Imperial College London

School of Public Health

Department of Epidemiology and Biostatistics

Integrating health and greenhouse gas emission metrics to promote a sustainable food system

Allison Gaines

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Doctor of Philosophy

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Statement of originality

I hereby declare that this thesis and the work reported herein was composed by and originated entirely by me and has not been submitted to another university of institution. All information derived from the published and unpublished work, of both me and others, has been recognised in the text and included in the reference list. This thesis was supervised by Dr Bruce Neal (The George Institute for Global Health; Imperial College London), Dr Paul Elliott (Imperial College London) and Dr Paraskevi Seferidi (Imperial College London).

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Abstract

Background

Uptake of healthy and sustainable diets is required to reduce the non-communicable disease burden and protect our planet. This thesis sought to calculate product-specific greenhouse gas emission (GHGe) estimates for products available in Australian supermarkets in 2019. It assessed the association between GHGe estimates and nutrient profiles and the potential reductions in total GHGe achieved by switching purchases to lower-GHGe products.

Methods

The GHGe values for each ingredient in each product were weighted and summed to determine a GHGe estimate for each product, with further adjustments to account for level of processing and transport. The significance of trends between GHGe estimates and the four nutrient profiling scores were assessed. Product switches were evaluated based on GHGe percentiles to test the impact of progressively switching towards lower GHGe products.

Results

23,550 products were included in these analyses. The median product-specific GHGe estimate (95% UI) for all products was 2.24 (1.22-4.20) kg CO_2eq/kg product (range [0.0002, 73.5]; interquartile range (IQR) [1.03 (0.81-1.64), 6.94 (5.13-18.5)]. 'Meat and meat products' and 'Confectionery' had a disproportionately higher median GHGe contributions when compared to all other categories. Products with better nutrient profiles were more likely to have lower median GHGe estimates than products with worse nutrient profiles (all p-values<0.001). Switching higher-emission products for lower-emission products had the potential to reduce total emissions by over 70%.

Conclusion

Standardised metrics to communicate the GHGe of supermarket products alongside nutrient profiling metrics can help to make great strides in minimising adverse health and environmental impacts. A substantial reduction in the GHGe attributable to supermarket products could be achieved by directing manufacturing and marketing towards healthier and lower GHGe impact products. Dual health and GHGe impacts of specific products should be used to define food policy and industry regulation.

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Outputs relevant to this thesis

Published papers

- **Gaines A**, Shahid M, Huang L, Davies T, Taylor F, Wu JH and Neal B. Deconstructing the Supermarket: Systematic Ingredient Disaggregation and the Association between Ingredient Usage and Product Health Indicators for 24,229 Australian Foods and Beverages. *Nutrients*. 2021;13(6):1882.

  This publication contains material that is similar to the contents of Chapter 3; permission to reproduce is not required. A copy of this manuscript is provided in Appendix D.

- **Gaines A**, Davies T, Shahid M, Taylor F, Wu JHY, Hadjikakou M, Pettigrew S, Seferidi P and Neal B. A Novel Approach to Estimate Product-Specific Greenhouse Gas Emissions for 23,550 Australian Packaged Foods and Beverages. *Journal of Cleaner Production*. 2023:138816.

  This publication contains material that is similar to the contents of Chapter 4; permission to reproduce is not required. A copy of this manuscript is provided in Appendix D.

Papers under review

- **Gaines A**, Shahid M, Hadjikakou M, Jones A, Pettigrew S, Taylor F, Seferidi P, Neal B. The association between nutritional quality and greenhouse gas emission estimates for 23,550 Australian packaged foods and beverages. *BMJ Nutrition, Prevention & Health*.

  This publication will contain material that is similar to the contents of Chapter 5.

- **Gaines A**, Shahid M, Coyle DH, Barrett E, Hadjikakou M, Wu JHY, Taylor F, Pettigrew S, Neal B, Seferidi P. Reducing greenhouse gas emissions in Australia by switching food and beverage product purchases. *Nature Food.*

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Conferences and events

- Oral presentation (TGI George Street Office, Sydney, Australia), *April 12, 2023.*
  "Can we reduce diet-related greenhouse gas emissions using packaged food and beverage data?" The George Institute for Global Health Seminar Series.

  This was informed by the outputs of Chapter 6.

- Oral presentation (ICL White City Campus, London, England), *November 22, 2022.*
  The George Institute at Imperial: Launch Event. Launch of The George Institute for Global Health at Imperial College London | Events | Imperial College London.

  This was informed by Chapters 3-6.

- Oral presentation (Adelaide, South Australia), *September 22, 2022.*
  "Estimating product-specific greenhouse gas emissions for 23,550 Australian packaged foods and beverages." Healthy Environments. Public Health Congress 2022.Public Health Association of Australia (PHAA). Population Health Congress 2022 - Public Health Association of Australia Inc (phaa.net.au)

  This was informed by Chapter 4.

- Abstract (online), *December 15, 2021.*
  "Method to estimate product-specific greenhouse gas emissions for packaged foods and beverages: an application to the Australian food supply." **Gaines A**, Davies T, Shahid M, Huang L, Wu JHY, Taylor F, Hadjikakou M, Pettigrew S, Neal B. Food security, safety, and sustainability. 2021 Global Food Governance Conference. https://oneill.law.georgetown.edu/events/global-food-governance-conference/

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- Oral presentation (online), *July 13, 2021.*
  "Australian member country dialogues: What role does food labelling play in helping to shift consumers towards healthier, safe and sustainable consumption?" United Nations Food Systems Summit. FSS Food Labelling Webinar (vimeo.com).

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- Poster presentation (online), *April 28, 2021.*
  "Breaking down the supermarket: the composition of ingredients representing the Australian packaged food and beverage supply." Planetary Health Alliance Annual Meeting. https://www.planetaryhealthannualmeeting.com/

  This was informed by Chapter 3.

Related papers

- Barrett EM, **Gaines A**, Coyle DH, *et al.* Comparing product healthiness according to the Health Star Rating and the NOVA classification system and implications for food labelling systems: an analysis of 25,486 products in Australia. *Nutrition Bulletin*. 2023; In press.

- Shahid M, **Gaines A**, Coyle DH, Alessandrini R, *et al.* The effect of mycoprotein intake on biomarkers of human health: a systematic review and meta-analysis. *The American Journal of Clinical Nutrition*. 2023;118(1):141-50. DOI: 10.1016/j.ajcnut.2023.03.019

- Melville H, Shahid M, **Gaines A**, *et al.* The nutritional profile of plant-based meat analogues available for sale in Australia. *Nutrition & Dietetics*. 2023; 80(2): 211-222. doi:10.1111/1747-0080.12793

- Coyle DH, Huang L, Shahid M, **Gaines A**, *et al.* Socio-economic difference in purchases of ultra-processed foods in Australia: an analysis of a nationally representative household grocery purchasing panel. *International Journal of Behavioural Nutrition and Physical Activity.* 19, 148 (2022). https://doi.org/10.1186/s12966-022-01389-8

- Roca-Barcelo A, **Gaines A**, Sheehan A, Thompson R, Chamberlain RC, Bos B, *et al.* Making academia environmentally sustainable: a student perspective. *The Lancet Planetary Health.* 2021;5(9):e576-e7. DOI: https://doi.org/10.1016/S2542-5196(21)00199-6

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Abbreviations

ABS	Australian Bureau of Statistics
ACCC	Australian Competition and Consumer Commission
ADG	Australian Dietary Guidelines
AHA	American Heart Association
AU$	Australian Dollar
CO_2eq	Carbon dioxide equivalents
EURO	Regional Office for Europe
FAO	Food and Agriculture Organisation
FICRCD	Food Intakes Converted to Retail Commodities Database
FSANZ	Food Standards Australian New Zealand
FVNL	Fruit, vegetables, nuts and legumes
GHGe	Greenhouse gas emissions
HSR	Health Star Rating
IOA	Input-output analysis
IQR	Interquartile range
LCA	Life cycle assessment
NCD	Non-communicable disease
PUFA	Polyunsaturated fatty acids
SD	Standard deviation
TCFAC	Technical Conversion Factors for Agricultural Commodities
UI	Uncertainty interval
UK	United Kingdom
US	United States
USD	United States Dollar
USDA	United States Department of Agriculture
WHO	World Health Organisation

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Chapter 1: Introduction

Food has been a key driver of evolution over the past 500 million years. Humans started out by eating a diet of scavenged vegetation and small, dead animals from their immediate surroundings, struggling to obtain sufficient calories to survive, conserving their energy by minimising movement, and adapting to their environment with negligible impact on it. Progressively, humans improved their abilities to hunt resulting in a prey-predator hierarchy such that finding food, and not becoming food, became the daily priority.[1] The turning point occurred when humans began to understand agriculture, the notion of intentionally harvesting plants and herding animals, and the shift from the nomadic existence of our early ancestors to industrialisation began.[2] The reality of the agricultural revolution was twofold. First, it enabled modern human existence by providing adequate food and nutrition to large populations around the world so that the energy needed for cognitive function could be used to progress business and society. However, at the same time, it perpetuated disease, resource depletion and even war with the centralisation and emergence of urban hubs and social hierarchies. In this new reality, humans could modify land and the environment to suit their needs.[1]

The synergy between the field of agriculture and the modern commercial and industrial revolution led to the industrialised agricultural movement that makes up the food system as we know it today – a system that aims to minimise costs and maximise profits and demand. Through this transformation, there has been a stark change in the composition of both diets and food.[3] Previously, diets were made up of foods that largely resembled plants and animals that could be found in nature and land was used and reused to produce outputs. Now, diets are made up largely of products of industrialised agriculture and manufacturing, which are often comprised of processed edible matters that rarely resemble foods in their original form.[4] These products require large amounts of energy and inputs to make an abundance of yields regardless of quality or equity of distribution.[5]

Until very recently, almost all humans were active in the growing and preparation of their own food. However, in today's world, few people are aware of the complex steps and network of actors that make up the global food system and result in the food that appears on a plate or, often now, in a package on a doorstep. Further, even fewer are aware that their foods and beverages are negatively affecting them and their planet.[6,7] Little has been done to bring to light either the costs of industrialised agriculture or the more environmentally-conscious, nutritionally sound alternatives.

1.1 The global food system

The modern global food system that has materialised from industrial agriculture refers to the network of actors, organisations, and dynamic practices involved in the production, distribution, and

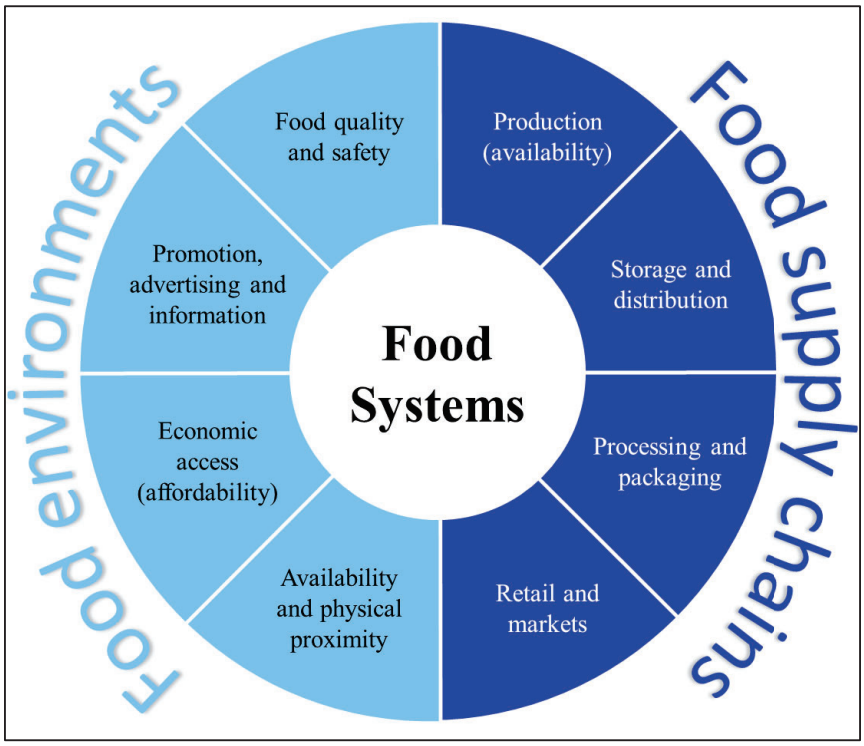
consumption of food across communities worldwide.[8,9] Subsidiaries of the global food system exist at local, regional, national and international scales, and are influenced by environmental, economic, social and political conditions.[10] Relying on both human activity and natural processes, food systems encompass the entire food and beverage supply chain, from agricultural inputs to processing, packaging, transportation, marketing, retail and disposal.

Alongside the change from a farm-based to a manufacturing-based food system have come changes in where food is purchased and the content of the foods themselves. Driven by rapid global economic growth, this change in the food system spread quickly around the world.[11] The immense dual impacts on population health and the environment were only considered after the fact. Australia is a prime example of a transformed food system centred around purchasing food at supermarkets and convenience stores and requiring policy intervention to mitigate the dual adverse impacts.[12]

1.1.1 Players and processes

The global, industrialised food system of today requires the coordination of a broad range of decision-makers, including food producers, policy-makers and consumers, and ever-evolving industrialised processes. Various institutions govern the food system using controlled markets and trade agreements; these institutions, in turn, make up the food system's supply chains and food environments (**Figure 1.1**).[12] Food supply chains encompass food system activities and processes that progress commodities through stages from production to consumption based on the decisions made by food system actors.[9] Food environments include physical and online outlets along with the social and political contexts in which consumers acquire, purchase or consume foods and beverages.[9] The interconnection across all parts of the system infers that any action, stemming from any of the actors, may affect one or more of the others.

Figure 1. 1. Conceptual framework of food supply chains and environments



Source: Adapted from Figure 3 in HLPE. 2017. Nutrition and food systems. A report by the High Level Panel of Experts on Food Security and Nutrition of the Committee on World Food Security, Rome.

Consumers interact with the global food system in diverse environments including grocery stores and wet markets from which food is generally taken home and self-prepared. There are also multiple venues for eating food prepared outside of the home such as dine-in and take-away restaurants, hawker stands, event catering, and supermarkets and convenience stores at which meals can be found pre-prepared and often processed. Price, accessibility, taste and culture all have major effects on the desirability and consumption of different foods, while choice of retail environment, health and environmental considerations are often of lower priority.[13]

1.1.2 Food system transformation from agrarian to industrialised

The change in the way the world produces, processes, distributes and consumes food has been termed the global food system transformation.[14] The transformation began in response to the mounting challenges of population growth, societal and industrial pressures, economic fluctuations and environmental degradation.[15] Advancements in technology allowed for industry actors to vastly increase profits and opened the doors to improved accessibility to adequate calories and more efficient, often automated, agricultural and production solutions.[14] Transition between transformation phases also

required significant changes in investments and behaviours, as well as collective action and collaboration among stakeholders at all levels.[16,17] The magnitude of the transformation was highlighted by the stark difference between the hunter-gatherer lifestyle lived at the beginning of human history and today's convenience-centric lifestyle. Less immediately apparent, but nonetheless hugely impactful differences are seen in more modern history with, for example, the move from home cooking towards dining out and convenience foods.[18]

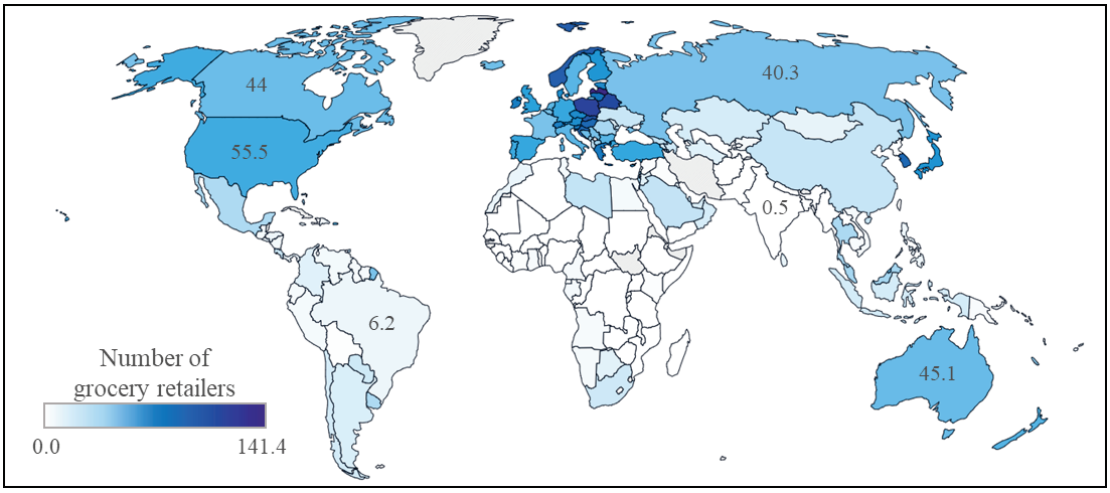
As a result of the global food system transformation, there was a need to understand the stages of change across diet and health outcomes (e.g., prevalence of obesity) that were occurring as countries underwent economic, social and demographic transformations. This has been coined the 'nutrition transition' and previously described in five stages (**Supplementary Table S1.1**).[3,19,20] Stages one and two were the 'collecting food' and 'famine' stages respectively, and they make up only a small proportion of food environments today.[3] The health outcomes associated with these early stages were most commonly low life expectancies and stunting.[21] Stage three, described as 'receding famine', marks the start of the industrial revolution which saw progress towards reaching adequate nutrition for most. Stages four and five, 'diet-related noncommunicable diseases' and 'behavioural change' respectively, were characterised by societal drivers including urbanisation, globalisation and changes in food production, retail and marketing, from which the need to individually compete for food in nature was replaced with mass production of food and high levels of food processing.[19] Stage four largely represents the current era for most of the world's population, in which resulting impacts on health outcomes are substantial and nuanced by country, geographic region, politics and economy. There is an urgent need for behavioural change (stage five), though the complexity of the global food system and required multi-sectorial cooperation is hindering progress.[16]

The shift in dietary intake habits and food retail environment types largely aligns with the agricultural revolution and advancements in food processing and distribution technologies. Grocery outlets, stores that predominantly sell food and beverage products, are typically a part of large corporations that have multiple locations.[9] Grocery outlet types include large chain supermarkets, smaller scale grocers, convenience stores and wet markets.[22] Higher-income countries that have transitioned to industrialised, corporate-driven food environments earlier tend to have a much larger number of grocery outlets than lower-income countries (e.g., 45.1 outlets per 100,000 people in Australia versus 0.5 outlets per 100,000 people in India in 2017) (**Figure 1.2**).

Around the world, different retail environment types also make up different proportions of sales and consumption. In higher-income countries, while growth in number of retail outlets in recent years has slowed (e.g., 5% growth in the past five years in Australia) (**Figure 1.3**), over half of consumption is comprised of food and beverage products purchased in supermarkets and other smaller grocery retail outlets.[23] In lower-income countries, the proportion of consumption from supermarkets is still lower

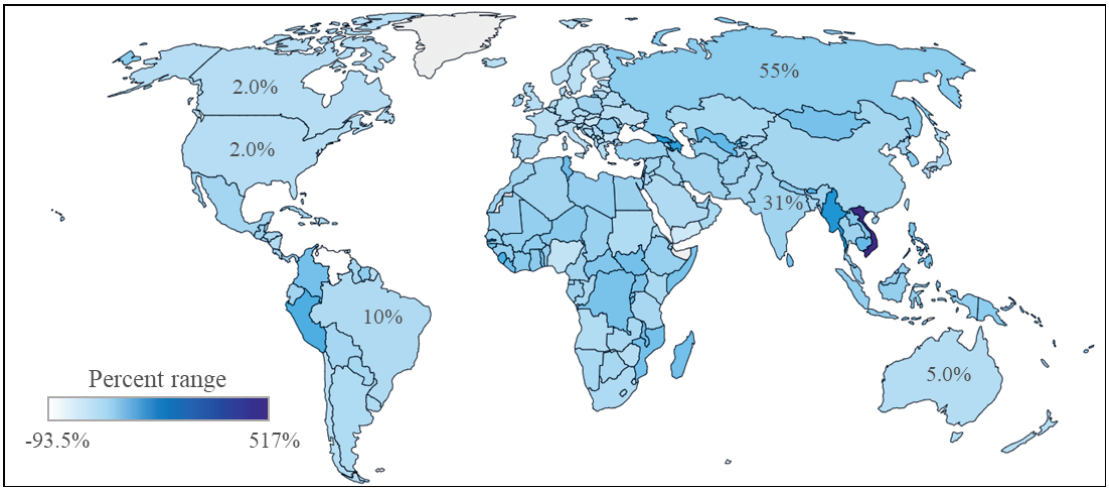
than higher-income countries, though the number of retail outlets has grown rapidly in many over the past few years (e.g., 31% growth in the past five years in India) (**Figure 1.3**).[3,24,25]

Figure 1. 2. Number of grocery outlets per 100,000 people by country



Source: Adapted from the 2022 Food Systems Dashboard using Euromonitor Data from 2017: Number of modern grocery retailers per 100,000 population – FSD (foodsystemsdashboard.org). Euromonitor grocery retail outlet types include hypermarkets, supermarkets, discounters, forecourt retailers (grocery outlets attached to gas/petrol stations), and convenience stores.

Figure 1. 3. Percent change in number of grocery retail outlets by country over five years



Source: Adapted from the 2022 Food Systems Dashboard using Euromonitor Data from 2014 to 2019: Growth in number of modern grocery retailers, 5 years – FSD (foodsystemsdashboard.org). Euromonitor grocery retail outlet types include hypermarkets, supermarkets, discounters, forecourt retailers (grocery outlets attached to gas/petrol stations), and convenience stores.

1.1.3 Ingredients and manufacturing

In parallel with overarching food system changes, there have been significant changes to food ingredients, products and their nutrient composition over the years,[3] driven by advances in technology as well as the influence of brand manufacturers and changes in consumer demand.[22] New agricultural techniques and industrial processing have opened the doors to mass production of new ingredients and products.[26] This is also reflected in the rise in prevalence of large-scale processing methods, additives, preservatives, highly processed products and animal-based products. Advances in food processing technology and the ability of industry players to feed more people while increasing profit margins have driven both positive and negative changes in food composition.[11] For example, the invention of high-pressure processing which kills bacteria and other pathogens allowed for the mass production of fresh-tasting and nutritious foods.[26] However, other technologies have been used to manipulate whole foods into highly processed products. The purpose of many of these ingredients is to imitate less processed foods while making the final product more appealing, and in some cases addictive.[27]

The use of additives and preservatives in food has increased significantly over the past few decades, driven by the desire to extend shelf life and maintain the quality of food during longer transportation and storage periods.[28] Some additives are used for preservation with little impact on nutrition or taste, such as sodium benzoate and sorbic acid, and support the longevity and reach of packaged foods.[29] Other additives such as sweeteners (both full-calorie and low-calorie), artificial colours and flavours, may contribute negatively to nutrition as well as overall diet composition.[30]

Ultra-processed products are industrial formulations often containing numerous additives that aim to make the final product more appealing. They are characterised as being energy-dense and high in salt, sugar, oils and fats.[31] The NOVA classification has been developed to categorise products into four groups based on the nature, extent and purpose of processing (**Table 1.1**).[32] NOVA group 4 classifies ultra-processed foods as those that include food substances not naturally found or commonly used in home cooking, such as modified starches and hydrogenated or interesterified oils.[27] As opposed to fresh, whole foods which are often prepared and eaten in the home, ultra-processed products are deliberately ready-to-eat and cater to the convenience of consumers in the fast-paced, work-centric world of today.[27,33]

One of the newest ultra-processed food groups is plant-based meat alternatives based on proteins extracted from sources such as wheat, peas and soy.[34] Minimally processed plant-based alternatives such as tofu, tempeh and seitan (NOVA group 3), take up some of the market share, but there is rising availability of ultra-processed options aimed at replicating the taste and texture of meat (NOVA group 4) that are more commonly marketed to consumers. Research around meat alternatives is still nascent. Some have found that these products have better nutrient profiles, are high in protein and dietary fibre, low in energy and fat, and are associated with lower blood lipids.[34,35] Others have found them to be

lacking in essential micro-nutrients, containing excess added sugars and fats, with little known about the long-term effects of some of their unnatural ingredients (e.g., hydrolysed proteins and methylcellulose).[34,36]

Table 1. 1. NOVA group classifications

Group	Description	Examples
Group 1 Unprocessed and minimally processed foods	*Unprocessed* Edible parts of plants (fruit, seeds, leaves, stems) or from animals (muscle, fat, eggs, milk), fungi, algae and water. *Minimally processed* Foods altered by industrial processes such as removal of inedible parts, drying, powdering, squeezing, grinding, steaming, roasting, and pasteurisation, freezing, non-alcoholic fermentation, and other methods that do not add salt, sugar, oils or other food formulations.	Fresh, squeezed, chilled, frozen, or dried fruit and leafy and root vegetables; grains and cereals; legumes; fungi; meat, poultry, and seafood, whole or cut; fresh, powdered eggs; fresh, powdered or pasteurized milk or yoghurt; fresh or pasteurized fruit or vegetable juices (with no added sugar or flavours); nuts and seeds; herbs and spices; tea, coffee, and water. Includes foods made up from two or more items in this group, and foods with vitamins and minerals added.
Group 2 Processed culinary ingredients	Foods altered by industrial processes such as pressing, refining, extracting or mining. The nutritional significance of these ingredients should always be assessed in combination with foods.	Vegetable oils crushed from seeds, nuts or fruit (notably olives); butter and lard; sugar and molasses obtained from cane or beet; honey and maple syrup; starches extracted from corn and other plants; vegetable oils with added antioxidants; salt. Includes foods made up from two or more items in this group, and foods with vitamins and minerals added.
Group 3 Processed foods	Products made by adding salt, oil, sugar or other group 2 ingredients to group 1 foods, using preservation methods such as canning, and using non- alcoholic fermentation. The methods used to make processed food products are originally ancient and are still used domestically.	Canned vegetables and legumes in brine; salted or sugared nuts and seeds; salted, dried, cured, smoked or canned meats and fish; fruit in syrup; freshly made breads and cheeses.
Group 4 Ultra-processed foods	Formulations of ingredients, mostly of exclusive industrial use, made by a series of industrial processes including the fractioning of whole foods into substances, chemical modifications, extrusion. and pre-frying and sophisticated packaging. Ingredients are often sources of energy and nutrients that are of no or rare culinary use such as high fructose corn syrup, hydrogenated oils, and protein isolates; classes of additives whose function is to make the final product palatable such as flavour enhancers, colours, emulsifiers, sweeteners, thickeners, and other agents.	Carbonated soft drinks; sweet or savoury packaged snacks; chocolate, candies; ice-cream; mass-produced breads and buns; margarines and other spreads; cookies, pastries, cakes; sweetened breakfast cereals, energy bars; flavoured milk drinks, fruit-flavoured yoghurts; 'instant' sauces. Pre-prepared ready-to-heat products including pies and pasta and pizza dishes; shaped and breaded poultry and fish; burgers and hot dogs; and powdered and packaged soups, noodles desserts; meal replacement shakes and powders.

Source: Monteiro, C.A., Cannon, G., Lawrence, M., Costa Louzada, M.L. and Pereira Machado, P. 2019. *Ultra-processed foods, diet quality, and health using the NOVA classification system*. Rome, FAO.

The growing interest in meat alternatives is driven by concerns over the environmental impact of meat production and animal welfare.[37] The global production of meat has seen a large increase over recent decades. Including both commercial and farm slaughter, production has risen from 235 million tonnes in 2001 to 355 million tonnes per year in 2019.[38] This, again, is in line with the availability of technology that allows for the mass production, slaughter, processing and transport of meat products as well as the ability to refrigerate and preserve without spoiling. Further, higher consumption of meat in a country tends to align with higher mean income.[39] The meat industry has been particularly successful in monetising consumers with marketing that has ensured their products have become central to the majority of meals, despite detrimental impacts on both public health and the environment.[40]

1.1.4 Health and environmental challenges and opportunities

A successful food system provides adequate food to the population, supports equitable trade and distribution, and encourages healthy and environmentally sustainable diets. Providing and distributing adequate calories does not ensure optimal nutrition. Currently, the food system largely supports the profitability of international food and beverage corporations and lacks policies to ensure health and sustainablity.[6] Food systems at all levels are driving both the rising burden of non-communicable diseases (NCDs) and the global climate crisis.[6,41] Mortality due to non-communicable disease is increasing at record rates, with one-quarter of deaths directly attributable to poor diet.[42,43] Simultaneously, the indirect consequences of global warming, predominantly caused by human activities that release greenhouse gas emissions (GHGe), pose the most substantial health risks to the global population this century.[44]

There is a need to combat the complex and ongoing pandemic of NCDs by promoting nutrient-rich diets adequate to feed the population while also protecting the planet.[43] Global food system transformation must create a more equitable, healthy and sustainable food system that can meet the needs of the global population while safeguarding the natural resources and biodiversity on which food production relies. This will involve a range of interventions that promote agroecological practices, advance food development and processing technologies (e.g., lab grown meats), reduce food waste, increase the use of renewable energy and enhance food safety and nutrition.[37] Dual food policy to combat both health and environmental consequences will be required.[45,46]

To achieve these outcomes, a multi-sectoral solution is necessary. Continued innovations in science and technology, which produced the tools and means driving much of the problem of widespread consumption of low quality, ultra-processed foods, will likely also be key to the solution.[11] Despite the need for the food system to support human growth and development, decisions made by food system actors since industrialisation have been profit-driven rather than human and planetary health-focussed. For example, around $9 trillion (USD) is spent on global food consumption but the costs of poor diet

to human life in terms of reduced quality because of disease, healthcare expenses and environmental change is more than double that (around $20 trillion).[47] Enhanced technology will be needed to ensure the production of a sufficient quantity of healthy foods with little to no effect on the environment. This will require simultaneous development of new policies to regulate the usage of these technologies, incentivise industry and drive change in consumer behaviour.

1.1.5 The food system and its impacts in Australia

The food system in Australia is a prime example of a transformed industrialised network, encompassing agricultural production, food manufacturing, retail distribution, consumption, a complex food policy infrastructure and international trade. Over the past 60 years, Australian diets have changed considerably in line with the rise in urbanisation, advances in production technologies and the influence of corporate marketing.[48] Food purchases have steered away from home cooking of unrefined foods towards convenience eating of processed supermarket products and restaurant foods.[15,49] Further, 95% of Australian adults are not eating the daily recommended servings of vegetables and 70% are not eating the daily recommended servings of fruit.[50] Over the past 20 years, Australian household food expenditure has nearly doubled (from AU$65 billion to AU$117 billion adjusted for inflation using the consumer price index in 2018), largely driven by population growth.[51] Exported foods make up 33% of food production expenditure while imports comprise 15%.[51] The proportion of expenditure on pre-prepared foods (including meals out and packaged foods) has increased from 25% to 34% between 1989 and 2016, whereas expenditure on grocery products has slightly decreased, largely driven by the uptick in consumer marketing and increasing numbers of dual-income, time-pressed families choosing convenience.[51]

Though there is increasing interest in healthy and sustainable food options, the majority of Australians are not meeting Australian Dietary Guidelines (ADGs).[52,53] First released in 1982, the ADGs were developed to provide evidence-based dietary recommendations to help Australians meet their nutrition requirements.[54] The ADGs are reviewed and updated every five years; over half of the products on supermarket shelves do not align with the ADG recommendations and there is no mention of environmental impacts of foods in the guidelines.[55] Thus, poor diets are the leading modifiable risk factor for NCDs, which drive 90.9% of total deaths in Australia each year.[56] This is in part because ultra-processed convenience products now make up over 40% of energy consumed by Australians each year.[12]

Public health experts in Australia are further challenged by the current food system, as it supports over-nutrition, industry influence on consumer marketing and overall environmental degradation. While Australian diets have become more diverse and multicultural, they have also become underpinned by supermarket products. Alongside health goals, the sustainability and resilience of the food system must

be improved by reforming industry and producers, reducing waste, increasing efficiency, and promoting healthier and more sustainable food choices.[37,57] It is clear that major strides still need to be achieved with respect to Australian food policy in order to align food environments with evidence-based research.

1.2 Healthy food systems

Key to achieving an optimal industrialised food system is ensuring that food environments promote healthy and nutritionally adequate foods and enable equitable access to these foods across the population. This requires that a food system be comprised of a wide variety of nutritious foods that meet individuals' daily nutrient requirements, with products that contain whole grains, protein, fibre as well as bioavailable vitamins and minerals.[58] The food system directly affects the prevalence of disease because it defines the makeup of retail outlets, what they sell and how they sell it, which determines the healthiness of diet composition.

Today's food systems, from local to international, are failing to deliver healthy diets to their communities.[59] Instead, diets are composed increasingly of ultra-processed product formulations and diet-related disease is steadily increasing around the world as a consequence.[11] Collective and coherent action across food, health, corporate and political systems is needed to ensure the food supply is nutritious, affordable and accessible. By supporting the research needed to understand the solutions for transforming the food system, there is huge potential to mitigate the risk of NCDs and improve the overall health of populations.

1.2.1 Dietary trends and disease burden

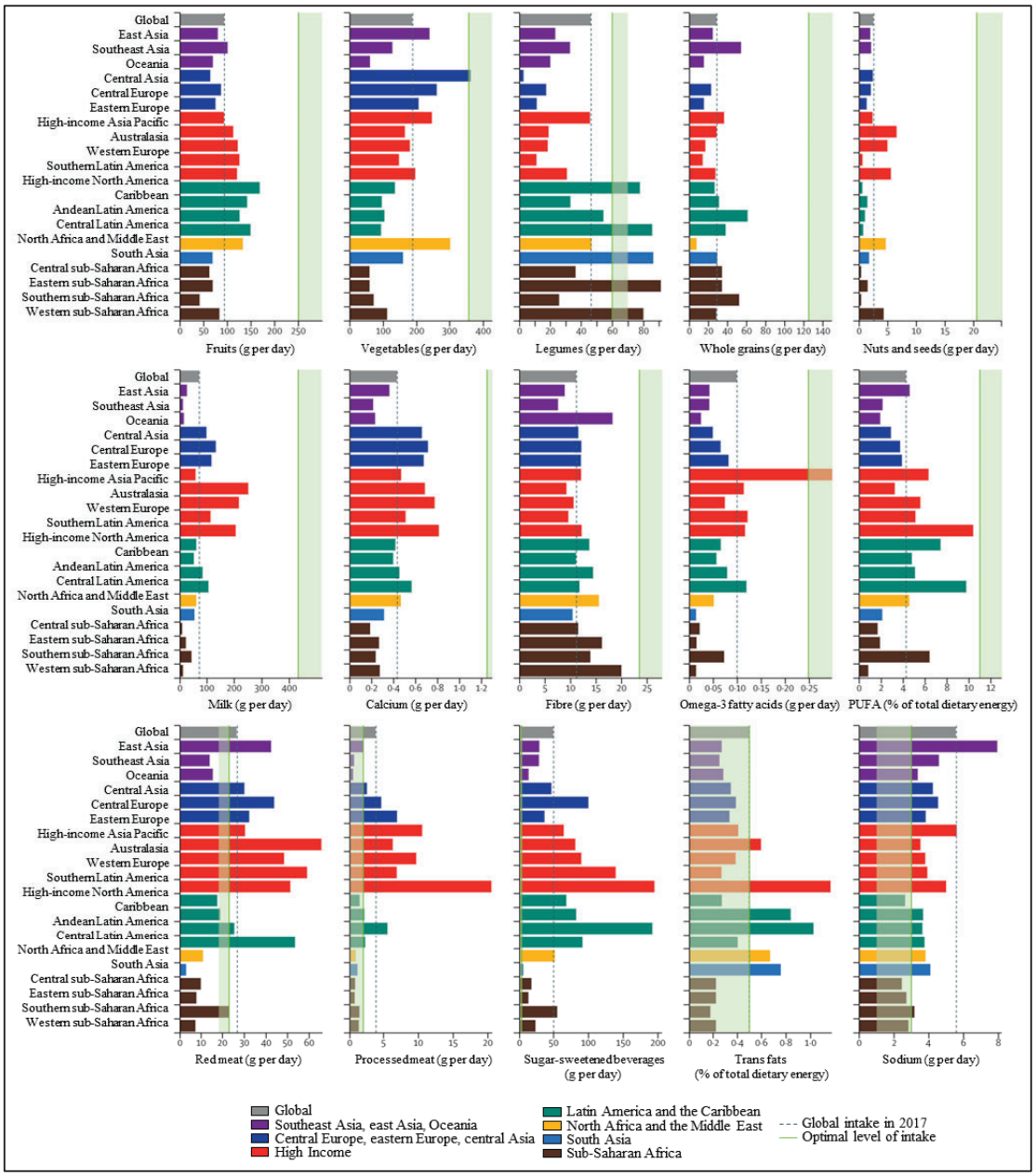
The food system plays a highly significant role in the current global burden of NCDs. NCDs are mostly preventable chronic diseases that result in long term health consequences and include heart disease, stroke, diabetes, obesity and cancer.[42] As mentioned in Section 1.1.2, across high, middle and low income countries, there has been a shift from traditional diets based on locally grown, whole foods to more processed, refined, and high-calorie products.[4] In high income countries, these changes in consumption have led to increased rates of diet-related NCDs attributing to an annual burden of over 250 million disability-adjusted life years.[42,60] For example, the widespread availability and increased consumption of convenience and ultra-processed products in Australia between 1989 and 2010 is a leading cause of the very high rates of obesity in the adult population (65%).[61,62] In low and middle income countries, the changes in consumption patterns have been highly inequitable across the population, leading to a double burden of malnutrition, where obesity rates are now soaring, though undernutrition coexists in the most disadvantaged.[6] For example, across Asia, a rapid change from diets based on agricultural staples to diets higher in processed, packaged and branded foods between 2000

and 2013 has been driven by transnational food and beverage corporations.[18] This has paralleled a rapidly increasing prevalence in obesity and diet-related NCDs, particularly in urban centres, though moderate rates of undernutrition persist in rural farmlands.[6,18]

The 2017 and 2019 Global Burden of Disease studies both showed that consumption of healthy foods and nutrients (i.e., fruits, vegetables, legumes whole grains, nuts and seeds, milk, calcium, fibre, omega-3 fatty acids and polyunsaturated fatty acids) was systematically lower than optimal intake levels, while consumption of unhealthy foods and nutrients (i.e., red meat, processed meat, sugar-sweetened beverages, trans fats and sodium) was systematically above optimal levels (**Figure 1.4**).[42,43] For example, the average global intake of sugar-sweetened beverages was 50 grams per day (g/day), where optimal intake is 1 g/day or less. By contrast, for fruits and vegetables, global average intake was around half of the suggested optimal intake - 95 g/day compared to 250 g/day for fruits and 195 g/day compared to 360 g/day for vegetables. Diets that are low in fruit, vegetables, nuts and legumes, which are important sources of vitamins, minerals, and dietary fibre, increase the risk of NCDs.[43] Fruits, vegetables and whole grains tend to be lower in energy, salt and harmful fats, higher in water content, and are associated with higher satiation and lower disease risks.[63]

Poor diet and NCDs are underpinned by a food system that promotes over-consumption of unhealthy food and beverage products worldwide.[20,64,65] Food marketing directly influences consumer demand for such products and contributes substantially to the burden of NCDs by promoting the consumption of unhealthy foods.[41,66] Diets higher in ultra-processed products (NOVA group 4)[32] tend to correlate with an overconsumption of calories.[67] Often these packaged products are high in salt, added sugar and harmful fats, which are direct causes and modifiable risk factors associated with NCDs.[68,69] A number of studies assessing ultra-processed food intake have found an association between greater proportions of ultra-processed food consumption and increased risk of obesity, cardiovascular disease and mortality.[69-71] Further development of food policies to limit marketing of unhealthy food and promote the consumption of healthy foods will be crucial to public health nutrition outcomes.[72]

Figure 1. 4. Food and nutrient intake among adults at the global and regional levels



Source: Adapted from Figure 1 in Afshin, Ashkan et al. *Health effects of dietary risks in 195 countries, 1990–2017: a systematic analysis for the Global Burden of Disease Study 2017.* The Lancet, Volume 393, Issue 10184, 1958 – 1972. https://doi.org/10.1016/S0140-6736(19)30041-8.
For this study, intake was standardised by age and determined by the midpoint of the optimal range of intake.
Adults were considered anyone 25 years or older.
PUFA: Polyunsaturated fatty acids

1.2.2 Measuring product nutrition

Diet can be assessed in many ways spanning from high-level indicators of food healthiness to the composition of an individual's consumption. While most overlap in the types of foods or food components evaluated, each type of assessment method has strengths and weaknesses.[73,74] Measures

should be carefully selected for different investigations depending on the data available, the scope of interest and the purpose of analysis (such as academic research setting or policy development).[75] Commonly used measures to evaluate diet quality include assessments of dietary intake survey data; whereas, in the absence of consumption information, food and beverage product quality is often assessed using nutrient profiling (**Table 1.2**).[76,77]

Table 1. 2. Example indicators of nutritional quality of consumption and products

Type of Nutritional Quality Assessment	Description	Use Cases	Examples
Evaluation of population or individual consumption			
Dietary guidelines and dietary score indices	Evidence-based recommendations for healthy eating that are developed by government agencies and public health organisations; they often promote the consumption of certain food groups and advise limits on intake of nutrients such as saturated fat, sodium, and added sugars.	To provide holistic guidance on overall dietary patterns rather than evaluating individual food products; To advise on the consumption of various food groups and nutrients to limit	• Health Eating Index (USDA) • Mediterranean Diet Score (AHA)
Evaluation of food and beverage products			
Nutrient profiling	A reductionist method of assessing the nutritional quality of foods based on their nutrient content and general composition (i.e., amount of protein, fat, sodium, fibre and sometimes added sugar) and assigning a score or rating to foods based on the nutrient density (i.e., amount of nutrient/component per calorie).	To compare different foods or products; to develop nutrition policies and guidelines.	• Australasian Health Star Rating • Nutrient Profiling Model of the WHO • Nutri-Score

USDA: United States Department of Agriculture
AHA: American Heart Association
WHO: World Health Organization

Nutrient profiling, as defined by the WHO, is "the science of classifying or ranking foods [and beverages] according to their nutritional composition for reasons related to preventing disease and promoting health".[78] Nutrient profiling models employ algorithms that take into account the presence or quantities of nutrients or other food components that are associated with reduced risks of health outcomes, such as fruits, vegetables and whole grains, as well as those that are associated with increased

risks of health outcomes, such as sodium, sugar and fat.[79] Though nutrient profiling models are used to measure products rather than diets, they have also been used in conjunction with dietary surveys to explore associations of consumption patterns with disease outcomes.[80,81] The transparent, standard, replicable and objective nature of nutrient profiling models has made them valuable in supporting public health policy makers to develop nutrition-related policies.[82,83]

Despite some controversy around the usage and validation of nutritional quality indicators,[84,85] since publication of the nutrition guidelines developed by Codex Alimentarius Commission, established by the Food and Agriculture Organization (FAO) and WHO, nutrient profiling has become commonplace in numerous countries.[86] Nutrient profiling is widely used in modern food and beverage environments to compare the nutritional quality of individual products as well as groups of products and to develop nutrition policies and guidelines.[87] For example, nutrient profiling models have been used to regulate health and nutrition claims, restrict commercial marketing of unhealthy foods to children, develop food taxes and subsidies and underpin food labelling schemes.[83,88,89]

1.2.3 Nutrition labelling

Many governments and organisations are working to improve food systems by providing consumers with point-of-sale information that identifies better choices.[90,91] Front-of-pack nutrition labels are systems that display an icon or metric, such as hierarchical scoring scales or warning labels, on food and beverage products (**Figure 1.5**).[92] The display of front-of-pack nutrition labels on product packaging has been a useful tool in communicating product contents or quality with consumers and have been found to influence behaviour by encouraging healthier food choices.[92,93] They have also driven industry competition and incentivised reformulation to reduce amounts of sugar, salt and fat and informed government taxation and subsidy policies aimed at increasing healthy food intake.[9,94,95]

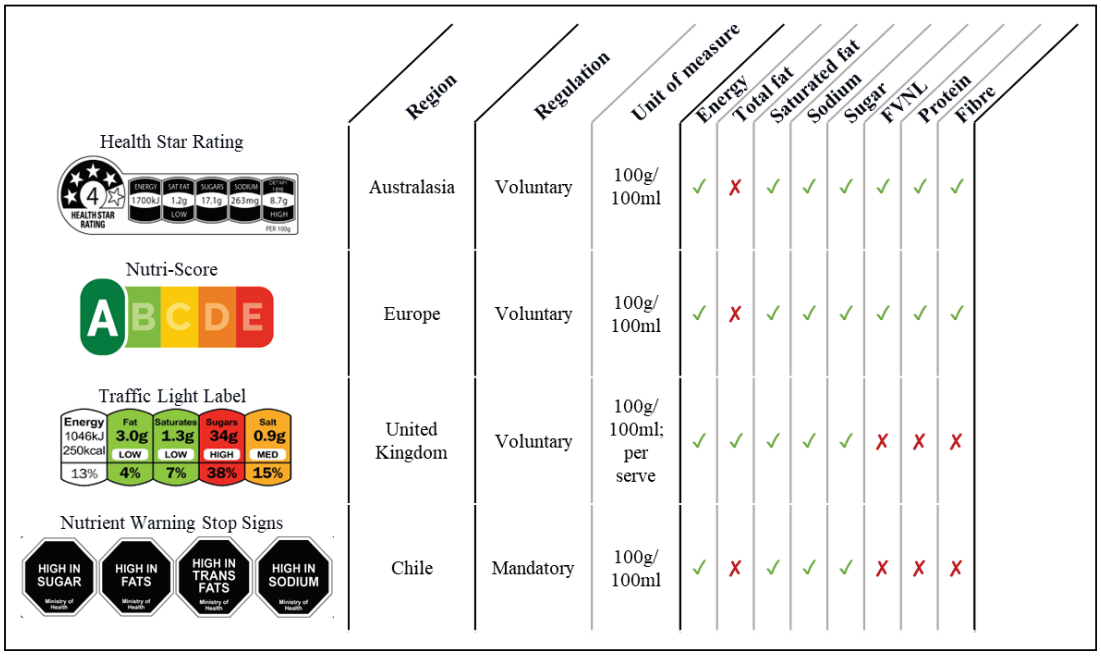
Nutrient profiling models are used to inform some front-of-pack nutrition labels seen in the food supply today, and benefit from incorporating numerous food components into a single label.[89] The Health Star Rating (HSR) system,[96] developed by Australasian governments, has been implemented to facilitate in-category comparisons of the nutritional quality of products to consumers and promote competition amongst manufacturers[97,98] by assigning products between half a star and five stars using a nutrient profiling algorithm. Nutri-Score, a system developed in France, similarly uses positive and negative food components to categorise food products into one of five hierarchical groups, each associated with a colour and letter indicating better versus worse scores: (A) dark green, (B) light green, (C) yellow, (D) light orange and (E) dark orange.[99]

Front-of-pack warning labels are used in a number of settings to highlight the presence of different nutrients and have proven to be effective in enabling consumer understanding of product quality and influencing purchasing behaviour.[100] In Chile, bolded stop signs aim to limit consumption of products

that are high in specific nutrients associated with adverse health outcomes.[101] In the United Kingdom, coloured traffic light labels aim to encourage the consumption of products low in harmful food components.[102]

The biggest hurdle with respect to consumer acceptability of front-of-pack nutrition labelling is that it requires some degree of nutritional literacy.[103] Recent research[100] shows that incorporating both colour and an easy-to-interpret rating (such as a letter score or relative number of stars) is found to be more widely understood, and highlighting negative food components tends to be more effective than highlighting the positive.[90,101,104] Further, it is important to distinguish that front-of-pack nutrition labels do not necessarily designate healthy and unhealthy products.[89] Instead, they are best designed to be used as a comparative tool and careful consideration in regulation and implementation is required to ensure that consumers are not being misled.[103,105]

Figure 1. 5. Comparison of front-of-pack nutrient profile labelling models from various regions



The four nutrient profiling labels pictured here are implemented by governments in four different countries: Australia and New Zealand, Europe, the United Kingdom and Chile. Each label is underpinned by a unique model that incorporates different nutrients and food components with varying weights.
FVNL: Fruit, vegetables, nuts and legumes

Ingredient labelling may be leveraged as another way to evaluate supermarket food and beverages.[106] In Australia, ingredient lists and labelling conventions are governed by Food Standards Australia New Zealand (FSANZ) and is designed to provide consumers with transparency into product composition. FSANZ legislation requires a statement of ingredients arranged in descending order by ingoing weight, allowing consumers to discern the primary components of a product's recipe.[107] In addition, explicit

percentage labelling is required for 'characterising ingredients' (e.g. strawberry in a strawberry yoghurt).[108] There is potential for this data to be collated and incorporated into consumer facing tools in order to enhance existing systems, particularly with the growing interest in assessing whole-food diets and the impacts of food processing.[109]

1.3 Environmentally sustainable food systems

A healthy food system must also be sustainable in order to meet social, economic and environmental needs.[110] An environmentally sustainable food system is one that provides nutritious food to people while simultaneously minimising the negative impacts on the environment and ensuring longevity of agricultural infrastructure.[111] To do this, the food system will need to promote low-impact methods, meals and products which can help shift consumers towards more sustainable dietary patterns and away from overconsumption. Achieving a sustainable food system will also require innovation in nature-positive production methods at scale by reducing emissions, regenerating ecosystems, and reducing food loss and energy usage.[37]

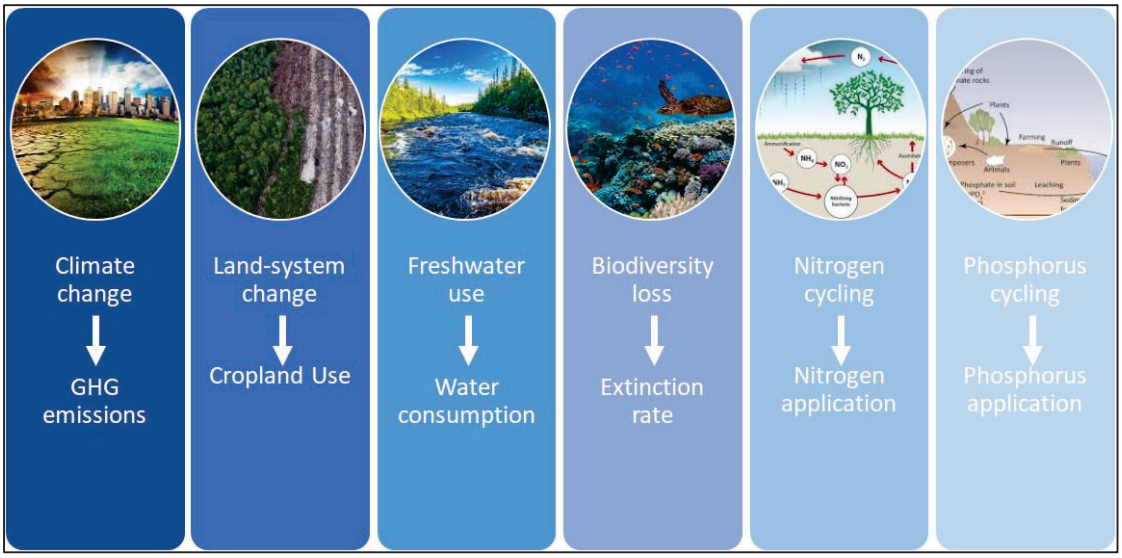
Currently, inefficiencies in production, trade and consumption, mean that the food system causes more than one-third of global, anthropogenic GHGe and is a major contributor to the depletion of habitable land and usable water.[112] If all countries were to adopt a modern "Western diet",[113] food-related GHGe would exceed established boundaries by 263% in 2050.[114] The goals of the Paris Climate Agreement, an international and legally binding treaty with the aim of mitigating climate change and limiting the rise in average global temperatures to less than 2°C above preindustrial levels, can only be achieved if global food system emissions are addressed, as the complete elimination of emissions in both the energy and transportation sectors would not be sufficient.[115] "Western diets", which tend to be high in ruminant meats and ultra-processed foods, are central to the issue.[116] One-quarter of producers, mostly of animal products, contribute over half of the attributable environmental impacts.[117]

1.3.1 Diet and planetary health

The impact that food production and consumption have on environmental systems is complex.[118] The EAT-Lancet Commission emphasises six bio-geophysical factors affected by food production and sustainable diets while other reviews recognise up to 30 potential environmental impact indicators (**Figure 1.6)**.[119,120] Also, the relationship between climate change and food systems is bidirectional. Climate change affects crop production, nutritional content and distribution of foods,[121] whilst agricultural practices and increasing global meat consumption significantly contribute to climate change.[111] Understanding the impacts, how each environmental impact factor is defined and how the

food system contributes will be key to mitigating environmental change and building towards a sustainable food system.[115]

Figure 1. 6. Environmental impacts and corresponding bio-geophysical factors



The six bio-geophysical factors and their respective impact measurement as described in *Food in the Anthropocene: the EAT–Lancet Commission on healthy diets from sustainable food systems* (2019).

