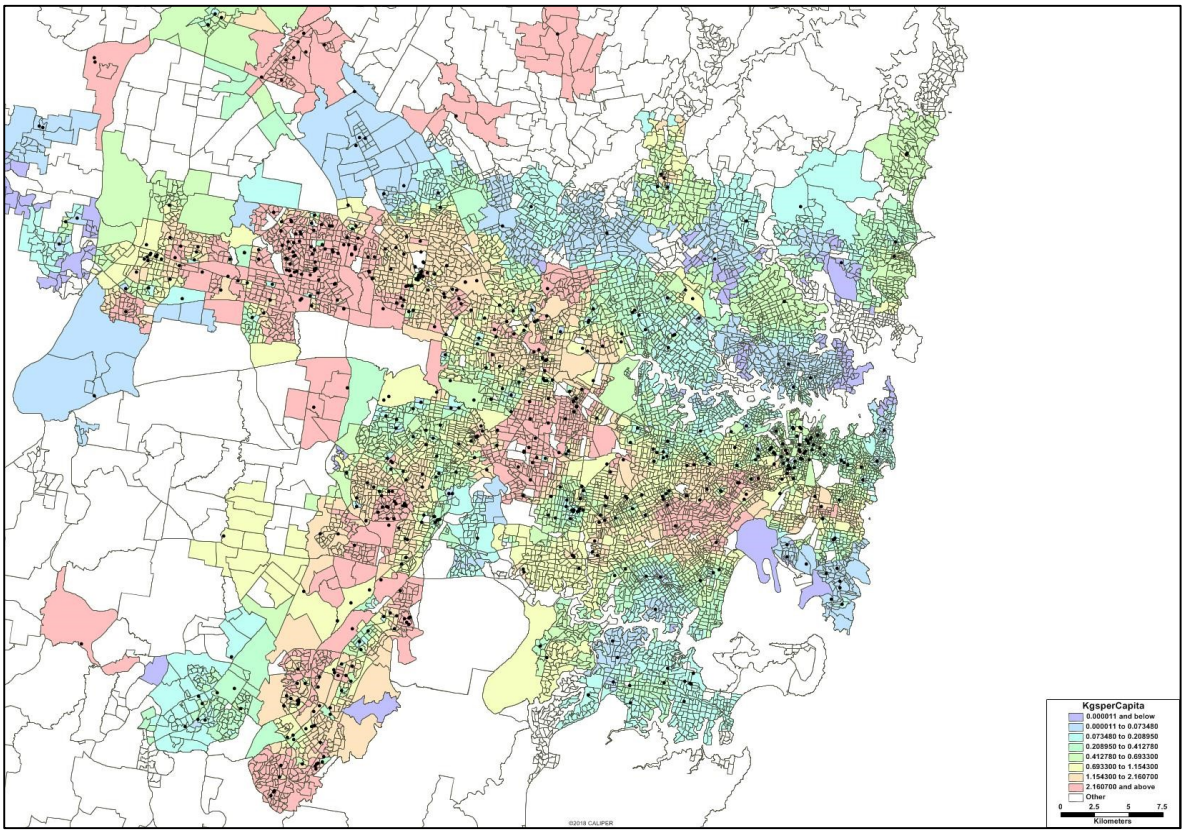
A gravity model is generally defined as “A model that compares the volume of flow, or spatial interaction, between two or more places based on the mass (population) of these places and the distance between the places.” (Wheeler, 2005). Several approaches to gravity modelling exist but the usual intent is to quantify the relationship between demand and supply of some service or product in spatial terms. This can include undersupply and oversupply measurement relative to population and in fields as diverse as retail analysis to access to medical practices and the like (Luo, 2004). Initial gravity models focused on the ‘floating catchment method’ (FCM) as described by Peng (1997) and Wang (2000) primarily with a focus on employment access. The FCM approach developed an alternate two-step floating catchment model (2SFCM) based on the work of Radke and Mu (2000). While this method also focused on healthcare, its application has become more diverse over time. It was also modified by Luo and Qi (2009) to address distance decay factors within catchment areas.