GHGe are measured as the total output of carbon dioxide, methane and nitrous oxide (often in terms of carbon dioxide equivalents (CO_2eq)). GHGe are driving climate change by causing global warming and are the most commonly researched environmental impact factor.[115] Agriculture, food processing and food production are major contributors of GHGe, largely contributed by the ruminant meat and dairy sectors.[117] As a by-product of enteric fermentation, ruminant animals such as cows and sheep emit methane, which is 28 times more potent than carbon dioxide as a cause of global warming.[122] These animals are now mass produced and killed in slaughterhouses causing 5.7 billion tonnes of carbon dioxide equivalents per year, representing 80% of global emissions attributable to livestock.[123] Though ruminant meats are found to emit hugely more GHGe per kilogram of product than other food categories, it is still important to consider the emissions from non-ruminant meat and other processed foods, because they constitute a large proportion of total production and sales.[117] For example, while ultra-processed foods mostly have lower emissions per kilogram of product than ruminant meat, large consumption volumes means that ultra-processed foods make up 33% of diet-related GHGe, with emissions from the processing facilities contributing over half of the total emissions from ultra-processed foods.[124]

Land use change, the conversion of natural ecosystems such as forests and grasslands to cropland or pasture, and scarcity-weighted water use, freshwater use weighted by regional water scarcity, also

contribute to GHGe, biodiversity loss and reduced soil quality.[44] The expansion of agriculture to meet the growing demand for food has led to deforestation, which releases carbon dioxide into the atmosphere and reduces the amount of carbon stored in trees and soil.[44] Deforestation is most prominently an issue for meat production, which requires land clearance for growing and producing cattle feed, as well as for cocoa, soya and palm oil production.[117] The transformation of land often also requires vast irrigations systems, driving the global issue of scarcity-weighted water use. Currently, agricultural irrigation systems contribute to 90% of the water scarcity burden due to the limited recyclability of water used for agriculture and low returns of irrigation water to rivers or groundwater.[117]

Acidification, the process of increasing acidity in water or soil, and eutrophication, the excessive bioavailability of nitrogen and phosphorus in water bodies, have led to increased plant and algae growth.[125] Acidification occurs because of industrial emissions and agricultural practices that release acids into aquatic ecosystems. Eutrophication is a result mainly of agricultural runoff, wastewater discharges, and the use of fertilizers.[125] Both impact plant and animal health and nutrient availability by creating habitats in which existing biosystems cannot survive.[117] Addressing acidification and eutrophication requires reduction of polluting emissions and enhanced management of nutrient inputs through better agricultural practices.

There is immense complexity of assessing environmental impact factors which is rooted in their interrelationships.[126] Land use change and scarcity-weighted water use are drivers of acidification and eutrophication. All of these in turn, are linked to, and can be measured in terms of, GHGe. Whether considered independently or as a whole, there is inadequate information about the environmental impacts for most foods, with data particularly lacking for sectors such as seafood and multi-ingredient products.[127] Increasing the availability of nuanced, product-specific environmental data will be an important next step towards an environmentally sustainable food system.

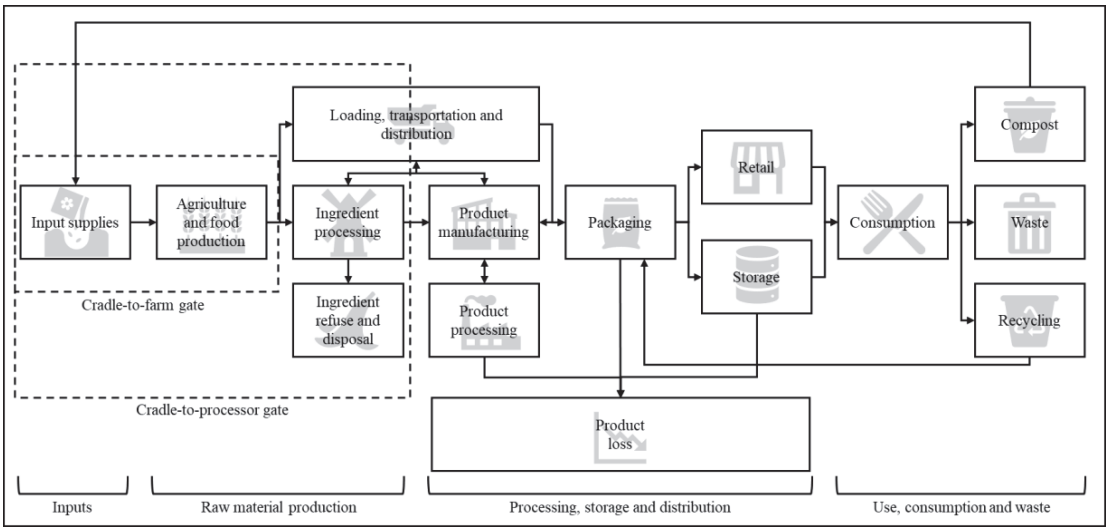
1.3.2 Measuring product greenhouse gas emissions

Over the last decade, a growing body of research has emerged describing the GHGe associated with foods, beverages and different dietary patterns.[128,129] Food-related GHGe are measured using either life cycle assessment (LCA) or an input-output analysis (IOA). LCA, a bottom-up approach, is more apt for considering a wider range of products where production-level detail is available whereas IOA, a top-down approach, uses high-level manufacturing sector data to make comparisons between food commodities. These measures have been used to create food profiling models for food product sustainably, parallel to those for the nutrient profiling of foods.[130]

LCAs have defined the environmental impact of multiple food supply chains and individual products around the world as a means to differentiate GHGe attributable to factors such as ingredient composition,

type of production system (conventional, organic, etc.), transportation distances, processing methods, and waste management practices.[131] LCA is a comprehensive approach that evaluates the environmental impact of a product throughout a life cycle with defined boundaries which can include production, processing, transportation, use, and disposal stages.[132,133] LCAs require the definition of the system boundary so that it is clear which stages of the food's life cycle have been considered (**Figure 1.7**). Data collection for each stage of the food's life cycle involves gathering information on inputs (e.g., energy, water, fertilizers) and activities (e.g., land use, transportation distances) associated with the production and processing of the food. The data is used to estimate the amount of GHGe generated at each stage of the food's life cycle from energy use, agricultural practices, transportation, and waste management.[134] Emissions specific to each stage are applied to calculate the total GHGe, or carbon-footprint in terms of CO_2eq as a common scale. Although specific LCA protocols provide a standardised scientific framework (e.g., ISO Standard 14067, GHG Protocol, PAS2015),[135-137] definitions and inclusions of system boundaries and data fields can vary across implementations resulting in a limited ability to compare across products.[134]

Figure 1. 7. Food and beverage life cycle stages used for defining system boundaries



This graphic represents the typical stages, including both actors and processes, in a food supply chain life cycle assessment study across the four main phases: (1) 'Inputs', (2) 'Raw material production', (3) 'Processing, storage and distribution' and (4) 'Use, consumption and waste'. Each box represents a food system process that performs one or more key food production tasks requiring inputs and outputs and associated with environmental impacts. The single and bi-directional arrows represent the common path of the flow of food and beverage production inputs and outputs.

Environmentally extended IOAs are an analysis tool used to assess food emissions by quantifying the flow of goods, services and money between industries and sectors, incorporating economic interdependencies.[138] Emission factors are assigned to each industry based on known or estimated emissions representing the average emissions associated with producing a unit of output in a specific

industrial sector. By combining the inter-industry relationships, emission factors, and supply chain information, IOAs estimate the emissions associated with the production and consumption of different foods.[139] This includes direct emissions from agricultural activities, as well as indirect emissions resulting from the use of inputs like energy, fertilizers, and machinery. While IOAs can provide insights into the emissions hotspots within the food supply chain and guide strategies for emissions reduction, they are limited by the absence of granularity about different food sectors in the economic data.[140] IOAs have not been widely used for estimating the GHGe associated with individual products as a consequence. Combining conventional LCAs and environmentally extended IOAs to do hybrid LCAs could be a strategy to improve the ability to assess a large number of products without having to limit system boundaries.[140]

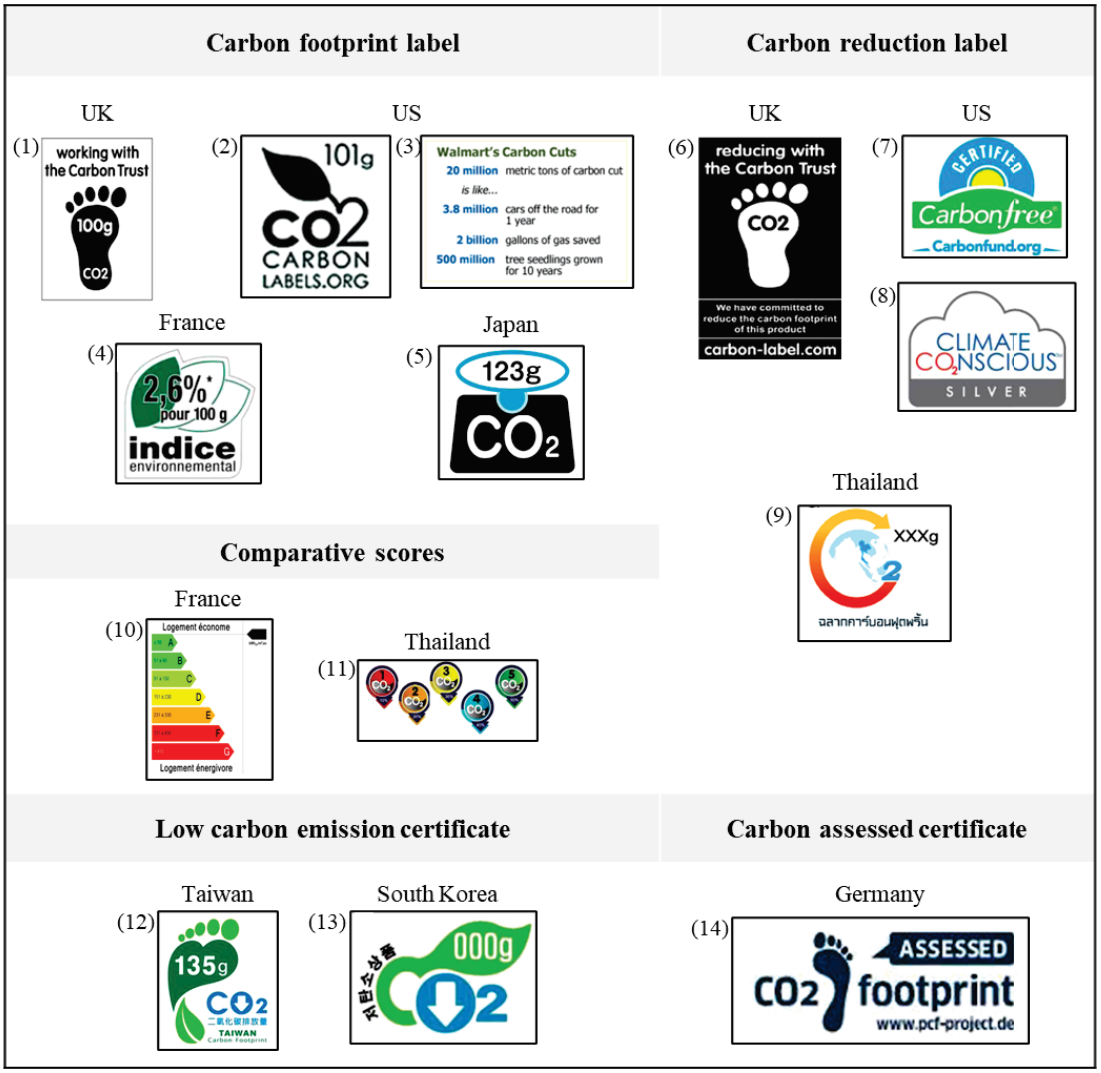
1.3.3 Greenhouse gas emission labelling

Carbon labelling is a form of eco-labelling that can capture impact associated with GHGe for a product's ingredients and life cycle stages.[141,142] The beneficial effects of carbon labelling have been shown in other industries, namely with household appliances.[143] The point-of-purchase information required to discern dietary choices optimal for sustainability alone, or nutrition and sustainability combined, are currently limited.[141] Although many consumers and manufacturers report that they are willing to alter behaviours so as to reduce climate impact,[144] the average consumer significantly underestimates the emissions, waste and environmental degradation associated with the food they purchase.[7] Given the increasing breadth and depth of food and beverage GHGe information, standardised and high quality carbon labelling on foods and beverages could help significantly progress towards a more sustainable food system. Carbon labels could not only evoke consumer response, but also create competition amongst industry players to lower their emissions,[142] as has been observed with front-of-pack nutrient profile labelling.[90,145]

Organisations such as the Carbon Trust and CarbonFree have developed methods to promote product environmental footprint reductions.[146-148] However, this demand-side implementation of carbon labels on food and beverage products has used diverse and non-standardised life cycle assessment protocols that are poorly understood by consumers. Tesco Supermarkets in the UK, for example, developed an independent carbon labelling program in 2007, but rollout was abandoned due to cost-prohibitive resource requirements for both label implementation and building the required consumer knowledge base.[149] Better, standardised and more widely applied carbon labels could, nonetheless, help meet demands for transparency in food product reporting and encourage more sustainable purchasing behaviours.[150] Some governments have now started to introduce carbon emission limits and regulations, but large-scale uptake in the food sector is still sparse.[142]

Carbon labelling types range from absolute emission information to comparative scores to general eco-certifications (**Figure 1.8**).[142] Carbon footprint labels provide a specific value, often numeric in terms of CO_2eq, which reflects the life cycle assessment associated with that product. These are the most detailed type of carbon label but they are rare due to the high cost of implementing and are often difficult for the average person to interpret.[146] Carbon reduction, carbon neutral and low carbon labels, are more common since they indicate that the emissions associated with a specific product are either offset (usually through an offset investment in renewable energy or reforestation) or low compared to other similar products (usually based on the uptake of efficient production practices).[151] Certification services are available for products and businesses with reduced carbon footprints. For example, products displaying the Carbon Trust label have undergone an assessment and met specific criteria related to emissions reduction.[146] Due to the variability in existing labelling schemes, consumer understanding is limited and overall impact has been minimal.[142]

Figure 1. 8. Carbon label types in various countries



Source: Adapted from Liu T, Wang Q, Su B. A review of carbon labeling: Standards, implementation, and impact. *Renewable and Sustainable Energy Reviews*. 2016;53:68-79. (1) CarbonTrust footprint label in the UK, (2) Timberland green index in the US, (3) Walmart's sustainability index in the US, (4) Indice carbone in France, (5) Carbon footprint label in Japan, (6) CarbonTrust reduction label in the UK, (7) Carbon free certified label in the US, (8) Climate conscious carbon label in the US, (9) Carbon reduction label in Thailand, (10) Bilan carbone in France, (11) Carbon footprint label in Thailand, (12) Carbon label in Taiwan (13) Low carbon product certificate in South Korea (14) Carbon assessment certificate in Germany.

1.4 Healthy and environmentally sustainable food systems

The global food system needs to address the joint needs of human health and environmental sustainability. To meet both human and environmental needs, there must be an understanding and acceptance of the goal and an identified pathway to achieving it. While the need for such a food system are widely understood, the pathway to implementation requires much work.[120]

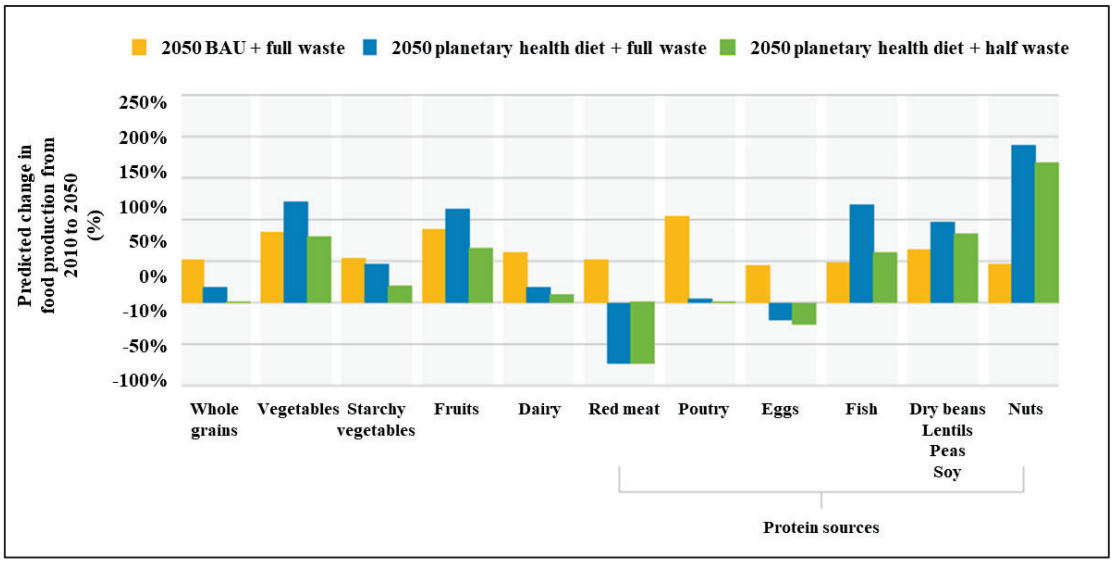
1.4.1 Goals and barriers to change

A dually sustainable food system will require integrated global collaboration among diverse actors, including agricultural producers, food manufacturers, policymakers, consumers and researchers.[120] Upstream stakeholders should be driving towards the aligned goal of providing healthy and environmentally sustainable foods and beverages to the population. Simultaneously, they should enable food environments to promote dually sustainable products and purchasing behaviours that do not lead to breach of planetary boundaries, as set out by the Paris Climate Agreement and the United Nation's Sustainable Development Goals.[152,153] Finally, research and data must be better used to close the gap between stakeholder practices and the known food system goals.[57,154]

A governance structure is needed to build out a dually sustainable food system. Cohesive policy action is required to enact these changes in the makeup of food environments efficiently and effectively. As laid out in the EAT-Lancet Commission, achieving healthy diets from sustainable food systems requires a directed change in the quality and quantity of foods produced in each food category (**Figure 1.9**). The production of animal-based products must decrease significantly, while the production of plant-based proteins must increase significantly.[120] Improving the management of global land use, manufacturing and trade is pivotal to achieving this change. Meanwhile, continued urgent research is required to continue to increase the availability of information regarding dual impacts of food supply chains and food environments.[155]

Addressing corporate influence at all levels is critical to the development of processes and policies that enable a dually sustainable food system. Industrial growth led to the emergence of large corporate food companies, and corporate influence over today's food system has resulted in their control of the makeup of the food supply as well as food policy and decision making.[156] As made apparent in the 2021 United Nations Food Systems Summit, corporations have embedded themselves in the existing socio-political food systems infrastructure to protect their profit margins, often at the cost of public health.[157] In grocery outlets, transnational corporations spend billions of dollars (USD) to market products.[158] Over 80% of this expenditure aims to promote products that are high in fat, sugar and sodium, and low in whole grain, protein and fibre, with little regard to environmental impact.[158]

Figure 1. 9. Projected change in food production sectors based on EAT-Lancet Commission scenarios



Source: Adapted from Table 6 in the EAT-Lancet Commission *Food in The Anthropocene: the EAT-Lancet Commission on Healthy Diets From Sustainable Food Systems*. The predicted change in food production from 2010 to 2050 (% based on the 2010 scenario) for three scenarios: (1) the business as usual (BAU) with full waste, (2) the planetary health diet with full waste and (3) the planetary health diet with halved waste.

Another major barrier to change is the lack of available data to underpin new policies. Structured data must be better publicised and tracked to ensure updates to production methods, food environments and consumption patterns are in line with the goals required to deliver a dually sustainable food system. The discrepancy between the current knowledge we have about the action steps needed and the current practices employed by food system stakeholders has been coined the 'Missing Middle' and is indicative of global failure to progress towards a dually sustainable global food system.[154] While a breadth of information is available with respect to nutrition, the global burden of disease and the environmental impacts of the food system, the data are not presented in informative and interpretable ways and are not used to hold food system actors to account. Building the capacity to use this data could enable stakeholders to better understand how to develop and choose healthier and more environmentally friendly food and beverage product options as well as see them enforced.[155]

1.4.2 Co-benefits

The food system has the potential to generate a range of co-benefits for human health and the environment. As previously mentioned, food and diets are driving increased global GHGe and adverse health and mortality from NCDs.[6] A dually sustainable food system can promote human health by increasing the availability of healthy and nutritious food, reducing the consumption of unhealthy and

ultra-processed food and enriching the land used for agriculture resulting in more nutrient-dense produce.[159]

Dually sustainable interventions can also have positive impacts on the environment by increasing implementation of sustainable agriculture practices, water conservation practices and soil reuse.[160] For example, sustainable agriculture practices like agroforestry can help sequester carbon in soil and reduce GHGe, while reducing the use of pesticides and fertilizers can help protect water quality and reduce soil degradation.[161] A sustainable food system can also generate socio-economic benefits for local communities by mitigating the negative impacts of climate change on vulnerable populations and creating new jobs in sustainable agriculture and food production.[162]

1.5 Food policy for health and sustainability

Immediate political action is required to protect the planet and promote human health.[46,120,127] Government-endorsed food-based dietary guidelines and country or region-specific recommendations on how to adopt healthy diets, have started to integrate environmental sustainability into their criteria. For example, in Brazil, Sweden and Italy consumers are encouraged to maintain diets that are majority plant-based, include minimal red and processed meats, ultra-processed foods and sugar-sweetened beverages and have reduced food waste.[163] However, while the co-benefits of healthy and sustainable diets are recognized,[159] a recent review found that only 37 of 83 country-specific guidelines included in the analysis even mentioned environmental sustainability.[164] Dietary guidelines alone will be entirely insufficient. The considerable required improvements to public health and the environment will only be achieved if knowledge and guidance can be translated into actionable policies that deliver on the dual benefits sought.

Dual healthy and environmentally sustainable food policy must influence consumer demand and industry innovation to encourage optimal impacts on public health and the climate. Policy must also reflect the local culture, ecology and economy to account for the diverse nature of food systems and the different practical solutions that will be required.[10] However, while local tailoring of implementation solutions will be key, developing and enforcing regulation aimed at monitoring industry influence and improving human and planetary health will be a core component of most successful interventions.[165]

1.5.1 Food system regulation

Policies targeting food systems and food environments can be highly effective in improving population diets and public health;[166] however, effective implementation is lacking. Taxation on products associated with negative health impacts and subsidies on products associated with positive health impacts appear to be the most effective in altering the purchasing of targeted foods and beverages.[167]

For example, the soft drink industry levy in the UK, which saw increased prices, changes in product size and change in product availability, resulted in a 30% reduction in the amount of sugar purchased from soft drinks between 2015 and 2018.[168] However, fiscal interventions are rarely implemented and not generally appealing to consumers, industry or policymakers.[100] Policies regulating the availability of certain product types in retail outlets, product formulation and portion size to reduce the obesogenic makeup of public settings such as schools or hospitals are also effective.[167] Reformulation efforts, such as the WHO's initiative to reduce global salt consumption by 30% by 2025,[169] are much too lenient given the rigorous goals and the substantial change that needs to be made to current consumption trends. Similarly, these are rarely put in place, often due to strong industry opposition and lobbying efforts.[165] Industry leaders in food retail, such as Tesco's in the UK and Woolworths in Australia,[149,170] are showing strong interest in combating climate change by devising business plans for becoming zero-emission or net-positive. However, the focus has centred on investing in energy-saving technologies rather than food production and promotion, despite evidence of the contribution of agriculture and food to overall company footprints.[149] There is a need to consider the whole of data available in conjunction with end-to-end food system stakeholders, while also incorporating effective instruments such as consumer education and affordability.[171]

To improve the implementation of successful food policy, a systematic approach is required. The concept of 'implementation science' has helped create a framework for future policy development aimed at achieving specific public health goals.[172] Implementation science considers both the need to identify data gaps in food system research and to understand current barriers to change. It also aims to ensure the ability to follow through on impact and effectiveness. For example, targeted regulation requiring year-over-year reporting of corporate social responsibility commitments could be a powerful tool to track food system improvements, provided appropriate governance. This is because it not only allows for the collection of new data, but also addresses corporate influence and benefits brand building alongside public health and climate impacts.[157,173]

1.5.2 Regulation in Australia

Currently, few countries' governments have defined dually sustainable diets or developed policy that addresses the dual human and planetary health challenges of the food system.[174] In Australia, neither the food-based dietary guidelines nor government regulations affecting the food system have been updated to incorporate dual impacts. To accelerate the transition to a sustainable food system, the Australian Dietary Guidelines could be expanded to include information on the environmental benefits in addition to health benefits, similar to New Zealand's Eating and Activity Guidelines updated in 2020.[175] Australian universities have commenced governance driving towards sustainable food systems

though efforts are limited and have focused on lower impact strategies such as waste management and fair trade products, rather than encouraging changes in food production and in dietary intake.[176]

There is a need to advance environmental sustainability by amending nutrition-centric regulation and policy to incorporate strategies that also address the climate crisis. Fiscal incentives should be used to promote healthy and low environmental impact products, though the Australian government has shown little appetite for any form of taxation targeting public health nutrition objectives. Mandatory labelling legislation should be considered, as mandatory schemes are always more effective than voluntary schemes, which often result in highly biased and suboptimal uptake.[105] Similar to nutrient limits defined by FSANZ to meet population health needs,[177] the implementation of category-specific GHGe limits could help promote products that are better for people and the planet.[178] For example, the existing HSR and country-of-origin labels, which aim to educate consumers about nutritional quality and the sourcing of retail outlet products, could be expanded to include environmental impact information.[96,179] While private carbon-labelling schemes have been implemented on a small number of Australian products,[141,180] broader GHGe labelling implementation in the Australian context could greatly enhance consumer decision-making and industry competition.[181,182]

Chapter 2: Scope, aim and objectives

While it is well understood that supermarket food and beverage products contribute simultaneously to unhealthy diet and climate change,[183] there is little information available about the individual food and beverage products in supermarkets and convenience stores.[184] In Australia, these now amount to 58.8% of total retail sales.[23] Product-specific environmental impact assessments are time-intensive and costly, and therefore, rarely performed. Because of this, the supermarket food and beverage supply lacks information required to develop comprehensive policy with respect to its environmental impacts and, in turn, its dual impacts on human and environmental health.

To understand product-specific GHGe impacts and develop informed dual policies that effectively manage the continually expanding product database, there is a need for a repeatable environmental impact assessment method.[151] The availability of product composition,[106,185] product-specific GHGe[183] and uncertainty data pertaining to emissions is key. This will provide stakeholders with the additional information required to align product development and supply with both health and environmental research evidence. GHGe estimates for supermarket foods and beverages will enable an environmental and dual health-and-environmental assessment of products as they are marketed to consumers. Finally, a better understanding of patterns of what people are most frequently purchasing and eating from within supermarket products will help identify drivers of adverse impacts and gauge the potential to enable positive changes.

2.1 Aim and scope

This thesis aims to estimate product-specific GHGe across the Australian supermarket food and beverage supply and the potential to reduce diet-related GHGe attributable to food and beverage retail products while enabling dual analyses using existing nutrient profiling metrics. It also outlines a standard, replicable method primarily using the information that is currently available on product packaging and assessing environmental impacts based on reported purchases representative of the Australian population.

This thesis focuses on the food and beverage supply available in Australian supermarkets, for which there is access to transparent and representative data to make novel contributions in this space. Australia has implemented voluntary front-of-pack nutrition labelling, country of origin labelling, industry codes for marketing guidelines and a reformulation programme.[186] Due to the high proportion of packaged products in the average Australian diet and the historically progressive food policy compared to other high-income countries, the Australian setting is apt for creating new nutrition and sustainability data to be used for further research as well as innovative sustainable food policy. There is a need for structured

dual policy that could not only impact national health and environmental sustainability policy, but global policy as well.

This thesis investigates the GHGe attributable to supermarket products in depth, as there are more global and Australian ingredient LCAs available for GHGe than any other environmental indicator (e.g., land use, scarcity-weighted water use, and eutrophication). While acknowledging the significance of this trade-off, the decision to concentrate on only GHGe was motivated by the overarching goal to discern nuances across over 20,000 supermarket products, rather than superficially exploring a broader spectrum of impact factors. However, it is important that future research include additional factors in order to represent a more comprehensive perspective of the environmental impacts of products.

2.2 Objectives and thesis structure

The thesis aim has been met by the following four objectives with each chapter in the thesis fulfilling one objective (**Figure 2.1**):

1. To identify ingredients in the Australian supermarket food and beverage supply and estimate the composition of ingredients in each product (*Chapter 3*);

2. To determine ingredient environmental impacts in terms of GHGe contribution and calculate the environmental impact of supermarket food and beverage products in Australia in terms of the GHGe from its ingredients, processing and transport *(Chapter 4*);

3. To dually assess the nutrient profile and GHGe contribution of Australian supermarket food and beverage products (*Chapter 5*);

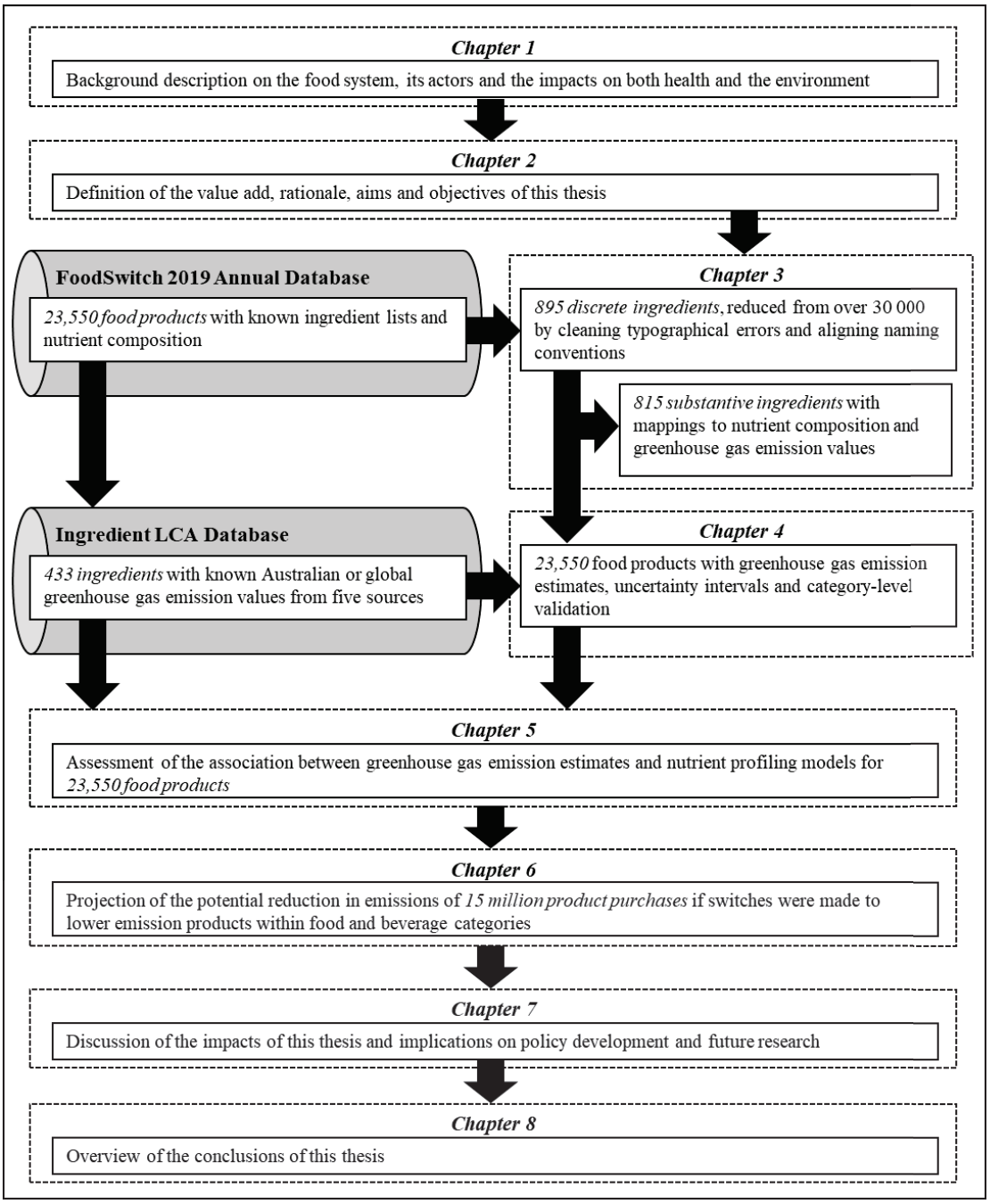
4. To evaluate the total GHGe attributable to Australian supermarket food and beverage product sales and the potential to reduce total emissions if higher-emission products were switched with lower-emission products (*Chapter 6*).

2.3 Ethics and funding

My doctoral studies were funded by an Imperial College London President's PhD Scholarship and supported by The George Institute for Global Health's Food Policy team. This thesis did not require ethics approve because it utilised only secondary product and purchasing data that has been previously approved by projects associated with The George Institute for Global Health's Food

Policy and FoodSwitch teams. The ethics approval granted to The George Institute for the original data is specified in Chapter 6.

Figure 2. 1. The process flow for thesis chapters



Chapter 3: Ingredients and ingredient weight proportions for individual products

3.1 Introduction

In most high-income countries, supermarkets and convenience stores contribute to poor diets and the over-consumption of unhealthy food and beverage products.[20,64] In Australia, major supermarket chains dominate the food retail sector and four retailers make up over 80% of the total grocery market share (Woolworths Group, Coles, Aldi and Independent Grocers of Australia).[187] Supermarkets are stocked primarily with processed, multi-ingredient food and beverage products, which now make up more than half of food purchases by Australian households.[23,70] Aforementioned, many of these products tend to be high in disease-causing components including excess calories, sodium and added sugars.[20,188]

One key step to improving the food supply is by assessing and clearly communicating the contents of such supermarket products. The Health Star Rating[96] (HSR) nutrient profiling model is used as a front-of-pack label in Australia and New Zealand to surface product-specific nutrient information and guide purchasing behaviours with the goal of improving health outcomes.[189] The HSR assesses products based on the nutritional characteristics of the individual components of each food (e.g., sugars, fats and fibre).[84] There are established associations between the consumption of products with poorer HSR scores and increased risk of diet-related disease incidence and mortality.[69-71,190] The NOVA classification[32] has been introduced as an alternative method to assess food and beverage products based upon information about the types of ingredients and product processing. The NOVA classification is not displayed on product packages in Australia or elsewhere. In part this may be because ingredient data are incompletely available and processing information is not described on package labelling which makes assignment of a NOVA grade difficult to standardise or automate.

Better availability of ingredient data, including the numbers, types and proportions of ingredients in products, could improve the capacity to make nutritional assessments, particularly for scales like the NOVA classification.[191-193] Food Standards Australia New Zealand (FSANZ) governs and upholds the product and ingredient labelling regulation used by food and beverage product manufacturers in Australia for a breadth of use cases including relaying information regarding product healthiness, quality and allergens.[108,194] However, while this legislation requires ingredient declarations to be included on supermarket products, the depth of the required data is limited and standardisation of terms is lacking.[195,196] More detailed data about ingredients could also provide a basis for novel approaches to sustainability labelling because the production of ingredients used in products is typically responsible for the majority of the environmental impact. For example, similar products often use some similar and some different ingredients in varying proportions, which can result in different nutrient profiles and

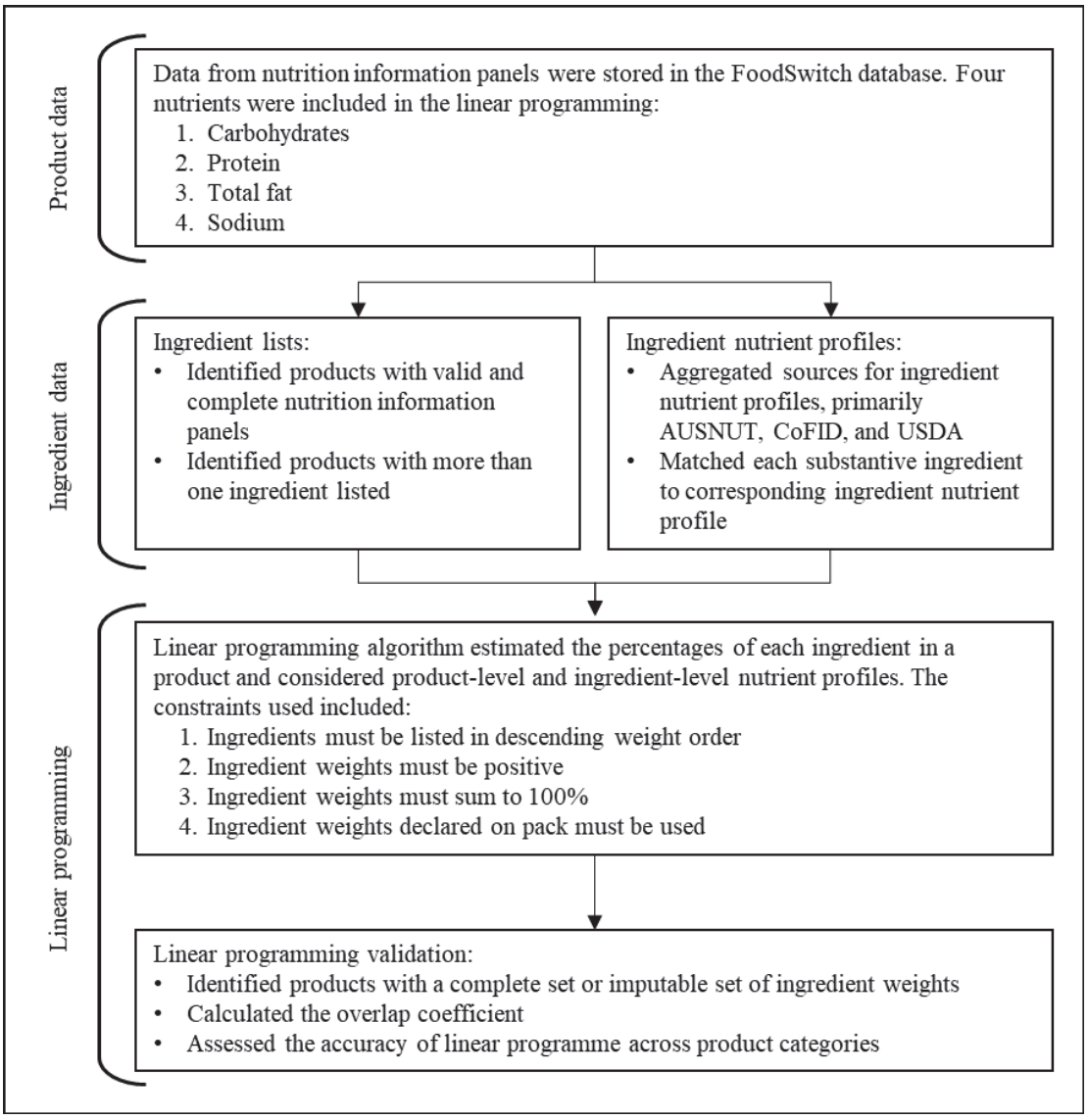
environmental impacts. These are not commonly disclosed due to brand-specific manufacturing techniques and product formulations because, in some cases, they are considered trade secrets.

To help surface these nutritional and environmental differences between products, Chapter 3 aimed to describe and categorise the ingredients contained in products available at major supermarket outlets in Australia. It evaluated the association between the number of ingredients in each product and both the product's HSR and NOVA classification to understand trends and alignment. Chapter 3 also established a method to estimate complete ingredient proportion information in products using a linear programming model to predict the ingredient proportions not reported on product packaging.

3.2 Methods

The cross-sectional examination of supermarket food and beverage products in the Australian food supply used the 2019 FoodSwitch Annual Database and focused on the ingredient composition of these products (**Figure 3.1**).

Figure 3. 1. Chapter 3 methods workflow



This workflow diagram describes each step of the methods as laid out in this chapter: (1) product data collection and inclusion; (2) ingredient data collation and cleaning; and (3) linear programming methodology and validation.

3.2.1 Product data

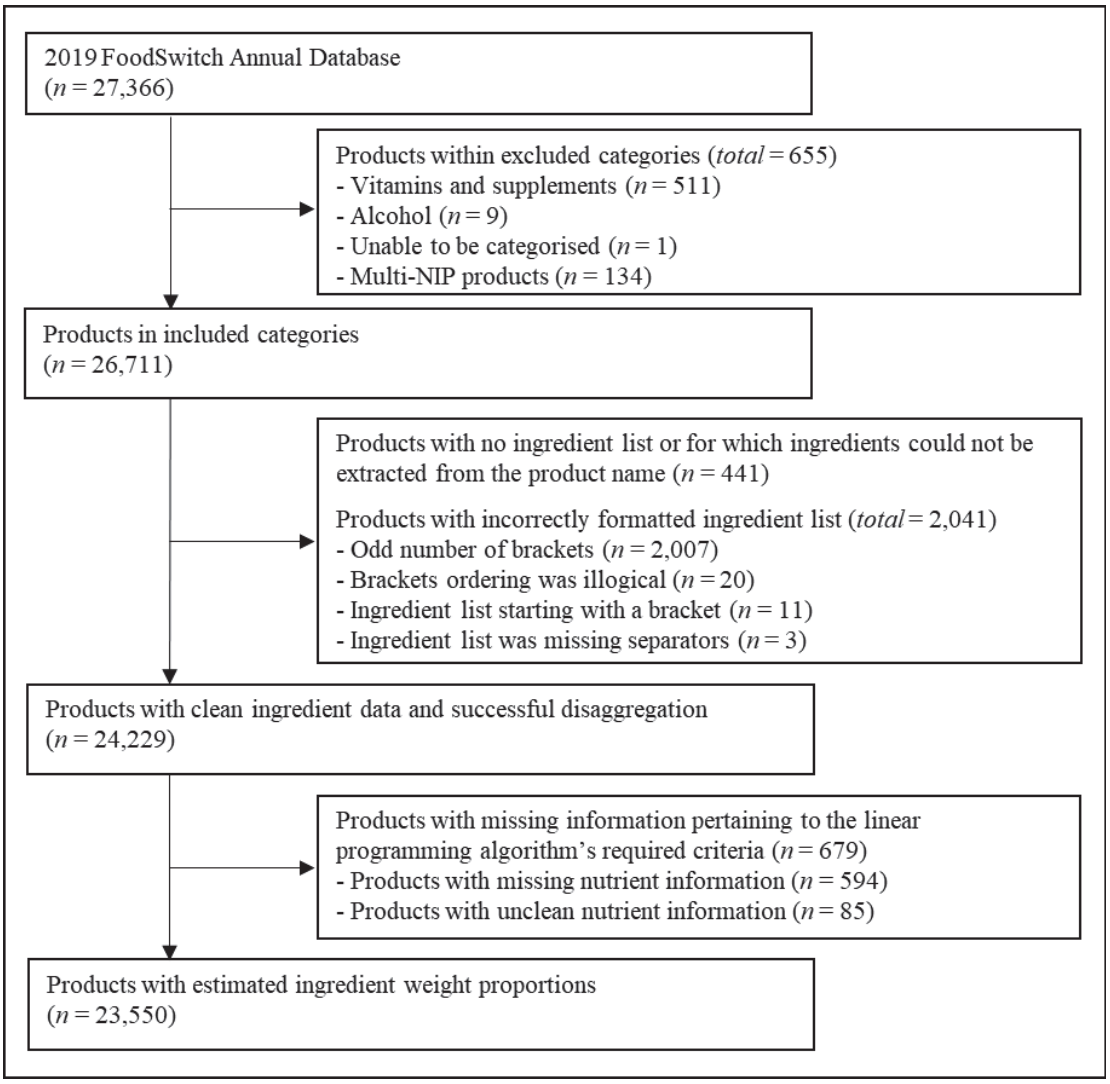
FoodSwitch is a database developed and operated by the George Institute for Global Health.[197] For each included product, the FoodSwitch database holds up to 400 data attributes that were extracted or derived from images of product packaging. Examples of data obtained directly from packaging include product name, package size, ingredients, nutritional claims and nutrient content while examples of derived data are added sugars, HSR score and NOVA classification. Products collected in the FoodSwitch database were categorised into a hierarchical tree based on a system developed by the Global Food Monitoring

Group.[198] The categorisation system allows for yearly descriptive analyses of products and tracking of changes to nutrient composition of product categories that are meaningful to diverse stakeholders (e.g., industry, government, consumers and researchers).[186,199] There are broad major food and beverage categories (e.g., 'Bread and bakery products'), then products are further allocated into finer minor categories (e.g., 'biscuits') and subcategories (e.g., 'savoury biscuits' and 'breadsticks').

The 2019 FoodSwitch Annual Database was generated from in-store surveys done in Australia at five large supermarkets (Woolworths Group, Coles, Aldi, Independent Grocers of Australia and Harris Farm) between August and November 2019.[198] Each identified product underwent extensive data cleaning and rigorous data quality checks when processed into the database.[200] The dataset represented the majority of supermarket food and beverage products purchased by Australian households in that year.[55,197]

Products were included in this analysis if complete ingredient and nutrient information was available on pack with selected exclusions. Of the 27,366 available products, the 520 products from the 'Alcoholic beverages' and 'Vitamins and supplements' major categories were excluded as they were not commonly included in the scope of nutrient profiling systems. 135 products were excluded because they could not be categorised or were multi-pack products with more than one nutrition information panel (e.g., variety packs). A further 2,482 products were excluded due to errors or inadequacies in ingredient data and 679 were excluded due to unclean nutrient data. This left 23,550 products from the Australian 2019 FoodSwitch database that were included (**Figure 3.2**).

Figure 3. 2. Flowchart describing product inclusion



The 2019 FoodSwitch Annual Database used in this analysis is comprised of products scanned during the in-store surveys done between August and November 2019 in Sydney locations of each of five supermarkets. Product inclusion criteria was based on the robustness of the ingredient list and nutritional information provided on pack and transcribed into the FoodSwitch database.

3.2.2 Ingredient data

3.2.2.1 Ingredient identification and categorisation

The first step in assessing the products sold in Australian supermarkets was to identify each unique ingredient. Ingredients were identified from either the product name or the product's ingredient list. For products without an ingredient list but whose ingredient information could be determined from the product name, a text matching algorithm and a systematic ingredient identification process to extract ingredient information was developed. For example, the ingredient 'blueberry' was extracted from the

product name ‘Fresh blueberries’. In some cases, multiple ingredients were extracted from the product name, for example, the ingredients ‘pork mince’ and ‘veal mince’ from the product ‘Pork & veal mince’. This was done because the FSANZ Ingredient Labelling of Food standard does not require a product to have an ingredient list: (1) where the product is labelled with the name of the food and the name of the food includes all ingredients; (2) where the product is water in a packaged form; and (3) where the product is contained in a small package (surface area less than 100cm^2) (**Supplementary Table S3.1**).[107]

For products with an ingredient list, the delimited text strings reflecting the format provided on pack were disaggregated using an automated process to create separate fields for each ingredient and extract compound ingredient information when present (**Supplementary Table S3.2**). Compound ingredients are ingredients made up of two or more sub-ingredients.[107] Sub-ingredients must be declared if they constitute more than 5% of the final food or beverage product or contain a known allergen.[55] The three forms of compound ingredients included in this analysis were: (1) those for which listed sub-ingredients made up the entire compound ingredient (complete sub-ingredients), for example, where fortified wheat flour sub-ingredients were listed as wheat flour, thiamine, folic acid; (2) those for which listed sub-ingredients comprised only the additives or fortifications (incomplete sub-ingredients), for example, where fortified wheat flour sub-ingredients were listed as just thiamine, folic acid; and (3) those for which sub-ingredients were not listed.

A robust cleaning of the disaggregated ingredient data was conducted using a semi-automated process (**Supplementary Figure S3.1**). Key elements of the process were the removal of symbols (e.g., reduced-fat milk became reduced fat milk), the correction of spelling errors (e.g., miilk became milk) and the alignment to singular terminology (e.g., blueberries became blueberry). The terms for ingredients with various common names were standardised manually (e.g., arugula became rocket). Descriptive words were removed from ingredient names (e.g., natural freshly pressed apple juice became apple juice) (**Table 3.1**).

Table 3. 1. Examples of ingredient cleaning steps conducted after ingredient disaggregation

Issue in ingredient name	Example product name	Example ingredient list	Resolution
Descriptive words and phrases preceding the ingredient name	Dewlands Orange and Grape Fruit Juice	***Ingredients made from*** concentrate | orange juice (with pulp) (75%) | grape juice (25%) | vitamin c	Identified and stored unnecessary phrase and removed from further processing
Other unnecessary words contained in the ingredient list	Fine Fettle Real Veg Squished into Snack Flats - Zucchini and Almond	Zucchini (68%) | almonds (16%) | linseed | water | lemon juice | garlic | thyme | salt | spices | ***love and lots of taste***	
Promotional detail included in the ingredient list	Simon Johnson Organic Extra Virgin Olive Oil	Extra virgin olive oil from organic farming | ***harvested without the use of pesticides or chemical fertilizers***	
Disclaimers included in the ingredient list	Hugo's Fresh Trio Sprouts Selection	Crunchy combo (legumes such as mung | peas (blue | chick | caloona | etc) | lentils | ***actual blend can vary due to seasonal availability***) |alfalfa | snow pea shoots	
Allergy statement at any location within the ingredient list	Cracker Barrel Infused Cheddar Cheese with Maple & Toffee Bites	Cheese (pasteurised milk | salt | start cultures | non-animal rennet) | toffee pieces (8%) (***contains wheat and soy***) | maple flavour (1%)	
Ingredients not separated by commas, instead by words including 'and', 'and/or', or unexpected other symbol	Mayver's Goodness to Go Dark Roasted Peanut Butter	Roasted peanuts (99.3%) ***&*** sea salt	Replaced symbol or phrase with ingredient separator "|"

Numerous flags were created to denote further descriptors of ingredients. First, when a term relating to an agricultural technique was identified (i.e., organic or free-range), it was removed from the ingredient name and stored as a separate flag. Ingredients that constitute either a substantive portion of products (substantive ingredients) or a small proportion of products (non-substantive ingredients) were also identified. Non-substantive ingredients were defined as those usually comprising less than 2% of a product formula. For instance, some ingredients have maximum legal usage rates such as certain preservatives, vitamins and minerals; other ingredients are always used at low levels to provide functional benefits such as gums and other stabilisers.[194] Colours, flavours and most additives were also considered non-substantive ingredients.

Finally, less common substantive ingredients were grouped under a more common ingredient name where possible (e.g., garam masala powder was listed as dried herb). Similarly, E numbers were listed under the ingredient's common designation, such as the chemical name or additive type (e.g., E100

through E199 were listed under the ingredient 'colour'). Approximately 20% of the final ingredient extractions were manually validated by a second researcher.

Once fully cleaned, ingredients were categorised into a hierarchical tree structure using major and minor categories (**Supplementary Table S3.3**). Category naming conventions and the category structure were guided by the terminology used by two specialty ingredient companies, Cargill and ADM.[197,199] Where possible, contents of categories were further verified against existing literature, such as the categories pertaining to sweeteners that have been defined in detail in a publication on sugar types contained in supermarket retail products.[186]

3.2.2.2 Ingredient nutrient profile data

Each ingredient required mapping to a food composition data source to obtain nutrient information. Food composition databases provide information on the nutrient content of common foods and ingredients.[201,202] In Australia, the Australian Food, Supplement and Nutrient Database (AUSNUT), managed by FSANZ, is the main source for national nutrient data to support diet-related research.[203] The majority of FoodSwitch ingredients were mapped to the nutrient profiles of ingredients contained in AUSNUT. Additional ingredient-level nutrient profiles were obtained from food composition databases used in other high income countries (e.g., the UK's McCance and Widdowson's Composition of Food Dataset and the USDA Food Composition Database) (**Table 3.2**).[202,204,205]

Table 3. 2. Food composition data sources for ingredient nutrient profiles

Data source	Ingredients mapped
AUSNUT	823
FoodSwitch	28
2019 McCance and Widdowson's Composition of Foods Dataset	16
USDA Food Composition Database	12
Nutritionix	6
MyFitnessPal	5
Healthline	3
Bobs Red Mill	2
Total	895

3.2.3 Linear programming

Each product's nutrition information and the list of ingredients reported on the packaging, along with the nutrient profiles of the ingredients, were used to define the linear programming model. The linear programme was developed to estimate the proportion of each ingredient in each product. The algorithm incorporated any weight proportions on pack and predicted weight proportions in descending order, as

per the FSANZ standard.[107] To validate the model, the algorithm was tested on the small subset of products that reported a complete set of ingredient weight proportions on pack.

3.2.3.1 The objective function

As with previous implementations of linear programming,[206,207] three pieces of information were required to predict ingredient weight proportions: (1) the nutrition information panel as printed on product packaging, (2) the complete ingredient list, and (3) the nutrient composition of ingredients. The linear programming algorithm chose ingredient weight proportions that minimised the level of discrepancy between the product nutrient profile reported on the packaging versus the product nutrient profile derived from different possible combinations of ingredient weight proportions, as expressed in the objective function error:

$$Objective\ function\ error = \sum_{i=1}^{4} \frac{|C_i - r_i|}{SD_i}$$

$$= \frac{\text{Error in Carbs}}{\text{Carbs tolerance}} + \frac{\text{Error in Protein}}{\text{Protein tolerance}} + \frac{\text{Error in Total Fats}}{\text{Total Fats tolerance}} + \frac{\text{Error in Sodium}}{\text{Sodium tolerance}}$$

where i referred to one of four nutrients (carbohydrates, protein, total fat, sodium). Nutrient values obtained from the nutrition information panel on the packaging were represented by r_i and those calculated from the ingredient list and ingredient compositions were represented by C_i. SD_i referred to the standard deviation, or in this case the nutrient error tolerance, of the i-th nutrient in the product database (**Table 3.3**). Dividing by the nutrient error tolerances ensured the objective function placed a similar emphasis on nutrients with different units and distributions and that the total error was balanced across the different ranges and scales. Nutrient tolerances were based on nutrient-specific biological significance and were developed by researchers from the Nutrition Coordinating Center at the University of Minnesota.[207] The resulting objective function error was used to compare how well the model performs across different products.

Table 3. 3. Nutrient standard deviations used to normalise the linear programming objective function

Nutrient	Nutrient error tolerance[1]
Carbohydrates (g/100g)	10.0g
Protein (g/100g)	5.0g
Total fat (g/100g)	2.5g
Sodium (mg/100g)	100mg

[1]Nutrient error tolerances represent 10% of daily recommended intake values. They were used so that the objective function places equal emphasis on nutrient differences of equal nutritional significance, providing a form of standardisation. For example, a sodium difference of 10mg and a protein difference of 10g would not be treated with equal significance.

3.2.3.2 Nutrient selection

Of the seven nutrient declarations on the nutrition information panel that are required by Australian food standards,[208] four were determined to be of primary relevance for the linear programming model: carbohydrates, protein, total fat and sodium. While sugars and saturated fat are also mandatory, their values highly correlate with carbohydrates and total fats respectively, making their inclusion in the model redundant. Similarly, energy content was prominent on all labels but unnecessary in the model as the value was obtained by a simple calculation summing the energy based on grams of carbohydrates, protein, and total fat. Fibre was also considered for use in the model, but it is not mandated on package labels and was found to be missing for about 75% of products.

3.2.3.3 Constraints

In addition to minimising the objective function, ingredient weight proportion predictions were required to satisfy four constraints, which were informed by FSANZ ingredient labelling regulation[107,108]:

(1) Ingredient weight proportions must be in descending order

As defined by both FSANZ, UK.GOV and USDA regulation, stated ingredients must be listed in descending order of ingoing weight.[107,205,209]

$$w_j \geq w_{j+1} \text{ for j=1 to n-1}$$

(2) Ingredient weight proportions must sum to 100%

It can be assumed that the sum of all ingredient weight proportions must add to 100%.

$$\sum_{j=1}^{n} w_j = 100\%$$

(3) All ingredient weight proportions must be positive

It can be assumed that all ingredient weight proportions must be greater than 0%.

$$w_n > 0$$

(4) All ingredient weight proportions declared on pack must be used

FSANZ Standard 1.2.10 defines the requirements for labelling of characterising ingredients and components of food.[108] When a characterising ingredient is declared on product packaging, the regulation requires the weight of that ingredient in the final product must be declared as a percentage. In such cases where the percentage of an ingredient is already available, this was used as baseline information to enhance the performance of the linear programme.

$$w_j = Q_1 \quad \text{(where } Q_1 \text{ is on pack)}$$

j referred to the indicated ingredient in the product and *n* referred to the total number of ingredients in the product. Constraints were applied to ingredients and then separately applied to sub-ingredients for

any ingredient that was composed of two or more sub-ingredients (**Table 3.4**). Non-substantive ingredients were automatically assumed to make up 1% of the product based on regulations that limit the allowed amounts of these types of substances.[210]

In **Table 3.4**, an end-to-end example shows how the linear programming model was used to predict the weight of each ingredient in each product using the prescribed constraints. Each ingredient was enumerated with its respective ingredient mapping to nutrient information and its estimated weight in the final product. The second to last row in the table details the product nutrition information as stored in the FoodSwitch database. The last row in the table presents the estimated nutrient values for the product based on the results of the linear programming algorithm. The objective function is displayed as a metric describing how well the linear programme performed. An objective function value of 0 would be indicative of the linear programme performing perfect perfectly. For this analysis, all products eligible for the linear programme were included regardless of the objective function value.

Table 3. 4. Example application of the ingredient proportion prediction algorithm

Product name		**Ingredient list**					
Chia and apple snack		chia seed gel (40%) [filtered water | chia seed] | apple puree (35%) | coconut milk | diced apple (8%) | organic cane sugar | lemon juice concentrate | cinnamon (0.4%)					
Ing ID	**FoodSwitch ingredient**	**Mapped AUSNUT ingredient**	**Carbs (g/100g)**	**Protein (g/100g)**	**Total fat (g/100g)**	**Sodium (mg/100g)**	**Predicted %**
1	Chia seed gel (40%[1])		-	-	-	-	**-**
	Filtered water	Water, tap	0.0	0.0	0.0	3.0	***29.0%***
	Chia seed	Seed, chia dried	7.7	16.5	30.7	16.0	***11.0%***
2	Apple puree (35%[1])	Apple, unpeeled, raw	12.7	0.3	0.2	1.0	***35.0%***
3	Coconut milk	Coconut, milk, regular fat	1.7	1.3	12.8	18.0	***12.0%***
4	Diced apple (8%[1])	Apple, unpeeled, raw	12.7	0.3	0.2	1.0	***8.0%***
5	Organic cane sugar	Sugar, white, granulated	100	0.0	0.0	0.0	***4.2%***
6	Lemon juice concentrate	Juice, lemon, concentrated	39.6	0.2	0.0	37.0	***0.4%***
7	Cinnamon (0.4%[1])	Cinnamon, dried, ground	25.5	4.2	2.7	18.0	***0.4%***
		Reported profile[2]	11.0	2.0	5.0	3.0	
		Calculated profile[3]	*11.0*	*2.1*	*5.0*	*4.9*	*Objective function 0.037*

[1]Derived from the ingredient weight proportion declared on pack. [2]Derived from the nutrient profile declared on pack. [3]The nutrient profile is calculated using ingredient nutrient profiles and ingredient weight proportions. In this example, seven ingredients were extracted from the ingredient list, one of which had two sub-ingredients and four of which already had ingredient weight proportions defined. All ingredients were successfully mapped to AUSNUT Food Composition Database entries providing ingredient-level nutrition information.

3.2.3.4 Validation of the linear programme

For validation, the set of products with complete ingredient weight proportion information included on the package labelling was identified. This comprised 2,451 FoodSwitch products. As there was no gold

standard approach to measure the accuracy of a set of weight predictions, an accuracy metric called the overlap coefficient was derived. This metric determined accuracy by measuring the level of overlap between the predicted and given recipes.

As seen in the example in **Table 3.5**, 65% of the product was tuna and this was predicted as 61% by the algorithm. A further 34% of the product was olive oil, and this was accurately predicted by the algorithm as 34%. Finally, 1% of the product was salt but this was predicted as 4% by the algorithm. The overlap of each ingredient weight prediction contributed to the overall accuracy metric for each product (61%, 34% and 1%, respectively). Thus, for Tuna in Olive Oil, a total of 96% of the predicted recipe overlapped with the given recipe.

Table 3. 5. Example overlap coefficient calculation to assess accuracy of the linear programme

Product name	**Ingredient list**		
Tuna in Olive Oil	Yellowfin tuna | olive oil | salt		
Ingredient	**Weight (%)**		**Known ∩ Predicted**
	Known	**Predicted**	
Yellowfin tuna	65	61	61
Olive oil	34	34	34
Salt	1	5	1
Formulation	100	100	96

Let:
A = known formulation from product packaging
B = predicted formulation
Overlap coefficient(A, B) = $|A \cap B| / (\min(|A|, |B|))$

3.2.4 Statistical analysis

The total number of ingredients was calculated by tallying the number of main and sub-ingredients after removing any duplicate ingredients listed across both levels of disaggregation (e.g., "canola oil, butter (cream, water, salt), eggs, white vinegar, salt" contains just six ingredients since salt was listed twice). Ingredients different prior to cleaning but the same after cleaning (e.g., E101 and E102 were both classified as 'colour' after cleaning but ultimately refer to different original colour additives) were treated as distinct ingredients in the overall and product-specific ingredient count. Compound ingredients that contained an incomplete or missing sub-ingredient list were tallied as a single ingredient.

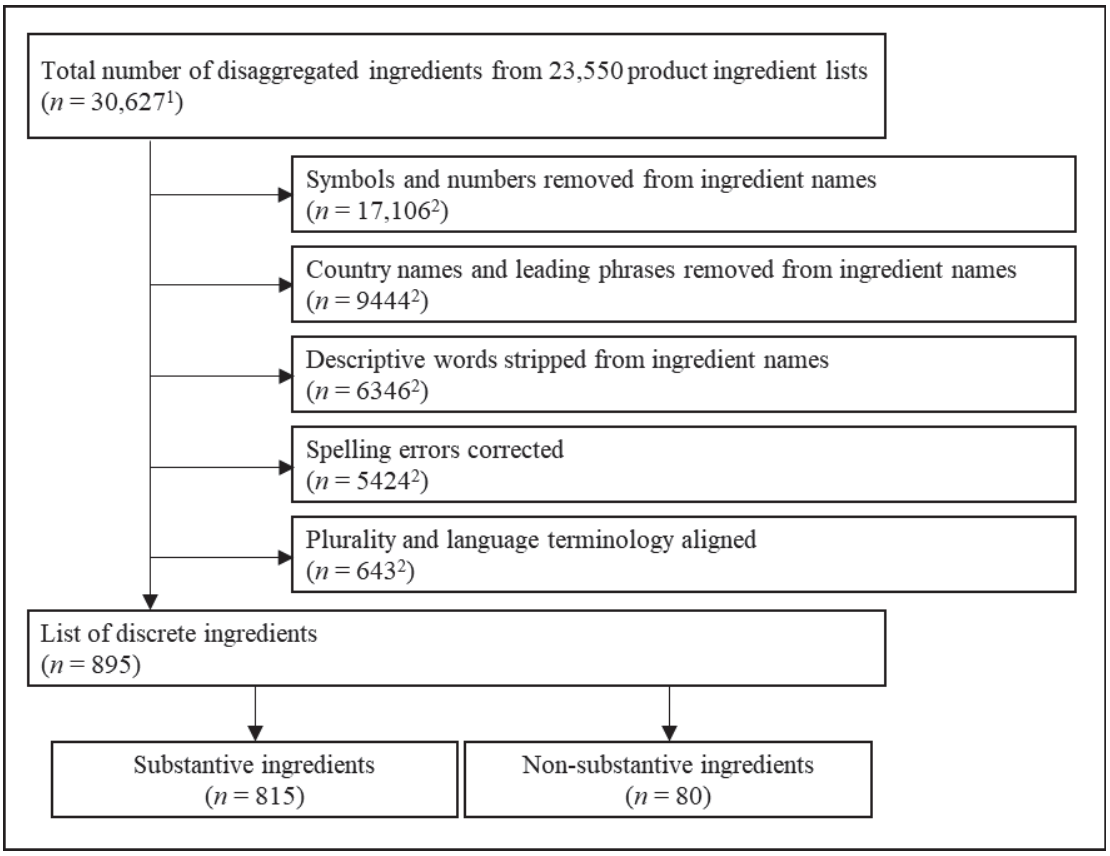
Descriptive statistics were presented overall as well as for the 16 major categories. The differences in the median (interquartile range (IQR)) number of ingredients across HSR score and NOVA classification were evaluated using 1-factor ANOVA with Tukey post-hoc analyses. A subsidiary analysis was done assessing main ingredient counts by excluding sub-ingredients. The outputs of the linear programme were used to determine which ingredients make up the highest proportion of the

supermarket food supply in Australia. The accuracy of the linear programme was evaluated by assessing the mean (standard deviation (SD)) of the overlap coefficient across product categories and for ingredients by their position, or order of appearance in the ingredient list. All ingredient data preparation and statistical analyses were conducted using Stata BE 17 (StataCorp) and a two-sided p-value<0.05 was considered statistically significant. The linear programming algorithm was written in *Python 3* using the *Pandas* and *NumPy* libraries.

3.3 Results

The 23,550 products listed a total of 227,209 ingredients with 30,627 unique ingredient names. Semi-automated cleaning reduced this number to 895 distinct ingredients (**Figure 3.3**). The 895 distinct ingredients were categorised into 18 major categories (**Table 3.6**) and 138 minor categories (**Supplementary Table S3.3**). 815 of the ingredients were identified as nutritionally substantive and 80 were identified as nutritionally non-substantive. Across all products, 9,212 (20.9%) contained at least one compound ingredient in its ingredient list. Of the 227,209 ingredients, 160,753 (70.8%) were main ingredients and 15,056 (9.4%) of the 160,753 main ingredients were compound ingredients. 7,210 (47.9%) compound ingredients contained a complete sub-ingredient list, 4,426 (29.4%) contained an incomplete sub-ingredient list, and 3,420 (22.7%) did not contain sub-ingredients which could be disaggregated.

Figure 3. 3. Flowchart describing ingredient cleaning and classifications



Source: Adapted from Gaines A, Shahid M, Huang L, Davies T, Taylor F, Wu JH, et al. Deconstructing the Supermarket: Systematic Ingredient Disaggregation and the Association between Ingredient Usage and Product Health Indicators for 24,229 Australian Foods and Beverages. Nutrients. 2021;13(6):1882.

[1]The original 31,934 ingredients were a result of the original ingredient disaggregation and consolidation into unique ingredient names. [2]A number of ingredients required multiple cleaning steps, so the number of ingredients cleaned in each step sums to more than the total number of disaggregated ingredients removed.

Table 3. 6. Ingredient frequencies by major ingredient category

Major ingredient category	No. of unique ingredients	Proportion of unique ingredients	No. of non-substantive ingredients[1]	Frequency across all products[2]	Proportion across all products[3]
Additives	88	9.7%	68	15,181	64.5%
Herbs and spices	34	3.8%		13,268	56.3%
Nutritive sweeteners	26	2.9%	6	12,052	51.2%
Liquids	72	8.0%		11,411	48.5%
Fruits and vegetables	227	25.4%		10,477	44.5%
Oils and fats	33	3.7%		9,558	40.6%
Dairy	54	6.0%		7,022	29.8%
Flours and starches	17	1.9%		6,936	29.5%
Baking ingredients	10	1.1%	1	4,759	20.2%
Compound ingredients[4]	117	13.1%	1	4,524	19.2%
Grains	48	5.2%		3,918	16.6%
Nuts and seeds	30	3.4%		2,755	11.7%
Meat	56	6.3%		2,606	11.1%
Legumes	27	3.0%		2,548	10.8%
Eggs	8	0.9%		1,675	7.1%
Seafood	40	4.5%		1,042	4.4%
Dietary fibres	4	0.5%	2	905	3.8%
Non-nutritive sweeteners	4	0.5%	2	340	1.4%
	895	***100%***	***80***		

Source: Adapted from Gaines A, Shahid M, Huang L, Davies T, Taylor F, Wu JH, et al. Deconstructing the Supermarket: Systematic Ingredient Disaggregation and the Association between Ingredient Usage and Product Health Indicators for 24,229 Australian Foods and Beverages. Nutrients. 2021;13(6):1882.

[1]Non-substantive ingredients were defined as ingredients usually less than 2% of a product formula, such as preservatives, vitamins and minerals, gums and other stabilisers. [2]Frequency and [3]proportion across all ingredient lists describes the number/proportion of the 23,550 foods for which one or more of the ingredients in each major ingredient category was included in the ingredient list on pack. [4]The 'Compound ingredients' category captured any main ingredients which were clearly composed of multiple sub-ingredients based on their names (e.g., chocolate).

3.3.1 Most commonly listed ingredients

The majority of unique ingredients belonged to the major category 'Fruit and vegetables' (n=227), followed by 'Compound ingredients' (n=117), 'Additives' (n=88) and 'Liquids' (n=72). 'Additives' were the most widely used ingredient across all products, as they were contained in 64.5%, (15,181/23,550) of products, followed by 'Herbs and spices' (56.3% (13,268/23,550)) and 'Nutritive sweeteners' (51.2% (12,052/23,550)). 44.5% (10,477/23,550) of products had at least one ingredient categorised under 'Fruits and vegetables' and only 10.8% (2,548/23,550) had at least one ingredient under 'Legumes'. Across all included products, salt (15,149/23,550) and sugar (11,978/23,550) were

the most frequently used ingredients. 'Additives' (i.e., flavours, colours, emulsifiers, acidity regulators, preservatives and thickeners) represented 6 of the 10 most frequently used ingredients (**Table 3.7**).

Table 3. 7. The top 15 ingredients in the 2019 Australian supermarket food and beverage supply

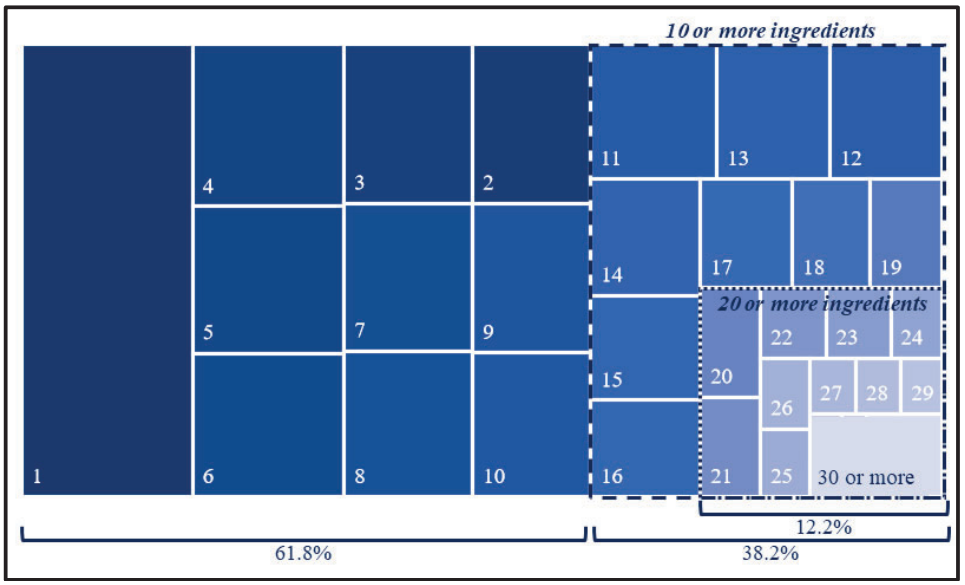
Ingredient rank[1]	Ingredient	Ingredient major category	Substantive ingredient	Frequency[2]	Proportion[3]
1	Salt	Herbs and spices	Y	15,149	64.33%
2	Sugar	Nutritive sweeteners	Y	11,978	50.86%
3	Water	Liquids	Y	9,609	40.80%
4	Flavour	Additives	N	8,181	34.74%
5	Colour	Additives	N	4,701	19.96%
6	Emulsifier	Additives	N	4,553	19.33%
7	Wheat flour	Flours and starches	Y	4,070	17.28%
8	Acidity regulator	Additives	N	3,302	14.02%
9	Preservative	Additives	N	3,269	13.88%
10	Vegetable oil	Oils and fats	Y	3,082	13.09%
11	Thickener	Additives	N	3,043	12.92%
12	Milk powder	Dairy	Y	2,987	12.68%
13	Yeast	Baking	Y	2,940	12.48%
14	Dried herbs	Herbs and spices	Y	2,851	12.11%
15	Glucose	Additives	N	2,642	11.22%

Source: Adapted from Gaines A, Shahid M, Huang L, Davies T, Taylor F, Wu JH, et al. Deconstructing the Supermarket: Systematic Ingredient Disaggregation and the Association between Ingredient Usage and Product Health Indicators for 24,229 Australian Foods and Beverages. Nutrients. 2021;13(6):1882.
[1]Rank: ingredients are ranked according to how many of the ingredient lists they are included on out of the 23,550 included food and beverage products. [2]The frequency is the number of products for which the ingredient is listed. [3]The proportion is the percent of the 23,550 total products evaluated.

3.3.2 Number of ingredients per product across product categories

Products had between 1 and 62 ingredients, though about 90% of products had 20 or fewer ingredients and single-ingredient products made up 18.6% (4,375/23,550) of the total (**Figure 3.4**). Across all products, the mean (SD) number of ingredients was 9.65 (8.33) and the median (IQR) was 8 (3-14). 'Convenience foods' have the greatest median number of ingredients per product (20 (14-27)), followed by 'Foods for specific dietary use' (12 (7-22)) and 'Meat alternatives' (14 (9-19)) (**Table 3.8**). When only assessing the 160,753 main ingredients, the range in number of ingredients was decreased to 1 to 39, the mean (SD) was decreased to 6.21 (7.09) and the median (IQR) number of main ingredients across all products was decreased to 5 (2-8). The median number of ingredients was reduced across all major food categories and markedly for 'Convenience foods' (from 20 to 11).

Figure 3. 4. Distribution of the number of ingredients per product



The tree map displays how many products contain the specified number of ingredients in the product ingredient list, including sub-ingredients.

Table 3. 8. Measures of variability of ingredients, overall and in major product categories

	Total products	Number of Ingredients						
		Mean[1]	SD[2]	Min	25%	50%	75%	Max
All products	23,550	9.65	8.33	1	3	8	14	62
By FoodSwitch product category								
Convenience foods	1418	20.99	10.07	1	14	20	27	61
Foods for specific dietary use	722	15.03	10.61	1	7	12	22	50
Meat alternatives	195	14.78	8.73	2	9	14	19	53
Bread and bakery products	2345	14.44	7.3	1	9	13	18	49
Sauces, dressings, spreads and dips	2,327	11.84	6.42	1	7	12	16	43
Snack foods	682	11.80	6.53	2	6	12	17	38
Meat and meat products	1724	11.57	9.66	1	1	11	17	52
Confectionery	1277	10.85	5.95	1	7	10	13	62
Cereal and grain products	1952	9.26	8.72	1	1	6	15	58
Dairy	2956	8.36	6.74	1	4	6	11	56
Seafood and seafood products	761	7.18	6.08	1	3	5	11	41
Non-alcoholic beverages	2436	5.50	4.61	1	1	5	8	37
Fruit, vegetables, nuts and legumes	3766	4.12	4.35	1	1	3	6	50
Sugar, honey and related products	405	3.87	4.20	1	1	2	6	26
Edible oils and oil emulsions	495	3.38	3.88	1	1	1	3	16
Egg and egg products	89	1	0	1	1	1	1	1

Source: Adapted from Gaines A, Shahid M, Huang L, Davies T, Taylor F, Wu JH, et al. Deconstructing the Supermarket: Systematic Ingredient Disaggregation and the Association between Ingredient Usage and Product Health Indicators for 24,229 Australian Foods and Beverages. Nutrients. 2021;13(6):1882.

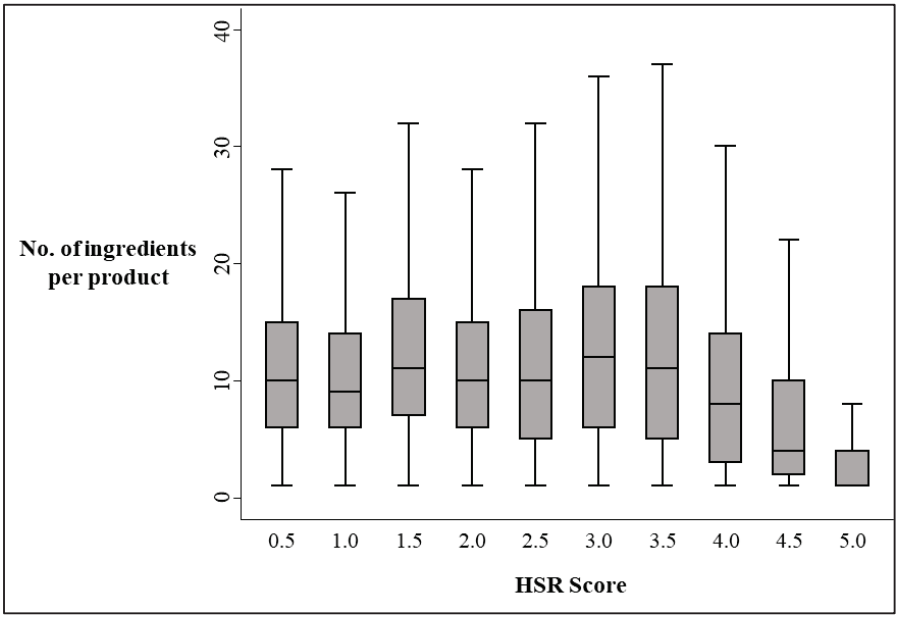
[1]Mean: the average number of ingredients in products based on the on-pack statement of ingredients. All main and first-level sub-ingredients are included in the total count of ingredients. [2]SD: standard deviation.

3.3.3 Associations between number of ingredients and nutrient profiling score

The number of ingredients in a product was lower in products with higher HSR scores and lower NOVA classifications (i.e., indicators of better nutritional quality in the majority of cases). For HSR, products with a rating of 4 or more stars had a significantly lower median ingredient count than all other HSR values (all *p*-values<0.001). The highest HSR, a 5-star rating, had the lowest median number of ingredients (1 (1-3)). Ultra-processed foods (NOVA group 4) tended to have the most ingredients (8 (3-13)) while minimally processed foods (NOVA group 1) tended to have the least ingredients (1 (1-2)). The median number of ingredients per product was significantly higher in ultra-processed products (NOVA group 4) compared to all other NOVA groups (all *p*-values<0.001); similarly, the median number of ingredients in processed products (NOVA group 3) was significantly higher compared to NOVA groups 1 and 2 (all *p*-values<0.001).

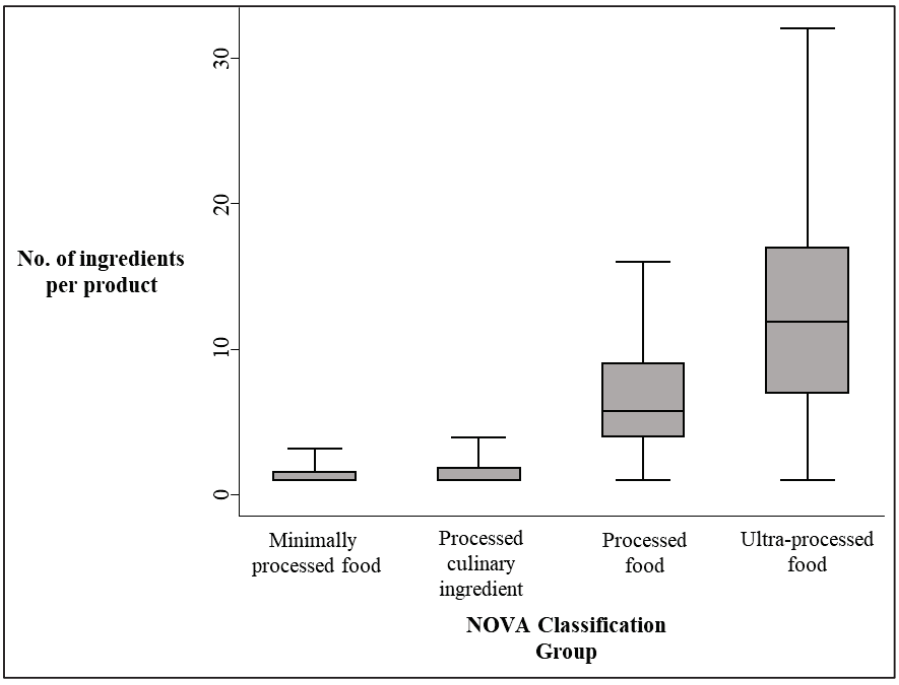
The association between number of ingredients and both HSR and NOVA was, however, not linear. Products with HSR scores from 0.5 to 3.5-stars had approximately similar median ingredient counts while products with HSR scores from 3.5 to 5.0-stars showed a step-wise decline in median ingredient counts (**Figure 3.5**). For NOVA, both minimally processed foods (NOVA group 1) and processed culinary ingredients (NOVA group 2) had similar median ingredient counts (**Figure 3.6**). When looking at only main ingredients, the difference in ingredient count medians across HSR scores and NOVA groups displayed the same overall patterns.

Figure 3. 5. Descriptive statistics on the number of ingredients across Health Star Rating scores



The boxplot shows the median and interquartile range (IQR) number of ingredients in products for each Health Star Rating (HSR) scores. The whiskers are defined as the lower quartile-1.5*IQR and the upper quartile+1.5*IQR. Outliers are excluded from the graph.

Figure 3. 6. Descriptive statistics on the number of ingredients across NOVA classification groups



The boxplot shows the median and interquartile range (IQR) number of ingredients in products for each NOVA classification groups. The whiskers are defined as the lower quartile-1.5*IQR and the upper quartile+1.5*IQR. Outliers are excluded from the graph.

3.3.4 Ingredient weight proportions and validation

The majority of multi-ingredient products in this dataset (57.0% (10,920/19,175)) contained at least one ingredient with a reported ingredient weight proportion but only 10.8% (24,474/202,737) ingredients had their weight listed. 40.7% (9,585) of multi-ingredient products reported ingredient weights totalling at least 50% of the total product composition, and 32.0% (7,543) reported ingredient weights totalling at least 75%.

Ingredient weights were either reported on packaging or imputable for all main ingredients for 2,451 (10.4%) multi-ingredient products. We estimated ingredient weight proportions using the linear programming algorithm for the remaining 21,099 (89.6%). For the 2,451 products with on-pack ingredient weight proportions, comparison against the weight estimated using the linear programming algorithm resulted in a mean overlap coefficient of 85%. Across product categories, the mean overlap coefficients varied from 72% to 90% (**Table 3.9**); overlap coefficients tended to be higher in products with fewer ingredients.

Known and estimated ingredient weights differed by an average of -0.18%. The linear programme tended to slightly underestimate ingredient weights for ingredients in the first position and slightly overestimate ingredient weights for ingredients in the second and third positions, ingredients higher on

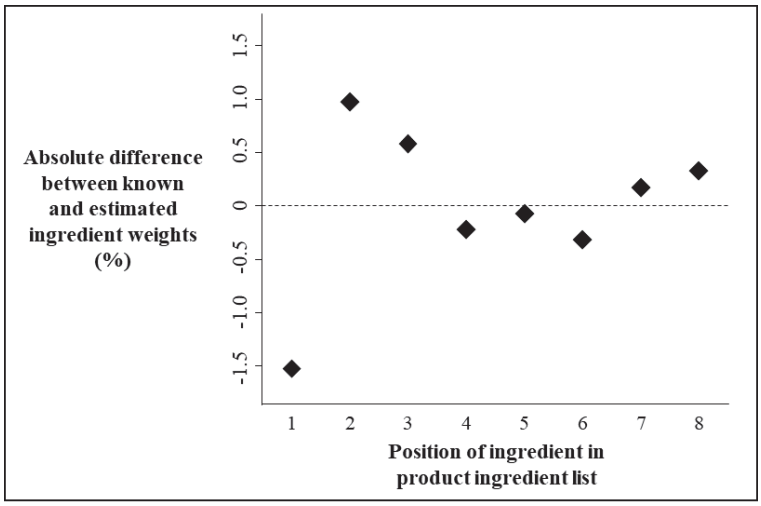
the list had slightly larger absolute differences (1.0-2.0%) than ingredients lower on the ingredient list (0.5-1.0%) (**Figure 3.7**).

Table 3. 9. Accuracy of the linear programming algorithm by product category

FoodSwitch product category	n (%)	Overlap coefficient	
		Mean	SD
Fruit, vegetables, nuts and legumes	637 (25.0)	88%	15%
Non-alcoholic beverages	379 (14.9)	83%	16%
Cereal and grain products	246 (9.7)	86%	14%
Seafood and seafood products	234 (9.2)	85%	13%
Foods for specific dietary use	151 (5.9)	80%	14%
Sauces, dressings, spreads and dips	128 (5.0)	90%	13%
Confectionery	101 (4.0)	87%	10%
Snack foods	96 (3.8)	89%	12%
Dairy	67 (2.6)	82%	17%
Edible oils and emulsions	61 (2.4)	72%	19%
Meat and meat products	55 (2.2)	75%	18%
Bread and bakery products	50 (2.0)	88%	14%
Sugars, honey and related products	42 (1.6)	85%	17%
Convenience foods	25 (1.0)	80%	14%
Total	**2,451**	**85%**	**15%**

The overlap coefficient measures the level of agreement between the predicted and known product formulations using the following formula: Overlap coefficient(A, B) = $|A \cap B| / \min(|A|, |B|)$. Values range from 0 to 1, where 1 indicates a perfect prediction. On average, the linear programming algorithm accurately predicted 85% of the product's ingredient profile.

Figure 3. 7. Difference between known and estimated ingredient weights based on ingredient position



The calculation was (Estimated weight) – (Known weight); positive values indicate the linear programme overestimates the weight of the ingredient and negative values indicate the linear programme underestimates the weight of the ingredient. The values were calculated using the 2,451 products in the validation dataset.

3.4 Discussion

The large number of supermarket products available on retail shelves in Australia in 2019 were made up of a much smaller number of ingredients, though the breadth of ingredient naming conventions made this difficult to tell without significant data cleaning and alignment. The systematic approach to standardising, reporting and quantifying product ingredients provided in this chapter can enable a wide range of new analyses on the makeup of these products. The most commonly used ingredients were salt (including sea salt, iodised salt, etc.), sugar, flavours, colours and other additives - all ingredients that are characteristic of ultra-processed foods.[211,212]

3.4.1 Comparison with existing literature

As with previous research, this analysis found that products with higher ingredient count medians tended to have lower HSR scores (i.e., less optimal nutrient profiles) and greater degrees of food processing according to the NOVA classification.[106,173] Conversely, the association between lower median ingredient counts and products with both higher HSR scores and less processed NOVA classification groups was also evident.[213] In products with HSR scores between 0.5- and 3.5-stars, there were only a minimal difference in median ingredient counts. While there may be an abundance of reasons for this, it is likely that the difference in composition and nutritional quality of products with 1 or 2 ingredients and those with 10 ingredients is much more apparent than the difference between those with 10 and those with 20 ingredients. Most often, ingredients listed after the 10th position on an ingredient list were more likely to be a preservative, colourant or food additive. Accordingly, products with higher median ingredient counts were associated with higher degrees of product processing, which aligned with the definition of ultra-processed foods.[31,214] Ultra-processed foods often contain many cosmetic food additives in order to enhance the end-product's taste, shelf-life and overall appeal.[27] In many cases the use of a large number of additives aligned with poorer nutrient profiles, however, it is important to note that in some cases the inclusion of certain additives (e.g., in canned foods for the purpose of preservation) did not reflect nutritional value.[31,215]

Based on this sample of products available in 2019 in Australia as well as an analysis on products available in the United Kingdom,[183] most ingredient weight proportions were not disclosed on the ingredient list. Though this was the first research available that utilised a linear programming model to close this data gap, linear programming models have been used by organisations (e.g., the United States Department of Agriculture) to impute nutrition information that are not presently available, including missing nutrient values (for use in food composition tables) and added sugar content.[206,207] In lieu of linear programming, the research in the United Kingdom estimated ingredient weights using characterising ingredient information and other weight percentages provided on packaging. Specifically, they imputed unknown ingredient weights by aggregating the provided data and ingredient list rank

(based on how far down the ingredient list) for similar product types.[183] The use of a linear programme aimed to better capture the product-specific variability within food and beverage categories than the imputation method achieved.

3.4.2 Strengths and limitations

This was the first ingredient-specific analysis of the Australian supermarket food and beverage supply that supported a reproducible way to assess ingredients in retail products. Most notably, this chapter resolved the issue that the same ingredient can be represented in numerous ways due to non-standardised labelling legislation.[106,216] Disaggregated ingredient data can improve understanding of the ingredients used in commercial settings. For example, it can be used to understand impacts of ingredient co-occurrence, research on food ontology and diet-related artificial intelligence tools.[106]

This chapter also provided a way to estimate all ingredient weight proportions, including those for non-characterising ingredients, which benefits both researchers and policymakers by better reporting the contents of the foods available in supermarkets. The linear programming methodology allows for large-scale, automated application across existing products as well as new products added to the market, as all information used is publicly available, either on product packaging or relevant government web pages.

There were several limitations in this analysis. It was found that approximately 10% of products did not contain an analysable ingredient list and products with longer lists were more likely to contain inconsistencies preventing disaggregation of ingredient terms. In addition, food additives were in many cases grouped together due to the sheer number of different terms (e.g., E numbers). Though this may add to the research on understanding the health implications of some additive types,[217,218] it will not allow for comparing the impacts of similar additives. Future work to refine this data would allow for more targeted research on usage and impacts of different additives on both product quality and health outcomes.[219]

The linear programming algorithm used to predict ingredient weight proportions performed well but was also imperfect. The algorithm relied on nutrient information panels from manufacturers and food composition tables, both of which can vary from truth for a given product, with the potential to introduce both systematic and random errors. Data contained in food composition tables can differ based on the agricultural techniques used in the specified region, the micro-climate and even the soil content. For this reason, Australian nutrient composition data from AUSNUT were used where possible.

3.4.3 Study implications and future research

This chapter brought to light potential next steps for ingredient research and labelling policy. First, the extensive ingredient cleaning and alignment required for this analysis identified a clear opportunity to standardise ingredient labelling and regulation to improve transparency into product composition. Ingredient terminology, which often differed based on product manufacturer, can include descriptive terms that distract consumers from understanding nutritional content and complicate research initiatives. As many consumers are overwhelmed by the complexity of the nutrition information provided on supermarket products and are sceptical of food label reliability, it is important to improve standards in a manner that will benefit the public and their ability to make healthy food choices.[220] Second, this chapter raised that there is no clear standard for displaying compound ingredients or their nested sub-ingredients. Though the 'Compound ingredients' category had 117 different ingredients, many of these ingredients were used only in a small number of products. Currently, there is flexibility in using generic terms in lieu of specific ingredients (e.g., a product containing blueberry, strawberry and raspberry can have a valid ingredient list either with listing all three ingredients or with listing a generic ingredient of 'fruit').[107] Finally, this chapter highlighted that ingredients not considered common allergens do not have to be disclosed if they comprise only a small percentage (less than 2%) of the final product. Although these ingredients may not always be critical to food supply analyses, research on additives and fortifications is expanding so these ingredients may become more important to specify.[26,31]

Modern nutrition science works, which focus on the nexus of biological, environmental and social impacts of food and consumption,[221] can also benefit from the novel ingredient-level data developed from the large and representative set of products in this analysis.[222] Food categorisation systems such as FoodOn and LanguaL™, food thesauruses used to systematically describe foods for a range of stakeholders including food scientists, nutritionists and policymakers,[223,224] could be further optimised with ingredient-specific data from a large number of commercial products. Distinguishing flags for 'organic' and 'free-range' ingredients provides the opportunity to study potential health and environmental impacts of such products.[106]

3.5 Conclusion

More and more, consumers and policymakers are trying to understand what is in the foods being eaten to better track both diet and disease patterns. The assessment of product ingredients described in this chapter provided a novel means of evaluating supermarket food and beverage products. Standardised ingredient information can help enhance research and dietary assessment tools. Specifically, the associations between the number of ingredients in a product and both HSR score and NOVA classification suggested that additional research on the ingredient composition of supermarket products may provide insights into their effects on health outcomes.