The Huff model precedes much of this discussion in that it came from a business context and its application was focused on spatial patterning of consumer behaviour in relation to retail service provider locations. It too has undergone various developments and extensions over time. Originally, David Huff’s algorithm was developed in 1962 and emerged at the nexus of his background in academic and applied geography and business studies (Huff, 1963, 1964). The Huff algorithm became more popular through its application in geographic information systems modelling activities. To some degree then, while it preceded easily available GIS software, it has grown in popularity alongside developments in GIS (Kurowska et al, 2017). These developments included variety of choices (proprietary and open-source applications), ease of use, a growing breadth and depth of potential and actual users (students, business), and an expanding variety of application scenarios. The approach taken was to map the relationships between kilograms of food per person distributed over a 12-month period relative to the population distribution and the site location of Foodbank service distributors.

Figure 9 illustrates the overall pattern of food distribution by kilograms against population (per capita) and the site locations of services. This provides the baseline for the gravity model developed. In the following two

maps, specific site examples are provided included the modelling of their influence or ‘pull’ relative to the pattern of per capita food distribution, the distribution of population and other food distributors. What this illustrates is the capacity to quantify the relative influence of any one provider and build a map of territorial influence of all providers by correlating their degrees of influence across space. This allows Foodbank to identify the areas of influence of individual agencies and the impact of multiple agencies within an area with a view to identifying patterns of oversupply or undersupply by SA2 region.

Figure 9 Pattern of food distribution in Sydney by kilograms against population (per capita) and the site locations of services



USDA Food Insecurity Index by GeoSegments for Stage 1 and Stage 2 Data Analysis

The table below illustrates the development of spatial segments for both urban and rural areas of Australia based on a combination of the USDA Food Insecurity Index and the Australian SEIFA Index. The resulting segments include age cohort clusters and quantification measured against the key USDA indexation of: (1) high food insecurity; (2) marginal food insecurity; (3) low food insecurity; and (4) very low food insecurity. This analysis provides a food insecurity segmentation for the Australian context and geographic distribution of population. The colours below indicate the *probability* that a respondent within each age cohort by segment is likely to fall within each of the USDA classifications. The SEIFA table is a sorting of the segments to show how education and wealth impact/reflect on that probability.

Hence this is an estimation of overall insecurity, including general insecurity associated with socio-economic variables, by geo-segments that can also be tempered further by the addition of temporal considerations and, as has occurred during the current pandemic, specific event occurrences. A key reason for this segmentation approach was to permit the comparison of similar regions across Australia in a consistent manner.

A cautionary note with spatial modelling lies in the concept of the ecological fallacy (Piantadosi et al 1988), The fallacy arises here in that not all people within a given spatial area will be food insecure and nor will those who are food insecure be insecure at the same time. This is important in that over-determination of statistical inference can lead to the misrepresentation of the variation in and complexity of a generalised, aggregate pattern in the data analysis.

Table 4 Development of spatial segments for both urban and rural areas of Australia

USDA x GeoSegment Stage 1 and Stage 2

			Metropolitan Segments						Rural Segments		
			m9	m8	m10	m4	m5	m6	r1	r3	r2
	SEIFA_Disadvantage	index	1085	1044	1010	990	972	880	1007	976	879
	SEIFA_AdvDisad	index	1104	1050	1037	979	968	887	994	958	869
	SEIFA_Economic	index	1069	1026	916	985	989	922	1017	991	894
	SEIFA_Education	index	1112	1053	1111	981	952	885	980	962	916
	Ages	USDA	m9	m8	m10	m4	m5	m6	r1	r3	r2
High Food Security	1:Lt 34 Years	1 High	52.200	48.600	41.200	32.100	37.900	30.100	42.300	23.800	43.500
	2:age 35 to 44	1 High	61.900	54.100	41.800	50.000	47.500	31.400	46.200	32.300	46.700
	3:age 45 to 54	1 High	71.900	68.800	56.300	72.400	50.000	57.100	53.800	53.300	35.800
	4:Age 55 to 64	1 High	77.800	78.900	78.600	74.400	86.700	73.700	78.900	72.400	57.100
	5:Age 65 Plus	1 High	96.300	90.600	87.500	78.300	88.500	75.000	85.700	88.700	92.300
Marginal Food Security	1:Lt 34 Years	2 Marginal	11.400	17.100	20.600	15.200	13.800	13.500	15.700	9.500	21.700
	2:age 35 to 44	2 Marginal	9.500	12.100	7.000	9.400	8.200	14.300	9.200	3.200	6.700
	3:age 45 to 54	2 Marginal	6.300	16.700	25.000	10.400	4.500	9.500	3.800	0.000	35.700
	4:Age 55 to 64	2 Marginal	11.100	5.300	7.200	7.700	0.000	15.800	5.300	0.000	21.400
	5:Age 65 Plus	2 Marginal	1.900	4.700	0.100	10.800	3.800	21.900	11.700	5.600	0.000
Low Food Security	1:Lt 34 Years	3 Low	11.400	16.200	14.700	20.600	17.200	21.600	21.700	28.600	17.400
	2:age 35 to 44	3 Low	16.700	12.200	16.300	12.500	16.400	20.000	7.700	22.600	13.300
	3:age 45 to 54	3 Low	6.200	8.300	6.200	6.900	13.600	4.800	19.200	6.700	7.100
	4:Age 55 to 64	3 Low	3.700	7.900	7.100	7.700	6.700	5.300	5.300	17.200	7.200
	5:Age 65 Plus	3 Low	1.900	1.600	6.200	3.600	7.700	0.000	2.600	2.800	7.700
Very low Food Security	1:Lt 34 Years	4 Very Low	25.000	18.100	23.500	32.100	31.100	34.800	20.300	38.100	17.400
	2:age 35 to 44	4 Very Low	11.900	21.600	34.900	28.100	27.900	34.300	36.900	41.900	33.300
	3:age 45 to 54	4 Very Low	15.600	6.200	12.500	10.300	31.900	28.600	23.200	40.000	21.400
	4:Age 55 to 64	4 Very Low	7.400	7.900	7.100	10.200	6.600	5.200	10.500	10.400	14.300
	5:Age 65 Plus	4 Very Low	0.000	3.100	6.200	7.300	0.000	3.100	0.000	2.900	0.000

Dependents per Adults per Segment by Food Security Classification

The final ten (10) geographic segments identified for metropolitan and rural areas are tabled below showing the index category of food insecurity associated with each segment and the estimated proportion of dependents for each adult in that segment. This is meaningful for estimating overall food insecurity and tracking likely changes in the food insecurity environment over time as changes occur.

Table 5 Geographic segments identified for metropolitan and rural areas

GeoSegment	1 High	2 Marginal	3 Low	4 Very Low
M10	0.214	0.213	0.061	0.212
M4	0.301	0.301	0.136	0.302
M5	0.400	0.404	0.216	0.406
M6	0.408	0.410	0.255	0.417
M8	0.339	0.335	0.177	0.334
M9	0.333	0.331	0.203	0.330
R1	0.373	0.376	0.220	0.380
R2	0.337	0.346	0.168	0.349
R3	0.325	0.332	0.156	0.335

Visualising Metropolitan Sydney and Melbourne Estimates of Food Insecurity

As noted above, a key concern in this modelling exercise was not only to be able to quantify food insecurity across Australia but also to present that information in several visual formats that users could access and engage with to better inform their practice. This process is illustrated below showing the scenarios developed for metropolitan Melbourne (Figure 10) and Sydney (Figure 11). These maps isolate the estimate of very low food security (from general or average food insecurity) to inform and support agency actions. This element is important because one finding of the research was that the existence of a service will generate demand in local areas. In other words, if food delivery agencies establish service provision in an area it will effectively generate local demand. This mapping of very low food security can, therefore, inform where best to locate new services if they are not already available in that area. As the modelling above has shown, this is a viable process given the geocoding of food delivery agencies. The next potential step is a service gap analysis. Here too, the spatial scientific aspect of this modelling is illustrated because it can better inform opportunities for developing the network of service delivery and quantifying the likely extent of unmet demand for such services.