Chapter 4: Product-specific greenhouse gas emission estimates

4.1 Introduction

Measuring the GHGe impacts of supermarket food and beverage products is needed to portray the broader environmental impacts of the food and beverage supply. Numerous research manuscripts have recently emerged describing the environmental impacts of foods at a high level by examining dietary patterns and life cycle assessments (LCAs) of different commodities.[128,129,131] Minimally processed fruits, vegetables and grains were consistently found to have the lowest carbon footprint while red meat, other animal-based meat and dairy have the highest.[120,160] While this information has helped to progress research on food system sustainability, more is needed to meet planetary health goals.[131] Specifically, many packaged and prepared products sold at supermarkets and convenience stores that contain high-emitting ingredients and ultra-processed components[23,216,225] have infrequently undergone LCAs. The findings in Chapter 3 showed that 11.1% of the included supermarket products contained at least one meat ingredient, 29.8% contained at least one dairy ingredient and 64.5% contained additives. These types of multi-ingredient products make up around three-quarters of food purchases in high-income countries like Australia[23,185] and already over half in some low- and middle-income countries.[4,24]

A standardised methodology to estimate a broad range of product-specific GHGe, similar to what has been developed in the UK,[183] could help distinguish between apparently similar products that may have markedly different GHGe.[117] LCAs measuring GHGe impacts require end-to-end supply chain information including data on soil and agricultural techniques, manufacturing energy readings and geo-spatial data in order to optimise the accuracy of outputs.[136,226] Though these data are not often available for supermarket products, it may be possible to surface differences in product-specific GHGe using an alternative scalable approach based on publicly available or imputable information, such as a product's unique ingredient list and composition as derived in Chapter 3.[142,183,227] In turn, enhanced information on the carbon footprints of individual products could encourage actions from both upstream and downstream stakeholders. Product-specific GHGe values in conjunction with on-pack GHGe labelling could not only enable consumers to make food choices based on environmental sustainability,[7,141] but also drive producers, manufacturers and retailers towards actions that reduce their GHGe impact.[120,150,183]

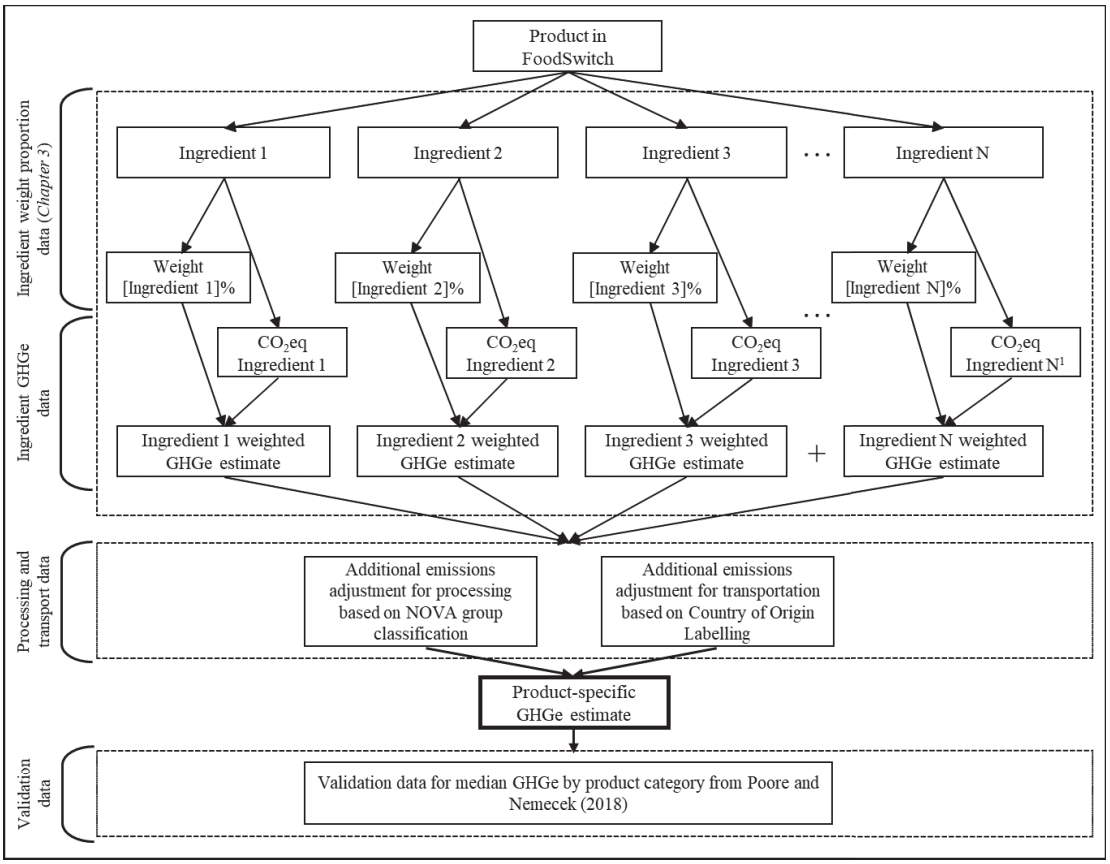
The work in Chapter 4 advanced the data on food and beverage products in available in major Australian supermarkets by producing product-specific GHGe estimates and uncertainty intervals of these GHGe estimates. This chapter aimed to enable the comparison of product-specific GHGe across the retail food

and beverage supply and assessment of the variability in GHGe attributable to products within each product category.

4.2 Methods

In this chapter, the ingredient weight proportion outputs from Chapter 3 were combined with existing ingredient GHGe data and high-level processing and transport information to estimate the GHGe attributable to each product and a corresponding uncertainty interval. The methods utilised widely available information including ingredient LCA data and the product's ingredient list, NOVA group classification and country of origin. The range of GHGe values for product categories were quantified and the results were validated the against the most comprehensive consolidation of GHGe information for main food groups (**Figure 4.1**) (**Supplementary Figure S4.1**).[117]

Figure 4. 1. Chapter 4 methods workflow



In this visual representation of the product-specific greenhouse gas emission (GHGe) estimation method, the ingredient-based estimate is explained in four steps: ingredient identification, ingredient proportion prediction, ingredient GHGe assignment and weighted ingredient GHGe calculation. The weighted ingredient GHGe estimates were summed to obtain the product-specific GHGe estimate. Adjustments were made to the product-specific estimate for transport and level of processing.

[1]All relevant ingredient conversion factors (explained further in Section 4.2.1) were applied in this step.

4.2.1 Ingredient greenhouse gas emission data

GHGe estimates were determined for each ingredient using a two-step process. The first step was a structured search for LCA data sources conducted to obtain GHGe values of food ingredients (**Table 4.1**). The search was performed on five online databases with the support of a librarian based at St Mary's Library. Eligibility of the search results was determined by screening the title and abstract, and then by review of the full-text and associated data source(s). The LCA data were identified either in a manuscript's results or in a citation within a manuscript. LCA data sources that were not freely available were accessed through an Imperial College London license to SimaPro, a software for collecting, analysing and monitoring the sustainability performance of commodities and services.[228] Ingredient LCA data containing Australian data and/or global averages were included, with preference given to Australian data where possible. Search results containing LCA data that were not global and were specific to any country other than Australia[229] were excluded because a large proportion of products available in Australian supermarkets are produced in Australia (66.7% based on the country of origin label group 1, further described below). LCA data were included if all ingredient system boundaries could be aligned to cradle-to-farm gate (refer to **Figure 1.7**). An LCA system boundary is defined by the processes and activities included in the respective GHGe or environmental impact calculation. The functional units of all included LCA data sources were aligned to kilograms of carbon dioxide equivalents per kilogram of ingredient.

Table 4. 1. Systematic search strategy for food-related life cycle assessment data

Online search databases	Search criteria	Search terms[1]
PubMed Scopus Web of Science Engineering Village EBSCO	*Year of publication*: All *Exclusions:* Non-English language *Regions*: Australia, Global *Data*: Must contain life cycle assessment data with a system boundary of cradle-to-farm gate	"Life cycle assessment" OR "Life cycle analysis" AND "Greenhouse gas emissions" OR "Carbon footprint" OR "Carbon equivalent" AND "Food" OR "Food product*" OR "Packaged food*" OR "Diet"

[1]Manuscript titles and abstracts were used to match to search terms. Life cycle assessment (LCA) data were found either within a manuscript's results or within data sources cited in a manuscript.

In the second step, additional emissions were incorporated for certain ingredients using conversion factors identified from commodity trade data sources. Three types of conversion factors were incorporated to account for GHGe attributable to farming, preparation and cooking modifications for relevant produce and animal ingredients. These allowed for the final functional unit for each ingredient to be in terms of kilograms of carbon dioxide equivalents per kilogram of edible ingredient (kg CO_2eq/kg ingredient). The "Technical Conversion Factors for Agricultural Commodities" (TCFAC)

published by the statistics division of the FAO were included to account for rates of extraction and waste of supply.[230] The "Food Intakes Converted to Retail Commodities Database" (FICRCD) published by Bowman *et al.* were included to account for ingredient mass lost during ingredient processing and production (e.g., refuse losses including skin and stalks or waste occurring during production).[231] Ingredient conversion factors associated with emissions attributable to industrial ingredient cooking upstream of retail (e.g., industrial roasting, sweetening or breading) were incorporated based on relative values made available in previous research.[232-234] Finally, a factor was applied to account for the known mass change when producing cheese from milk (about 10 kg of milk are required to make 1 kg of cheese).[235] This was relevant to any cheese product with milk listed as the first ingredient and any cheese ingredient with milk listed as the first sub-ingredient.

The final GHGe estimate for each ingredient listed on the included products was obtained by matching an ingredient-specific GHGe value identified through either the search or after a conversion factor was applied. The ingredient GHGe estimate captured most of the emissions attributable to each ingredient from cradle-to-farm gate. Ingredients were assumed to be non-organic, raw and unaltered unless otherwise specified on product packaging. Nuances that may further contribute to ingredient GHGe values, such as greenhouse-heated vegetable production, beef from dairy herds, industrial processing and storage, were not included in this analysis due to limited data availability on product packaging. Post-production ingredient losses due to processing occurring after the farm gate (e.g., the evaporation of milk when baked into a cake) were also not included.

The ingredient GHGe data were matched to the FoodSwitch ingredient data derived in Chapter 3. In many cases, multiple similar FoodSwitch ingredients were assigned the same GHGe value. If an exact match did not exist for an ingredient, the closest possible match was used (e.g., 'goji berry' was mapped to 'currants and gooseberries'). Organic ingredients were matched to organic LCA values where possible.

4.2.2 Product-specific greenhouse gas emission calculation

Each product-specific GHGe estimate (kg CO_2eq/kg product) was calculated from the ingredient data by summing the GHGe value for each ingredient, proportioned by the ingredient weight in the product. Product-specific estimates were further adjusted to account for GHGe attributable to processing and transport. The product-specific GHGe estimates and uncertainty intervals were determined using a Monte Carlo simulation, also known as a multiple probability simulation or probabilistic sensitivity analysis. The simulation iteratively generated random values based on provided probability distribution functions for input variables to derive a probability distribution for the product-specific GHGe output.[236] The three input variables considered in the Monte Carlo calculation were (1) ingredient GHGe values, (2) the processing adjustment factor and (3) the transportation adjustment factor.

4.2.2.1 Incorporating uncertainty attributable to ingredient GHGe values

Each ingredient greenhouse gas emission value was assigned a probability distribution informed by the number of identified LCAs for that ingredient and by the granularity of the underlying LCA data. For ingredients with values reported in two or more LCA databases (224/433; 51.7%), a PERT distribution (a three-point estimation technique with a bell-shaped curve)[237] was assumed based on previously reported ingredient LCA data.[117] A PERT distribution requires a minimum, maximum and mode to produce a defined mean and variance:

$$Mean: \mu = \frac{(min + (4 * mode) + max)}{6}$$

$$Standard\ deviation: \sigma = \frac{(max - min)}{6}$$

The minimum was assigned as the lowest GHGe value for each ingredient, the maximum was assigned as the highest GHGe value for each ingredient and the mode was assigned as the median of all values.

The remaining ingredients had only one LCA data source (209/433; 48.3%). One of the LCA data sources was a meta-analysis of published producer-level GHGe data and provided a mean and SD for the majority of ingredients.[128] For the 13/433 (3.0%) ingredients mapped to GHGe values from this database, a normal distribution was assumed and the provided mean and SD were used. The other data sources contained only a point estimate of GHGe for each ingredient without a measure of variance. For these ingredients (196/433; 45.3%) a PERT distribution was assumed. The known value was assigned as the mode. The minimum and maximum values were imputed based on the values for similar ingredients with two or more GHGe values. Specifically, the mean proportional difference between ingredient modes and ingredient minimums for all ingredients with two or more values was calculated by major ingredient category. This proportional difference was applied to determine the lower bound for ingredients of the same major ingredient category with only one GHGe value. This meant that all ingredients of the same major ingredient category with one GHGe value and no provided distribution data had the same proportional difference between the minimum and the mode. The same was done to determine the maximums.

4.2.2.2 Incorporating uncertainty attributable to adjustments for processing and transport

The base GHGe estimates derived from the ingredients were all adjusted for processing and transport and the variability in these adjustment factors were reflected in the uncertainty interval provided for the GHGe estimate of each product. This was done based on methods developed for previous research that estimated the uncertainty associated with whether products were domestically-sourced or imported.[238]

Briefly, based on that study, the adjustment factor distributions for both processing and transport in this analysis were assumed to be triangular. The triangular distribution has continuous probability with a triangular shaped density defined by a mode and inclusive lower and upper limits.[239]

The variability in the processing and transport adjustment factors were determined using data in the Poore and Nemecek (2018) report,[117] which contains GHGe information broken down by life cycle phase for food and beverage commodities. For this analysis, the processing and transport GHGe values contained in the Poore and Nemecek report were isolated and calculated as a percentage of the total emissions for each commodity. Then, the relevant commodities reported in Poore and Nemecek were mapped to each product category in FoodSwitch. This provided a minimum and maximum value for the proportion of emissions attributable to processing and transport for each product category. The minimum value was assigned as the percentage contribution of GHGe of the commodity with the lowest contribution mapped to each product category, and the maximum value was assigned as the percentage contribution of GHGe of the commodity with the highest contribution. The mode for the processing and transport adjustment factors was determined based on the distribution of product NOVA classification groups and country of origin label groups across product categories (**Table 4.2**) (**Supplementary information S4.1**).

Table 4. 2. Adjustment factor ranges for level of processing and transport

Poore and Nemecek category[1]	FoodSwitch product category	NOVA classification			Country of origin		
		Min	Mode	Max	Min	Mode	Max
All[2]	Bread and bakery products	0.006	0.231	0.294	0.047	0.216	0.654
	Convenience foods	0.002	0.198	0.268	0.047	0.135	0.579
	Confectionery	0.001	0.264	0.276	0.047	0.225	0.431
	Non-alcoholic beverages	0.002	0.143	0.279	0.048	0.211	0.713
	Snack foods	0.001	0.223	0.280	0.047	0.206	0.713
	Foods for specific dietary use	0.000	0.216	0.277	0.043	0.141	0.420
	Sauces, dressings, spreads and dips	0.001	0.213	0.275	0.043	0.132	0.683
Grains	Cereal and grain products	0.000	0.076	0.151	0.048	0.111	0.248
Sugars	Sugars, honey and related products	0.014	0.120	0.158	0.378	0.413	0.727
Pulses, nuts and soy	Meat alternatives	0.000	0.208	0.277	0.065	0.127	0.238
Nuts and seeds	Fruit, vegetables, nuts and legumes (nuts and legumes)[3]	0.025	0.063	0.149	0.109	0.157	0.240
Oils	Edible oils and oil emulsions	0.050	0.074	0.166	0.046	0.051	0.080
Fruits and vegetables	Fruit, vegetables, nuts and legumes (fruit and vegetables)[3]	0.000	0.059	0.132	0.235	0.302	0.430
Meat	Meat and meat products	0.021	0.047	0.072	0.020	0.025	0.047
Milk and cheese	Dairy	0.035	0.051	0.054	0.026	0.028	0.032
Eggs	Egg and egg products	0.000	0.008	0.100	0.000	0.003	0.019
Seafood	Seafood and seafood products	0.001	0.003	0.005	0.019	0.033	0.049

[1]The Poore and Nemecek categories were created by combining two or more products to align with the FoodSwitch categories. [2]'All' considers the data from across relevant Poore and Nemecek food commodities. [3]The FoodSwitch category 'Fruit, vegetables, nuts and legumes' was separated in to two subgroups of 'Nuts and legumes only' and 'Fruit and vegetables only' for the purpose of applying more granular proportions.
The adjustment factor values displayed are the estimated proportion of emissions that processing and transport, respectively, add to the base greenhouse gas emission estimate. The proportion, which varies by food category as well as by processing and transport group, is based on the median percentile according to the distribution in number of products in each processing and transport group. Processing emissions were defined as those associated with butchering, pasteurizing, dehulling, milling and similar practices. Transport emissions were defined as those contributed by the movement of product from farm to processor and processor to retail.

The NOVA classifications available in FoodSwitch were used (**Supplementary Table S4.1**).[27,29,32,214] FoodSwitch product categories were each assigned a NOVA classification (Group 1, 2, 3, 4) based on the definitions outlined previously in **Table 1.1**. The presence of one or more specified additives on the ingredient list was used to further refine the NOVA classifications to be product-specific. This was done using the ingredient disaggregation and categorisation described in Chapter 3. Additives signifying ultra-processed products were defined as any ingredient considered an acid or acidity regulator, agent, colour, flavour, emulsifier, extract, preservative, thickener or stabiliser; any sweeteners other than sugar, maple syrup, and honey (e.g., dextrose, fructose, maltitol); and protein powders (**Supplementary Table S4.2**). Vitamins, minerals and live cultures used as product fortifications were not considered additives. Any product containing one of the specified additives, which was not originally classified as Group 4,

was reclassified as Group 4. Similarly, products classified in Group 4 during category assignments that were found to have none of the specified additives were reclassified to Group 3.

The country of origin groupings were determined using the mandatory Australian country of origin label, which includes information about the proportion of ingredients acquired onshore or offshore and the site of the product's processing (**Supplementary Table S4.3**).[240,241] Since its implementation in 2016, the FoodSwitch database has stored data pertaining to the Australian country of origin label. The label is governed by the Australian Competition and Consumer Commission (ACCC) and aims to promote transparency in the food supply and enable data to support future policy on both the health and environmental impacts of products.[242] The standard country of origin label has up to three components: (1) the green and gold kangaroo which is only printed on packaged products if they were grown, produced, or made in Australia, (2) the bar chart showing the minimum proportion of Australian ingredients in the food and/or (3) the text statement used to make a claim about whether the food was grown, produced, or made in Australia or overseas. For the purpose of this analysis, the 9 label types defined by the ACCC were collapsed into four groups (**Table 4.3**).

Table 4. 3. Country of origin label groups and distribution for FoodSwitch products

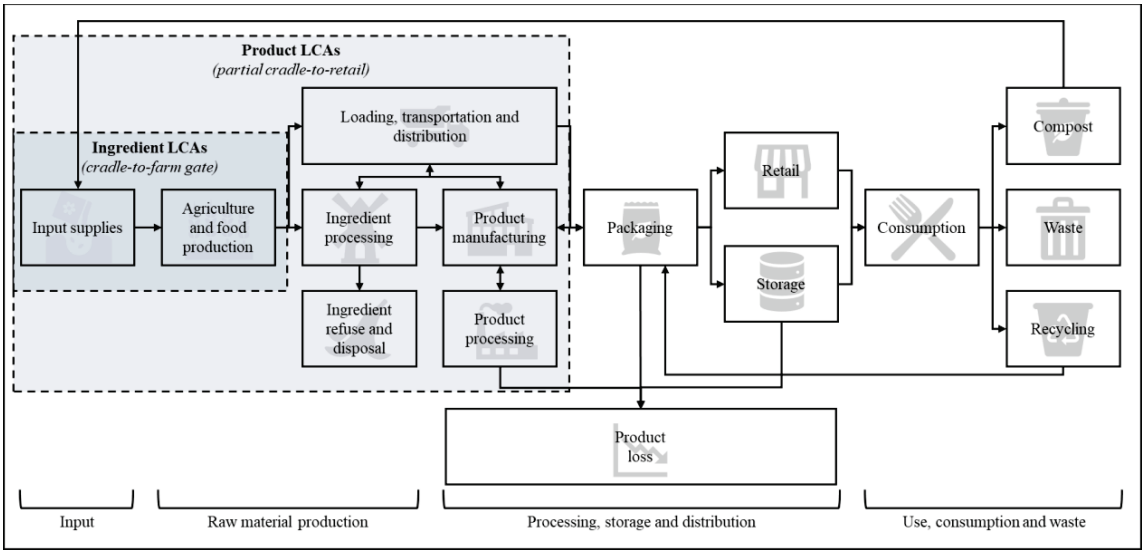
Country of origin group	Label type[1]	No. of products	Percentage
Group 1	Made in Australia from Australian ingredients	12,084	51.3%
	Grown in, produced in or product of Australia	2,399	10.2%
	Packed in Australia from Australian ingredients	2,653	11.3%
Group 2	Made, produced or imported from overseas	4,780	20.3%
	Packed overseas from imported ingredients	472	2.0%
Group 3	Made in Australia from Imported ingredients	204	0.9%
	Packed in Australia from Imported ingredients	893	3.8%
Group 4	Made overseas from Australian ingredients	45	0.2%
	Packed overseas from Australian ingredients	20	0.1%
		23,550	*100%*

[1]The four internally defined groups were determined based on the distance travelled depending on the origin of ingredients (Australia or overseas) and the location of packaging and production (Australia or overseas). Products made of Australian ingredients and packaged in Australia would have travelled least; whereas products made of Australian ingredients, packaged overseas and then imported back to Australia would have travelled most.

The median (50th percentile), IQR (25th and 75th percentiles) and corresponding 95% uncertainty interval (95% UI from the 2.5th and 97.5th percentiles) for each product's GHGe estimate was determined using 1,000 Monte Carlo simulation iterations. For each iteration, ingredient-level GHGe values, an adjustment factor for processing emissions and an adjustment factor for transport emissions were repeatedly and randomly selected based on the provided distributions. The estimated product-specific GHGe represents the majority of emissions attributable to product development from cradle-to-retail including processing and transport upstream from retail (**Figure 4.2**). In this analysis, emissions

attributable to post-production product waste, packaging materials and refrigeration have not been included, so the GHGe estimates represented *partial* cradle-to-retail values.

Figure 4. 2. System boundaries used for ingredient and product greenhouse gas emission estimates



This graphic represents the stages, including both actors and processes in a food system life cycle assessment study across the four main phases: (1) 'Inputs', (2) 'Raw material production', (3) 'Processing, storage and distribution' and (4) 'Use, consumption and waste'. Each solid line box represents a food system actor that performs one or more key food production tasks requiring inputs and outputs and associated with environmental impacts. The single and bi-directional arrows represent the common path of the flow of food and beverage production inputs and outputs. The dashed line boxes represent the system boundaries used to estimate ingredient greenhouse gas emission values and product-specific greenhouse gas emissions based on the methods in this thesis.

4.2.3 Data validation

Product-specific GHGe estimates were validated by comparing to the results reported in the Poore and Nemecek (2018) report. Poore and Nemecek summarised data from farms, processors, manufacturers and retailers[117] and used a meta-analysis to produce cradle-to-retail gate LCA estimates on GHGe and other impact factors for broad food groups. Poore and Nemecek also quantified the contribution of GHGe across production phases including agriculture, processing, transport, packaging and retail. To use the data for validating the product-specific GHGe estimate ranges, the 732 relevant product categorisations available in FoodSwitch were aligned with 34 Poore and Nemecek food groups. For optimal comparability, the GHGe values from the Poore and Nemecek supplemental database included only the emissions from agriculture through to transport for each food group (i.e., excluding emissions associated with packaging, retail and product losses).

4.2.4 Statistical analysis

First, product ingredients were analysed. Descriptive statistics regarding the mapping of FoodSwitch ingredients to GHGe values from LCA data sources were reported. Statistics on the application of ingredient conversion factors were also described. Second, products and product categories were analysed. Descriptive statistics (median (95% UI) and IQR) of GHGe estimates were calculated overall and for the 16 FoodSwitch categories based on the results of the Monte Carlo simulation. The median estimated GHGe contributed by processing and transport were assessed as a proportion of attributable total emissions for each category.

To validate the results, median values derived from the product-specific GHGe estimates were compared against the values for the corresponding GHGe values for the 34 Poore and Nemecek food groups.[117] Then, the median product-specific GHGe estimates and 95% UIs were plotted against Poore and Nemecek values and the data were assessed using the coefficient of determination (R^2) and the Spearman's rank coefficient (ρ). All statistical analyses were conducted using Stata BE 17.

4.3 Results

4.3.1 Ingredient greenhouse gas emission mappings

Five LCA data sources containing ingredient GHGe values pertaining to cradle-to-farm gate emissions were used: Clune *et al.,*[128] Ecoinvent 3.7.1,[243] dataFIELD v1.0,[184] CleanMetrics[244] and Agri-footprint 5.0[245,246] (**Table 4.4**). 433 ingredient GHGe values were identified: 376 were non-organic ingredient GHGe values, 45 were organic ingredient GHGe values and 12 were composite ingredient GHGe values. Of the 433 unique ingredients extracted from the LCA databases, 224 (51.7%) had two or more associated ingredient LCAs with GHGe values. For the remaining 209 (48.3%) ingredients with only one underlying GHGe value, 196 (45.3%) had only point estimates with no variance estimate, and 13 (3.0%) came from the Clune *et al.* database containing a mean and SD.

Table 4. 4. Life cycle assessment data sources containing food ingredient data

Ingredient data source	Description	System boundary[1]	No. of ingredient LCAs	No. of ingredient LCAs used	No. of organic ingredient LCAs used
Clune *et al.* 2017	Systematic review of fresh produce GHGe data	Cradle-to-regional distribution centre	213	162	32
Ecoinvent v3.7.1	Worldwide lifecycle inventory database	Cradle-to-farm gate	197	122	7
dataFIELD v1.0	Food GHGe data gathered by US researchers	Cradle-to-farm or processor gate	352	235	-
CleanMetrics	Simplified food GHGe calculator based on a subset of CarbonScopeData	Cradle-to-farm or processor gate	287	185	16
Agri-footprint 5.0	Life cycle inventory database for the agriculture sector	Cradle-to-farm gate	185	83	-
Ingredient GHGe Database	*An aggregated dataset of the above 6 sources*	*Cradle-to-farm or processor gate*		*433*[2]	*45*[2]

[1]Listed as provided in original source; additional information was obtained from authors to align the end boundary to farm gate. All functional units are specified to be kg CO_2eq/kg product, where CO_2eq = Carbon dioxide emissions equivalent. [2]433 was the total (organic and non-organic) number of unique ingredient LCAs after matching across the data sources; 45 was the number of unique organic ingredient LCAs after matching across the data sources.

All FoodSwitch ingredients were matched to an ingredient GHGe value from the aggregated LCAs. For 263 (29.4%) of the 895 FoodSwitch ingredients, there was an exact match to one of the LCA values. For the other 632 (70.6%), the closest possible match was made. 575 (64.2%) of ingredients required the application of one or more conversion factor (**Table 4.5**). For example, the GHGe value for the ingredient 'almond meal' was derived from the GHGe value for 'almond' and required the application of two conversion factors: 1.03 for change in mass and 2.00 for ingredient processing. Additives required the largest proportion of matches to the most similar ingredient (542/895; 60.4%) rather than the exact ingredient. The 45 organic ingredients were matched to 622 out of the 3,978 (15.6%) ingredients in FoodSwitch identified as organic ingredients. Organic ingredients that could not be matched to an organic GHGe LCA were assigned the non-organic value.

Table 4. 5. Ingredients and greenhouse gas emission data available from life cycle assessments

Ingredient type	No. of ingredients	Identical match	Matched with farming conversion factor[1]	Matched with preparation conversion factor[2]	Matched with cooking conversion factor[3]	Matched with most similar ingredient[4]
Additives	*86*	32	1	1	0	52
Baking ingredients	*10*	7	0	1	0	2
Compound ingredients	*118*	44	2	13	6	53
Dairy	*55*	24	2	3	1	25
Dietary fibres	*4*	2	0	0	0	2
Eggs	*8*	5	0	2	0	1
Flours and starches	*17*	4	4	0	6	3
Fruits and vegetables	*225*	10	34	36	138	9
Grains	*48*	25	11	1	2	9
Herbs and spices	*35*	9	4	3	5	14
Legumes	*24*	3	17	0	2	2
Liquids	*72*	31	5	6	11	19
Meat	*56*	12	2	39	0	3
Nuts and seeds	*34*	5	2	9	14	4
Oils and fats	*33*	19	2	2	1	9
Seafood	*40*	19	0	16	0	5
Sweeteners	*30*	13	3	0	0	14
	895	*264*	*89*	*132*	*186*	*226*

[1]Ingredient conversion factors accounting for the removal of seeds, peels, stalks and other excess occurring during farming and ingredient processing (*Source:* Technical Conversion Factors for Agricultural Commodities (TCFAC). Food and Agricultural Organization of the United Nations). [2]Ingredient conversion factors accounting for ingredient mass lost during ingredient processing and production such as refuse losses including skin and stalks or waste occurring during production (*Source:* Bowman SA, *et al.* 2013. Food Intakes Converted to Retail Commodities Databases: 2003-08: Methodology and User Guide. U.S. Department of Agriculture, Agricultural Research Service). [3]Ingredient conversion factors accounting for emissions associated with cooking and other ingredient alterations such as sweetening, breading and drying. [4]Similarly matched ingredients are defined as any ingredient for which a proxy was used to determine the suggested GHGe value. Ingredient emissions data regarding greenhouse-heated vegetable production, beef from dairy herds and industrial storage were not included in this analysis due to limited availability.

4.3.2 Product-specific greenhouse gas emission estimates

The median (95% UI) product-specific partial cradle-to-retail GHGe estimate for all products was 2.24 (95% UI: 1.22-4.20) kg CO_2eq/kg product (range [0.0002, 73.5]; IQR [1.03, 6.94]) (**Table 4.6**). Across main categories, the first and third quartiles differed by three-fold and by up to seven-fold for some subcategories. 'Fruit, vegetables, nuts and legumes' had the lowest median GHGe value (1.04 (95% UI: 1.02-1.06) kg CO_2eq/kg product; IQR [0.48, 2.01]). 'Egg and egg products' (IQR [3.49, 4.24]) and 'Edible oils and oil emulsions' (IQR [2.89, 4.13]) had the smallest ranges in values.

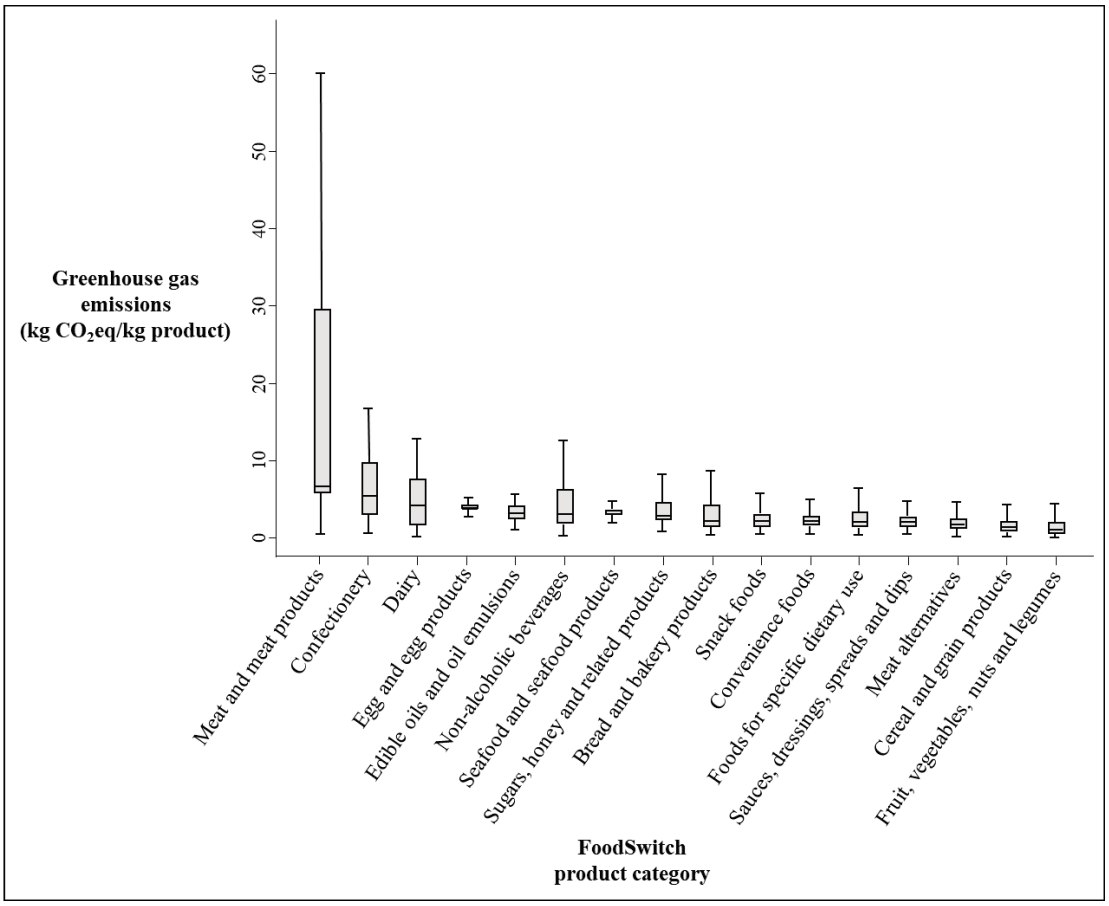
Table 4. 6. Descriptive statistics for product-specific greenhouse gas emissions by product category

FoodSwitch product category	No. of products	Median GHGe estimate	[IQR]
Overall	*23,550*	*2.24*	*[1.03, 6.94]*
Bread and bakery products	2,345	2.29	[1.32, 3.56]
Cereal and grain products	1,952	1.34	[0.70, 2.22]
Confectionery	1,277	6.07	[3.31, 9.88]
Convenience foods	1,418	2.23	[1.25, 3.89]
Dairy	2,956	4.14	[2.81, 7.95]
Edible oils and oil emulsions	495	3.48	[2.79, 4.38]
Egg and egg products	89	3.87	[3.50, 4.23]
Foods for specific dietary use	761	2.13	[1.18, 4.25]
Fruit, vegetables, nuts and legumes	3,766	1.04	[0.48, 2.01]
Meat alternatives	195	1.66	[1.06, 2.43]
Meat and meat products	1,724	6.93	[5.78, 29.7]
Beef and game	234	53.9	[48.6, 57.4]
Beef and game products	76	44.1	[39.1, 46.7]
Lamb	127	27.9	[26.8, 31.9]
Lamb products	3	23.7	[15.3, 25.0]
Meat-based meals	315	5.14	[4.12, 7.78]
Other meat products	88	36.5	[6.44, 47.6]
Pork	130	7.38	[6.98, 8.06]
Pork products	463	6.42	[5.88, 6.80]
Poultry	213	6.41	[6.18, 6.99]
Poultry products	75	5.89	[4.69, 5.98]
Non-alcoholic beverages	2,436	3.17	[1.64, 6.08]
Sauces, dressings, spreads and dips	2,327	1.82	[1.11, 2.75]
Seafood and seafood products	682	2.66	[2.01, 4.75]
Snack foods	722	2.25	[1.48, 3.21]
Sugars, honey and related products	405	2.37	[1.66, 3.26]

The median and IQR values for each FoodSwitch product category are derived from the results of a Monte Carlo simulation of 1,000 iterations.
GHGe: Greenhouse gas emission estimates, provided in (kg CO_2eq/kg product)
IQR: Interquartile range

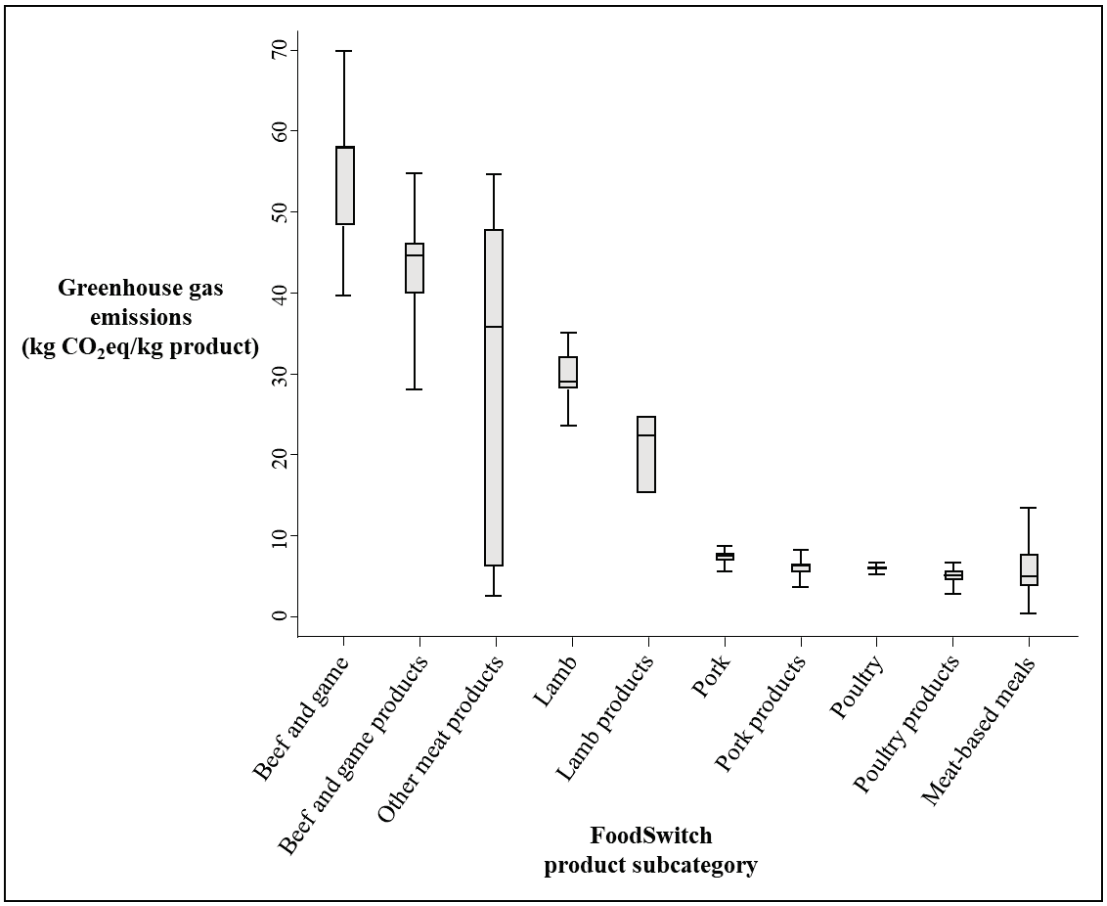
'Meat and meat products' had the highest median GHGe value (6.93 (95% UI: 5.39-14.8) kg CO_2eq/kg product and broadest range in IQR values ([5.78, 29.7]) (**Figure 4.3**). Median GHGe values for beef, game and lamb products were over four times greater than that of other meat products and 10-20 times greater than that of plant-based meat alternatives (**Figure 4.4**) (**Supplementary Figures S4.2 and S4.3**). 'Poultry products' and 'Meat-based meals' (pre-made foods containing portions of vegetables and grains alongside meat) had the lowest median GHGe values amongst the 'Meat and meat products' subcategories (5.89 (95% UI: 5.73-5.99) kg CO_2eq/kg product and 5.14 (95% UI: 4.89-5.33) kg CO_2eq/kg product, respectively) (**Supplementary Table S4.4**).

Figure 4. 3. Product-specific greenhouse gas emission estimates across main product categories



This box-and-whisker plot displays the interquartile range of greenhouse gas emission values and the median value is marked by the line within the box. The whiskers extend to the lowest datum within 1.5 times the lower quartile and the highest datum within 1.5 times the higher quartile. Outlier values are excluded from the visualisation. The 16 categories are defined within FoodSwitch.

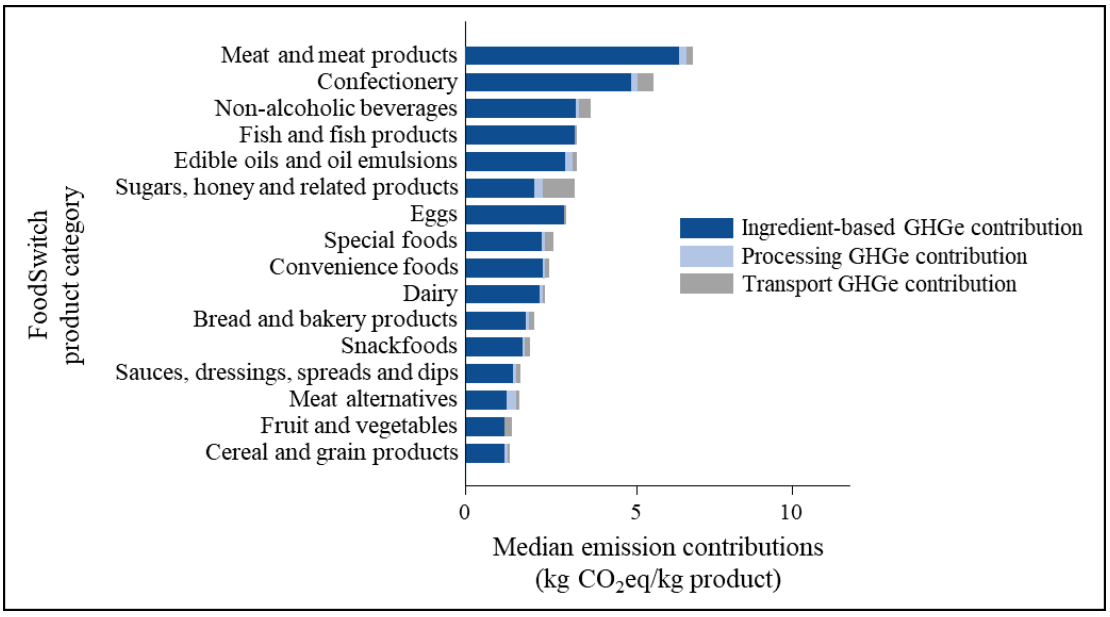
Figure 4. 4. Product-specific greenhouse gas emission estimates across meat and meat product subcategories



This box-and-whisker plot displays the interquartile range of greenhouse gas emission values and the median value is marked by the line within the box. The whiskers extend to the lowest datum within 1.5 times the lower quartile and the highest datum within 1.5 times the higher quartile. Outlier values are excluded from the visualisation. The 'Other meat products' category includes dried meats and mixed meat products.

Based on the median value derived from the Monte Carlo analysis, 88.7% of GHGe were attributable to emissions generated from cradle-to-farm gate, 4.5% to processing and 6.8% to transport. The proportion of emissions attributable to the processing and transport production phases varied greatly by product category; 'Meat and meat products' had the smallest percentage contribution (2.2% by processing and 1.4% by transport) and 'Sugars, honey, and related products' had the largest (7.9% by processing and 28.7% by transport) (**Figure 4.5**).

Figure 4. 5. Median greenhouse gas emission contributions for ingredients, processing and transport across product categories

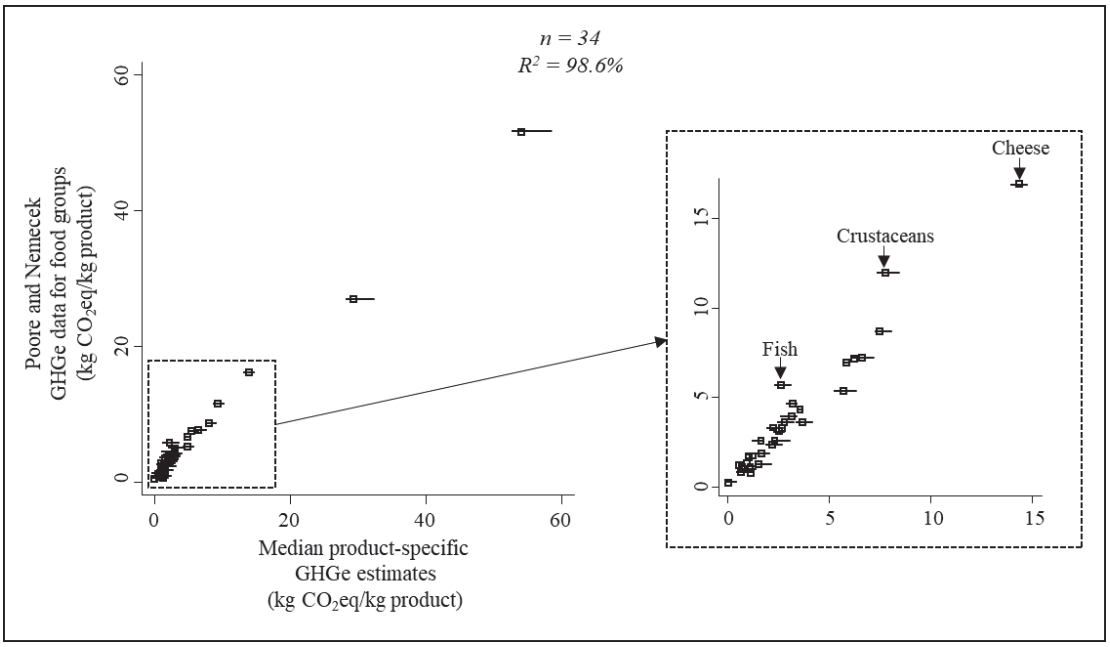


The stacked bar chart visually represents the contribution of the median estimated greenhouse gas emissions attributable to each of three production phases across sixteen FoodSwitch categories, as derived from the 1,000 iterations of the Monte Carlo analysis. The three included production phases were: (1) ingredient cultivation and processing, (2) product processing and (3) product transport.

4.3.3 Validation of estimates by product category

The median GHGe estimates calculated using product-specific GHGe values largely aligned with the median GHGe data for 34 food groups previously reported by Poore and Nemecek (R^2=92.3%, ρ=94.8% and *p*-value<0.001) (**Figures 4.6 and 4.7**). The product-specific GHGe values slightly underestimated the Poore and Nemecek GHGe data (2.24 kg CO_2eq/kg product over all products compared to 2.42 kg CO_2eq/kg product over all food groups). Twenty-one of the 34 product-specific GHGe median estimates underestimated the Poore and Nemecek GHGe data for food groups. 'Fish' and 'Crustacean' products were substantially underestimated by the product-specific calculations (2.84kg CO_2eq/kg product compared to 5.08 kg CO_2eq/kg product and 8.93 kg CO_2eq/kg product compared to 11.3 kg CO_2eq/kg product, respectively).

Figure 4. 6. Validation of median product-specific greenhouse gas emissions estimates

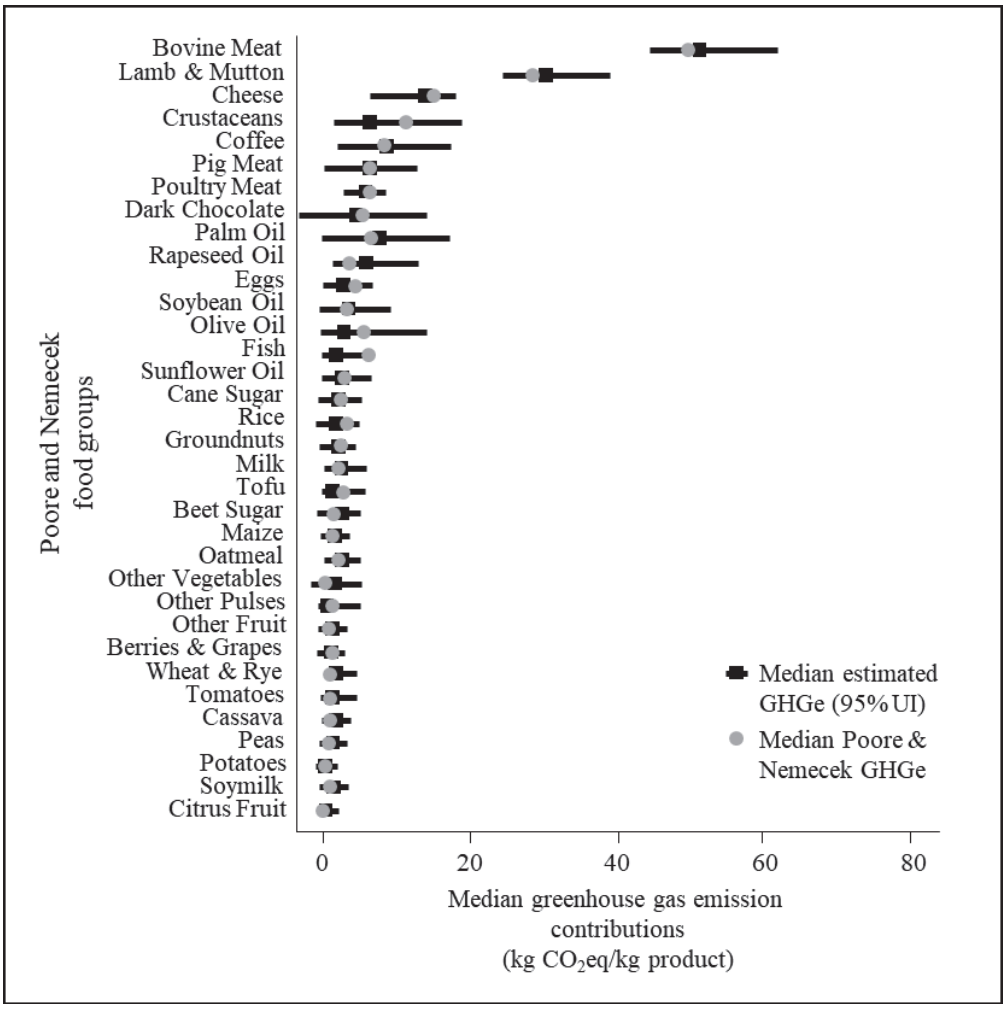


Source: Adapted from Gaines A, Davies T, Shahid M, Taylor F, Wu JHY, Hadjikakou M, Pettigrew S, Seferidi P and Neal B. A Novel Approach to Estimate Product-Specific Greenhouse Gas Emissions for 23,550 Australian Packaged Foods and Beverages. *Journal of Cleaner Production*. 2023:138816.

This scatterplot shows data points for each of the 34 Poore and Nemecek food groups. The points represent the median GHGe estimates for FoodSwitch products compared to the Poore and Nemecek GHGe values. The error bars represent the 95% uncertainty intervals around the median. Underestimated values are considered those that fall to the left of the 45° line. R^2 is the coefficient of determination, which represents the proportion of variance in GHGe as explained by the estimation methodology, where 100% indicates a perfect fit.

GHGe: Greenhouse gas emissions

Figure 4. 7. Validation of range in product-specific greenhouse gas emission estimates



Source: Adapted from Gaines A, Davies T, Shahid M, Taylor F, Wu JHY, Hadjikakou M, Pettigrew S, Seferidi P and Neal B. A Novel Approach to Estimate Product-Specific Greenhouse Gas Emissions for 23,550 Australian Packaged Foods and Beverages. *Journal of Cleaner Production*. 2023:138816.

The black boxes show the median and the black error bars show the 95% uncertainty intervals around the median GHGe values derived from the Monte Carlo analysis. The 34 median GHGe values for food groups shown are defined in Poore and Nemecek 2018 report and are indicated by the grey circles.

GHGe: Greenhouse gas emissions

4.4 Discussion

The methodology described above used widely available product and GHGe data to determine product-specific GHGe estimates for the majority of food and beverage products sold in Australian supermarkets in 2019. The product-specific GHGe estimates enabled an assessment of the breadth in GHGe associated with products within a given category. The 'Meat and meat products' category had a significantly higher median GHGe estimate than all other product categories, driven by the high GHGe

attributable to beef, game and lamb. The broad range in product-specific GHGe estimates within the 'Meat and meat products' category was due to the more than 5-fold difference between GHGe attributable to poultry ingredients and the GHGe attributable to beef ingredients.[117] On average, there were 3-fold or greater differences between the products with the lowest versus highest estimated GHGe in every category, and up to a 20-fold difference in GHGe estimates for products within the 'Convenience foods' and 'Non-alcoholic beverages' categories. The breadth in GHGe estimates within the 'Convenience foods' category was largely due to the presence of small amounts of meat and dairy in some of the included products; whereas the breadth in GHGe estimates within the 'Non-alcoholic beverages' category was largely attributable to coffee and coffee-based products.[117]

4.4.1 Comparison with existing literature

One similar study exists that also estimated the GHGe of specific retail products using ingredient LCA data and publicly available product data, however it used food and beverage data from supermarkets in the United Kingdom and Ireland.[183] The results presented by Clark *et al.* largely align with the work presented here, with animal-based products contributing higher levels of GHGe per product and plant and fruit-based products contributing lower levels of GHGe per product. As was done in this analysis, they concluded that there was large variability in product-specific GHGe estimated within each product category. The Clark *et al*. research benefitted from assessing GHGe along with three additional environmental impact metrics (scarcity-weighted water use, land use and eutrophication potential) as well as an environmental impact score that combined all four factors. The primary difference between the product-specific GHGe estimation methodology used in Clark *et al.* and in this work was the alternative approach used to determine non-disclosed proportions of ingredients. Instead of a linear programming algorithm, Clark *et al.* interpolated missing ingredient proportion data using similar products which provided the ingredient proportion along with the ingredient rank (how far down the ingredient list the ingredient of interested was found).[183] As discussed in Chapter 3, it is likely that interpolation does not capture as many differences in recipes of similar products as the linear programming method does.

There are a small number of studies and non-academic organisations that have assessed GHGe at the product level using methods that rely on accessing additional private data and are only applied to a subset of available retail products. The Eco-Score, the Eaternity score and SHARP-ID[148,233,247] are examples of such works that provide product-specific GHGe metrics for foods and beverages. These approaches also benefit from including a broader range of sustainability measures such as water use, land use and acidification. However, the Eco-Score and Eaternity score, both implemented as labels, are limited in scope by their reliance on manufacturers providing supplementary data about aspects such as ingredients, processing and packaging.[148,247] The SHARP-ID database is limited in that it contains data for less than 200 data retail products.[233] In this analysis, only GHGe was assessed at this time

because there were far more ingredient-specific LCA data for GHGe than for other measures of environmental impact, which increased the ability to differentiate between similar products.[117] It has been found that GHGe was most effective in influencing stakeholder decision making compared to other environmental factors.[150] Including a wider range of sustainability metrics (e.g., water use, land use and acidification) is, however, important and will be planned as information becomes available for a larger proportion of ingredients.

The majority of existing research assessing GHGe attributable to food and beverage products presents results for general commodities and broad categories.[117,128,248] Such studies provide only high-level GHGe values and cannot be mapped to products as available in retail stores. Overall, the product-specific method presented in this chapter provided good approximations of corresponding values derived for main product categories reported by the most comprehensive consolidation of food and beverage GHGe information to date.[117] This adds substantially to literature by producing the first GHGe estimates of products as purchased by consumers in Australia.

4.4.2 Strengths and limitations

A tenet of this approach was to use ingredient list information available on product packaging, providing the potential to produce a GHGe estimate for every product on the supermarket shelf. The capacity to differentiate between GHGe for thousands of foods and beverages using only standard information available on a product's packaging represented a significant step forward because it makes the comparison of individual products feasible at scale and at low cost. Defining product-specific GHGe estimates provided the opportunity to make more granular, within-category comparisons. For example, the disparity in GHGe associated with pre-packaged sandwiches can be attributed to simple differences in filling ingredients such as beef versus chicken, information which is available on pack but not often with any indication of GHGe impact.[249]

The Monte Carlo simulation provided a sensitivity analysis of how uncertainty in ingredient LCA, processing and transport GHGe data may influence a product's estimated attributable GHGe. The results suggested that variable GHGe information on ingredient sourcing, processing and transport was unlikely to have a major impact on relative analyses comparing product-specific GHGe estimates within and across broad product categories (**Supplementary information S4.2**). Still, these data are important to consider for future research because they can improve the accuracy of each product-specific GHGe estimate.

While this methodology is a significant advance, it required a series of assumptions and approximations. The GHGe adjustments made to account for product processing and transportation were limited by the availability of standardised and regulated product information. There is no standardised system to

categorise foods according to their level of processing.[250] The NOVA classification[29] was used as it is currently the most commonly employed system and has been used in diet-related research.[109,251] Though it has been criticised for the lack of standardisation when applied individual products, I improved the NOVA classification assignment in FoodSwitch by making it product-specific rather than group-level using information on additives in the ingredient list (from Chapter 3) and aligning the classification assignment with existing work.[67] Transportation emissions were estimated using country of origin information which was also very crude. Previous research has used distance travelled (often referred to as 'food miles')[240] but this information is not available in the FoodSwitch database and is typically not available for large product databases. However, as processing only comprises around 4-8% of food system emissions, and transportation only around 5-10%,[5] errors in estimating GHGe attributable to processing and transport should not have a major impact on the final product GHGe estimates. Particularly for products produced and marketed within Australia, it should be noted that this adjustment method underestimated the differences between similar products. For example, products produced and marketed in Western Australia will have the same values as products produced in Western Australia but marketed in New South Wales, despite the 3,000km difference in distance travelled. Improvements in ingredient list specification criteria (e.g., for ingredient processing methods and ingredient origin) as well as the product's overall extent of processing would enable a more comprehensive and generalisable methodology for estimating product-specific processing and transport emissions.

The product-specific GHGe estimates, both overall and for most product categories, were a slight underestimation compared to the corresponding average Poore and Nemecek values. In addition to the limitations of processing and transport GHGe data described above, while ingredient refuse was accounted for, this method did not account ingredient losses from post-production processing. For example, mass change during the transformation process from ingredient to product (e.g., the evaporation of milk when baked into a cake) was only addressed in the case of cheese where the mass change factor is particularly large (approximately 10) when converting milk to cheese. This is likely an issue affecting more food ingredients, albeit with smaller mass change factors. Further, the GHGe values for an ingredient can vary depending on the farming technique (e.g. greenhouse versus field grown), year of production and the type of LCA protocol used.[117,191,252] Ingredient lists do not require standard reporting of the descriptors required to differentiate these characteristics. While the aggregate database of GHGe for ingredients used here expanded substantially upon the largest compiled to date,[233] a number of GHGe values assigned to ingredients were still estimated from a generic ingredient, a less-processed version of the same ingredient, or by using estimates for the closest matching ingredient. For example, the underestimation of GHGe attributable to fish and crustacean products is likely due to the focus on farmed seafood in the Poore and Nemecek report. There was an absence of comprehensive LCA data for specific farmed versus wild-caught seafood products to inform the findings presented here.[253]

In addition to underestimation of product-specific GHGe, the absence of precise ingredient GHGe data will likely also have contributed to underestimation of the true variability in GHGe between food products. The level of granularity available on product ingredient lists did not enable comparisons of more subtle differences in production systems, such as information on the use of renewable energy in the supply chain. As is commonly the case in LCA studies,[183] this compromises the capacity of this approach to discriminate between GHGe estimates, particularly for single- and minimal-ingredient products. For example, many products categorised under 'Egg and egg products' were assigned the same single GHGe value available for eggs, but in practice there are likely to be significant differences between products using eggs from battery versus free-range facilities.

The system boundary used in this analysis, which included ingredient LCA data from cradle-to-farm gate with additional adjustments for product processing and transport, was designed to account for the majority of emissions prior to retail but did not include emissions attributable to packaging, refrigeration or home preparation. The Poore and Nemecek data suggest packaging constitutes on average about 6% of cradle-to-retail emissions, but it is well established that GHGe attributable to packaging can vary by a large amount between product categories and between otherwise identical products that use optimally sustainable versus least sustainable forms of packaging.[5,117] Because ingredient-specific LCA data are sparse for refrigeration,[117] these were not included in the present analyses.

There were several ingredients for which both organic and non-organic forms were specified on product labels, and for which separate LCAs for the organic and non-organic ingredient GHGe data were available. When available, these data were used to explore the potential impact of absent reporting about the organic status of ingredient type and/or the absence of LCA data for organic and non-organic ingredients. The inclusion of available organic ingredient GHGe values had minimal impact on product GHGe estimates - the GHGe values for organic versus non-organic ingredients were generally similar (**Supplementary Figure S4.4**). LCA data were particularly sparse for food additives, though this probably had very limited overall impact because additives usually constituted a small proportion of the final product.

The absence of a robust gold standard against which to compare the product-specific results limited their reliability. There are few publicly available LCA data for individual supermarket products in Australia, and therefore the results presented here were compared against product category estimates made by Poore and Nemecek.[117] However, while the comparison of these product-specific GHGe estimates to individual product data would have been ideal, the broad alignment of the grouped estimates provided reassurance about the likely validity of the method.

4.4.3 Study implications and future research

This availability of product-specific GHGe estimates could be a powerful tool for driving food system actors towards more sustainable practices, as is being done for the nutritional quality of products.[150] As discussed above, much of the existing research compares average emissions of broad product categories,[117,128] ignoring potential differences between multi-ingredient products that currently comprise most of the packaged food supply. The work in this chapter could also push consumers, producers and processors, alike, to purchase and manufacture lower carbon-footprint products.[181,254-257]

In addition, it will be important to expand upon the data presented in this chapter in future research. The incorporation of additional environmental impact factors will ensure a holistic assessment of planetary impacts. Also, addressing emissions attributable to ingredient refrigeration, preparation, loss and waste will also be important for evaluation of the food system's overall GHGe contribution (see more detailed discussion in Chapter 7).

4.5 Conclusion

Our novel approach for calculating product-specific GHGe estimates had a sound underpinning rationale and provided plausible estimates across a broad range of food and beverage products. While a series of assumptions and approximations were required, the findings add significantly to the field. These data can be used to empower those seeking to choose foods that have lower carbon footprints and will help policy makers develop targeted interventions aimed at mitigating GHGe attributable to supermarket products.

Chapter 5: Associations between product greenhouse gas emissions and nutrient profiles

5.1 Introduction

Research around sustainable diets has become prominent and, similar to what was found in Chapter 4, highlights the importance of plant dominant diets and reducing meat intake while maintaining adequate nutrient consumption.[40,258] Increased awareness about the environmental impact of the food supply has prompted the development of tools for rating the environmental impact of food and beverage products.[259] This is seen commonly in eco-labels that feature certain credentials of ingredients, products, or processes, such as if an ingredient is organically farmed.[182] Carbon labelling, used to declare the GHGe associated with a product, is a form of eco-labelling that can capture impact associated with a product's ingredients and life cycle stages.[141,142] Though carbon labels are beginning to be developed at national levels, the implementation and acceptability of carbon labels is still sparse.[146-148] There is an expectation that better and more widely applied carbon labels could help meet demands for transparency in food product reporting (e.g., relativity for which products are high-emission versus low-emission) as well as encourage more sustainable purchasing behaviours.[150] However, there is also concern that carbon labels in addition to health labels will lead to consumers being misled or confused by the overabundance of information.[171,180,260]

Front-of-pack nutrition labels are commonly informed by nutrient profiling models and aim to help improve consumer behaviours and industry practices.[90,91] In Australasia, the Health Star Rating (HSR) front-of-pack nutrition label has been implemented both to highlight the nutritional quality of products to consumers and promote competition amongst manufacturers.[97,98] In other countries such as the United Kingdom, France and Chile, nutrient profiling models have been used to develop labels that aim to limit consumption of products that are high in nutrients associated with adverse health outcomes.[81,101,104] Several longitudinal studies clearly show that diets scoring worse based on nutrient profiling models are associated with increased risks of mortality and diet-related non-communicable disease outcomes.[63,80,81]

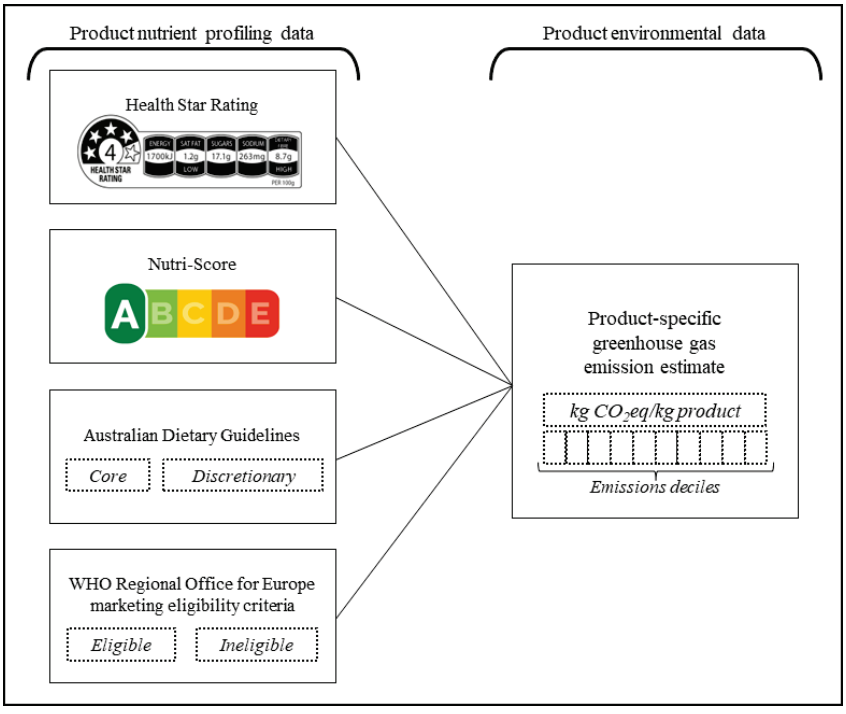
Little has been done to explore how nutrient composition and carbon labelling might be combined to promote more coordinated policies in Australia. Prior work has defined a general association of worse GHGe with food categories receiving worse average nutrient profiling scores, according to the respective model used to inform policy at the local setting.[248,261] A detailed understanding of the alignment of numerous nutrient profiling models and GHGe for individual food and beverage products is needed to drive further action from national and international governing bodies towards a sustainable

food system (e.g., to develop a national sustainable food strategy, create competition amongst major manufacturers to improve recipe formulations and production techniques or enforce a dual front-of-pack label). Thus, this chapter aimed to build upon the product-specific GHGe estimates calculated in Chapter 4 to explore the product-specific association between four nutrient profiling model outputs and GHGe estimates, both overall products and for product categories.

5.2 Methods

The FoodSwitch nutrient profiling model data and the product-specific GHGe values described in Chapters 3 and 4 were used in this analysis (**Figure 5.1**). Four nutrient profiling model scores were compared to the product-specific GHGe estimates. Two categorical nutrient profiling models (HSR, Nutri-Score) and two dichotomous nutrient profiling models (Australian Dietary Guidelines, WHO Regional Office for Europe marketing eligibility criteria) were selected for assessment. The GHGe were assessed both as a continuous variable and as deciles, or ten ordered, equally sized groups of products segmented from the continuous GHGe data.

Figure 5. 1. Chapter 5 methods workflow



The four different nutrient profiling models being compared to product-specific greenhouse gas emission (GHGe) estimates are shown above. The Australasian Health Star Rating and French Nutri-Score are categorical models. The Australian Dietary Guidelines and WHO Regional Office for Europe marketing eligibility criteria are dichotomous models. GHGe were assessed using both continuous values and ten ordered, equally sized groups (deciles).

5.2.1 Product-specific nutrient profiling models

Scoring data for each nutrient profiling model have been previously calculated within the FoodSwitch database. The scores were assigned to all applicable products using the governmental and/or publicly available guidelines and the nutrition information associated with each product.[186] The nutrient profiling models were strategically selected in order to consider regulatory systems and definitions developed by governments across different countries. Two categorical systems were included, both of which are adaptations of the Food Standards Agency nutrient profiling system developed in the United Kingdom and have been assessed for validity against food-based dietary guidelines.[262,263] In addition, two dichotomous scoring systems, which incorporate the nutritional qualities of food groups as well as product-specific nutrient profiles, were included.

5.2.1.1 Health Star Rating

The HSR has been implemented voluntarily on products in Australia and New Zealand since 2014.[96] The HSR algorithm outputs a score from 0.5 stars (worst relative nutrient profile) to 5.0 stars (best relative nutrient profile), resulting in ten groups at half-star increments. A product's HSR is determined by an overall calculation that adds points for the presence of 'positive' food components (i.e., protein, fibre and fruit, vegetable, nut and legume content) and deducts points for the presence of 'negative' food components (i.e., total energy, total sugars, saturated fat and sodium). Similar to most relevant literature, the HSR cut-point of ≥3.5 stars has been used in this study to classify products with better nutrient profiling scores.[55,264]

5.2.1.2 Nutri-Score

The Nutri-Score was developed in France for use as a front-of-pack nutrition label to inform consumer choice.[99] The Nutri-Score is similarly based on criteria that assess the inclusion of 'positive' food components (i.e., protein, fibre, fruits, vegetables, nuts, legumes and specified oil types) and 'negative' food components (i.e., energy, sugar, saturated fatty acids and salt).[99] The Nutri-Score algorithm generates a summary score with lower values representing foods with a more favourable overall profile. The model categorises products into one of five hierarchical groups, each associated with a colour and letter listed from lower to higher scores: (A) dark green, (B) light green, (C) yellow, (D) light orange and (E) dark orange. In this chapter, products categorised as (A) dark green or (B) light green were classified as having a better nutrient profile.

5.2.1.3 Australian Dietary Guidelines concept of 'core' and 'discretionary' products

Products were classified as either 'core' or 'discretionary' using definitions included in the Australian Dietary Guidelines (ADG).[55] 'Core' products were assigned based on the guidelines' Five Food Groups: (1) grain (cereal) foods, mostly wholegrain and/or high cereal fibre varieties; (2) vegetables and legumes/beans; (3) fruit; (4) milk, yoghurt, cheese and/or alternatives, mostly reduced fat; and (5) lean meats and poultry, fish, eggs, tofu, nuts and seeds and legumes/beans. 'Discretionary' products were assigned based on their levels of saturated fat, added sugars and/or salt.[54] FoodSwitch ADG classifications used the Australian Bureau of Statistics (ABS) 'Discretionary Foods' list, as ABS provides the best-available reference for classifying products specified or inferred by the ADG documentation.[187] ABS category classifications were matched to FoodSwitch categories to assign each product subcategory as 'core' or 'discretionary'.[55] 'Core' products were classified as having a better nutrient profile.

5.2.1.4 WHO Regional Office for Europe marketing eligibility criteria

The WHO Regional Office for Europe (EURO) criteria aim to restrict marketing of unhealthy products to children.[265] The WHO takes into consideration eight nutrients to limit (energy, total sugars, added sugar, non-sugar sweeteners, total fat, saturated fat, trans fat and salt), with different limits set for 21 defined categories. EURO categorises products as 'eligible' or 'ineligible' for marketing to children. Seven categories do not rely on nutrient profiling and are automatically classified as 'eligible' (i.e., fresh and frozen meat/poultry/fish and fresh and frozen fruits/vegetables/legumes) or 'ineligible' for marketing (i.e., confectionery, sweet bakery products, juices, energy drinks and edible ice).[265,266] 'Eligible' products were classified as having a better nutrient profile.

5.2.2 Statistical analysis

Descriptive statistics were calculated for the four nutrient profiling models (median for categorical models, *n* for dichotomous models) and for GHGe (median and IQR). A complete case analysis was done for each nutrient profiling model, as scores for some models could not be imputed for certain product types.

The association between individual nutrient profiling scores and GHGe was assessed by plotting the median and IQR of GHGe estimates for products with each score in the nutrient profiling models. Differences in the median GHGe estimates across the ordinal scores for each of the four nutrient profiling models (HSR, Nutri-Score, ADG and EURO) were evaluated using the Jonckheere-Terpstra test. Subsidiary analyses were done for product subsets divided into 16 main categories and a

supplemental analysis was done for 10 ‘Meat and meat products’ subcategories to align with existing research categories and allow differentiation across meat types (ruminant and monogastric).

The proportion of products classified as having a better nutrient profile by each nutrient profiling model was assessed overall and across GHGe deciles. Significance testing was again done using the Jonckheere-Terpstra test and a sensitivity analysis was performed to understand the impact of altering the cut-off points used to define products with better nutrient profiles for the categorical models. All data preparation and statistical analyses were conducted using Stata BE 17 (StataCorp) and Excel. A two-sided p-value<0.05 was considered statistically significant.

5.3 Results

All 23,550 products were assigned an ADG classification and a GHGe estimate. An HSR was available for 92.2% of products, a Nutri-Score for 89.8% and a EURO classification for 88.5%.

5.3.1 Descriptive statistics

Across all products, the median value for HSR was 3.0 and Nutri-Score was ‘C’. 49.2% of products had better HSR scores (i.e., HSR ≥ 3.5), 39.8% had a better Nutri-Score assignment (i.e., A or B), 55.3% had a better ADG classification (i.e., ‘core’) and 27.6% had a better EURO classification (i.e., eligible for marketing to children). ‘Meat and meat products’, ‘Confectionery’ and ‘Dairy’, which were found to have the highest median GHGe in Chapter 4, also had among the worst median nutrient profiling scores (**Table 5.1**). ‘Meat and meat products’, which had the broadest range of GHGe estimates, also had the widest spread of nutrient profiling scores. However, there was a clear distinction between higher emission products from ruminants (e.g., beef and lamb) and lower emission products from monogastric animals (e.g., pork and poultry), as well as the better nutrient profiling scores of plain meats and worse nutrient profiling scores of meat-based products (e.g., sausage rolls and pies) (**Table 5.2**).

Table 5. 1. Median greenhouse gas emissions and nutrient profiles across product categories

FoodSwitch product category	No. of products	Nutrient profiling models						Median GHGe [IQR] (n=23,550)	
		Median HSR (n=21,712)	Median Nutri-Score (n=21,155)	ADG Discretionary Products [N %] (n=23,550)		WHO EURO Ineligible products [N %] (n=20,838)			
Overall	*23,550*	*3.0*	*C*	*10,520*	*44.7%*	*15,086*	*72.4%*	*2.24*	*[1.03, 6.94]*
Bread and bakery products	2345	2.5	D	1246	53.1%	1891	80.7%	2.29	[1.32, 3.56]
Cereal and grain products	1952	4.0	A	171	8.8%	908	46.7%	1.34	[070, 2.22]
Confectionery	1277	1.0	E	1277	100%	1274	100%	6.07	[3.31, 9.88]
Convenience foods	1418	3.5	B	105	7.4%	528	37.3%	2.23	[1.25, 3.89]
Dairy	2956	3.0	D	711	24.1%	2540	88.2%	4.14	[2.81, 7.95]
Edible oils and oil emulsions	495	3.0	D	184	37.2%	183	37.0%	3.48	[2.79, 4.38]
Egg and egg products	89	4.0	B	0	0.0%	0	0.0%	3.87	[3.50, 4.23]
Foods for specific dietary use	722	4.0	C	630	87.3%	245	99.6%	2.13	[1.18, 4.25]
Fruit, vegetables, nuts and legumes	3766	4.5	B	1021	27.1%	1964	74.8%	1.04	[0.48, 2.01]
Meat alternatives	195	4.0	A	0	0.0%	23	11.8%	1.66	[1.06, 2.43]
Meat and meat products	1724	2.0	D	919	53.3%	649	51.3%	6.93	[5.78, 29.7]
Non-alcoholic beverages	2436	2.0	C	944	38.8%	1535	79.6%	3.17	[1.64, 6.08]
Sauces, dressings, spreads and dips	2327	2.5	C	2225	95.6%	2117	91.8%	1.82	[1.11, 2.75]
Seafood and seafood products	761	4.0	B	0	0.0%	147	19.4%	2.66	[2.01, 4.75]
Snack foods	682	2.5	C	682	100%	682	100%	2.25	[1.48, 3.21]
Sugar, honey and related products	405	1.0	D	405	100%	400	100%	2.37	[1.66, 3.26]

HSR: Health Star Rating
ADG: Australian Dietary Guidelines concept of ‘core’ and ‘discretionary’ products
WHO EURO: The World Health Organization’s Regional Office for Europe marketing eligibility criteria
GHGe: Greenhouse gas emissions

Table 5. 2. Median nutrient profiles and greenhouse gas emissions across 'Meat and meat products' subcategories

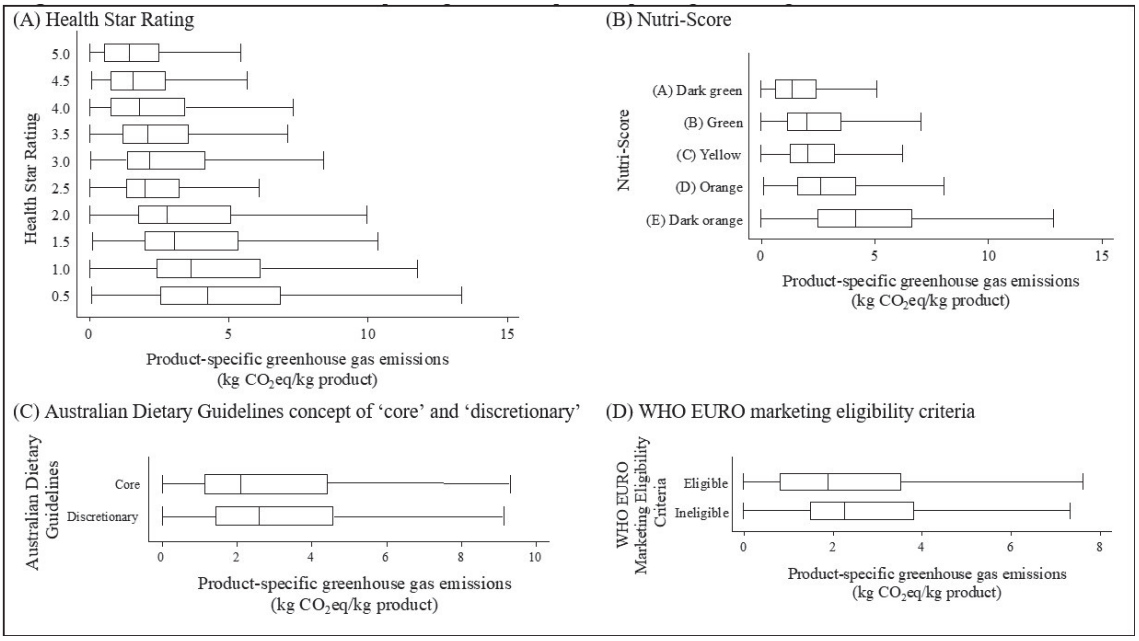
FoodSwitch product category	No. of products	Nutrient profiling models						Median GHGe [IQR] (n=1724)	
		Median HSR (n=1261)	Median Nutri-Score (n=1266)	ADG Discretionary Products [N %] (n=1724)		WHO EURO Ineligible products [N %] (n=1266)			
Meat and meat products	*1724*	*2.0*	*D*	*919*	*53.3%*	*649*	*37.6%*	6.93	*[5.78, 29.7]*
Beef and game	234	3.5	C	18	7.7%	20	8.5%	53.9	[48.6, 57.4]
Beef and game products	76	1.5	D	59	77.6%	35	46.1%	44.1	[39.1, 46.7]
Lamb	127	3.5	C	0	0.0%	8	6.3%	27.9	[26.8, 31.9]
Lamb products	3	1.5	D	3	100%	3	100%	23.7	[15.3, 25.0]
Meat-based meals	315	3.0	C	260	82.5%	56	17.8%	5.14	[4.12, 7.78]
Other meat products	88	1.5	D	81	92.0%	61	69.3%	36.5	[6.44, 47.6]
Pork	130	3.5	C	0	0.0%	7	5.4%	7.38	[6.98, 8.06]
Pork products	463	1.5	D	434	93.7%	418	90.3%	6.42	[5.88, 6.80]
Poultry	213	4.0	B	0	0.0%	7	3.3%	6.41	[6.18, 6.99]
Poultry products	75	3.5	C	64	85.3%	34	45.3%	5.89	[4.69, 5.98]

HSR: Health Star Rating
ADG: Australian Dietary Guidelines concept of 'core' and 'discretionary' products
WHO EURO: The World Health Organization's Regional Office for Europe marketing eligibility criteria
GHGe: Greenhouse gas emissions

5.3.2 Associations between nutrient profiling scores and greenhouse gas emission estimates

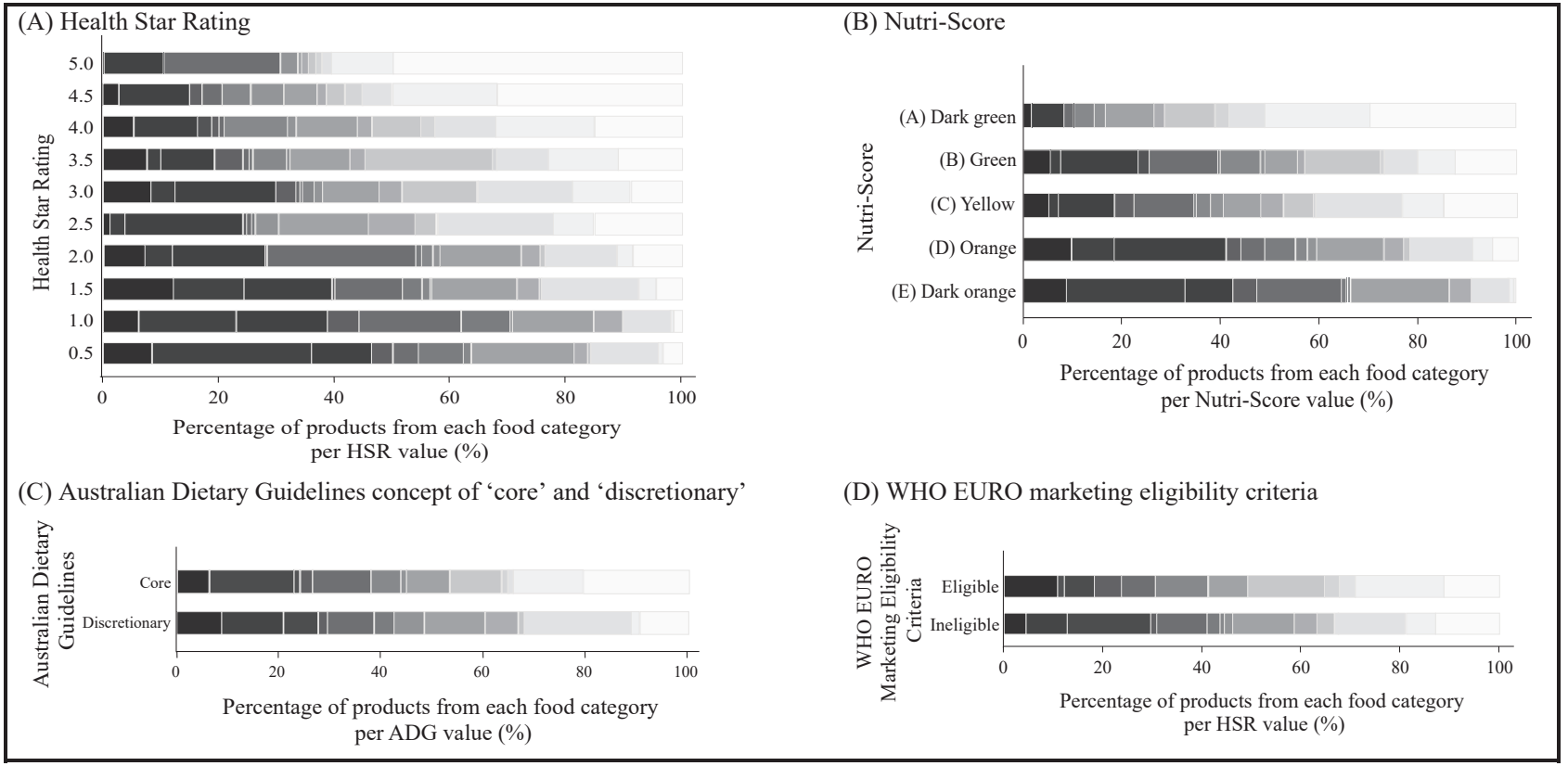
Across all products, there was a clear and consistent association between the four nutrient profiling models and GHGe estimates - products with better nutrient profiling scores had lower median GHGe estimates than products with poorer nutrient profiling scores (all *p*-values<0.001) (**Figure 5.2**). This pattern was generally true when analyses were done by product category, with 35 of the 52 (67.3%) possible category-specific analyses across the four nutrient profiling models showing that better nutrient profiling scores were associated with lower GHGe (all *p*-values<0.05) (**Figure 5.3**) (**Supplementary Figures S5.1-S5.4**). No pattern was observed for 10 out of 52 (19.2%) analyses by product category and a significant association in the opposite direction, whereby better nutrient profiling scores were associated with higher GHGe (all *p*-values<0.05), was observed for 7 out of 52 (13.5%). For 12 of the 64 (18.8%) category-specific analyses, evaluations could not be performed because all products were assigned the same nutrient profiling score (e.g., all 'Egg and egg products' were assigned an HSR of 4.0 stars).

Figure 5. 2. Associations between nutrient profiling models and product-specific greenhouse gas emissions



These box-and-whisker plots display the interquartile range of greenhouse gas emission values, with the median value marked by the line within the box. The whiskers extend to the lowest datum within 1.5 times the lower quartile and the highest datum within 1.5 times the higher quartile. Outlier values are excluded from the visualisation. A Jonckheere-Terpstra test for trend was used to evaluate the difference in median values across values for each scoring system (all *p*-values<0.001).

Figure 5. 3. Proportion of products in each product category across nutrient profiling scores



These bar charts display the proportion of products represented by each of the 16 product categories for each possible value across the four nutrient profiling models. The colour gradient for product categories is ordered from the category with the highest median greenhouse gas emissions value ('Meat and meat products') to that with the lowest median greenhouse gas emissions value ('Fruit, vegetables, nuts and legumes').

Null associations between nutrient profiling scores and GHGe were observed primarily for meat and meat alternative categories: 'Meat alternatives' and 'Seafood and seafood products' when assessed using HSR and Nutri-Score and 'Meat and meat products' and 'Seafood and seafood products' when assessed using EURO. The opposite associations, whereby better nutrient profiling scores were associated with higher GHGe, were observed across a breadth of product categories including 'Meat and meat products' when assessed using Nutri-Score and ADG and 'Dairy' and 'Non-alcoholic beverages' when assessed using ADG (**Table 5.3**).

Table 5. 3. Association of nutrient profiling models with greenhouse gas emissions by product category

FoodSwitch product category	GHGe & HSR	GHGe & Nutri-Score	GHGe & ADG	GHGe & EURO
Overall				
Bread and bakery products				
Cereal and grain products				
Confectionery			-	-
Convenience foods				
Dairy				
Edible oils and oil emulsions				
Egg and egg products	-		-	-
Foods for specific dietary use				-
Fruit, vegetables, nuts and legumes				
Meat alternatives			-	
Meat and meat products				
Non-alcoholic beverages				
Sauces, dressings, spreads and dips				
Seafood and seafood products			-	
Snack foods			-	-
Sugar, honey and related products			-	-

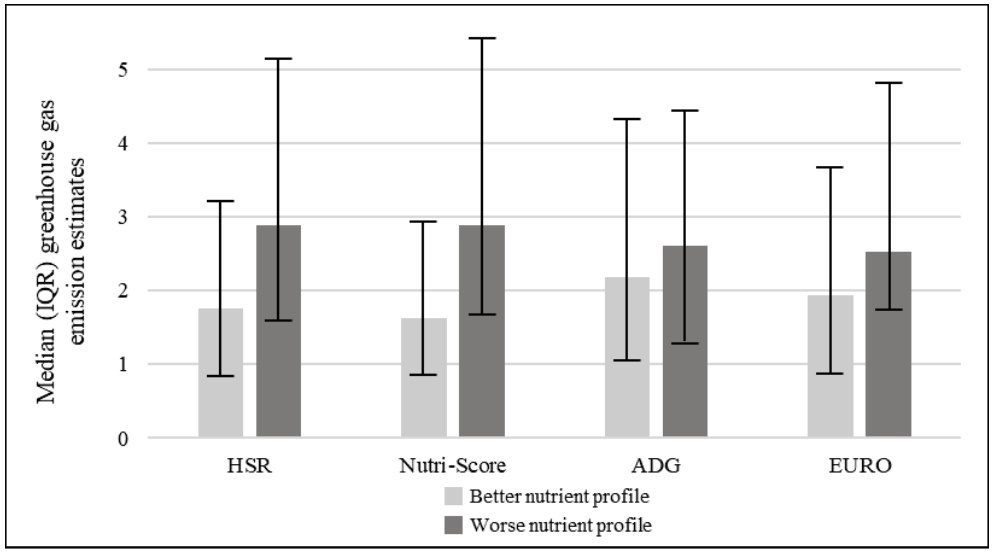
Green indicates statistically significant association of better nutrient profiling scores with *lower* GHGe.
Grey indicates no significant association.
Red indicates statistically significant association of better nutrient profiling scores with *higher* GHGe.
White indicates that category-specific analyses could not be performed because all products were assigned the same nutrient profiling score.

5.3.3 Associations between proportions of products with better nutrient profiling scores and greenhouse gas emission deciles

For all four nutrient profiling models, the median GHGe estimates for food and beverage products with better nutrient profiling scores were lower than the median GHGe estimates for products with worse scores (all p-values<0.001) (**Figure 5.4**). Likewise, across GHGe deciles, the proportion of foods and

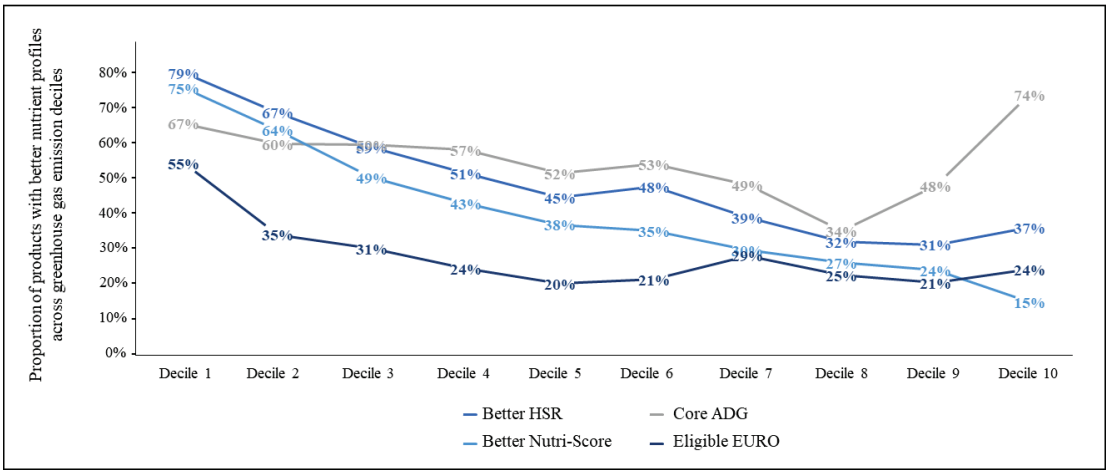
beverages classified as having better scores by each nutrient profiling model was generally higher in deciles with lower GHGe estimates (all *p*-values<0.001) (**Figure 5.5**).

Figure 5. 4. Median greenhouse gas emission estimates across four nutrient profiling models



This clustered bar char displays the median greenhouse gas emission value and inter-quartile range (IQR) for products with better or worse nutrient profiling scores for each of the four nutrient profiling models: the Health Star Rating (HSR), the Nutri-Score, the Australian Dietary Guidelines (ADG) concept of 'core' and 'discretionary' products and the WHO Regional Office for Europe (EURO) marketing eligibility criteria.

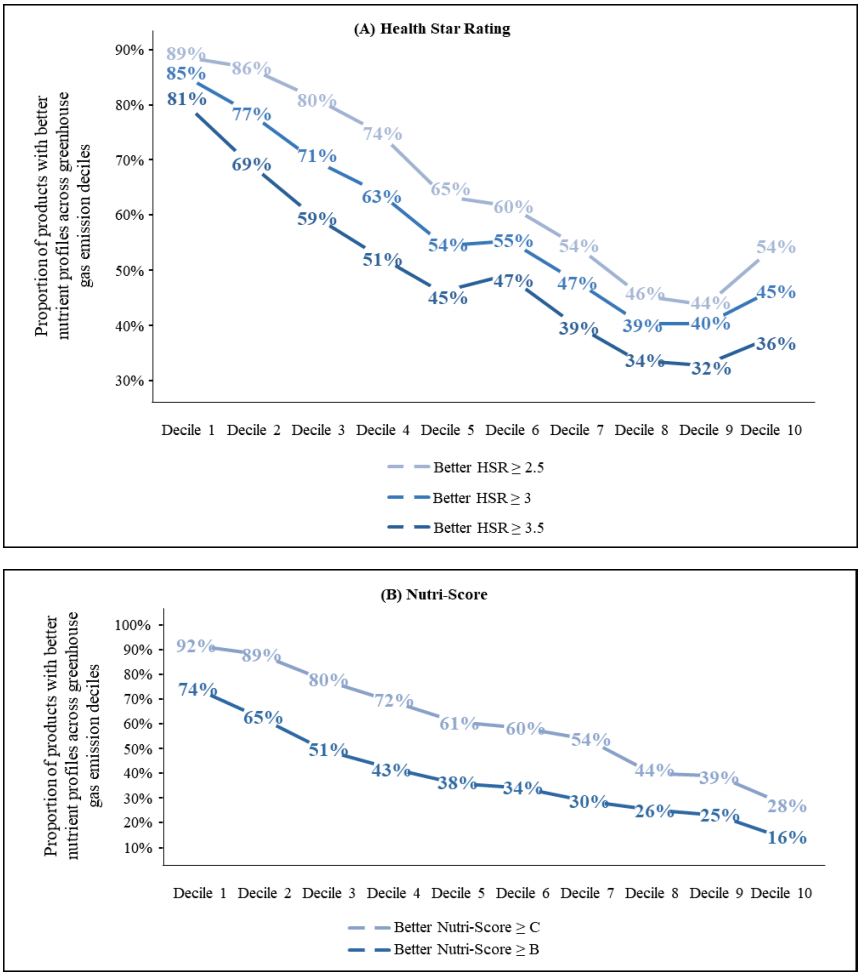
Figure 5. 5. Proportion of products with better nutrient profiling scores across greenhouse gas emission deciles



This line graphs display the proportion of products with better nutrient profiling scores across greenhouse gas emissions deciles (n ~ 2,355 products per decile). The four nutrient profiling models included are: the Australian Health Star Rating (Health HSR), the French Nutri-Score (Healthier Nutri-Score), the Australian Dietary Guidelines concept of 'core' and 'discretionary' products (Core ADG) and the World Health Organization's Regional Office for Europe marketing eligibility criteria (Eligible EURO).

The sensitivity analysis showed that the trend was not significantly impacted by changing the cut-off points classifying products with better scores for both HSR and Nutri-Score (**Figure 5.6**). The proportion of products with better nutrient profiling scores classified by the ADG appeared to have a non-linear association across GHGe deciles, most evident for products with the highest GHGe. This is because the ADG classified more animal-based foods as having a better nutrient profiling score than any other model. For example, more than 97% of 'Dairy' products and 64% of 'Meat and Meat products' with the most intensive GHGe were classified as better by the ADG, versus just 36% and 33% respectively, by the HSR.

Figure 5. 6. Proportion of products with better categorical nutrient profiles across greenhouse gas emission deciles



This line graphs display the proportion of products with better nutrient profiling scores across greenhouse gas emissions deciles (n ~ 2,355 products per decile). The sensitivity analysis was performed to understand the difference in the trend across deciles when using different cut-off values to determine products with better nutrient profiling scores for each of the two categorical nutrient profiling models: the Australasian Health Star Rating (HSR) and the French Nutri-Score.