Figure 10 Very Low Food Security by Percentage of Households in Melbourne

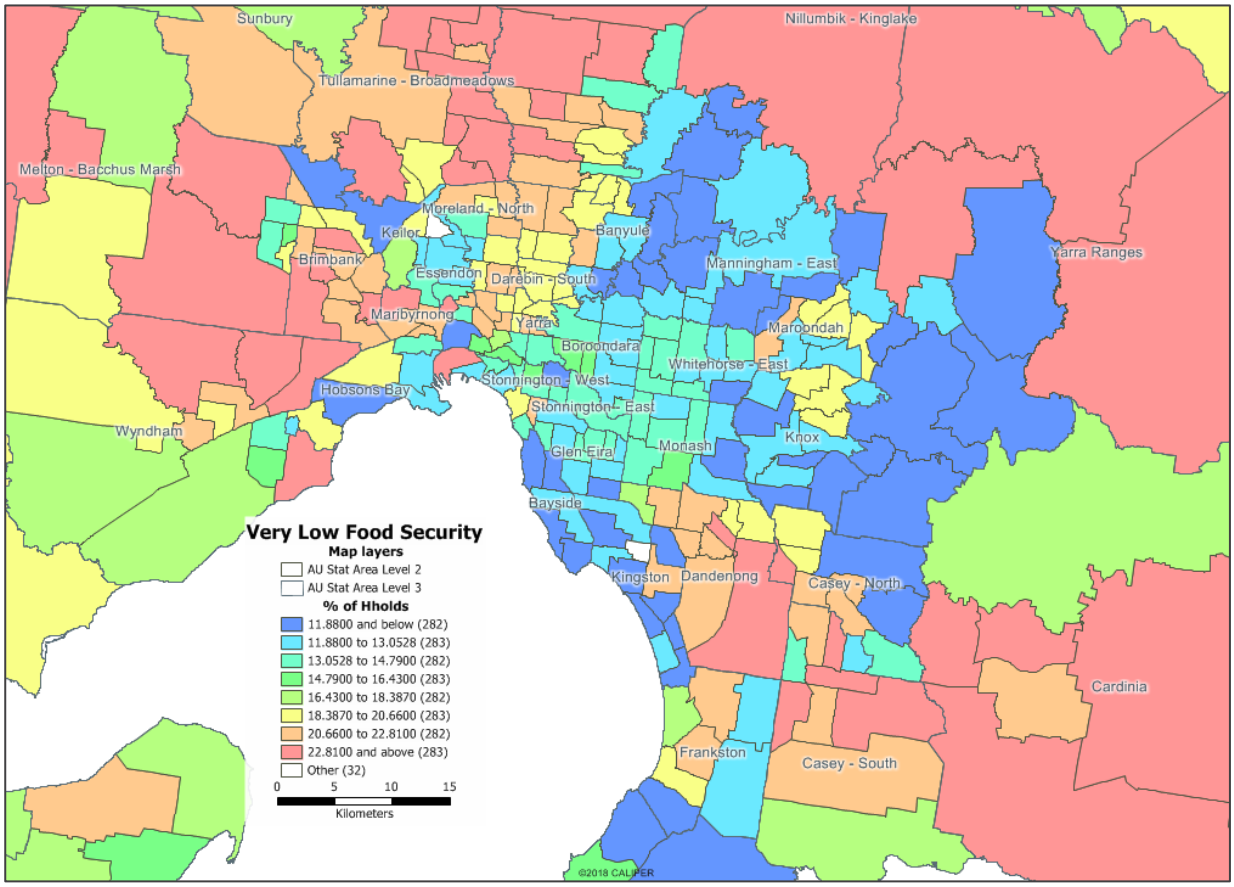
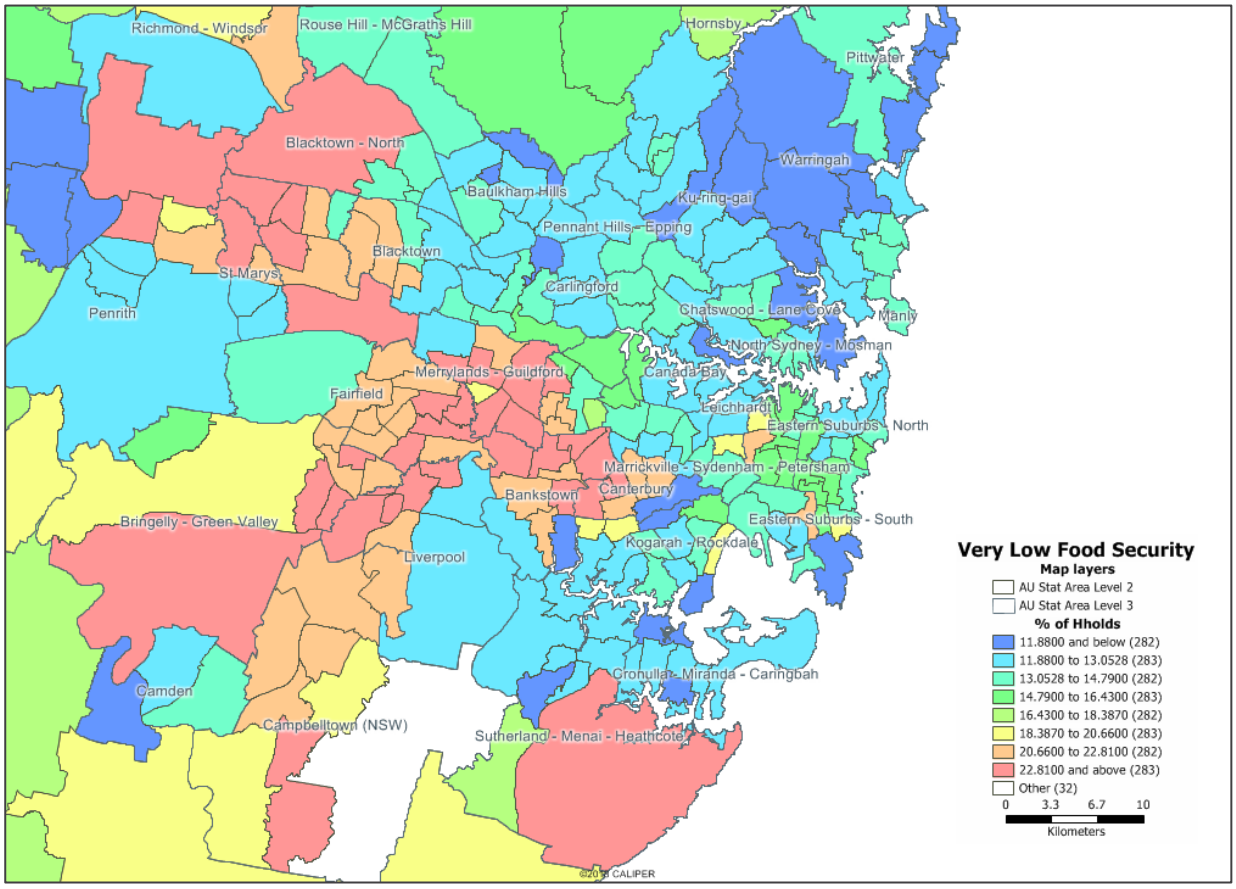