5.4 Discussion

The overall associations observed across all four nutrient profiling models indicated that, on average, food and beverage products with better nutrient profiling scores had lower GHGe. Central to this finding were the patterns observed across each of the 16 product categories, and namely that fresh fruits and vegetables and minimally processed grain and legume-based foods tended to rank better based both on their nutrient profiles and GHGe impacts.[37,183,267,268] Conversely, the results suggested that animal-based foods and non-alcoholic beverage products with many ingredients typically have worse nutrient profiling scores and higher GHGe. The overall pattern from the analyses was clear, however there was still considerable variability in the GHGe of products when grouped by nutrient profiling score and in the relative nutrient profiling scores of products when grouped by GHGe deciles. This reflected the variability in the types of products available in Australia and highlighted the importance of granular datasets for both nutrient composition and GHGe at the individual product level, not just for broad product categories.

The association between worse nutrient profiling scores and higher GHGe was broadly consistent across the major product categories studied, but there were a few categories for which there was either no detectable association or the opposite association. Higher GHGe were associated with significantly better nutrient profiling scores for 'Meat and meat products' for two models (Nutri-score and ADG). In general, animal-based product contribute disproportionately high GHGe,[117,234,268] and single ingredient animal products, such as raw unflavoured meats, have favourable nutrient profiling scores. At the same time, animal products mixed with other lower emission ingredients can have better GHGe profiles but worse nutrient profiling scores because of the large quantities of salt, sugars and/or fat added during processing. There were no significant associations observed for three of the analyses of nutrient profiles and GHGe for 'Seafood and seafood products' (HSR, Nutri-score and EURO), which was due to the breadth in seafood product types (e.g., farmed and wild-caught fresh fish and crustaceans to canned products). The overall associations between nutrient profiling scores and GHGe were clearer for the ordinal models (HSR and Nutri-Score) than for the dichotomous models (ADG and EURO). This is likely because the criteria for assigning continuous measures allow for more variation in nutrient profiling scores across similar products, enabling greater disaggregation and thereby increasing the power of the statistical tools to identify patterns in the data.

5.4.1 Comparison with existing literature

This chapter built upon previous research that has linked nutrient profiling and environmental impacts of food.[159,261,269,270] In previous analyses, product groups linked with better nutrient profiling scores also tended to have lower environmental impacts and vice versa.[183,248] This research further expanded the granularity of the analyses done in Australia by exploring associations between nutrient profiling scores

and GHGe for over 20,000 products, whereas previous work focused on a much smaller number of product groups (between 20 and 100).[117,128] In a similar study (Clark *et al.*), 57,000 unique products available in the United Kingdom and Ireland were assessed for both their nutrient profiles and their environmental impacts.[183] This groundbreaking research compared four nutritional characteristics (sugar, saturated fat, sodium and energy) to four environmental impacts (GHGe, water scarcity, land use and eutrophication potential).[183] It aligned well with this chapter in concluding that there was variability in nutritional and GHGe impacts even when assessing products within a given category. The Clark *et al.* study captured additional key insights in the potential misalignment of different environmental indicators. For example, Clark *et al.* found while coffee has higher GHGe than other beverage types, it tended to have lower impacts on land use and scarcity-weighted water use.[183] Thus, there is a need to include this in future research on Australian products as such data becomes available.

5.4.2 Strengths and limitations

This chapter used multiple nutrient profiling models to quantify the association between measures of nutrient components in products and GHGe. The ordinal data available from two of the nutrient profiling models allowed for well-powered statistical analyses even within individual product categories. The consistency of the main findings across several different nutrient profiling models strengthened the conclusions and suggested generalisability of the findings across different regions. Though the validation of nutrient profiling models against health outcomes is still nascent and under ongoing debate,[84,266] the nutrient profiling models employed in this paper represented the vast majority of tools currently used to inform product classifications for food policy globally, highlighting the potential of this research to shape policy discussions.[54,105,271] Some nutrient profiling-based labels have been found to help consumers to make healthier choices and correlate with reductions in adverse health outcomes and mortality.[63,80,81] However, other studies have expressed limitations of nutrient profiling systems (e.g., being based on reductionist methods), and no association between nutrition labels, consumer behaviour and nutrition outcomes, emphasizing the need to expand research in this area.[272]

While this analysis looked at the overall association of nutrient profiling scores and GHGe impact and added significantly to product-specific data as pertaining to modern diets, it recognised that nutrient profiling models are limited. As they are best equipped to compare products within categories, conclusions were focused on the category level. The assessment of two categorical nutrient profiling models (HSR and Nutri-Score) was complemented with the assessment of the two dichotomous dietary guidelines systems that take into consideration the holistic nature of product groups on top of product nutrient composition.[54,265] There was some missingness of HSR, Nutri-Score and EURO data, but, in general, data quality for nutrition information was good and unlikely to have introduced significant errors.

5.4.3 Study implications and future research

This chapter offered useful insights needed to develop dual policies that concurrently address healthy and sustainable diets.[6,14] Recent analyses of food-based dietary guidelines in 85 countries identified widespread opportunity for improvement regarding the dual assessment of health and sustainability of products, particularly with respect to animal-based products.[152] Better access to granular GHGe impact data across the food and beverage supply and the use of standard nutritional and GHGe assessments across different manufacturers and producers, such as those presented here, could enhance the quality and influence of dual health and environmental policy by allowing for comparison of products within product categories.[130] Policymakers can use this information to inform targeted policies, such as combined nutrient and GHGe labelling, that were previously not possible due to lack of coordinated research.[273] For example, dual policies can encourage consumers towards both healthy and sustainable product choices,[274] such as fresh fruits and vegetables that are not processed with added sugars, bread and bakery goods without added oils or confectionery (e.g., chocolate chips), or minimally processed, non-ruminant meat products that are produced on farms that capture and reuse methane emissions.

Moreover, this research highlighted the importance of considering both the nutrient and GHGe profiles of products that have inverse nutrient and GHGe impacts. Nutrient-focussed policies may encourage the consumption of products with better nutrient profiles but high GHGe, unintentionally resulting in detrimental environmental impacts. Dual policies can avert this risk by encouraging producers towards more sustainable production techniques, while ensuring beneficial nutrient profiles, for example through reformulation policies to include more vegetables and fewer animal-based ingredients. Similarly, they can also ensure that actions to improve nutrition quality of products with low GHGe but less favourable nutrient profiles, such as by improving nutritional profile through salt and sugar substitutions, will be done in a sustainable manner, for example by considering the GHGe impact of substituting ingredients.

Future research should also investigate the associations between product-specific GHGe and product level of processing, for instance by using the NOVA classification system.[29,32] The NOVA classification provides a valuable framework for both researchers and policymakers to analyse and formulate strategies to mitigate the potential health and environmental impacts associated with highly processed foods.[192,275] Additional assessment of GHGe and nutrient profiling systems and NOVA could more effectively capture the complexity of implications as a more holistic approach. However, in this analysis, NOVA was not included due to its potential misclassification in FoodSwitch due to the nuanced nature of various food items.

5.5 Conclusion

Supermarket products are fundamental to address to achieve a sustainable food system. They are crucial to providing adequate nourishment for the growing population and, therefore, must maximise nutritional quality while ensuring associated GHGe remain within required planetary boundaries. While the nutrient profiling of products is under moderate regulation by many governments, there is a gap in regulation regarding the GHGe impacts of products. The research presented here provided novel information regarding the association between nutrient profiling models commonly used in food policy and the GHGe impacts of individual supermarket products in Australia. The messaging of such product information that jointly addresses human and planetary health to consumers, especially for ruminant meat products and confectionery, can enable more sustainable purchasing patterns and drive industry competition.

Chapter 6: Potential to reduce greenhouse gas emissions by switching product purchases

6.1 Introduction

Food and beverage consumption patterns, particularly in higher-income countries, need to change significantly to become environmentally sustainable according to the Paris Climate Agreement and the recent EAT-*Lancet* Commission report.[120,127,151] In these countries, half to three-quarters of consumption is comprised of food and beverage products purchased in supermarkets and other grocery retail outlets,[3,24] subsequently making this sector a substantial contributor to overall food and beverage GHGe. Ultimately, a change in national and global dietary habits would require an understanding of scenarios to determine the associated effects on attributable GHGe.[276] It would also imply changes to the type, composition and quantity of food and beverage products.

Currently, assessments and interventions targeting GHGe attributable to food and beverage products sold in retail stores are limited and no data has been combined with purchase information. The large volume of products available, the insufficient product-specific GHGe data and the complexity of global supply chains all present significant challenges to the development and implementation of effective interventions. Further, although recent research has emerged comparing the environmental impacts of broader dietary patterns,[277] there is a lack of data available on the attributable GHGe to purchasing and consumption patterns of supermarket products. Given that supermarket food and beverage products dominate consumer dietary intake, such evidence is needed to inform policy changes (e.g., mandatory GHGe labelling of products) that might meaningfully reduce GHGe.[17,278]

Recent advances in profiling the nutritional quality of foods in many nations have transformed the potential for policy interventions targeting diet-related ill health.[145] By combining nutrient profiling data with purchase and consumption data, it has been possible to identify the foods and beverages responsible for causing the most disease burden and to potentially mitigate risks by recommending switches to healthier foods.[279-281] Using these data, it has also been possible to evaluate the impact of different intervention strategies on consumer behaviour and health.[93,94,282] With the work presented in Chapters 4 and 5, as well as recent availability of product-specific GHGe data in other countries,[183] similar approaches will be key to assessing interventions targeting the environmental impact of the food supply and nudging consumers towards purchasing choices that are both healthier and lower-emission.

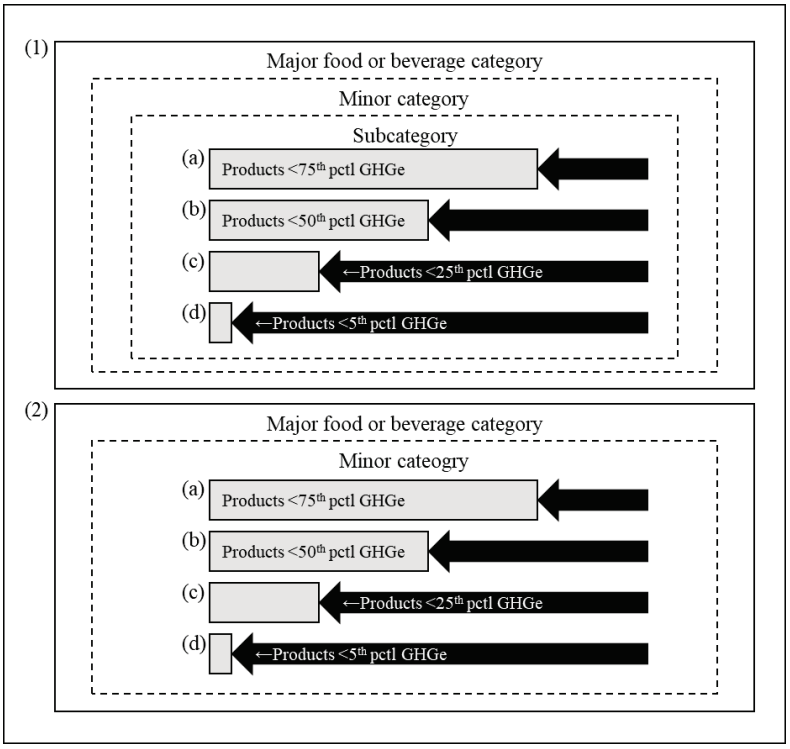
Therefore, this chapter aimed to use product-specific GHGe data from Chapter 4 to estimate the potential impact of switching higher-emission products to lower-emission products, within very similar

(e.g., higher GHGe white breads switched for lower GHGe white breads) and less similar categories (e.g., higher GHGe garlic breads to lower GHGe white breads). It also aimed to compare emissions attributable to product purchases and quantify the impact of switches on the average nutrient profiling score and energy density of purchases.

6.2 Methods

In this cross-sectional study, the annual GHGe attributable to major categories of products purchased from grocery retail outlets and brought into Australian homes in 2019 were calculated. The study described variations in food purchases across households of different socioeconomic position. It then ranked the relative contribution of product categories to household GHGe attributable to product purchases (**Figure 6.1**). The project was approved by the University of New South Wales Human Research Ethics Committee (approval number HC200244).

Figure 6. 1. Chapter 6 methods workflow



The potential reduction in greenhouse gas emissions (GHGe) attributable to food and beverage product purchases with implemented emissions cut-offs are assessed both by (1) categories of less similar products and (2) categories of similar products. The was done by subjecting products to emissions limits at the (a) 75th, (b) 50th, (c) 25th and (d) 5th percentiles (pctl). This was done by replacing the GHGe value for products falling above the respective percentile with the value of that percentile and was repeated for each percentile value to test the impact of progressively switching towards products with the lowest greenhouse gas emissions.

6.2.1 Study population

Grocery purchase information was used from the 2019 NielsenIQ Homescan Consumer Panel, a dataset that captured all products consumed at home by participating Australian households between January and December. The NielsenIQ Homescan panel included about 10,000 households that were surveyed to be representative of the demographic composition and geographic distribution of the Australian population. Data were collected by householders using handheld electronic scanners to record the barcodes of products purchased from all retail outlet types and brought into the home (i.e., does not include items that are eaten elsewhere).[197,280,281] In addition, 284 types of individual products without a barcode (such as unpackaged fruits and vegetables) were recorded by householders scanning the applicable barcode from a list provided by NielsenIQ in booklet form.

The dataset contained information on the characteristics of the households, including the number of household members, the number of children and area-level socioeconomic position. For assessment across socioeconomic positions, the Index of Relative Social Advantage and Disadvantage (IRSAD) system was used.[283,284] It ranks geographic areas using a range of indicators including education, income, occupation and housing. Using the information collected in the latest Australian Bureau of Statistics Household Income and Wealth survey,[284] household areas were divided into quintiles with quintile 1 representing the most disadvantaged and quintile 5 representing the least disadvantaged.

6.2.2 Food and beverage purchase data

The 2019 Australian FoodSwitch Annual database used in this analysis contains supermarket food and beverage data that have been described in previous chapters.[200] The NielsenIQ Homescan purchase data were linked to the 2019 FoodSwitch database in order to assess product nutrition information, HSR and the product-specific GHGe estimates. Products were matched in a three-step process. First, as many products as possible were matched by their unique barcodes. Products without barcode information were matched according to product name using previously described methods.[197,285] In brief, products were matched first using their exact product name and then using their product name after removing any nutritionally irrelevant descriptors (e.g., container type or product shape). Finally, the 284 unpackaged, unbarcoded NielsenIQ products were assigned the average GHGe for the closest corresponding leaf category in the FoodSwitch database.

6.2.3 Outcomes

The primary outcome for these analyses was the estimated tonnes of GHGe attributable to product purchases consumed at home in Australia in 2019. This was estimated by totalling the GHGe for each matched product based on the quantity (weight) purchased over the year to obtain an annual GHGe

value for product purchases made by each household for each product. The secondary outcomes were the average nutritional quality as defined by the mean HSR and the mean energy density, recorded in kilojoules (kJ) per 100g, of products purchased.

6.2.4 Statistical analysis

All results were weighted to represent the overall Australian population using survey sample weights based on the latest Australian Bureau of Statistics census data provided by NielsenIQ Homescan.[283] To control for under-reporting of purchases, households were included if they recorded at least one barcode per week for at least 50% of the 52-week period and spent an average of at least $5 per week on product purchases. Characteristics and purchasing patterns of included households were described both for the overall population and across quintiles based on the IRSAD. Differences across quintiles were assessed using one-way ANOVA. The GHGe contribution of purchases was described across the 16 major categories by socioeconomic position. Each of the major categories were ranked, first according to emissions per kilogram of product (i.e., kilogram GHGe per kilogram of product) and then according to the total emissions attributable to annual purchases of that product (i.e., tonnes GHGe purchased per year). This allowed for the exploration of the changes in ranking of product categories when weighted by purchases.

The potential impact on GHGe, mean HSR and mean energy density (in kJ/100g) was tested by switching product purchases in two ways. First, the impact of making small changes to initial purchasing patterns was examined by switching products within leaf categories (n=703), which include very similar products that could be easily switched (e.g., higher GHGe white bread products switched for lower GHGe white bread products). The very similar products within each leaf category are most similar in the functional sense (i.e., use and contribution to the diet), and often also similar in nutrient profile. Next, this was done to examine the potential impact of switching products within the broader minor categories (n=74) of less similar products (e.g., from ‘Garlic bread’ products to ‘White bread’ products). The less similar products still maintained likeness in functionality but had more variability in nutrient profile (**Table 6.1**).

Table 6. 1. Example minor and leaf product categories

Major category - Bread and bakery products			
Minor category - Bread			
Leaf categories	Bagels	Naan	Regular flat bread
	Bread rolls	Other grain breads not otherwise specified	Roti
	Croutons	Other plain bread not otherwise specified	Rye bread
	Crumpets	Other savoury bread not otherwise specified	Soy & linseed bread
	English muffins	Other sweet bread not otherwise specified	Taco shells
	Fruit bread	Pappudoms	Tortillas
	Garlic bread	Pita bread	White bread
	Mixed grain sourdough	Pizza bases	Wholemeal bread
	Multigrain bread	Plain ice cream cones	Regular flat bread

Major category - Meat and meat products			
Minor category - Processed meat			
Leaf categories	Bacon	Dried meat	Pork sausages
	Beef burgers	Hotdogs	Salami
	Beef sausages	Kangaroo sausages	Sausage rolls
	Cabanossi and twiggy sticks	Kebabs	Sliced beef
	Canned beef	Kransky	Sliced chicken
	Canned chicken	Lamb sausages	Sliced ham
	Canned ham (e.g. SPAM)	Meat pies	Sliced luncheon meat
	Canned other meat not otherwise specified	Other meat burgers not otherwise specified	Sliced pork
	Chicken burgers	Other meat with pastry not otherwise specified	Sliced turkey
	Chicken sausages	Pancetta and prosciutto	Uncoated frozen/chilled processed meat
	Chorizo	Pate and meat spreads	Whole hams and similar products
	Coated/breaded frozen/chilled meat	Polish salami	

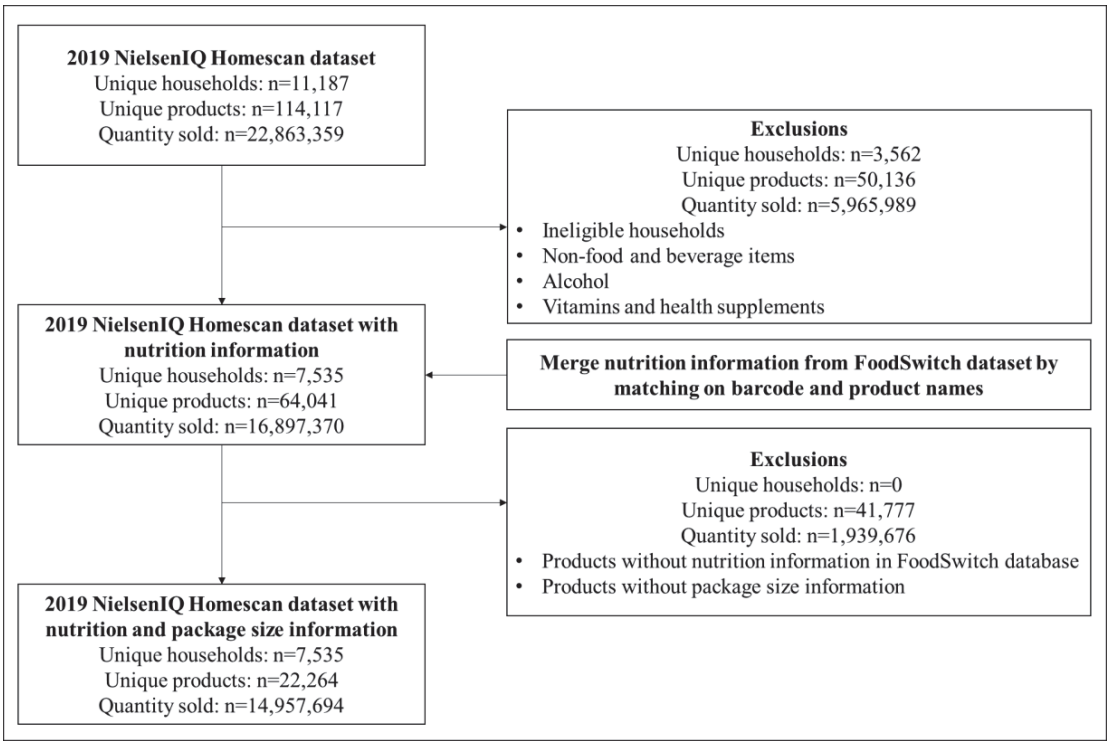
Minor product categories represent less similar switches and leaf product categories represent very similar switches. 'Bread and bakery products' and 'Meat and meat products' represent two of the sixteen major categories. 'Bread' and 'Processed meat' represent two of the 74 minor categories. In total, there are 703 leaf categories.

To estimate the effect of product switching, the 75th percentile GHGe value was determined within each leaf and minor category. The GHGe, HSR and energy density values of all purchased products with a GHGe value above the 75th percentile were then replaced with the GHGe, HSR and energy density values of the product at the 75th percentile. In turn, this process was repeated for the products lying above the 50th, 25th and 5th percentiles of GHGe to test the impact of progressively switching purchases towards those products with the lowest GHGe.[126,151] Potential impacts are presented overall and by the 16 major product categories. All data preparation and statistical analyses were conducted using Stata BE 17 (Stata Corp) and Excel. A two-sided p-value<0.05 was considered statistically significant.

6.3 Results

There were complete data available from 7,535 households that recorded purchases of a total of 14,957,694 products in 2019 (**Figure 6.2**). These data were weighted to represent the total Australian population of 25 million people, with an average of 2.58 (standard deviation (SD): 1.42) people per household (**Table 6.2**).

Figure 6. 2. Flowchart of data preparation and exclusion criteria for NielsenIQ Homescan data



Households were excluded from analyses based on eligibility criteria provided by NielsenIQ. To be included in the analyses, households must have been on the panel for the entire 12-month time frame and reported purchase data (at least one barcode per week) for at least 50% of the weeks. Households' data were deemed unreliable and excluded from analyses if they were missing any demographic information or if thresholds for expenditure were not met (≥$5 on average for each week over the time frame, i.e., at least $260 per household over the 52-week period).

Table 6. 2. Characteristics of Australian households and product purchases, overall and by households grouped according to socioeconomic position

NielsenIQ quintiles based on household IRSAD	Number of people (n)	Population represented[1] (n)	Mean number of people in household (n)	Total GHGe* (million tonnes CO_2eq per annum)	Mean GHGe* (tonnes CO_2eq per person per annum)	Volume of purchases* (mean kg per person per annum)	Healthiness of purchases (mean HSR[3])	Energy density of purchases* (mean kJ per 100g)
Most disadvantaged								
Quintile 1	3,826	4,605,682	2.49 (1.46)	6.73	1.71 (1.11)	344.0 (191.6)	3.58 (0.41)	723.4 (140.9)
Quintile 2	3,905	5,045,178	2.60 (1.42)	6.84	1.62 (1.24)	321.7 (180.1)	3.64 (0.41)	716.3 (144.7)
Quintile 3	4,030	5,097,491	2.69 (1.47)	6.55	1.58 (0.98)	316.4 (186.2)	3.66 (0.42)	709.6 (145.0)
Quintile 4	4,037	5,333,043	2.64 (1.38)	6.29	1.44 (0.97)	298.3 (181.1)	3.73 (0.42)	696.5 (148.3)
Quintile 5	3,692	4,922,338	2.50 (1.36)	5.37	1.32 (0.83)	286.1 (170.5)	3.80 (0.43)	681.5 (150.5)
Least disadvantaged								
Total		***25,003,732***	***2.58 (1.42)***	***31.8***	***1.53 (1.04)***	***312.8 (183.0)***	***3.66 (0.42)***	***705.1 (146.8)***

[1]Data represented is weighted means (standard deviation) from the NielsenIQ Homescan sample to the Australian population

*Indicated there is a statistically significant difference in values across quintiles based on IRSAD tested using ANOVA, where a two-sided p-value<0.05 was considered statistically significant.

ISRAD: Index of Relative Social Advantage and Disadvantage, where quintile 1 represents the most disadvantaged and quintile 5 represents the least disadvantaged

GHGe: Greenhouse gas emissions in terms of carbon dioxide equivalents, attributable to food and beverage purchases brought into the home

HSR: Health Star Rating, which outputs a score from 0.5 stars (least healthy) to 5.0 stars (most healthy)

There were 64,041 different products with unique barcodes included in the NielsenIQ Homescan database and 22,264 (34.8%) were matched to GHGe data in the 2019 FoodSwitch database. These products accounted for 88.5% of total units purchased (**Table 6.3**). Products included in this study were grouped according to the hierarchical FoodSwitch categorisation structure comprising 16 major categories (e.g., 'Bread and bakery products'), 74 minor categories (e.g., 'Bread') and 703 leaf categories (e.g., 'White bread'). The 41,777 products in the NielsenIQ Homescan database that could not be matched to a FoodSwitch product were distributed approximately evenly across different food and beverage categories, so were consequently omitted from analyses. NielsenIQ categories with the largest number of non-matched products were biscuits (5.00% of non-matched products), breads (4.81%) and snack foods (4.77%).

Table 6. 3. Success rate for matching products between the NielsenIQ and FoodSwitch databases

		Barcodes		Units sold	
Match Step 1 Direct match by barcode	Unmatched to GHGe values	44,557	(69.6%)	2,316,324	(13.7%)
	Matched to GHE values	19,484	(30.4%)	14,581,046	(86.3%)
	Total	***64,041***		***16,897,370***	
Match Step 2 Direct match by product name	Unmatched to GHGe values	41,819	(65.3%)	1,943,061	(11.5%)
	Matched to GHE values	22,222	(34.7%)	14,954,309	(88.5%)
	Total	***64,041***		***16,897,370***	
Match Step 3 Direct match by removal of nutritionally irrelevant descriptors	Unmatched to GHGe values	41,777	(65.2%)	1,939,676	(11.5%)
	Matched to GHE values	22,264	(34.8%)	14,957,694	(88.5%)
	Total	***64,041***		***16,897,370***	

Products were excluded from both the Nielsen Homescan and FoodSwitch databases if they were not relevant for analyses. This included non-food and beverage products, such as cleaning products. Variety packs with multiple NIPs and products were also excluded as these cannot be categorised. The databases were merged by matching products according to barcode (*Match Step 1*) followed by matching by exact product name (*Match Step 2*) and finally by matching product names after removing irrelevant descriptors (e.g., container type or product shape) (*Match Step 3*) to optimise the match rate. Most unmatched products were found to be unpackaged such as fruits, vegetables, store-prepared bakery items and ready-to-eat dishes which are not required to display the same level of nutrition information as packaged products.

6.3.1 Estimated greenhouse gas emissions in 2019

Based on the matched purchases, there were 31.8 million (M) tonnes of GHGe attributable to products consumed at home in Australia in 2019. The mean GHGe per person per annum was 1.53 (1.04) tonnes and the mean GHGe per household per annum was 3.98 (2.27) tonnes (**Table 6.2**). Households in areas with the greatest disadvantage, tended to purchase a higher volume of grocery retail products per person per year, and therefore contributed significantly higher GHGe per person per annum (p-value<0.05). In addition, these households purchased products with significantly higher average energy density than households in areas with the least disadvantage (p-value<0.05) (**Table 6.2**). Average HSR did not vary significantly across household socioeconomic position (p-value=0.37).

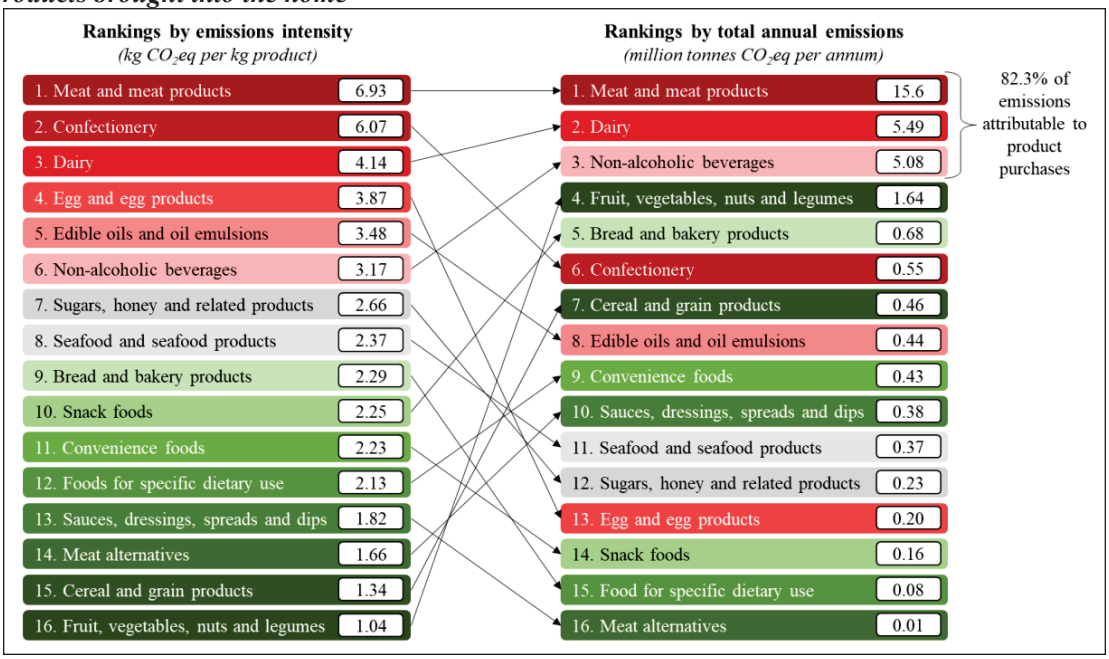
As found in Chapter 4, the three most GHGe-intensive product categories per kg of product were 'Meat and meat products' (6.93 kg GHGe per kg), 'Confectionery' (6.07 kg GHGe per kg) and 'Dairy' (4.14 kg GHGe per kg) (**Figure 6.3**). After weighting for purchase volumes, the categories that contributed the most to emissions in 2019 were 'Meat and meat products' (15.6M tonnes GHGe), 'Dairy' (5.49M tonnes GHGe) and 'Non-alcoholic beverages' (5.08M tonnes GHGe) (**Figure 6.3**). 'Meat and meat products' made up 49.1% of total emissions with only 11.2% of total purchases. By contrast, 'Dairy' and 'Non-alcoholic beverages', which were ranked 3rd and 6th in terms of kg of GHGe per kg of product, contributed the second and third largest proportions of total emissions (17.3% and 16.0%, respectively). This was a consequence of their high purchase volumes (21.1% and 20.9% of total purchases, respectively) (**Table 6.4**). The predominant contribution of 'Meat and meat products', 'Dairy' and 'Non-alcoholic beverages' to total GHGe in 2019 was apparent not just for the overall population but also for every socioeconomic group (**Figure 6.4**).

Table 6. 4. Proportions of greenhouse gas emissions contributed by purchases of different product categories across Australian households

FoodSwitch major category	**Total weight of purchases** *(million tonnes per annum)*		**Estimated total GHGe of purchases** *(million tonnes CO_2eq per annum)*		**Mean weight of purchases** *(kg per person per annum)*	**Mean GHGe of purchases** *(tonnes CO_2eq per person per annum)*
Bread and bakery products	0.39	(5.73%)	0.68	(2.14%)	17.5	0.032
Cereal and grain products	0.29	(4.26%)	0.46	(1.45%)	12.4	0.020
Confectionery	0.09	(1.27%)	0.55	(1.73%)	4.23	0.029
Convenience foods	0.12	(1.79%)	0.43	(1.35%)	6.21	0.022
Dairy	1.44	(21.1%)	5.49	(17.3%)	64.5	0.243
Edible oils and oil emulsions	0.11	(1.66%)	0.44	(1.38%)	5.07	0.021
Egg and egg products	0.05	(0.77%)	0.20	(0.63%)	2.41	0.011
Food for specific dietary use	0.03	(0.45%)	0.08	(0.25%)	1.26	0.005
Fruit, vegetables, nuts and legumes	1.70	(25.0%)	1.64	(5.16%)	79.3	0.077
Meat alternatives	0.004	(0.07%)	0.01	(0.03%)	0.22	0.0006
Meat and meat products	0.76	(11.2%)	15.6	(49.1%)	34.1	0.687
Non-alcoholic beverages	1.43	(20.9%)	5.08	(16.0%)	67.4	0.239
Sauces, dressings, spreads and dips	0.19	(2.83%)	0.38	(1.19%)	8.64	0.017
Seafood and seafood products	0.07	(1.08%)	0.37	(1.16%)	3.52	0.018
Snack foods	0.06	(0.88%)	0.16	(0.50%)	2.61	0.008
Sugars, honey and related products	0.07	(1.09%)	0.23	(0.72%)	3.39	0.012
Total	***6.82***	***(100%)***	***31.8***	***(100%)***	***19.6***	***0.090***

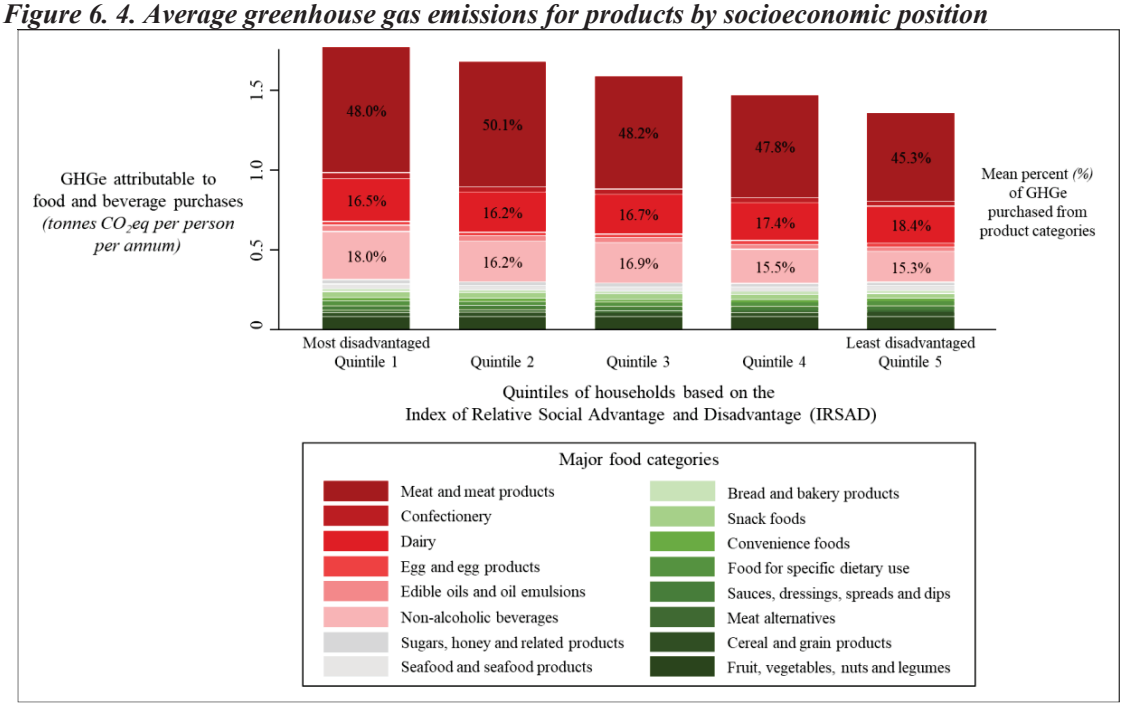
GHGe: Greenhouse gas emissions

Figure 6. 3. Ranking of product categories by emissions intensity and total emissions attributable to products brought into the home



In the left column, the emissions intensity data are based on the results of Chapter 4. In the right column, the data presented represents food and beverage purchases from supermarkets and brought into the home in Australia in 2019.

Figure 6. 4. Average greenhouse gas emissions for products by socioeconomic position



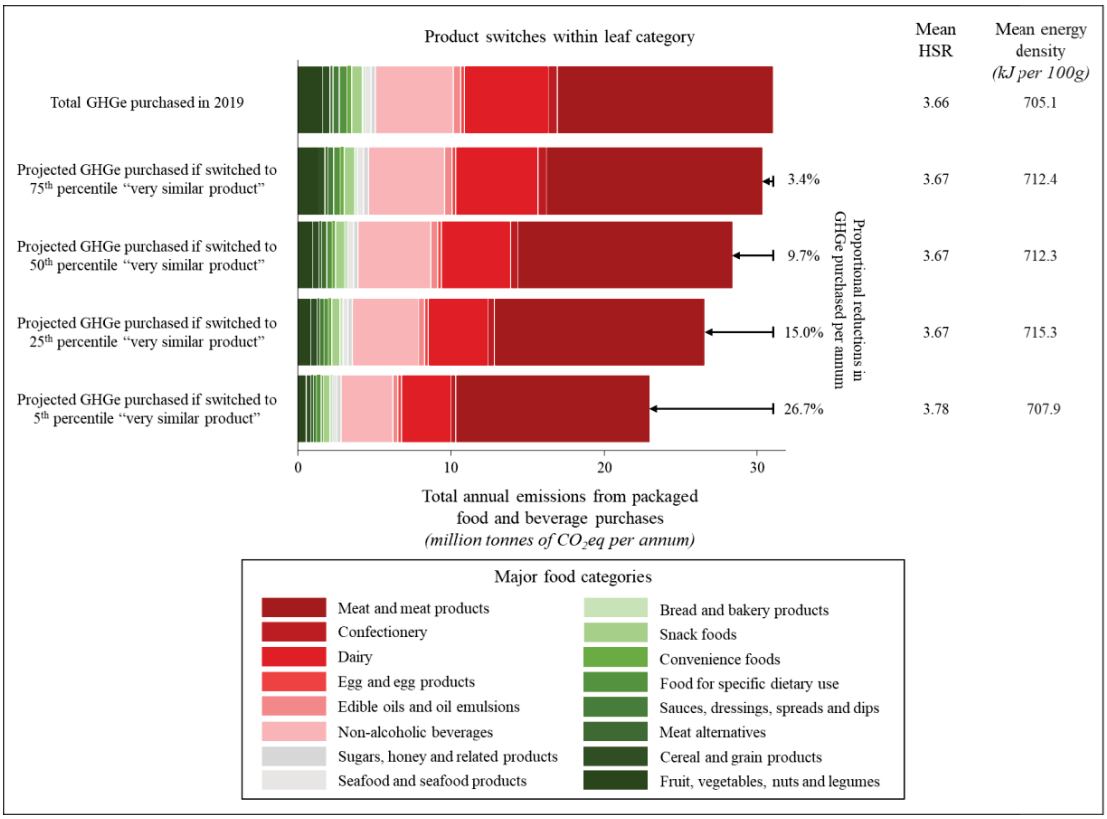
Data is presented per person in Australia in 2019 according to quintiles of socioeconomic position. Shading and per cent values indicate proportions of greenhouse gas emissions attributable to different product categories. Intake from restaurants and take-away venues are not considered here. For ease of presentation, 'Meat and meat products', 'Dairy' and 'Non-alcoholic beverages' have the percentage listed and all other categories which contribute less than 10% of emissions does not have the percentage listed.

6.3.2 Effects of switching product purchases to reduce greenhouse gas emissions

Switching higher GHGe products for similar lower GHGe products showed clear potential for reducing the GHGe attributable to products brought into the home (example product switches shown in **Supplementary Table S6.1**). First, the switches were made within the 703 leaf categories, where switched products were very similar to those initially selected. Total GHGe attributable to product purchases was decreased by 26.7% when all products above the 5th percentile of GHGe were replaced with the GHGe value of product at the 5th percentile. The total decrease was only 3.4% when products above the 75th percentile were replaced with the GHGe value of product at the 75th percentile (**Figure 6.5**). For less similar switches within the minor category, the potential reduction in GHGe was almost three times greater (70.2% and 16.1% when replacing products above the 5th and 75th percentiles, respectively) (**Figure 6.6**). In general, the greatest absolute and proportional reductions in GHGe all derived from switches made in 'Meat and meat products', 'Dairy' and 'Non-alcoholic beverages' categories (**Tables 6.5 and 6.6**).

Switching purchases to products with lower GHGe had only a small impact on the average HSR of purchased products. For example, the mean HSR of products purchased changed from 3.66 to 3.96 when products with GHGe estimates above the 5th percentile were replaced with less similar lower-emission products (**Figure 6.6**). Likewise, there was little impact on the average energy density of purchases when switching to products with lower GHGe (**Figures 6.5 and 6.6**).

Figure 6. 5. Potential reductions in greenhouse gas emissions attributable to purchases after very similar switches

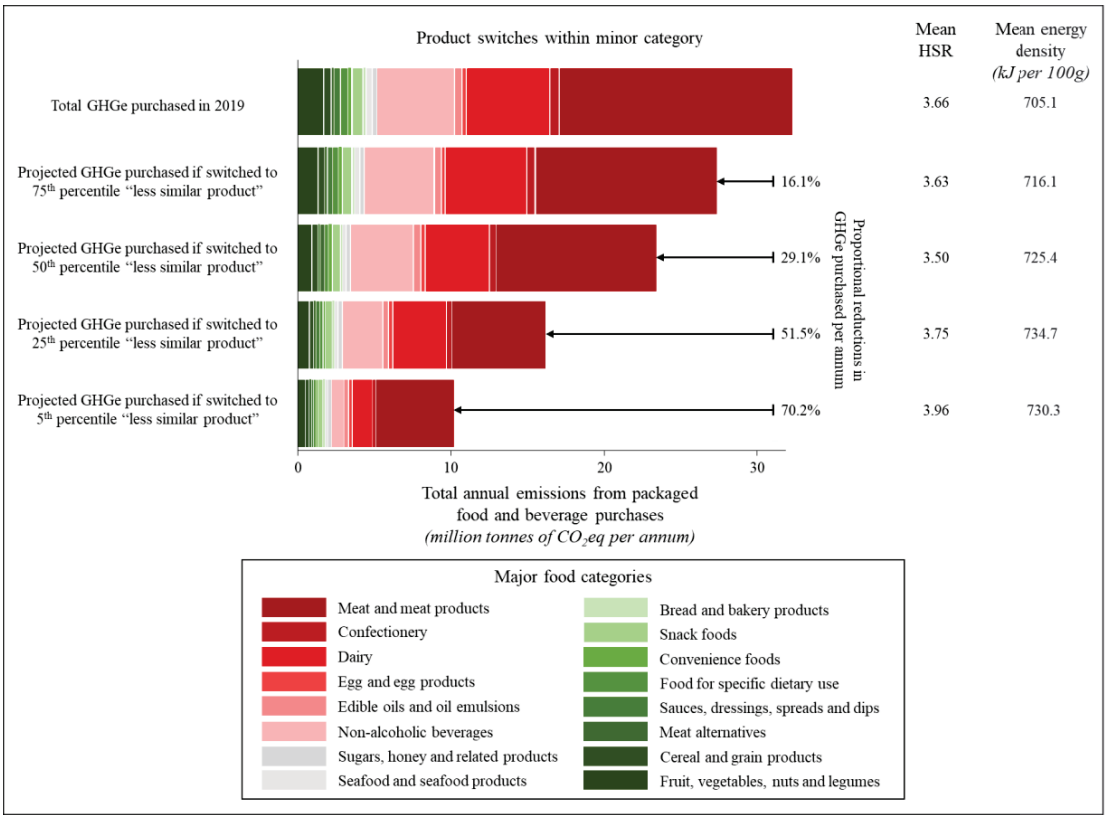


Data is presented per person in Australia in 2019 according to quintiles of socioeconomic position. Shading and per cent values indicate proportions of greenhouse gas emissions attributable to different product categories.

HSR: Health Star Rating: a score from 0.5 stars (least healthy) to 5.0 stars (most healthy)

GHGe: Greenhouse gas emissions, in terms of carbon dioxide equivalents

Figure 6. 6. Potential reductions in greenhouse gas emissions attributable to purchases after less similar switches



Data is presented per person in Australia in 2019 according to quintiles of socioeconomic position. Shading and per cent values indicate proportions of greenhouse gas emissions attributable to different product categories.
HSR: Health Star Rating: a score from 0.5 stars (least healthy) to 5.0 stars (most healthy)
GHGe: Greenhouse gas emissions, in terms of carbon dioxide equivalents

Table 6. 5. Description of product purchases after making switches to alternative very similar, lower-emission products

FoodSwitch major category	Estimated total GHGe of purchases *(million tonnes CO_2eq per annum)*		Estimated total GHGe of purchases, emissions limited at 5th percentile *(million tonnes CO_2eq per annum)*		Mean HSR		Mean energy density *(kJ per 100g of product)*	
					Original purchases	Purchases with emissions limited at 5th percentile	Original purchases	Purchases with emissions limited at 5th percentile
Bread and bakery products	0.68	(2.14%)	0.42	(1.80%)	3.63	3.76	724.8	719.0
Cereal and grain products	0.46	(1.45%)	0.26	(1.12%)	3.68	3.81	713.2	707.5
Confectionery	0.55	(1.73%)	0.29	(1.24%)	3.58	3.71	740.6	735.5
Convenience foods	0.43	(1.35%)	0.15	(0.64%)	3.61	3.73	716.4	710.9
Dairy	5.49	(17.3%)	3.21	(13.8%)	3.66	3.79	711.2	705.5
Edible oils and oil emulsions	0.44	(1.38%)	0.25	(1.07%)	3.68	3.80	709.2	703.9
Egg and egg products	0.20	(0.63%)	0.19	(0.82%)	3.70	3.82	701.3	695.4
Food for specific dietary use	0.08	(0.25%)	0.05	(0.21%)	3.72	3.83	692.2	686.8
Fruit, vegetables, nuts and legumes	1.64	(5.16%)	0.53	(2.27%)	3.74	3.86	689.9	684.1
Meat alternatives	0.01	(0.03%)	0.01	(0.04%)	3.88	3.98	664.4	657.2
Meat and meat products	15.6	(49.1%)	13.9	(59.7%)	3.64	3.77	712.9	707.7
Non-alcoholic beverages	5.08	(16.0%)	3.34	(14.3%)	3.61	3.74	715.5	710.4
Sauces, dressings, spreads and dips	0.38	(1.19%)	0.18	(0.77%)	3.66	3.78	709.8	704.8
Seafood and seafood products	0.37	(1.16%)	0.23	(0.99%)	3.59	3.73	740.7	735.4
Snack foods	0.16	(0.50%)	0.09	(0.39%)	3.64	3.78	716.4	712.0
Sugars, honey and related products	0.23	(0.72%)	0.20	(0.86%)	3.66	3.79	715.4	709.6
Total	***31.8***	***(100%)***	***23.3***	***(100%)***	***3.66***	***3.78***	***705.1***	***707.9***

Table 6. 6. Description of product purchases after making switches to alternative less similar, lower-emission products

FoodSwitch major category	Estimated total GHGe of purchases *(million tonnes CO_2eq per annum)*		Estimated total GHGe of purchases, emissions limited at 5th percentile *(million tonnes CO_2eq per annum)*		Mean HSR		Mean energy density *(kJ per 100g of product)*	
					Original purchases	Purchases with emissions limited at 5th percentile	Original purchases	Purchases with emissions limited at 5th percentile
Bread and bakery products	0.68	(2.14%)	0.31	(3.27%)	3.63	3.95	724.8	741.5
Cereal and grain products	0.46	(1.45%)	0.20	(2.11%)	3.68	3.98	713.2	729.8
Confectionery	0.55	(1.73%)	0.18	(1.90%)	3.58	3.91	740.6	756.9
Convenience foods	0.43	(1.35%)	0.09	(0.95%)	3.61	3.92	716.4	735.2
Dairy	5.49	(17.3%)	1.31	(13.8%)	3.66	3.96	711.2	727.7
Edible oils and oil emulsions	0.44	(1.38%)	0.24	(2.53%)	3.68	3.98	709.2	725.8
Egg and egg products	0.20	(0.63%)	0.19	(2.00%)	3.70	3.99	701.3	718.7
Food for specific dietary use	0.08	(0.25%)	0.04	(0.42%)	3.72	4.00	692.2	710.0
Fruit, vegetables, nuts and legumes	1.64	(5.16%)	0.45	(4.74%)	3.74	4.02	689.9	707.2
Meat alternatives	0.01	(0.03%)	0.004	(0.04%)	3.88	4.13	664.4	680.3
Meat and meat products	15.6	(49.1%)	5.14	(54.1%)	3.64	3.96	712.9	730.0
Non-alcoholic beverages	5.08	(16.0%)	0.82	(8.64%)	3.61	3.93	715.5	732.6
Sauces, dressings, spreads and dips	0.38	(1.19%)	0.13	(1.37%)	3.66	3.97	709.8	727.0
Seafood and seafood products	0.37	(1.16%)	0.14	(1.47%)	3.59	3.93	740.7	756.7
Snack foods	0.16	(0.50%)	0.06	(0.63%)	3.64	3.91	716.4	735.9
Sugars, honey and related products	0.23	(0.72%)	0.19	(2.00%)	3.66	3.97	715.4	730.9
Total	***31.8***		***9.49***		***3.66***	***3.96***	***705.1***	***730.3***

6.4 Discussion

The GHGe attributable to grocery retail purchases in Australia could be greatly reduced by making switches from higher- to lower-emission products. While a modest reduction in GHGe could be possible when switching purchases to very similar products, a larger reduction in GHGe could be achieved if switches were made to less similar products within product categories. The plausibility of switching purchases to very similar products is likely to be high but the consumer acceptability of more substantive switches to less similar products may be lower. The ability to compare products within categories and estimate the potential to reduce annual GHGe from product purchases consumed at home illustrated in these analyses provides a unique opportunity to strengthen Australia's efforts to reduce national GHGe.