Figure 11 Very Low Food Security by Percentage of Households in Sydney



Development of Community Personas

An additional activity undertaken utilising the modelling outputs was the development of a number of community personas to help clarify where the mix of individuals within a community (SA2) might fit since there is no one type of person who might be food insecure. As identified in the quantitative and spatial modelling above, individuals and even food supplying agencies can come into and out of the food security space over time. The pandemic is an influencing factor in this dynamic, but food insecurity was already a major factor in the Australian social landscape. The function of these community personas was to help people identify with the situations that food insecure people might be in and for those who are food sinecure to connect with their own need and the available support for those who find themselves food insecure. These personas drew on the urban/rural segments identified above but then contextualised these in a narrative form to enable this two-way engagement process. These community personas are shown in table format below.

Figure 12 Community personas for food insecurity

Review of Methodology and Application

Food Surveys undertaken by McCrindle

This section provides an expert review of the modelling approach described above. The key input into the Foodbank Hunger Report is an annual survey of food security. In 2021 this was conducted in four stages through the month of July. The headline figure, which of course dominates the discourse, is the reported 28% of individuals that experience low or very low food insecurity. Therefore, the focus is on the interaction between the survey methodology and that headline figure.

1. Individuals or Households

The survey is administered to individual adults but their responses relate to all adults in a household and all children in a household (when children are present in the respondent's household). This creates a slight conceptual issue – what proportion are we actually measuring? If we conceptualise a frame of all adults in Australia, and define:

$$Y_i = \begin{cases} 1 \; if \; individual \; i \; reports \; living \; in \; a \; household \; experiencing \; food \; insecurity \\ 0 \qquad if \; individual \; i \; reports \; living \; in \; a \; household \; with \; food \; security \end{cases},$$

our population proportion of interest is simply

$$\pi = \frac{1}{N}\sum_{i=1}^{N} Y_i$$

where N is the number of adults in Australia (or an appropriate sub-population). This is the **proportion of adults that report living in a household that is experiencing food insecurity**. That insecurity may apply to all adults in the household or may apply differentially. How it applies may also depend on the number of adults in a household. Therefore, we need to be careful to not impute:

- $Y_i = 1$ implies $individual \; i \; experiences \; food \; insecurity$

or

- $Y_i = 1$ implies $individual \; i's \; whole \; household \; experiences \; food \; insecurity$

We should also be clear if defining $Y_i = 1$ for a respondent's household is based on the adult score only or includes children. The USDA 18 score thresholds are adjusted to account for the inclusion of children but it is clearly possible that Y_i could change (in either direction) when child questions are included or excluded.

It should be noted that the USDA 18 score is designed to relate to households, in other words the instrument is deployed in a household survey with an individual responding for that household. The Foodbank Survey samples directly to individuals (and more than one individual could respond independently from the same household) so although the individual responds with respect to their household it is not a household-level response.

2. Selection of Stage One and Stage Two Samples

The selection of the main Stage One sample appears to be via an online Panel Survey. In other words, the survey organisation maintains a large panel of Australian adults and the survey is mounted online until certain quotas are realised[4]. Non-random samples are common but particular care is required when claiming they estimate an overall population total, mean or proportion as such quantities will be sensitive to informative selection. The key assumption (Smith, 1983) is that, conditional on the quota variables, whether an individual responds is not dependent on their food security status.

$$Pr[i \; responds \; to \; survey \mid Y_i, age, gender, state] = Pr[i \; responds \; to \; survey \mid age, gender, state] \quad (1)$$

[4] Note that detail on this aspect is vague in the methodology section of the Foodbank Hunger Report.

Approximating assumption (1) relies heavily on the recruitment strategy not over-emphasising the nature of the survey, leading to individuals not experiencing food insecurity considering the survey as not relevant to themselves or their household. If assumption (1) holds, and the quotas are in-line with population proportions, we can estimate our proportion as simply:

$$\hat{\pi} = \frac{1}{1{,}005}\sum_{i-1}^{1005} Y_i\,,$$

and the data in the Foodbank Hunger Report figures show the unweighted proportion for Stage One is in fact around 28%[5].

Stage Two is then a booster sample from some of the States (NSW, VIC, QLD, SA). Therefore, to estimate the proportion as:

$$\hat{\pi} = \frac{1}{1{,}727}\sum_{i-1}^{1727} Y_i\,.$$

would require

$$Pr[i\ responds\ to\ survey \mid Y_i, age, gender] = Pr[i\ responds\ to\ survey \mid age, gender]$$

as the sample particularly over-represents SA, QLD, VIC, and to a lesser extent NSW. In other words, the propensity for an individual to report their household experiencing food insecurity is independent of State / Territory after controlling age and gender; an implausible proposition. Alternatively, weighting is required to re-distribute the responding sampling across the States and Territories to match their relative population sizes.

3. Weighting Approaches

Through weighting at estimation, we can improve the viability of the sample giving unbiased population estimates by introducing additional variables such that

$$\begin{aligned} &Pr[i\ responds\ to\ survey \mid Y_i, age, gender, state, weighting\ variables] \\ &\qquad = Pr[i\ responds\ to\ survey \mid age, gender, state, weighting\ variables] \quad (2) \end{aligned}$$

and

$$\hat{\pi} = \frac{\sum_{i-1}^{1727} w_i Y_i}{\sum_{i-1}^{1727} w_i}$$

where w_i is a weight that recovers correct population distributions for age, $gender$, $state$, and $weighting\ variables$. Weights are typically created by 'calibrating' weighted sums to meet certain known population totals. The simplest approach is via post-stratification but can be extended to calibrate on multiple margins via iterative scaling (raking ratio) or through an implied linear model leading to the generalised regression estimator or GREG (Särndal et al, 1992). Embedding the weighting in a 'model' makes it clearer the conditioning that is occurring to approximate selection not depending on Y_i. This is important, in the absence of random selection population estimates are purely model-based (Royall, 1970). Inference is via the model with no robustness from random selection.