A key finding from the study is that 'Meat and meat products' contributed to almost 50% of all GHGe attributable to product purchases consumed at home in Australia in 2019, despite accounting for only 11.2% of purchases. The high contribution of 'Meat and meat products' to the attributable GHGe can be explained by the very high GHGe per kilogram of product.[117,128,184] 'Dairy' and 'Confectionery', ranked 2nd and 6th respectively when weighted by purchases, were leading contributors of attributable GHGe, driven by their high intensity of emissions per kilogram of product. While 'Dairy' products are often good sources of nutrients, targeted switching within the category could lead to higher HSR and lower GHGe purchases. As 'Confectionery' products are all discretionary, encouraging a lower volume of intake would be most beneficial for this category.[261] 'Non-alcoholic beverages', although ranked 6th for emissions intensity (kg CO_2eq per kg product), were ranked 3rd by total annual emissions weighted by purchases as a result of their high purchase volumes. The top three product categories ('Meat and meat products', 'Dairy' and 'Non-alcoholic beverages') are most important to address, as they make up 82.3% of total annual food and beverage emissions weighted by purchases. 'Fruit, vegetables, nuts and legumes' have very low GHGe per kilogram of product, so while they are the fourth highest contributor to total GHGe because they make up over one-quarter of total purchases, this amounts to only 5.16% of total attributable emissions.

This chapter found that households with greater area-level disadvantage tended to bring higher volumes of food and beverage purchases into the home, which is consistent with prior research,[197] and corresponds with their higher contribution of attributable GHGe. This is likely because these households tend to purchase a higher proportion of their consumed foods from supermarkets and grocery outlets.[286] Overall, the patterns of consumption, based on the proportion of products purchased per product category, were homogenous across different household socioeconomic positions.

6.4.1 Comparison with existing literature

Recently, a study modelling GHGe and other environmental impacts of vegan, vegetarian, fish-eating and low and high meat-eating diets highlighted the significantly lower impacts of vegetarian and low-meat diets.[277] Numerous other studies have shown a link between the healthiness and environmental sustainability of foods, with many of the more nutritious commodities found to be among those with the least environmental impact.[6,37,183,287] While these studies align with this analysis on the high impacts of meat and broad alignment between health and environmental impacts, this analysis was the first to further explore the impacts of product-specific switches within categories that would feasibly be accepted by most consumers. There was a more apparent improvement in average HSR when switching to lower GHGe products in less similar product categories than in very similar product categories. There are several possible explanations for why very similar switches made to reduce the GHGe of food purchases did not also improve the average HSR of product purchases. First, the product switches were mostly done within categories of foods that were organised based on characteristics more likely to result in homogeneity of nutritional quality than homogeneity of attributable GHGe. Second, associations between healthiness and GHGe have typically been reported for analyses comparing *between* broad product categories such as meat versus dairy versus bread, where differences in both healthiness and sustainability are likely to be large and easily documented.[126,288]

6.4.2 Strengths and limitations

This was the first analysis in Australia focused on the effects that food and beverage choices could have on reducing GHGe attributable to household product purchases and understanding the potential to optimise product choices based on both GHGe and nutrient profile. This work used product-specific GHGe estimates and household-level purchasing information for a broad range of foods and beverages, which provided a unique opportunity to compare emissions both between and within product categories. The NielsenIQ Homescan data are widely considered to provide a valid estimation of products consumed at home, and analyses based on these data have received significant attention from academia and policymakers.[280,281,289] They are nationally representative of Australian households by region and socioeconomic position and cover almost 90% of total product units purchased yearly. The underlying purchasing data employed here have been used previously to understand the potential health impacts of optimising nutrient intakes through interventions, such as salt reduction or the implementation of dietary guidelines.[152,255] Both the NielsenIQ Homescan and FoodSwitch datasets have been used in multiple prior analyses of product purchasing patterns in Australia and other jurisdictions.[289-292]

There are some well-established limitations to the use of NielsenIQ Homescan data for these types of analyses. The absence of information relating to products consumed outside the home (e.g., from restaurants and take-away outlets) may lead to an under-estimation of emissions attributable to products

purchased across Australia, especially among the least-deprived households.[281] Also, household-specific extrapolation from product purchases to consumption may be miscredited, as purchased products could be shared with, donated or otherwise consumed by persons outside of the household.

The switching method is also limited in that is does not put constraints on other aspects of food products. A different method called substitution analysis, which constrains switches by nutritional quality, volume and energy, could also be done,[293,294] though the minimal differences in the average HSR and energy density of switched products from current purchase patterns suggest that the conclusions from such analyses might be similar. It is also important to note that the potential impacts of product switches were not estimated for (i) costs, either overall or relative to the purchasing capacity of different socioeconomic positions, as the available price data were limited,[295] or (ii) other environmental factors (e.g., land degradation, scarcity-weighted water use and eutrophication), as these are not yet included in FoodSwitch.

It is also important to note that while the HSR is a useful, government-supported tool for assessing the relative healthiness of supermarket products,[80,85] it does not assess every aspect of product healthiness[96] or consider broader food consumption patterns.[213,296] As such, the effects on HSR reported in this paper may not fully reflect the impact of making switches on the healthiness of the diet.

6.4.3 Study implications and future research

The joint impact of emissions intensity and purchase volumes on total attributable GHGe highlighted the need for urgent policy interventions that target both the most GHGe intensive and the most widely purchased food and beverage products.[57,171] There is potential for product switches to significantly contribute to the reduction in food system emissions required to meet the Paris Climate Agreement goals or achieve net-zero for the sector.[151] Further, in all assumed emission-reduction scenarios, most of the potential reduction in GHGe was attributable to three food and beverage categories (i.e., 'Meat and meat products', 'Dairy' and 'Non-alcoholic beverages'), which identifies them as primary intervention targets. Since total GHGe due to 'Fruit, vegetables, nuts and legumes' were low compared to the leading three causes of GHGe and their average nutritional quality was high, environmental gains from targeting this and other categories making lesser GHGe contributions would be limited. There were only minor variations with respect to purchases of the leading GHGe-contributing product categories for households of different socioeconomic position. As such, while the implementation of interventions seeking to reduce GHGe may need to be tailored to suit different socioeconomic groups, the target categories for policy intervention (i.e., 'Meat and meat products', 'Dairy' and 'Non-alcoholic beverages') should be the same across communities.

Policy intervention options to promote better-for-environment products are not yet being implemented at the industry or consumer level in Australia. In the first instance, Australian policymakers could include the environmental impacts of products into the Australian Dietary Guidelines, following the example of New Zealand.[175] There is also the option to require on-pack labelling of GHGe, similar to the current implementation of the country of origin label.[179] While some private carbon-labelling schemes have been implemented on a few products,[141,180] the work here would enable broader labelling implementation in the Australian context that could greatly enhance consumer decision-making.[181,182] Discussed in more depth below, taxes could be applied to higher-emission and lower-nutritional quality products using category-specific limits, as this would promote products that are better for people and the planet, and allow accessible dietary variety across households from different socioeconomic positions.[178]

6.5 Conclusion

In conclusion, large reductions in GHGe attributable to foods and beverages could be achieved through relatively plausible switches in product purchases. 'Meat and meat products', 'Dairy' and 'Non-alcoholic beverages' were identified as the leading causes of GHGe attributable to product purchases consumed at home in Australia and are the three categories where there is clear potential to substantially reduce GHGe.[6,152] Intervention options are multiple and potential priority actions include a requirement for on-pack labelling of GHGe and the exploration of incentives that will drive industry production practices and consumer purchasing patterns towards more environmentally friendly choices.

Chapter 7: Discussion

The work done for this thesis produced meaningful environmental estimates for diverse individual food and beverage products by collating and leveraging existing product, GHGe and purchasing data. It developed and validated a novel method to estimate the GHGe of individual supermarket products and explored the variability in product-specific GHGe values within product categories. The results of this thesis found that switching to similar, but lower GHGe products could greatly reduce GHGe attributable to supermarket purchases in Australia based on 2019 data reflective of nation-wide shopping patterns. Further, this GHGe reduction could be achieved without adversely affecting the average healthiness of purchases in terms of HSR and energy density. This thesis was a first step in assessing the sustainability of foods in Australia and helped identify a number of future research opportunities to further improve this field of study. The data produced also provided a basis upon which policymakers could take action for the betterment of the environment without risk to public health nutrition, by supporting consumers, retailers and companies to take incremental actions.

7.1 Main findings

The first key finding from the thesis, derived from the ingredient disaggregation work, was that while there are many thousands of different products available on supermarket shelves, they are made up of a much smaller number of ingredients. Chapter 3 provided a systematic way to recognise unique ingredients across products, despite various naming conventions, and identified salt, sugar and food additives, ingredients often indicative of ultra-processed foods, as the most used ingredients in the supermarket food supply. Chapter 3 also differentiated between product formulas through its implementation of a linear programming algorithm to determine ingredient weights in a product. This standardised information about each product's ingredients enabled targeted research about the dual human health and environmental impacts of commonly purchased supermarket products in the subsequent chapters.

This thesis then provided the first product-specific GHGe estimates for 23,550 products in the supermarket food and beverage supply in Australia. The method described in Chapter 4 combined readily available ingredient information from Chapter 3, existing ingredient GHGe data, and product processing and transport data from FoodSwitch to enable the scaling of GHGe estimates in a way that cannot be achieved using current LCA techniques. The capacity to provide a single standardised approach to estimating GHGe across a broad range of product types, including different brands and manufacturers, is a significant stride towards achieving sustainable food systems. This method also differentiated between GHGe associated with apparently similar food and beverage products and

highlighted the large variability in product-specific GHGe values within each product category, a difference of between 3 and 20 times between the smallest and largest product-specific GHGe value in each. For example, 'Convenience foods' products containing meat or dairy tended to have much higher average GHGe values than 'Convenience foods' products without such ingredients. These data have the potential to empower both upstream and downstream stakeholders by bringing transparency to the GHGe attributable to the supermarket food and beverage supply.

The work in Chapters 5 used the product-specific GHGe estimates in Chapter 4 to examine the association between product GHGe values and nutrient profiling model scores. Chapter 5 surfaced that, in general, food and beverage categories with better average nutrient profiles contributed fewer GHGe. This pattern was true for the majority of product categories, including 'Fruit, vegetables, nuts and legumes', 'Convenience foods', 'Bread and bakery products', and 'Cereal and grain products', which had the strongest associations. However, for 'Meat and meat products' and 'Non-alcoholic beverages', there was considerable variability in the GHGe of products when grouped by nutrient profiling score and in nutrient profiling scores of products when grouped by GHGe deciles. This underscores the diverse range in products available in Australia by product category and the need for comprehensive datasets that encompass both nutrient composition and product-specific GHGe.

Chapter 6 expanded upon the variability product-specific GHGe values discussed in Chapter 4. It also illustrated that substantial reductions in GHGe attributable to supermarket products could be realised by making purchasing switches to similar, but lower GHGe products. While very similar product switches will likely result in a modest reduction in total attributable food supply GHGe, a more substantial decrease in GHGe could be attained by switching to products that are less similar but still within the same product categories. Further, product switches could be made without compromising the average nutrient profiles and energy density of purchases. These findings highlight the possibility for a coherent and coordinated approach towards policies that incorporate both nutrition and GHGe.

7.2 Strengths and limitations

7.2.1 Strengths

The work in this thesis was strengthened by using the comprehensive and high-quality FoodSwitch database. The large number of products and in-depth coverage of the food supply included in the FoodSwitch database is further supported by its rigorous data collection, cleaning and quality assurance protocols.[198,199] Since FoodSwitch data is collected by trained staff and is monitored by dieticians and public health researchers, it contains many nutrient and nutrient profiling model attributes and does not rely on industry stakeholder compliance.[297,298] The FoodSwitch database represents the majority of supermarket products purchased by Australian households.[197,198] While most previous works analysed only single-ingredient commodities,[117,128] this dataset (in which over 80% of products were multi-

ingredient as per the results in Chapter 3) allowed for more detailed assessments of available and purchased products. Utilisation of the FoodSwitch database, primarily the ingredient lists and robust product categorisation,[55] allowed for the development of granular product ingredient information that is only also available in the US and UK.[106,183] This identification and standardisation of product ingredients enabled the novel understanding of quantities of different ingredients in the supermarket product supply. It also enabled a more nuanced understanding of the GHGe attributable to Australian supermarket food and beverage products than has been achieved before. Finally, the FoodSwitch database allowed for the combined analyses of nutrient profiling model outcomes with the outcomes of the GHGe estimation across diverse food and beverage types.

This thesis was further strengthened by using NielsenIQ Homescan objective consumer purchasing data to assess household supermarket purchases in a nationwide sample of Australian consumers.[281] The combination of product-specific GHGe data, purchasing data and Australian household data is an innovative approach to estimate the contribution of GHGe by major product categories, as household data was not incorporated into similar research on UK product-specific GHGe data.[183] Furthermore, using NielsenIQ created the capacity to guide policy interventions that align with both planetary health and human health objectives. In addition to purchasing patterns, NielsenIQ includes average Australian household size, ages, income and location.[295] This helped enhance the relevance, applicability, and potential to drive positive changes in consumption patterns. By stratifying the final analysis across various household types in Australia, the research captured some of the disparities in GHGe contributions and consumer behaviour. This approach could enable the identification of targeted intervention opportunities tailored to specific demographics.

Another key strength of the work done in this thesis was the focus on a standardised and scalable approach to assess the GHGe attributable to individual Australian food and beverage products. It was the first estimation and assessment of product-specific GHGe across a breath of Australian supermarket products within product categories. The transparent description of the standardised methodology estimating product-specific GHGe presented in the thesis was designed to facilitate repeatability using product data available on packaging in conjunction with a comprehensive collation of ingredient LCA data containing GHGe values. Thus, as more and more products are added to the Australian supermarket supply, product-specific GHGe can be easily measured. The work contributed to expansion of the scope of GHGe product analysis and the potential for GHGe labelling of food and beverage products in Australia. It is also notable that the granular product-specific GHGe data allowed for comparison of products within product categories and highlighted the variability of product-specific GHGe values within product categories. This added greatly to existing research, as previous research presenting GHGe on foods and beverages in Australia is only available for high-level commodities or for products considered discretionary.[128,261]

Finally, the work presented in this thesis has potential for global application because of the use of readily available product and GHGe data. The FoodSwitch database used for the primary analyses not only reflects the typical offerings in supermarkets across Australia but also is likely representative of other upper-middle and high-income countries with similar food supplies. For many countries worldwide, product ingredients and core nutrient information are available on pack as they are data points mandated by food labelling governance.[183,205] Likewise, ingredient LCA information can be found in the public domain[133] and therefore, while the analysis presented here only details Australian products, there is clear potential to replicate these methods for many other food systems, allowing for direct testing and expansion of these research insights to other regions. These strengths collectively underscore the significance and utility of the study's findings in advancing both research and practical applications in the field of food sustainability.

7.2.2 Limitations

The approach to estimating product-specific GHGe used throughout this thesis had some general limitations. The ingredient GHGe values assigned to each ingredient in each product did not consider geo-spatial data specific to the region or farm from which the ingredients were produced; instead, average Australian or global GHGe values were used. The GHGe attributable to ingredients can vary greatly depending on if, for instance, the ingredient is grown in a native region or if it is grown in a greenhouse.[268] However, this could not be incorporated into the current methods because geo-spatial ingredient GHGe data is not widely available for supermarket products and would need to be obtained from producers and manufacturers. Also, the GHGe attributable to product processing and transportation were only considered based on averages for each major product category, despite potential variability based on different manufacturing facilities, processing technologies, distances travelled and modes of transportation used.[117] To account for these uncertainties, the Monte Carlo simulation described in Chapter 4 was performed, together with previous research,[5,117] and showed that the inclusion of more precise ingredient GHGe, processing and transport data does not significantly impact the results for most products. Thus, the presented results can still be used to inform high-level policies that are imminently needed.

Product-specific GHGe estimates were also limited because they do not consider GHGe attributable to the entire product life cycle from cradle-to-grave, or in this case, from farm-to-disposal. In particular, the GHGe associated with a product's refrigeration, packaging and preparation requirements (e.g., cooking or microwaving) were also not considered in product estimates. Though this information would help to provide more accurate product-specific GHGe evaluations, no single piece of research to date included GHGe attributable to all product system phases.[183]

While this thesis estimated and assessed GHGe associated with specific food and beverage products, it did not encompass a broader spectrum of environmental impact factors, such as land use change, water scarcity, and biodiversity loss, that contribute to sustainability challenges. In similar food and beverage impact assessments in the UK, scarcity-weighted water use, land use and eutrophication potential have been assessed for each ingredient in addition to GHGe and a weighted value for each ingredient was summed to obtain a product environmental score.[117,183] However, by only incorporating GHGe, this thesis benefited from using a much larger number of unique ingredient LCA values than used in Poore and Nemecek (2018) and Clark *et al.*, and the more detailed product-specific GHGe estimates enabled a more granular assessment of product variability within categories.

The research findings presented in this thesis were contingent upon the availability and reliability of the data sources used. While the FoodSwitch database includes all nutrients mandated by Australian regulation to be listed on product packaging,[208] it does not have complete information for additional nutrient content including calcium, fibre or fruit and vegetable content which could help to improve the dual health and environmental analysis.[198] Also this thesis acknowledged potential health implications of using nutrient profiling models applied to products, which have known limitations that have been discussed in depth previously (Chapter 5).[84,85,213] For example, nutrient profiling models consider a limited set of nutrients, such as fat, sugar, and salt, and may not account for other important factors like vitamins and minerals, bioavailability, food processing, or individual dietary needs.[272] They have also been criticised for failing to capture overall diet and oversimplifying complex foods as well as individual nutritional needs that may differ by age, sex and activity level.[299] However, nutrient profiling can be a useful tool for identifying healthier choices in a market that is overstimulating to consumers and recent research has linked diets with higher average nutrient profiling scores with lower risk of disease and adverse health outcomes.[63,80,81]

For the analysis of potential purchasing switches, the use of FoodSwitch data linked to NielsenIQ consumer panel data did not fully capture the entirety of an individual's dietary choices. Foods and beverages consumed outside the home, such as meals from restaurants and take-away outlets, were not evaluated. The exclusion of this information will have led to an underestimation of emissions attributed to foods and beverages purchased across Australia. This is particularly significant for the least-deprived households, where a larger proportion of food consumption tends to occur away from home.[286] The misreporting of product purchases (e.g., omission of products purchased but never brought into the home) from households on the NielsenIQ panel also contributed to an overall under-estimation of product emissions across households. While households with clear, systematic underreporting were excluded, smaller to moderate levels of underreporting may still be present with previous research suggesting underreporting rates of 10-20%.[300,301]

Given that this thesis analysed supermarket products available in Australia and purchasing patterns by Australian households, the findings may not be generalisable to all other countries. To make the GHGe estimates more applicable to Australian products, only Australian and global LCA values were used. However, this limits the ability to reuse the aggregated LCA database of ingredient GHGe values prepared in this thesis. Further, the product-specific GHGe estimation methods can only be reproduced in other countries with similarly robust ingredient and product nutrient labelling regulations and the availability of a large product database. Finally, the findings related to purchasing switches are limited to other countries or cultural contexts with similar consumer behaviours and preferences. These limitations emphasise the need for a cautious interpretation of findings and recognition that contextual factors could impact the applicability of results in various scenarios.

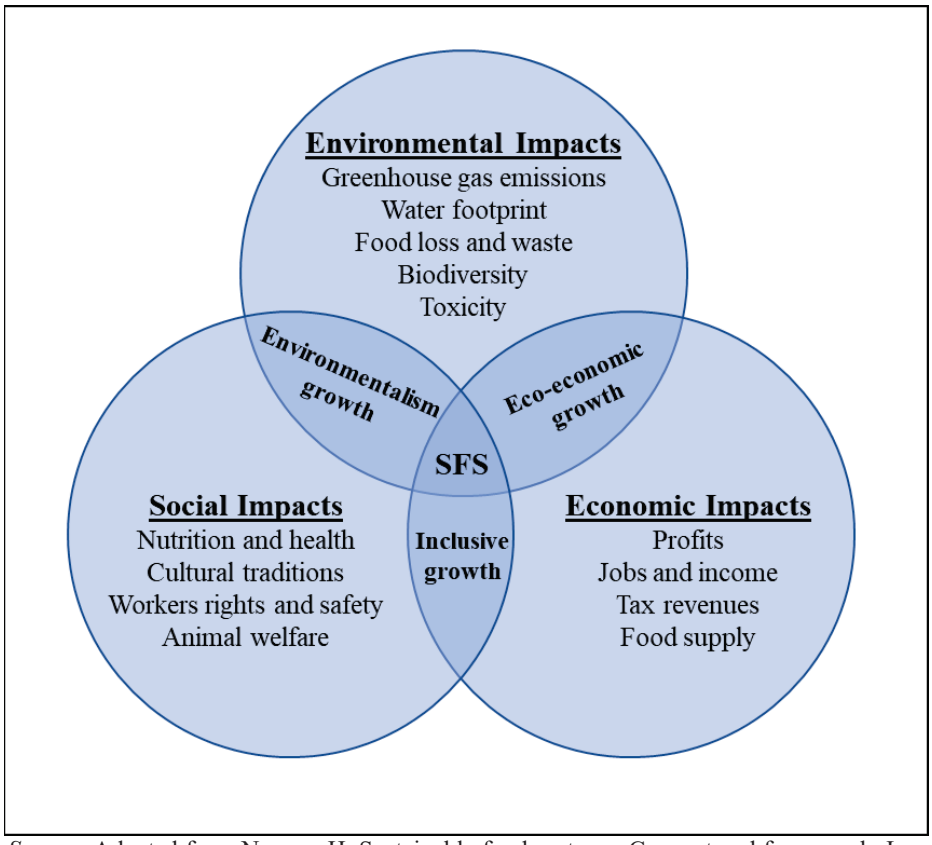
This thesis focussed on the snapshot of product GHGe impacts rather than considering longitudinal changes in food system impacts over time. While this thesis provided first ever product-specific GHGe estimates in Australia, it did not capture the effects that can arise from larger-scale changes in consumption patterns. For example, sales of pre-prepared meals and convenience foods have increased in the last decade, and the purchasing of different brands fluctuates often depending on trends and marketing.[302] The FoodSwitch database is systematically collected each year from all major Australian retailers, which allows for an expansion of this research by studying changes over time.[298] Replication of these analyses will be important for future research and tracking progress towards reaching regional and global GHGe reduction goals.

This thesis did not consider the potential economic, social or cultural factors related to the purchasing of food and beverage products or the suggesting of changes to product purchases. For example, it is important to acknowledge economic considerations, such as product prices, production costs or even projected financial implications resulting from adverse health and environmental impacts.[47] This would better contribute to a comprehensive understanding of the potential economic consequences of product choices. Further, the potential impacts on livelihoods, cultural practices, and community dynamics resulting from altering consumption patterns are not considered, which may present an incomplete view of the consequences of dietary shifts.

7.3 Food policy implications

Achieving a sustainable food system requires policy directions and practical solutions that use scientific evidence to drive governments, organisations and individuals to practice more sustainable diets.[8] A sustainable food system can only be established with the continued growth of credible and transparent data. The multifaceted dimensions of sustainable diets must be considered for effective policy and regulation, including nutrition, agriculture, industry and environmental inputs and impacts (**Figure 7.1**).[110]

Figure 7. 1. Impacts and growth opportunities for sustainable food systems



Source: Adapted from Nguyen H. Sustainable food systems: Concept and framework. In: Nations) FFaAOotU, editor.: FAO (Food and Agriculture Organization of the United Nations); 2018. https://www.fao.org/3/ca2079en/CA2079EN.pdf
SFS: Sustainable food systems

At present, supermarket outlets most often facilitate convenience and profit agribusiness and manufacturing giants, with little regard to environmental impacts.[303] There is a disconnect between public health needs and the reality of what is recommended or delivered by policy. Developing cohesive policy that aligns multistakeholder collaboration with public health goals will be key in addressing this discrepancy. Effective food policy will need to advocate for dually optimal dietary habits, such as increasing fruit and vegetable intake and reducing sodium and processed meats. Transparent and accountable governance structures can lead to policy formulation that successfully addresses the food supply chain, nutrition and the environment in both national and international contexts.[304]

The findings in Chapter 6 of this thesis showed that changes to product purchases, achieved either by redirecting consumers to different products or changing the make-up of the food and beverage supply, could have substantial impacts on attributable GHGe with little impact on nutrient profile. This can be used to help drive discussion around the need for food policy addressing public health, industry and the environment. While emphasising the critical role of policy in driving meaningful change, it is important to highlight the opportunities and challenges that may be faced.

7.3.1 Meat consumption

It is clear, both from this thesis and from previous research, that 'Meat and meat products' have the largest environmental impact when compared to other product categories; however, there are a broad range of products that fall under this major category.[117,183,277] This thesis indicated the potential to greatly reduce the GHGe attributable to these product categories. The two main factors driving this potential reduction are (1) the GHGe attributable to different types of meats - ruminant meats versus non-ruminant meats and (2) the variability of the amount of meat in different products and product subcategories.

Based on the collection of Australian supermarket products analysed throughout this thesis, there are more than 1,700 'Meat and meat products' with 500 unique products falling under the beef, game and lamb sub-categories. Non-ruminant meats such as pork and poultry are consistently found to have substantially lower GHGe than ruminant meats such as beef, lamb or game.[117,128,183] Per the results in Chapter 4, pork and poultry products were found to have one-quarter to one-sixth of the impact when compared to the latter products. The high median GHGe attributable to all animal products are a result of the large amounts of animal feed needed and the land use change required to raise animals for food; the GHGe attributable to ruminant meat products is even higher because of the methane emissions from livestock.[40] In a recent study looking at the variability of diet-related environmental impacts based on a large cohort in the UK, the GHGe associated with the diets of vegans and vegetarians was found to be approximately one-quarter of that of meat-eaters. However, the GHGe associated with meat-eaters could vary by more than one-third depending on the types and quantity of meat being consumed.[277] Thus, optimising and reducing, while not completely eradicating, meat consumption is a plausible next step in food policy.

The subcategories of 'Meat and meat products' included products with non-animal components such as plants and grains. 'Meat-based meals' had the lowest attributable GHGe based on product purchases of any 'Meat and meat product' subcategory, as seen in Chapter 6. In these, products meat comprises just a portion of the product, mixed in with vegetables, fruits and grains, significantly reducing the products' carbon footprints. However, only 18% (315/1724) of the broader 'Meat and meat products' category were 'Meat-based meals'.

Policy interventions aimed at replacing high-impact meat consumption with more low-impact meat and plant-based diets could include updating food-based dietary guidelines. A recent systematic review of national food based dietary guidelines found that the majority (46/83; 55.4%) do not consider environmental health and do not encourage habits to remain within planetary boundaries.[164] Further, those that do often only provide generalised descriptions of what a sustainable diet is rather than guidance on how to transition towards one. A modelling study found the impacts of existing guidelines would not be enough to achieve the goals of the Paris Climate Agreement, and more is needed to reduce

the consumption of animal-based foods.[152] In the UK, the Department for the Environment Food and Rural Affairs (Defra) has developed a national food strategy that encompasses various themes and policy considerations aimed at fostering a sustainable and resilient food system. It underscores the need for public awareness campaigns geared towards addressing the environmental consequences linked to a national food supply and population-level dietary choices.[305] A principle tenet of this initiative is calling for a 30% reduction in meat consumption by 2032; however, the UK is far from meeting this standard and the guidance is not an implemented policy.[305] In Australia, the use of political measures that prioritise the reduction of meat in the food supply is central to recommendations from the Climate and Health Alliance.[306] Embedding principles of environmental sustainability into the ADG and associated policies must be aggressive in order to have substantial impact. As current diets in Australia largely do not align with planetary health recommendations,[270] this is just a first step needed to promote the reduction in purchasing of meat products.

In addition, policies taxing high-carbon meat-based products could help to reduce the GHGe attributable to the retail food and beverage supply.[127,268] One study has modelled optimally taxing red and processed meats, globally, to assess the impacts on both deaths and health care costs attributable to consuming these foods.[307] It found that increasing prices of processed meats by an average of 25% and red meats by an average of 4% could result in significant gains for both human and environmental health. Similar results were seen in a study assessing the implications of a meat tax and fruit and vegetable subsidy in the Netherlands.[308] Further, taxes can be used to encourage industry reformulation as well as the introduction of new products in the market.[309]

Plant-based meat alternatives are increasing in availability, comparability to meat products with respect to nutrient profiles and are a potential solution to reducing the GHGe attributable to meat products and purchases.[34,310] New meat alternatives made in commercial facilities such as those made of mycoprotein, a fungal source of protein, are interesting potential solutions to the climate crisis.[311] However, it is again important to note the challenges. First, many of these plant-based meat alternatives are ultra-processed foods, which are commonly found to have adverse impacts on health,[312,313] and research regarding the health impacts of meat alternatives is still in early stages.[311] Also, the bioavailability of ultra-processed foods (i.e., effectively absorbed and utilised by the human body when consumed)[314] should be further understood to ensure that such products are sufficiently nutritious and environmentally friendly. Although in Chapter 4 ‘Meat alternatives’ were found to have much higher levels of processing than ‘Meat and meat products’, ‘Meat alternatives’ have exponentially lower attributable GHGe than animal-based meats, presenting a trade-off for human and planetary health aspects.[275] Finally, less similar switches such as these may not be preferred by consumers or align with cultural norms.[315]

7.3.2 Advanced food technologies and ultra-processed products

Due to the growth in advanced food technologies, particularly the production and consumption of ultra-processed products, the adverse health and environmental impacts of supermarket products have emerged as a focus of scientific inquiry and research.[124,316] Advanced food technologies encompass both the production machines and the modified foods that have cropped up in modern society for the betterment of food safety and reduced environmental impacts of food production.[317] Multiple aspects of technologies and ultra-processed foods, including their composition and production, must be considered to holistically address the GHGe of the food supply and dietary intake habits. The positive effects of advanced food technologies and negative effects of ultra-processed foods on both human and environmental health must be examined.

On one hand, if effectively regulated by public health policy, advanced food technology could be the solution to several environmental and food insecurity issues that exist globally today. In addition to increasing GHGe emissions, current farming and food production technologies contribute to water pollution, over-fertilisation and deforestation.[131,316] Though the idea of reverting to a locally grown diet is appealing for both public health and environmental sustainability, it is not entirely feasible as a result of continued urbanisation and the increased global population.[318] Advanced food technologies, such as urban vertical farms, are being explored to mitigate the overuse of natural resources due to agriculture and large-scale conventional farming.[319] It is likely that food production will need to increase in efficiency by 60%, by wasting less and bringing more product to market.[320] Such improvements in food technology can ensure that, for foods grown using alternative methods, waste is minimised and prepared meals are safe, nutritious and environmentally friendly.[321]

On the other hand, advanced technologies used in industrialised agriculture have little consideration of health or environmental impacts.[124,322] Firstly this is seen with the proliferation of ultra-processed foods. Ultra-processed foods are not a core component of healthy diets, implying that the attributable GHGe and other environmental impacts are largely unnecessary.[248,261] It is well established that ultra-processed products, which tend to have minimal nutrient density per quantity of product and addictive qualities, are associated with excess calorie intake, weight gain and adverse health outomces.[19,323] Also, the mass production of ultra-processed products at low cost, using low quality ingredients is associated with high rates of wasted ingredient byproducts and product losses, contributing even further to excess food system GHGe.[4,11]

Chapter 4 of this thesis allowed for the exploration and comparison of ultra-processed products, such as ‘Snack foods’ and ‘Convenience foods’, against their minimally processed counterparts. As expected and particularly for plant-based products with similar ingredient compositions, GHGe attributable to product processing were highest when the product was classified as NOVA Group 4, or an ‘Ultra-processed food’. This resulted in ultra-processed products often having higher total product-specific

GHGe estimates than similar, less processed products. However, despite high level partnerships and published guidance for consumer self-regulation, the Australian government has not delivered any diet-related environmental policy pertaining to ultra-processed foods.[57] This is in part due to the subversion of policymakers to neoliberalist agendas and industry lobbying.[41,173] Big ultra-processed food brands have come under scrutiny due to their potential to foster the consumption of unhealthy foods.[165] Marketing strategies wield a significant influence over consumer behaviour, with tactics like celebrity endorsements, animated mascots, and strategic product placements in media playing a substantial role in shaping dietary preferences.[324] It will be important to ensure that the creation of aggressive public health and environmental policies is informed by the health and environmental impact data pertaining to ultra-processed foods and not inhibited by industry.[124]

Further, the increased use of technology in developing food and beverage products may have negative downstream effects on the planet, such as the depletion of non-renewable resources used to create the technologies. While original technologies may be less efficient, the deployment of technologies marketed as sustainable as a part of energy transitions require a significant increase in the use of non-renewable precious metals and minerals.[325] Also, in some studies, foods from new farming techniques including from vertical farming have shown to emit more GHGe than locally grown foods and require up to 17 times more fuel.[318,319] Carbon offsetting is one emerging tactic used by multinational companies to improve the a company's image by taking into consideration environmentally friendly measures. A carbon offsetting platform, as defined by the United Nations committee on Climate Change, is a tool that can be employed by a company, organisation or individual to purchase carbon credits to compensate for GHGe.[326] However, it is likely that in many cases carbon offsetting has been used primarily as a marketing strategy and a way to divert the attention of consumers and stakeholders without needing to address the GHGe of the product itself.[327] Therefore, industry claims related to the implementation of sustainable technologies or investment in support of climate action must be closely regulated.

7.3.3 Expanding data on product environmental impacts

In this thesis, a method to calculate product-specific GHGe was defined and provided a foundational step in quantifying a product's environmental impact. The scope of data must be expanded in order to better distinguish between the overall environmental impact of similar supermarket products. Future research should assess additional impact factors for individual foods and beverages by incorporating both environmental measures such as land use, scarcity-weighted water use, biodiversity loss, and eutrophication potential. The inclusion of environmental impact factors requires significant additional data that are not currently available for individual ingredients or products. Recently published research on the environmental impacts of the UK supermarket product supply included four impact factors (GHGe, water scarcity, land use and eutrophication potential) using a growing environmental database called HESTIA.[183,328] The work in Clark *et al*. provides a more nuanced perspective of environmental impacts of products, allowing for discrepancies to be seen for products with low GHGe, but high water

and land use, such as almond production and certain baking ingredients.[117,328] However, HESTIA data tends to largely focus on European ingredients and contains many fewer ingredients with multiple impact factors than ingredients with only GHGe. As more robust data are made available, they could be used to make an improved case for government interventions, such as taxation or cost subsidies, to promote products that are not only better for human health and GHGe, but for the environment as a whole.[329]

To enable more precise assessments of product-specific GHGe and other environmental impact factors, future research should also improve and expand on the system boundary used. Product-specific information on ingredient sourcing, processing and transport practices, which could only be assessed by product category in this thesis, could greatly improve the accuracy of environmental estimates.[183] However, to ensure an adequate data standard and that all products are included, producers and manufacturers should not be held responsible to provide the data. Input-output models are one option to improve the scope of the system boundary being assessed without relying on industry compliance or policy change.[139] Input-output models capture the relationships and dependencies among industries and production technologies, allowing for a thorough analysis of environmental impacts as well as economic impacts.[138,330] For instance, input-output models can be helpful in better capturing the environmental impacts of ultra-processed foods by providing more detailed energy usage data by commodity sector.[140] Although there is now sufficient evidence that ultra-processed products are harmful to public health,[29,69] their environmental footprints with respect to the energy used to develop and run product machinery, their distribution, and their evolving composition still require further analysis.[331] Combined LCA and input-output models, called hybrid models, can help to identify leverage points for intervention and design measures that yield the most significant environmental benefits.[140] Further, including additional life cycle phase including packaging, refrigeration, disposal and waste will better differentiate between environmental impacts of very similar products. However, to date, no product-specific environmental works include ingredient data and packaging assessments combined due to limited available data.[183,249]

Though this thesis investigated the snapshot of GHGe attributable to Australian supermarket products available in 2019, the assessment of products year over year and the inclusion of products purchased and consumed at other types of outlets would improve the understanding of overall food system impacts. Applying the research in this thesis to multiple years of data would promote an understanding on if the contents of the food supply are changing or if the purchasing patterns are changing. This could inform what types of policies are needed, for instance, whether industry or consumer-centric interventions are more influential based on temporal trends. Better benchmarking food and beverage product portfolios based on environmental metrics could echo current practices centred on human health in order to measure and track progress in food system change. For example, The George Institute for Global Health releases yearly reports called 'The State of the Food Supply',[186] which provide detailed metrics on the nutritional content of supermarket products as well as changes in nutritional content year on year,

highlighting retailers, manufacturers and food sectors with key changes. Also, addressing the current gap in data related to products consumed outside the home is essential. Incorporating information on restaurant and take-away meals into analyses will provide a more comprehensive view of individuals' dietary habits and their associated environmental impacts. This information should be considered in conjunction with the work in this thesis to provide a more holistic perspective of the diet.[299]

Future research should also delve into what people are consuming and the underlying motivations behind their dietary choices. It is important to recognise the intricacies of human dietary preferences, what drives individuals' food choices and how these drivers change.[15] Exploring factors such as cultural, economic, and psychological influences can shed light on why specific products are chosen.[13,100] For example, this could include the integration of behavioural economics into the context of food choices, such as that food choice has been largely and consistently driven by taste and price for many decades.[332] This knowledge can help gain a more comprehensive perspective on food selections, paving the way for informed strategies aimed at promoting healthier and more sustainable dietary behaviours.

Finally, further research is needed to determine the best approach to replicating this model for Australia in other counties with a similar food system makeup. The food system is becoming more and more globally connected, affecting agricultural workers, producers and trade markets internationally.[58,333] Ensuring that future analyses capture these international products and markets will be important in achieving environmental and nutritional targets laid out by global organisations including the Paris Climate Agreement and United Nations Sustainable Development Goals.[153,334]

7.3.4 Product labelling

Food labels that communicate the GHGe impacts of products, referred to as eco-labels, are a key next step in transitioning to a sustainable food system. Labels can be used to enable consumers to make informed decisions, guide them towards environmentally conscious purchases and even motivate industry towards producing more sustainable products.[180,335] Therefore, calls for government to adopt labels incorporating environmental sustainability are imminent.[336,337] At the UN Food Systems Summit in September 2021, the urgency of fostering environmentally sustainable food systems was reinforced, placing emphasis on the role that consumers play in the trajectory of food systems and their need to incorporate sustainability while making purchasing decisions.[157,338] The growing global consciousness surrounding sustainability, encompassing climate change, environmental conservation, animal welfare, and labour rights, has notably shifted consumer behaviour.[339,340] Thus, recent research has emerged showing an association with the presence of eco-labels and the selection of lower GHGe products, and in some cases there is evidence of an increased willingness to pay higher prices.[150,341]

Though the implementation of eco-labels is sparse, some governments and businesses have responded to consumer interest in climate change by developing sustainability-related labels on products that align with GHGe reduction and net-zero goals (**Figure 7.2**).[148,149,247,342,343] The Eco-Score, an eco-label developed in France, evaluates the environmental impact of food products using sixteen different environmental indicators.[148] By assigning scores that encompass various dimensions of sustainability, the Eco-Score aims to empower consumers to make informed decisions aligned with their environmental values. Similar to how the Nutri-Score incorporates positive and negative food components into the final score, the Eco-Score includes a number of positive and negative environmental components including packaging recyclability and ingredient procurement. However, the correlation amongst the environmental indicators used is not fully considered. The Eaternity score, a growing but infrequently used label in Europe, provides consumers with clear information about four environmental impacts associated with specific food products (GHGe, water use, animal welfare and impacts on rainforests).[247] It uses a user-friendly design to communicate complex environmental data to consumers. However, the limited availability makes it hard for consumers to compare across products. A few individual companies have developed eco-labels as well, though they tend to be companies focusing on producing low footprint alternatives such as plant-based dairy and meats.[342,343] Because they are company-specific, they are also often difficult for consumers and other stakeholders to interpret and compare across products.

Figure 7. 2. Examples of existing government and industry eco-labels

Eco-Score[1]	Eaternity score	Oatly label	Quorn label
			

[1]The indicators used in the Eco-score are: greenhouse gas emissions, water use, land use, acidification, fine particles, marine eutrophication, fresh water eutrophication, terrestrial eutrophication, depletion of energy sources, depletion of mineral sources, depletion of ozone layer, photochemical ozone formation, ionizing radiation, freshwater ecotoxicity, carcinogenic human toxicity.

The method to calculate product-specific GHGe presented in this thesis could be used to improve upon existing labels. By utilising the methods presented in Chapter 4, a first-ever industry-wide, internationally implementable GHGe eco-label could be developed. This is largely because of the use of available product information, rather than reliance on industry manufacturers to provide data as is currently required by all four examples described above. Australian corporations, such as Woolworths with their initiative called Food Tracker done in partnership with HealthyLife,[170] are already working

to incorporate sustainability models and have shown interest in incorporating the methods included here. The George Institute for Global Health is also utilising this work to provide an eco-label within the FoodSwitch mobile application (**Supplementary information S7.1**). As many Australians tend to underestimate the GHGe associated with the production of food and beverage products, particularly the magnitude of differences between product categories (e.g., between vegetables and meats), the ability to clearly present this information alongside lower-emission switches as described in this thesis is greatly needed.[7]

The work presented in this thesis can also be used to inform dual labelling for health and environmental impacts, referred to as sustainability labelling. The patterns observed across each of the product categories in Chapter 5, specifically that fresh fruits and vegetables and minimally processed grain, nut and legume-based foods tend to rank better based both on their nutrient profiles and environmental impacts, are fundamental to developing such policy.[37,183,267,268] While some sustainability labels exist, they lack consistency and transparency in their methods across product categories, and therefore cannot easily be replicated.[130] The use of the combined methods described in Chapters 4 and 5 of this thesis would largely resolve this central issue, and with additional environmental impacts metrics, could provide a holistic assessment of a products nutritional and environmental footprints.

In order to be effective, environmental labelling must be both mandatory and standardised.[182] First, while voluntary labelling initiatives can be valuable as seen with nutrition labels,[344] they do not carry the same weight as mandatory guidelines in terms of shaping industry-wide practices and consumer choices.[345] The absence of mandatory labelling regulations, often attributed to industry lobbying, has impeded progress.[22] For example, the HSR and the Health Food Partnership Reformulation Program, a labelling policy and a product reformulation policy underpinned by the food-based ADGs in Australia, have been implemented with the aim of improving the nutritional quality of the food supply.[96,346] However, the current efforts have had limited effects in improving dietary quality and reducing sodium and sugar consumption due to their voluntary implementation.[280,281] Further, even fewer HSR scores, particularly when lower than 3-stars, are made available for online supermarket shoppers.[347] Similar policies could be developed to improve the GHGe impact of the food supply, though it is clear that a system with mandatory intervention requirements is needed.

Labels must also be both standard and transparent in order to avoid consumer misinterpretation. [90,260] Unclear labels that use terms or visuals that are not universally defined have the potential to result in unintended purchases that do not align with their desired sustainability goals.[142,348] For example, the proliferation of different labels and saturation of "greenwashing", or the practice of misrepresenting or exaggerating environmental credentials, by businesses in Australia underscores the need for close regulation of industry sustainability labelling.[349] To combat this issue, identifying a singular regulating organisation will be important to maintaining standard and effective food labels and ensuring the use

of reliable data. Likely this will need to be driven by a government or third-party organisation rather than industry. It can also help to ensure that a label's coverage of the food supply is sufficient to be effective. As seen with some labels that are only applied to a subset of products, such as the Roundtable on Sustainable Palm Oil certification, the limited coverage of products may have led to a reduced impact on consumers and the industry competition.[171]

7.4 Future research

To advance the field of research on the environmental impacts of food systems and inform evidence-based interventions, several key areas warrant further investigation built upon the product-specific GHGe works presented in this thesis. Future research requires additional understanding of the complexity of the food system, consumer behaviours and multiple environmental impacts. Given the dynamic nature of the food industry, there is a need to repeat these analyses year on year to track changes over time. This work should also be tested in other geographies, provided that there are available supermarket databases with sufficient coverage. The findings can then be used to test targeted interventions, policies, and strategies aimed at promoting sustainable food consumption and mitigating the environmental impacts of dietary choices.

7.4.1 Policy and impact evaluation

While this thesis provides first estimates of product-specific GHGe and applies this data to purchasing, there remains a knowledge gap with respect to the efficacy of potential interventions. First, the impacts of eco- and sustainability labelling on both consumers and industry stakeholders should be explored. Trials could be designed to compare the impact of environmental labels individually, as well as with health indicators like warning signs, traffic lights, Nutri-score, or Health Star Ratings. This approach presents an opportunity to utilise e-commerce technology to assess consumer behaviour.[124] For example, investigation of online supermarket shopping habits could be beneficial in assessing the implications of introducing point-of-sale labels. Such research could capitalise on the existing infrastructure of web browser extension tools that have been developed in Australia.[74,350] Further, product labels could be used to assess the feasibility of the switches presented in Chapter 6. The evaluation of consumer acceptability and likelihood of product switches using surveys and behavioural analyses will help inform more effective policy for transitioning to a more sustainable food system. Assessing the social acceptability of switches between major product categories (e.g., 'Meat and meat products' to 'Meat alternatives') is an important next step.[310]

Finally, there is a clear and immediate opportunity for the Australian government to implement policies that nudge industry towards producing and retailing a more sustainable food supply. Therefore, the

impacts of incentives, such as the meat taxes and fruit and vegetable subsidies mentioned above, aimed at regulating the food industry should also be considered. As discussed, GHGe limits could also be specified for product categories in the same way as the reformulation programme has outlined for adverse nutrients like sodium and added sugar,[280,281] resulting in the curation of product categories that are better for the environment as well as for population health. The outputs of such policy could encourage manufacturers to compete with products that appear better in both regards.

Chapter 8: Conclusion

The change from hunting and gathering for survival to the convenience stores of today's industrialised food system has drastically altered the makeup of the foods and beverages consumed. Food technology has supported a proliferation in the quantity and shelf life of foods and, in some cases, the ability to enhance consumption to optimise human health and development. However, it has also resulted in unforeseen consequences including an epidemic of NCDs and environmental degradation. The future of human and planetary health will require drastic change to the food system driven by policies and stakeholder collaboration that improve the health and environmental impacts of the food supply while continuing to progress food security and maintain socio-cultural wellbeing.