The weighting approach for the Foodbank Survey is a post-stratification approach based on 45 weighting cells defined by age group by 'hunger segment'[6] such that

$$\begin{aligned} &Pr[i\ responds\ to\ survey \mid Y_i, age\ by\ hunger\ segment] \\ &\qquad = Pr[i\ responds\ to\ survey \mid age\ by\ hunger\ segment] \quad (3) \end{aligned}$$

The weighting, based on assumption (3), ignores the differential sampling fractions across States and Territories once Stage Two sample respondents are included. It would give more robustness if the weights were (as a start) calibrated to the marginal State / Territory population totals (and correct population totals by male and female), as well as the current 45 weighting cells.

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[5] The report should confirm that all reported proportions are weighted.
[6] The creation of the 'hunger segments' is discussed in the following section.

The weighting for those suffering food insecurity (with the addition of Stage Three and Stage Four responders) relies on estimated population totals from the first set of weighting. The set of population totals should be similarly expanded to include at least State / Territory totals as the sample is skewed towards certain States and away from others.

The weighting section should provide some indication of the distribution of relative weights. This enables the user to understand how much the survey respondents required adjusting to meet the totals, and therefore some sense of the skewness of the distributions of respondents relative to the desired population distributions. It would also reassure users if distributions of say respondents' household income were also presented (before and after weighting). Direct comparison distributions are not available (ABS last published detailed household income distributions for 2017-18 while ATO income products are for individuals) but it would give an indication of whether the responding sample was skewed towards lower income households. Individual's education is another possibility with approximate distributions available from 2016 Census.

As a final comment, when working with a survey there should be some discussion of the uncertainty of estimates. As a first-order approximation, the standard error on the headline figure is approximately

$$\sqrt{\frac{0.27 \times (1 - 0.27)}{1727}} = 0.01$$

with an approximate inflation due to the variation in the weights. Of course, a failure of (3) can result in an unmeasurable bias that results in far larger sampling error.

Hunger Maps and Model undertaken by The Art of More

4. Creation of the Hunger Segments

The ten Hunger Segments are formed utilising a k-means clustering at the level of SA2. The innovative aspect is the identification of the input variables that drive the clustering.

To ensure relevance to the concept of food insecurity, the supply-side is mapped on to the geography at SA1 level. This comes from the operational information of Foodbank and its distribution of food to local agencies. The implementation of a gravity model assumes the population supplied from an agency is in a 5km radius, and this is supported by estimates that individuals generally operate within that distance from their household. Once the quantity of food supply is assigned to the populations in local areas, tree-based methods identify the social, economic, and demographic characteristics of areas that best explain variation in food supply. Information is then aggregated to SA2 level and that identifies the variables at the SA2 level that drive the k-means clustering.

Using Foodbank supply data ensures the variables driving the creation of the segments are those that are most associated with where food is supplied. While it is expected the system will not have supply perfectly matched to need[7], it is expected that need exists in areas with supply. The Hunger Segments are then a key component in the weighting of the Foodbank Survey as discussed in the previous section. Their localised relevance to prevalence of food insecurity is important for offering robustness with respect to the general weighting assumption (2), and the current weighting approach based on assumption (3).

5. Small Area Estimates of Demand Driven by Food Insecurity

Foodbank through its operational data understands the supply side and the spatial distribution of supply, but that does not mean supply is meeting actual need. The Foodbank Survey measures the need from individuals (and households) for food support through the measurement of food insecurity. An initial approach to map the true demand as measured by need has utilised geo-coded survey responses from previous surveys. Responses are assigned to a Hunger Segment based on their location, allowing the estimation of proportion of individuals experiencing food insecurity and average demand for those individuals

[7] We distinguish here between the known demand on an agency, which its supply is matched to, and the actual need for food support in an area.

by Hunger Segment. Those high-level estimates are then applied to each SA2 based on its Hunger Segment.

This approach to small area estimation (see Rao 2003) takes a unit-level relationship applied to all units at some aggregate level and then applies it down to a much finer geographic level. It is referred to as synthetic estimation as the model driving the estimate for a small area uses a model based on data from other areas to form the estimate. As proposed with the weighting, there is scope here to extend the structure of the unit-level modelling to improve the SA2 level estimates.

The propensity π_i for an individual to report food insecurity ($Y_i = 1$) can be modelled as a function of an individual's age group, gender, State / Territory and Hunger Segment. The inclusion of variables is limited to availability of suitably aggregated totals at the small area level to facilitate prediction within the small area. In this case, SA2 population totals for age group by gender. The model fitted at the national level gives $\hat{\pi}_i$. An estimate of the total number of individuals M_a experiencing food insecurity in SA2 a with total population N_a is then

$$\hat{F}_a = \sum_{i=1}^{N_a} \hat{\pi}_i \, \hat{\mu}_i.$$

Conclusion

The methodology developed in this model was a first stage, in an ongoing and developmental process, at modelling a highly complex and dynamic environment in which the available data was variable in both quantity and quality. The intention was, and remains, to refine and develop this modelling approach as new and improved data sets become available and, also, based on input from expert informants as to how best to improve the accuracy, utility and sensitivity of the modelling. This is, therefore, an ongoing and developmental process in which the aim is to inform Foodbank's approach to data management for improved service outcomes, logistics management and planning activities, in addition to which it informs the national level understanding of food insecurity in Australia. This is the first model of its type developed for Australia, with a unique focus on small area effects, and it will continue to inform the knowledge base as it develops. Through publication and presentation, it also aims to inform the broader food security literature and practice base by showing what is possible in terms of data management, analysis and visualisation. The aim is, as stated at the outset, to fundamentally improve the food security position in Australia, during and following the COVID-19 pandemic by developing both the knowledge and application bases available in this space through applying innovative data science methods. This whitepaper represents a first stage, point-in-time review of the methodology and offers recommendations for its further improvement and development by Foodbank Australia.

Recommendations

The following recommendations speak to the key issues identified in this whitepaper with a view to enhancing subsequent iterations of this modelling exercise and its associated Foodbank Australia data environment. As mentioned elsewhere, this project is both innovative in its conceptualisation and also constrained in its execution by a number of key data concerns. Addressing these would add to the robustness of the current modelling exercise and expand the value of Foodbank's longer term data strategy with a view to improving the scientific understanding of food insecurity in Australia and, potentially, beyond.

1. Improve the Agency Classification System

The agency classification index is currently limited to Foodbank agencies. A review of the Foodbank agency list shows agencies in a wide cross-section of the community, church and health groups including mental health support. A more extensive classification system should be included and an understanding of where each agency focuses its work. This will allow for greatly improved monitoring and managing of food insecurity trend patterns across particular vulnerable groups. This is especially topical in the context of the COVID-19 pandemic and anticipated mental health sequalae going forwards.

2. Improve End-to-End Data Capture

Foodbank has no data on where and how individual agencies are distributing food. So, while the agency is the link to the end user there is currently no information on whether, for example, food is delivered to a household, picked up by the end-user from a central agency location or used within the agency itself. This would add an important data element to the modelling as it currently stands and support strategic activities and developments by Foodbank Australia into the foreseeable future.

A strategy for understanding the distribution network and the mode of supply would be useful improvements to this current model. The gravity model developed was an attempt to overcome this limitation in knowledge, but the logistics and infrastructure are also important components of the food distribution network and, as yet, the route to the end-user has not been classified or quantified.

3. Develop a Comparable Queensland Data Scenario

Queensland Foodbank's database is currently undeveloped. There is no time series data available for that state nor even agency location details. This is a key development opportunity for actualising a fully national approach to data management and modelling.

4. Improve the Survey Data

The improvement of this source of data for the modelling will help develop the model as it is and in its future iterations. This will also improve the overall data quality scenario of Foodbank Australia. Further weighting methodologies that could be explored include:

- weighting it for representativeness of all states and territories and their populations;

- utilising some additional pre- and post-weight comparisons for variables such as household income;

- clarifying that all analyses and estimates within the report are based on the mode of weighting used;

- providing more details on the recruitment of the sample in the appendices of these and subsequent reports.

5. Analysis that Explores Causal Processes in the Food Security Equation

The question currently remains as to whether food insecurity is a *symptom* of broader insecurities (e.g. employment, financial and housing stresses) or an outcome of these and not a cause. The cause of food insecurity could be changes in income status, changes in expenditure status/patterns, family breakdown etc. While the survey (see above) does include some questions about the general 'security' status of the respondents, it does not currently allow for an understanding of sequence of events, respondent priorities or shifting patterns of behaviour. This could be best resolved by developing a study with a much larger sample and supported with longitudinal data analysis.

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