The work done for this thesis has provided the first application of a food-supply wide standard calculation of product-specific GHGe in Australia. In the GHGe estimation methodology, it has defined a novel approach to describing the ingredients contained in supermarket products and is the first of existing methods to use a linear programming algorithm to determine unknown ingredient proportions in those products. The work also indicates a general association between nutrient profiles and the GHGe of supermarket products that could guide the development of policies that jointly target health and sustainability, though nuances do exist for particular food and beverage categories. Finally, it highlights the potential for a substantial reduction in GHGe attributable to supermarket product purchases made by Australian households if similar but lower-emission products are purchased instead of current selections. The information made available as a consequence of this work could encourage beneficial changes to consumer behaviours, industry actions and government policies seeking to mitigate the adverse effects of poor diets on human health and the environment. Dissemination of the findings in diverse formats that inform stakeholders about product composition, drive innovations in development and implement controls on industry will be required to achieve this.

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Appendix A. Supplementary tables

Supplementary Table S1.1. The five stages described by the 'Nutrition transition'

Stage	Description	Health outcomes
Stage One *Collecting food*	The hunter-gatherer-based lifestyle, with diets primarily based on surrounding plants and, much less often, local prey. All societies, outside of a select few remaining remote peoples, have transitioned to stages 2-5.	Low fertility, low life expectancy
Stage Two *Famine*	Society centred around farming and agriculture, where diets had minimal variability (often based on a single starchy vegetable or grain) and bouts of extreme food shortages occurred, often due to crop diseases, climate-related natural disasters or war. A small number of societies remain in this stage, particularly in South Asia and other regions with migrant and refugee groups.	High fertility, high maternal mortality, low life expectancy
Stage Three *Receding famine*	Diets tend to be higher in meats and different types of whole fruits and vegetables. This stage also saw the beginnings of industrial innovations which helped in providing wider access to foods.	Increasing life expectancy; stunting
Stage Four *Diet-related noncommunicable diseases*	Diets high in fat, refined carbohydrates and added sugar and salt, and low in fibre and essential amino acids. This stage is notable as it is characterised by the significant increase presence of industry (and in turn ultra-processed foods) and it has the first signs of widespread highly sedentary lifestyles.	Long life expectancy; Diet-related noncommunicable disease (e.g., obesity, diabetes heart disease, stroke and many cancers); Double and triple burden of malnutrition
Stage Five *Behavioural change*	Diets revert toward whole and minimally processed foods, but without losing the advancement in the ability to feed large populations around the world. Reprioritisation of industry toward public health rather than profits and of consumers toward increased physical activity over sedentary alternatives is key.	Reduced diet-related non-communicable disease, lower risk of climate-related health issues

Source: Popkin, BM, Ng, SW. The nutrition transition to a stage of high obesity and noncommunicable disease prevalence dominated by ultra-processed foods is not inevitable. Obesity Reviews. 2022; 23(1):e13366. doi:10.1111/obr.13366.

Supplementary Table S3.1. FSANZ regulation codes relevant to ingredient lists and package labelling

Standard ID	Standard name	Relevant information
Standard 1.2.1	Requirements to have labels or otherwise provide information	- Defines when a retailed food product requires one or more of the labels detailed in the subsequent standards - Must be used in conjunction with all other food labelling standards
Standard 1.2.4	Information requirements – statement of ingredients	- Specifies which products require a statement of ingredients and which do not - Provides detail for what should be included in the statement of ingredients and multiple format which can comply with the legislation - Contains and additional user guide for interpreting the standard
Standard 1.2.7	Nutrition, health and related claims	- Defines the terms *fruit* and *vegetable* with respect to labelling requirements - Defines nutrients, both mandatory and optional (also in 1.2.8) - Describes differences in types of claims and what is required by each type
Standard 1.2.8	Nutrition information requirements	- Defines nutrients, both mandatory and optional (also in 1.2.7) - Defines how nutrients are to be included on the nutrition information panel - Provides measurement specifications - Specifies which products require a nutrition information panel and which do not
Standard 1.2.10	Information requirements – characterising ingredients and components of food	- Defines a characterising ingredient - Specifies requirements on how to differentiate characterising ingredients through package labelling declarations - Provides methods for calculating proportions of characterising ingredients in a product

Supplementary Table S3.2. Formatting requirements for successful disaggregation of a statement of ingredients

Required format for statements of ingredients	Example product name	Example ingredient list
General		
Statements of ingredients must contain a maximum of one colon (':'), as two or more colons indicate a multi-pack product	Arnott's Sao Biscuits	Biscuits: wheat flour | vegetable oil | salt | yeast | malt extract (from barley) | sugar | baking powder | emulsifier (soy lecithin) |antioxidant (e307b from soy)
Statements of ingredients must contain an equal number of opening bracket ('[') and/or parentheses ('(') as closing brackets (']') and/or parentheses (')')	Woolworths Pan Size Bacon	Pork | water | cure [salt | sugar | mineral salts (451 | 450) | antioxidant (316) | preservative (250)]
Main ingredients		
Ingredients are separated by a comma (',') or a pipe delimiter ('|')	McKenzie's Italian Style Soup Mix	Peas | beans | lentils
Ingredient weight percentages are included directly after the ingredient in parentheses ('()')	Val Verde Traditional Pasta Sauce	Tomatoes (96.6%) | onion | salt | onion powder | acidity regulator (citric acid (330))
Sub-ingredients		
Sub-ingredients are indicated using brackets ('[]') or parentheses ('()') directly after the compound ingredient	Mountain Bread Corn Wraps	Corn flour (70%) | wheat flour (flour | folate | thiamine) | filtered water | iodised salt
Each sub-ingredient is separated by a comma water | iodised salt (',') or a pipe delimiter ('|')		

Supplementary Table S3.3. Major and minor ingredient categories and their definitions

Field name	Definition
Additives	Any substance added to a food product with the intended use of becoming a component or affecting the characteristic of a food List of additives as defined by FSANZ: acid, antifoaming agent, acidity regulator, emulsifying salt, alkali, enzyme, anticaking agent, mineral salt, antioxidant, modified starch, bulking agent, vegetable gum, colour, emulsifier, firming agent, flavour enhancer, foaming agent, gelling agent, glazing agent, humectant, preservative, raising agent, stabiliser, sweetener, thickener
Baking	Ingredients and components with functional uses for baking including texture, flavour and leavening
Baking powder	A mixture of sodium bicarbonate and cream of tartar, used as a replacement for yeast
Baking soda	The powder form of sodium bicarbonate
Cocoa or cacao	Roasted (cocoa) and raw (cacao) cocoa bean derivatives
Gelatine	A translucent, flavourless pure protein derived from collagen
Vanilla	Extracts, pasts and other derivatives of the vanilla bean or pod
Yeast	Single-celled microorganisms which convert sugars to carbon dioxide enabling fermentation and the rising of baked goods
Composite ingredients	Ingredients created from two or more basic ingredients
Bakery goods	Pre-made food items including breads, cakes, cookies and
Chocolate	Pre-made confectionery items made of cocoa products
Condiment	Common spreads including ketchup, mustard and mayonnaise
Confectionery	Food items rich in sugar and carbohydrates
Dip	Includes salsa, hummus, tzatziki and other composite dips
Dressing	Oil or cream-based toppings often used for vegetables, salads or sandwiches
Ice cream	A sweetened frozen food typically made with a dairy or cream base
Meat sauce	Stewed meat and vegetables, usually used to top pasta or pizza
Pasta or noodle	A dish made with flour and water and formed into sheets or other shapes
Protein powder	Protein isolates combined with flavourings and preservatives
Other composite ingredients	Includes popcorn, soups, casseroles, and other powders
Sauce	Vegetable or cream-based toppings used to add moisture, flavour and visual appeal to dishes; includes curry pastes, cocktail sauce and plum sauce
Dairy	Ingredients sourced from the milk of mammals, namely cows, sheep and goats.
Cheese	Dairy ingredients formed by the coagulation of the milk protein casein
Dairy alternative	Dairy replacements made from plant proteins that resemble dairy products in texture and flavour
Milk or cream	Dairy ingredients produced in the mammary glands of mammals
Milk or whey powder	Dairy ingredients made by evaporating milk into a dry derivative
Other dairy	Dairy ingredients that are not further specified (e.g. 'dairy ingredient', 'lactose', or 'whey')
Yoghurt	Dairy ingredients produced via bacterial fermentation of milk

Field name	Definition
Dietary fibre	The edible portion of plants and other carbohydrates that are unable to be digested or absorbed
Dietary fibre	Dietary fibres that are not further specified
Inulin	Fibre found in a wide variety of fruits and vegetables
Psyllium	Fibre made from seed husks
Eggs	Reproductive body produced by female animals consisting of an ovum and its casing or shell.
Cooked egg	Eggs that have undergone heat treatment such as boiling, grilling and steaming
Egg powder	Egg derivatives made by evaporating eggs until dry
Uncooked egg	Raw, unmodified eggs
Flours and starches	Compounds creating through the milling of grains, legumes and other fibres or proteins.
Grain flour	Milled grains
Legume flour	Milled legumes
Corn starch	Starch derived from milled corn
Potato starch	Starch derived from milled potato
Tapioca starch	Starch derived from milled tapioca
Fruits and vegetables	Edible portions developing from the flower of a plant (fruit) and other portions of the plant (vegetable).
Cooked fruit	Fruits that have undergone heat treatment such as boiling, grilling and steaming
Cooked vegetable	Vegetables that have undergone heat treatment such as boiling, grilling and steaming
Dried fruit	Fruits that are heat-treated until the majority of the moisture is removed
Dried vegetable	Vegetables that are heat-treated until the majority of the moisture is removed
Fresh fruit	Raw, unmodified fruits
Fresh vegetable	Raw, unmodified vegetables
Processed fruit	Fruits that have undergone processing including dehydration, powder production and puree or paste development
Processed vegetable	Vegetables that have undergone processing including dehydration, powder production, pickling and roasting
Grains	Fruits or seeds cultivated from cereal crops.
Cooked grain	Grains that have undergone heat treatment such as boiling, grilling and steaming
Cooked rice	Rices that have undergone heat treatment such as boiling, grilling and steaming
Uncooked grain	Raw, unmodified grains
Uncooked rice	Raw, unmodified rices
Herbs and spices	Flavourful portions of plants; herbs come from the leafy part of a plant and spices come from the root, stem, bark, bulb or seeds.
Dried herb or seasoning	Herbs and spices that have been dehydrated and often crushed
Salt	Mineral composed sodium chloride; varieties include sea salt, rock salt, iodised salt and non-iodised salt

Field name	Definition
Legumes	A fruit or seed of a plant in the Leguminosae family, which includes alfalfa, beans, peas, lentils, and soybeans,
Cooked bean	Beans that have undergone heat treatment such as boiling, grilling and steaming
Cooked lentil	Lentils that have undergone heat treatment such as boiling, grilling and steaming
Cooked soy	Soybeans that have undergone heat treatment such as boiling, grilling and steaming
Uncooked bean	Raw, unmodified beans
Uncooked lentil	Raw, unmodified lentils
Uncooked soy	Raw, unmodified soybeans
Liquids	Substances of constant volume often used as wet ingredients.
Alcohol	Includes beer, wine and distilled spirits
Carbonated drinks	Liquids containing dissolved carbon dioxide, including soft drinks and kombucha
Fruit juice	Made from the pressing of natural liquids contained in fruits
Vegetable juice	Made from the pressing of natural liquids contained in vegetables
Tea or coffee	Liquid drink prepared by infusing hot water with leaves (tea) or roasted coffee beans (coffee)
Vinegar	Liquid solution of acetic acid
Water	Includes varieties such as mineral water, filtered water and spring water
Meat	Ingredients derived from the flesh of an animal (excluding seafood)
Cooked beef	Beef that has undergone heat treatment such as boiling, grilling and steaming
Cooked lamb	Lamb that has undergone heat treatment such as boiling, grilling and steaming
Cooked meat	Other meat that has undergone heat treatment such as boiling, grilling and steaming
Cooked pork	Pork that has undergone heat treatment such as boiling, grilling and steaming
Cooked poultry	Poultry that has undergone heat treatment such as boiling, grilling and steaming
Meat alternative	Meat replacements made from plant proteins that resemble meat products in texture and flavour
Other meat	Includes less frequently seen meats such as camel, kangaroo, rabbit and venison
Uncooked beef	Raw, unmodified beef
Uncooked lamb	Raw, unmodified lamb
Uncooked pork	Raw, unmodified pork
Uncooked poultry	Raw, unmodified poultry
Non-nutritive sweeteners	Sweeteners that add sweetness but little or no calories to a food product; they are often sweeter than sugar and only require small doses
Aspartame	An artificial non-saccharide sweetener
Erythritol	A low calorie sugar alcohol
Stevia	A natural sweetener derived from the stevia leaf
Sucralose	An artificial sugar-derived sweetener

Field name	Definition
Nutritive sweeteners	Caloric ingredients that enhance the flavour or texture of food by adding sweetness
Dextrose	A simple sugar made from corn
Fructose	A simple sugar made from the fruit of plants
Glucose	A simple sugar made by plants
Glycerol	A simple compound with sweet flavour
Honey	A sweet, sugary secretion made from bees
Maltitol	A natural sugar alcohol found in some fruits and vegetables
Maltodextrin	A sweet powder made from vegetable starch
Mannitol	A type of sugar alcohol
Other sweetener	Sweeteners that are not further specified
Pectin	A natural sweetener found in berries and other fruit
Sorbitol	A type of sugar alcohol that is lower in calories and sweetness
Sucrose	Another name for common sugar
Sugar	A generic name for sweet, soluble carbohydrates
Syrup	Includes maple syrup, golden syrup, cherry syrup and molasses
Xylitol	A natural alcohol sugar found in most plants
Nuts and seeds	Edible kernels either surrounded by a shell (nuts) or not surrounded by a shell (seeds)
Processed nut	Nuts that have undergone processed including blanching and grinding
Raw nut	Raw, unmodified nuts
Roasted nut	Nuts that have undergone oven heat-treatment
Raw seed	Raw, unmodified seeds
Oils and fats	Ingredients composed of triglycerides
Butter	Edible fat extracted from a dairy source
Cocoa butter	Edible fat extracted from the cocoa bean
Fat	Includes fats made from animals, dairy products and vegetables
Oil	Includes oils made from a range of seeds and plants
Seafood	Flesh of animals that reside in water, including fish, shellfish and molluscs
Cooked fish	Fish that has undergone heating such as boiling, grilling and steaming
Cooked shellfish	Shellfish that has undergone heating such as boiling, grilling and steaming
Roe	Mass of eggs that comes from fish or shellfish
Uncooked fish	Raw, unmodified fish
Uncooked shellfish	Raw, unmodified shellfish

Supplementary Table S4.1. Distribution of product-specific NOVA classifications for FoodSwitch products

FoodSwitch product category	NOVA Group Classification[1] N (%)			
	Group 1	**Group 2**	**Group 3**	**Group 4**
Total	*3,648 (15.5%)*	*849 (3.6%)*	*4,151 (17.6%)*	*14,902 (63.3%)*
Bread and bakery products	0 (0.0%)	0 (0.0%)	471 (20.1%)	1,874 (79.9%)
Cereal and grain products	555 (28.4%)	157 (8.0%)	210 (10.8%)	1,030 (52.8%)
Confectionery	0 (0.0%)	0 (0.0%)	80 (6.3%)	1,197 (93.7%)
Convenience foods	38 (2.6%)	1 (0.1%)	319 (22.5%)	1,060 (74.8%)
Dairy	191 (6.5%)	17 (0.6%)	356 (12.0%)	2,392 (80.9%)
Edible oils and oil emulsions	0 (0.0%)	369 (74.5%)	0 (0.0%)	126 (25.5%)
Egg and egg products	89 (100%)	0 (0.0%)	0 (0.0%)	0 (0.0%)
Foods for specific dietary use	0 (0.0%)	0 (0.0%)	196 (27.1%)	526 (72.9%)
Fruit, vegetables, nuts and legumes	1,812 (48.1%)	56 (1.5%)	693 (18.4%)	1,205 (32.0%)
Meat alternatives	0 (0.0%)	0 (0.0%)	67 (34.4%)	128 (65.6%)
Meat and meat products	483 (28.0%)	0 (0.0%)	92 (5.3%)	1,149 (66.6%)
Non-alcoholic beverages	358 (14.7%)	18 (0.7%)	661 (27.1%)	1,399 (57.5%)
Sauces, dressings, spreads and dips	0 (0.0%)	34 (1.5%)	524 (22.5%)	1,769 (76.0%)
Seafood and seafood products	122 (16.0%)	0 (0.0%)	263 (34.6%)	376 (49.4%)
Snack foods	0 (0.0%)	0 (0.0%)	186 (27.3%)	496 (72.7%)
Sugars, honey and related products	0 (0.0%)	197 (48.6%)	33 (8.2%)	175 (43.2%)

[1]Nova Classification groups are as follows: NOVA Group 1 = Unprocessed and minimally processed foods; NOVA Group 2 = Processed culinary ingredients; NOVA Group 3 = Processed foods; NOVA Group 4 = Ultra-processed foods.

Supplementary Table S4.2. Additives determined to be indicators of NOVA Group 4 products

Agar	Gums (Arabic, guar, vegetable, xanthan)
Agent (anti-caking, de-foaming, firming, glazing, etc.)	Humectant
Aspartame	Hydrogenated/interesterified oil
Binder	Improver
Beta carotene	Inositol
Caffeine	Invert sugar
Carbon dioxide	Lactose
Carrageenan	Maltitol
Casein	Maltose
Charcoal	Mannitol
Coffee essence	Menthol
Colour	Modified (maize/potato) starch
Confectioners glaze	Monoglyceride
Corn syrup (incl. high fructose)	Oligosaccharides
Dextrose	Pectin
Dextrin	Propane
Disodium guanosine monophosphate	Propellant
Emulsifier	Protein powder/isolate (including hydrolysed)
Emulsifying salt	Sodium nitrate
Erythritol	Sodium nitrite
Esters	Sorbitol
Extract	Soy lecithin
Flavour	Stabiliser/stabilizer
Food additive (processing aids, sequestrants (452), etc.)	Sucralose
Fructose	Sucrose fatty acid esters
Fruit juice concentrate	Sweetener (potassium (950), aspartame (951) etc.)
Glucose	Thickener
Glucuronolactone	Trehalose
Gluten	Triglycerides
Glycerine	Xylitol
Glycerol	

Source: adapted from Barrett EM, Gaines A, Coyle DH, *et al.* Comparing product healthiness according to the Health Star Rating and the NOVA classification system and implications for food labelling systems: an analysis of 25,486 products in Australia. *Nutrition Bulletin.* 2023; In press.
The terms listed here were considered cosmetic additives or industrial food substances and treated as markers of NOVA Group 4, or ultra-processed products when present on ingredient lists.

Supplementary Table S4.3. Distribution of product-specific country of origin labelling for FoodSwitch products

FoodSwitch product category	Country of origin label type* N (%)			
	Group 1	Group 2	Group 3	Group 4
Total	*17,136 (72.8%)*	*5,252 (22.3%)*	*1,097 (4.7%)*	*65 (0.3%)*
Bread and bakery products	1,864 (79.5%)	448 (19.1%)	24 (1.0%)	9 (0.4%)
Cereal and grain products	1,275 (65.3%)	531 (27.2%)	128 (6.6%)	18 (0.9%)
Confectionery	1,016 (79.6%)	228 (17.9%)	33 (2.6%)	0 (0.0%)
Convenience foods	1,122 (79.1%)	270 (19.0%)	26 (1.8%)	0 (0.0%)
Dairy	2,283 (77.2%)	590 (20.0%)	81 (2.7%)	2 (0.1%)
Edible oils and oil emulsions	302 (61.0%)	161 (32.5%)	29 (5.6%)	3 (0.6%)
Egg and egg products	88 (98.9%)	1 (1.1%)	0 (0.0%)	0 (0.0%)
Foods for specific dietary use	482 (66.8%)	195 (27.0%)	45 (6.2%)	0 (0.0%)
Fruit, vegetables, nuts and legumes	2,305 (61.2%)	1,029 (27.3%)	421 (11.2%)	11 (0.3%)
Meat alternatives	162 (83.1%)	31 (15.9%)	2 (1.0%)	0 (0.0%)
Meat and meat products	1,642 (95.2%)	67 (3.9%)	11 (0.6%)	4 (0.2%)
Non-alcoholic beverages	2,000 (82.1%)	256 (10.5%)	177 (7.3%)	3 (0.1%)
Sauces, dressings, spreads and dips	1,546 (66.4%)	722 (31.0%)	49 (2.1%)	10 (0.4%)
Seafood and seafood products	215 (28.3%)	529 (69.5%)	15 (2.0%)	2 (0.3%)
Snack foods	539 (79.0%)	117 (17.2%)	24 (3.5%)	2 (0.3%)
Sugars, honey and related products	295 (72.8%)	77 (19.0%)	32 (7.9%)	1 (0.2%)

*The four internally defined groups were determined based on the distance travelled depending on the origin of ingredients (Australia or overseas) and the location of packaging and production (Australia or overseas). Products made of Australian ingredients and packaged in Australia would have travelled least; whereas products made of Australian ingredients, packaged overseas and then imported back to Australia would have travelled most.

Supplementary Table S4.4. Uncertainty intervals for product category greenhouse gas emission medians and IQRs

FoodSwitch product category	No. of products	25th pct GHGe estimate (95% UI)	Median GHGe estimate (95% UI)	75th pct GHGe estimate (95% UI)
Overall	*23,550*	*1.03 (0.81-1.65)*	*2.24 (1.22-4.20)*	*6.94 (5.13-18.5)*
Bread and bakery products	2,345	1.32 (1.29-1.35)	2.29 (2.25-2.33)	3.56 (3.50-3.62)
Cereal and grain products	1,952	0.70 (0.69-0.72)	1.34 (1.32-1.36)	2.22 (2.18-2.26)
Confectionery	1,277	3.31 (3.21-4.73)	6.07 (5.96-6.23)	9.88 (7.65-10.2)
Convenience foods	1,418	1.25 (1.22-2.29)	2.23 (2.18-2.29)	3.89 (3.81-3.98)
Dairy	2,956	2.81 (2.53-3.01)	4.14 (4.11-4.37)	7.95 (5.87-10.4)
Edible oils and oil emulsions	495	2.79 (2.67-2.91)	3.48 (3.41-3.56)	4.38 (4.26-4.54)
Egg and egg products	89	3.50 (3.36-3.65)	3.87 (3.73-4.03)	4.23 (4.13-4.34)
Foods for specific dietary use	761	1.18 (1.13-1.79)	2.13 (2.06-2.21)	4.25 (4.07-4.45)
Fruit, vegetables, nuts and legumes	3,766	0.48 (0.47-0.49)	1.04 (1.02-1.09)	2.01 (1.99-2.04)
Meat alternatives	195	1.06 (1.00-1.14)	1.66 (1.57-1.81)	2.43 (2.26-2.66)
Meat and meat products	1,724	5.78 (4.74-11.9)	6.93 (5.39-14.8)	29.7 (26.8-33.7)
Beef and game	234	48.6 (45.9-55.2)	53.9 (50.1-56.6)	57.4 (56.9-61.7)
Beef and game products	76	39.1 (37.9-43.0)	44.1 (41.8-46.9)	46.7 (44.9-50.1)
Lamb	127	26.8 (24.0-29.1)	27.9 (26.0-29.9)	31.9 (28.0-34.4)
Lamb products	3	15.3 (14.1-19.2)	23.7 (22.1-24.0)	25.0 (23.6-26.9)
Meat-based meals	315	4.12 (3.99-4.87)	5.14 (4.89-5.33)	7.78 (6.22-8.93)
Other meat products	88	6.44 (6.03-25.0)	36.5 (30.1-39.6)	47.6 (38.7-51.9)
Pork	130	6.98 (6.79-7.32)	7.38 (7.01-7.72)	8.06 (7.82-9.12)
Pork products	463	5.88 (5.12-6.23)	6.42 (5.88-6.91)	6.80 (6.48-7.89)
Poultry	213	6.18 (5.73-6.22)	6.41 (5.97-6.93)	6.99 (6.43-7.37)
Poultry products	75	4.69 (4.48-5.71)	5.89 (5.73-5.99)	5.98 (5.91-6.76)
Non-alcoholic beverages	2,436	1.64 (1.58-1.70)	3.17 (3.12-3.23)	6.08 (5.93-6.25)
Sauces, dressings, spreads and dips	2,327	1.11 (1.09-1.14)	1.82 (1.79-1.86)	2.75 (2.70-2.81)
Seafood and seafood products	682	2.01 (1.96-2.05)	2.66 (2.59-2.98)	4.75 (4.57-4.94)
Snack foods	722	1.48 (1.43-1.53)	2.25 (2.20-2.31)	3.21 (3.13-3.31)
Sugars, honey and related products	405	1.66 (1.56-1.79)	2.37 (2.26-2.50)	3.26 (3.13-3.39)

Source: *Poore J, Nemecek T. Reducing food's environmental impacts through producers and consumers. Science. 2018;360(6392):987-92.*

GHGe: Greenhouse gas emission estimates, provided in (kg CO_2eq/kg product)

UI: Uncertainty interval

Supplementary Table S6.1. Examples of less similar switches for products in 12 of the major food categories

Major category	Minor category	Original product	75th percentile switch	50th percentile switch	25th percentile switch	5th percentile switch
Bread and bakery products	**Bread**	*Other sweet bread not otherwise specified*	*Regular flat bread*	*White bread*	*Bread rolls*	*White bread*
		Chocolate Chip Brioche Rolls	Mixed Grain Wraps	Sliced White Bread	Dinner Rolls	Sourdough Loaf
Cereal and grain products	**Breakfast cereals**	*Breakfast cookies/rusks etc.*	*Corn flakes*	*Breakfast bites*	*Flavoured oats*	*Plain oats*
		Breakfast Chocolate Biscuits	Corn Flakes	Crunchy Honey Bran Bite	Almond Pecan and Hazelnut Porridge Sachet	Quick Oats
Confectionery	**Chocolate and sweets**	*Block dark chocolate (no nuts)*	*Block dark chocolate (no nuts)*	*Single chocolate bars*	*Chocolate bars in packs*	*Mints*
		Baking 70% Cocoa Dark Chocolate	Dark Chocolate Peppermint Block	Original Chocolate Bar	Crunch Chocolate Bar	Chewy Dragees Mint Flavour
Convenience foods	**Soup**	*Canned other soup with meat*	*Canned pea and ham soup*	*Other soup with veg dry mix*	*Chilled other soup with veg*	*Canned other soup*
		Beef & Veg Soup	Pea & Ham Soup	Dutch Curry & Rice Soup	Curried Sweet Potato & Turmeric Soup	All Natural Three Bean Chunky Soup

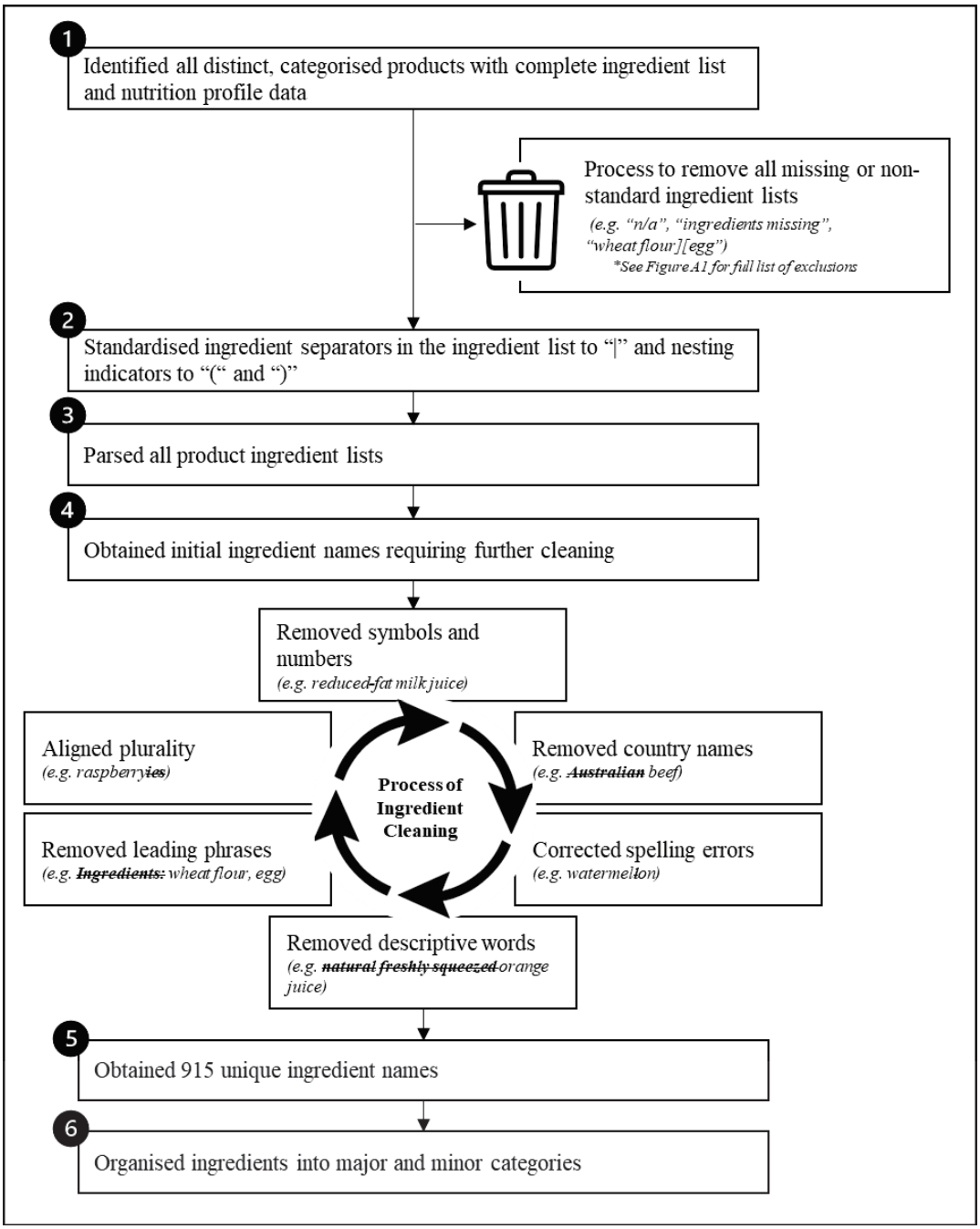
Major category	Minor category	Original product	75th percentile switch	50th percentile switch	25th percentile switch	5th percentile switch
Dairy	**Yoghurt and yoghurt drinks**	*Yoghurt with muesli or other non-fruit additions*	*Apple-based yoghurt*	*Strawberry yoghurt*	*Drinking yoghurt*	*Non-dairy yoghurts*
		Sweetened Greek Style Strained Yogurt with Honey Granola	Dairy Apple & Rhubarb Twist Yogurt	Strawberry Greek Style Yogurt	Strawberry Yoghurt Drink	Gluten Free Cultured Coconut Milk with Vanilla Yoghurt
Fruit, vegetables, nuts and legumes	**Vegetables**	*Plain frozen vegetables*	*Peppers/capsicum*	*Other canned vegetables not otherwise specified*	*Pickles/gherkins*	*Other canned vegetables not otherwise specified*
		Peas & Carrots	Capsicums	Baby Carisma Potatoes	Gherkins	Onions
Meat alternatives	**Meat alternatives**	*Other meat-free products not otherwise specified*	*Plain tofu*	*Other meat-free products not otherwise specified*	*Plain tofu*	*Meat-free burgers*
		Textured Vegetable Protein	Organic Tofu Hi-Protein Firm	Savoury Vegie Mince	Silken Tofu	Black Bean Beetroot Burger
Meat and meat products	**Processed meat**	*Dried meat*	*Meat pies*	*Kransky*	*Sliced ham*	*Coated/breaded frozen/chilled meat*
		Mini-Stick Biltong Peri Peri	Beef with Caramelised Onion & Cabernet Sauvignon	Traditional Kransky	Triple Smoked Ham	Chicken Breast Tenders Southern Style

Major category	Minor category	Original product	75th percentile switch	50th percentile switch	25th percentile switch	5th percentile switch
Non-alcoholic beverages	**Soft Drinks**	*Cola sugar-free* Sugar-free Vanilla Cola	*Sugar-sweetened cola* Original Cola	*Other sugar-sweetened soft drinks not otherwise specified* Dry Ginger Ale Soft Drink	*Other sugar-sweetened soft drinks not otherwise specified* Raspberry Soft Drink	*Ice tea drinks* Organic Kombucha Ginger Lemon
Sauces, dressings, spreads and dips	**Spreads and dips**	*Seafood-based dips* Prawn Seafood Dip with a Hint of Lemon	*Hummus* Hummus Dip	*Smooth peanut butter* Protein Peanut Butter Dip	*Spinach dips* Gluten Free Classic Spinach Dip	*Salsa* Chunky Tomato Salsa Mild
Seafood and seafood products	**Seafood**	*Other canned fish not otherwise specified* Skinless & Boneless Rainbow Trout Smoked Fillets	*Coated/battered frozen fish* Panko Squid Strips	*Chilled raw fish flavoured* Marinated Salmon Mustard & Dill Sauce	*Anchovies* Anchovies Fillets In Olive Oil	*Plain canned sardines* Sardines In Extra Virgin Olive Oil
Snack foods	**Crisps and snacks**	*Chicken flavour potato crisps* Roast Chicken Flavour crisps	*Corn chips* Roasted Beetroot & Ricotta Tortilla Chips	*Sweet chilli potato crisps* Sweet Chilli & Sour Cream Flavoured Potato Chips	*Popcorn* Natural Popcorn Sea Salted Caramel	*Wholegrain chips* Cheese Flavour Whole Grain Bites

Leaf categories are noted in *italics* in each cell above the product names. Brand names have been removed for anonymity of data.

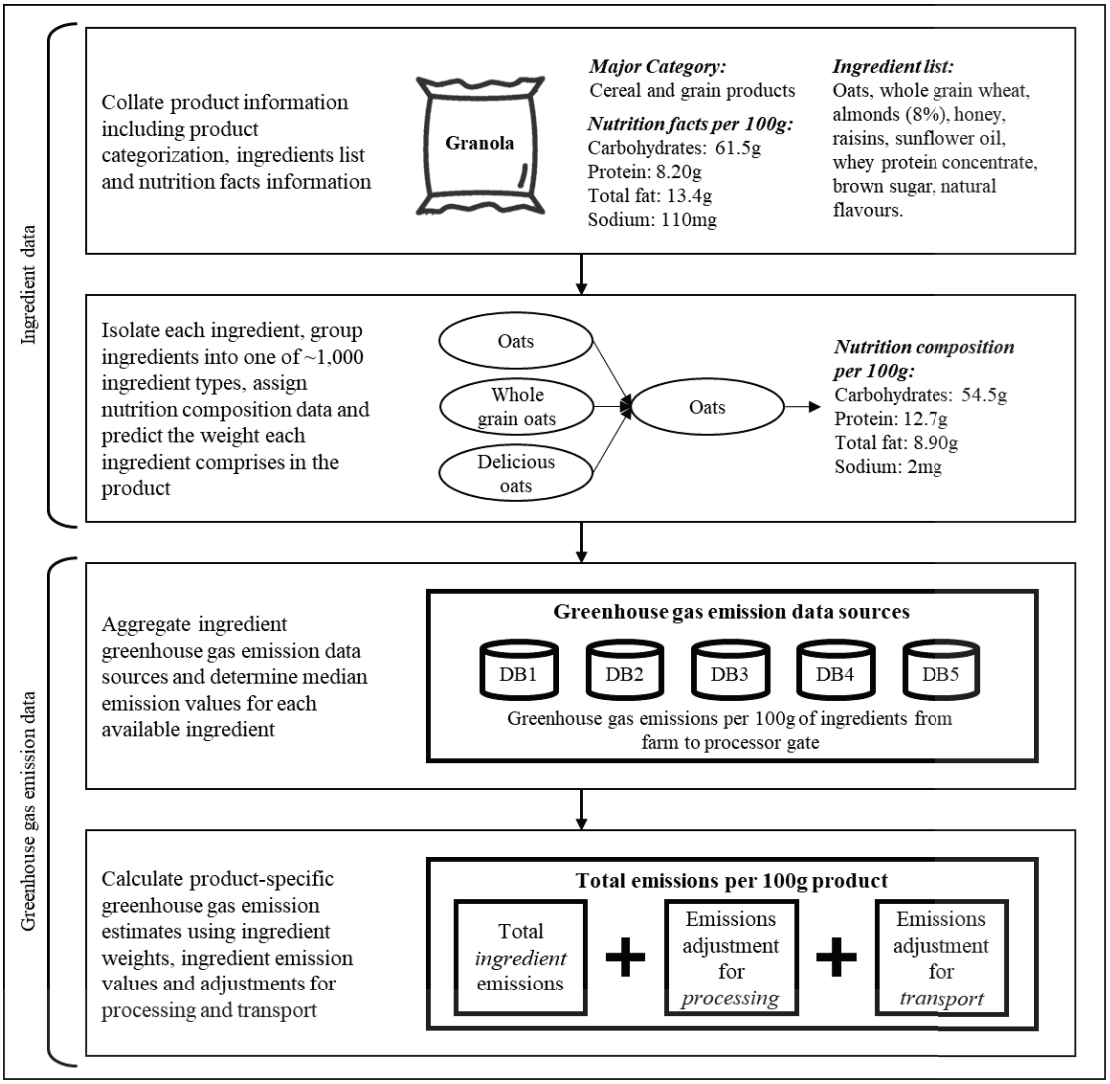
Appendix B. Supplementary figures

Supplementary Figure S3.1. Workflow for developing the list of unique ingredients in Australian supermarket food and beverage products



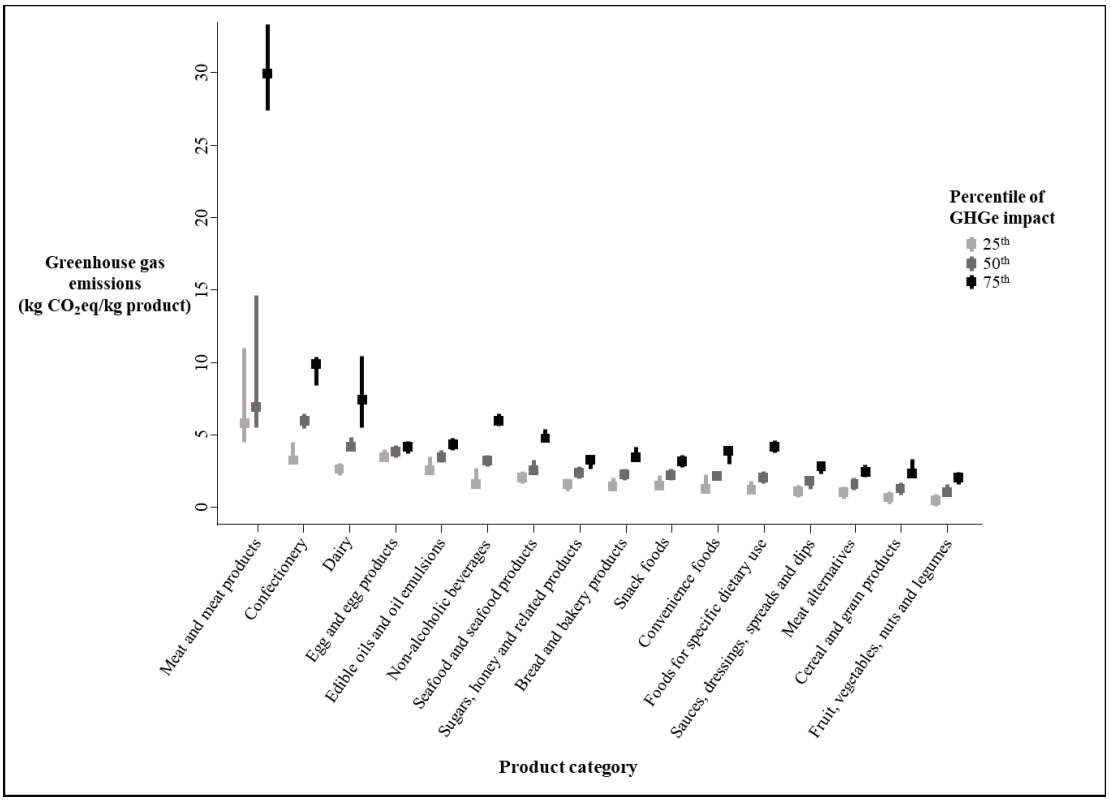
Source: Gaines A, Shahid M, Huang L, Davies T, Taylor F, Wu JH, *et al.* Deconstructing the Supermarket: Systematic Ingredient Disaggregation and the Association between Ingredient Usage and Product Health Indicators for 24,229 Australian Foods and Beverages. Nutrients. 2021;13(6):1882. Struck-through words and descriptions are examples of terms that were removed or aligned during the process of ingredient cleaning.

Supplementary Figure S4.1. Breakdown of product-specific greenhouse gas emission estimates



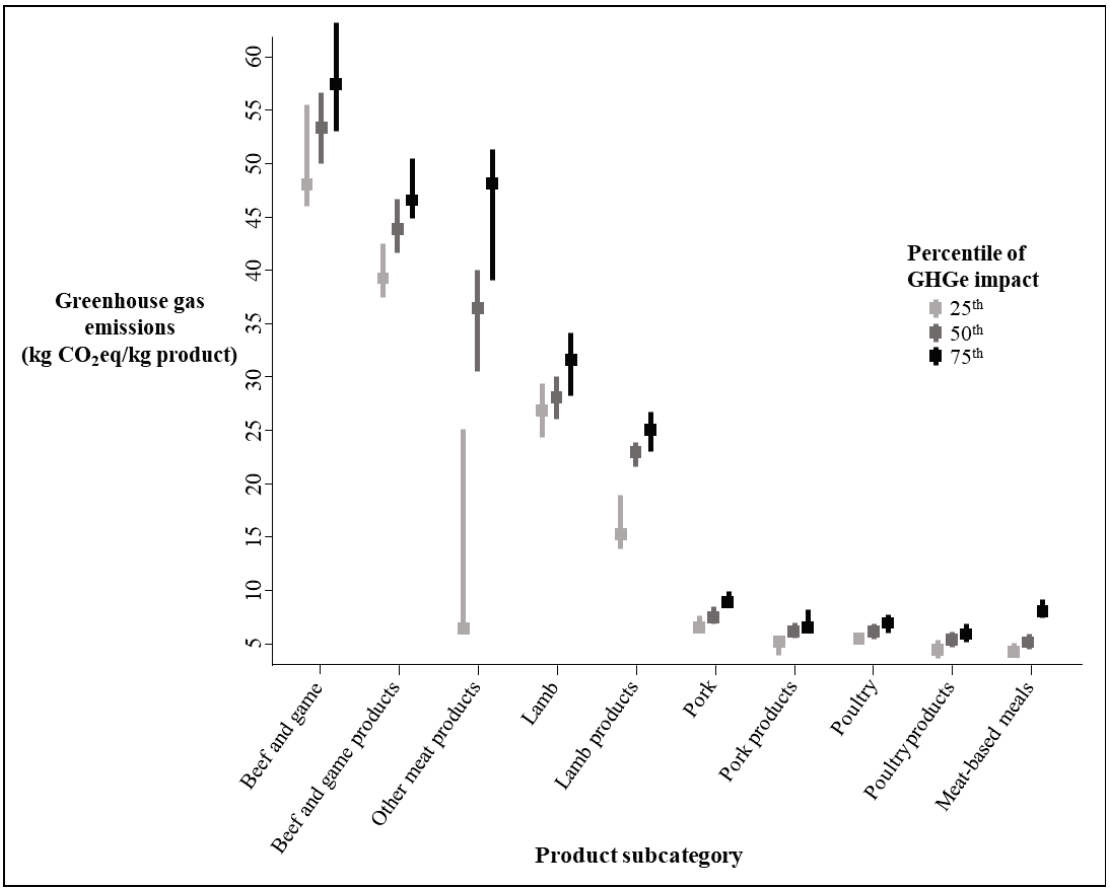
This figure outlined the approach to estimating product-specific greenhouse gas emissions for individual packaged food and beverage products. Ingredient lists for each product were disaggregated and a linear program was used to predict individual ingredient weights in each product (Chapter 3). Ingredient-specific GHGe values were identified from five life cycle assessment data sources: Clune *et al.*, Ecoinvent 3.7.1, dataFIELD v1, CleanMetrics and Agri-footprint 5.0. Weighted GHGe values for each ingredient were summed to define a product-specific GHGe estimate that was then adjusted for processing and transport (Chapter 4).
DB: Database

Supplementary Figure S4.2. Product-specific greenhouse gas emission estimates across 16 main product categories



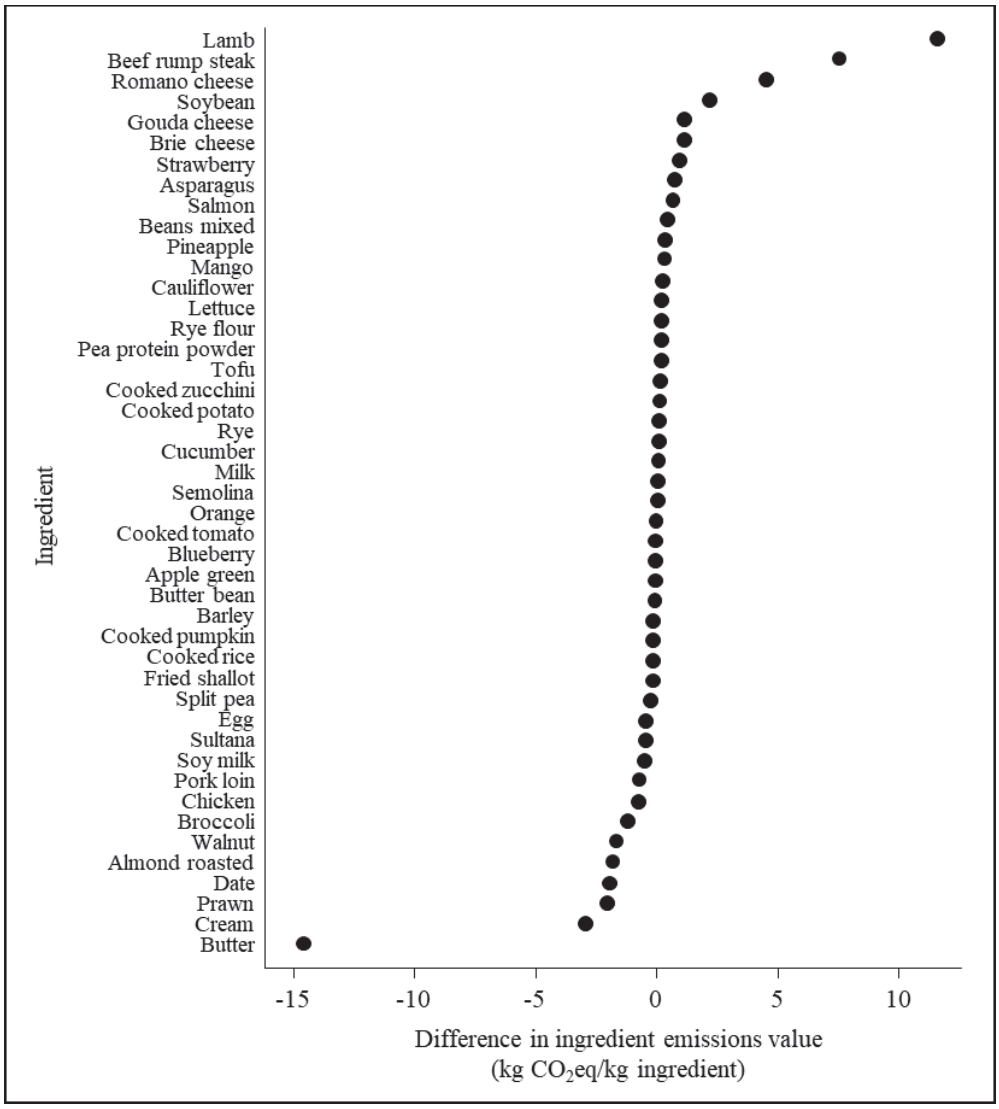
The boxes show the median and the error bars show the 95% uncertainty intervals around the median for the 25th, 50th and 75th percentiles of greenhouse gas emission values for each product category. The shade of the boxes and bars indicate the corresponding percentile, whereby the percentile is derived from the Monte Carlo analysis (i.e., the 25th percentile corresponds with the 25th% of the 1,000 estimated iterations calculated. For some boxes, the error bar is not visible due to the small the uncertainty range, as detailed in Table 4.8.

Supplementary Figure S4.3. Product-specific greenhouse gas emission estimates across 10 meat and meat product subcategories



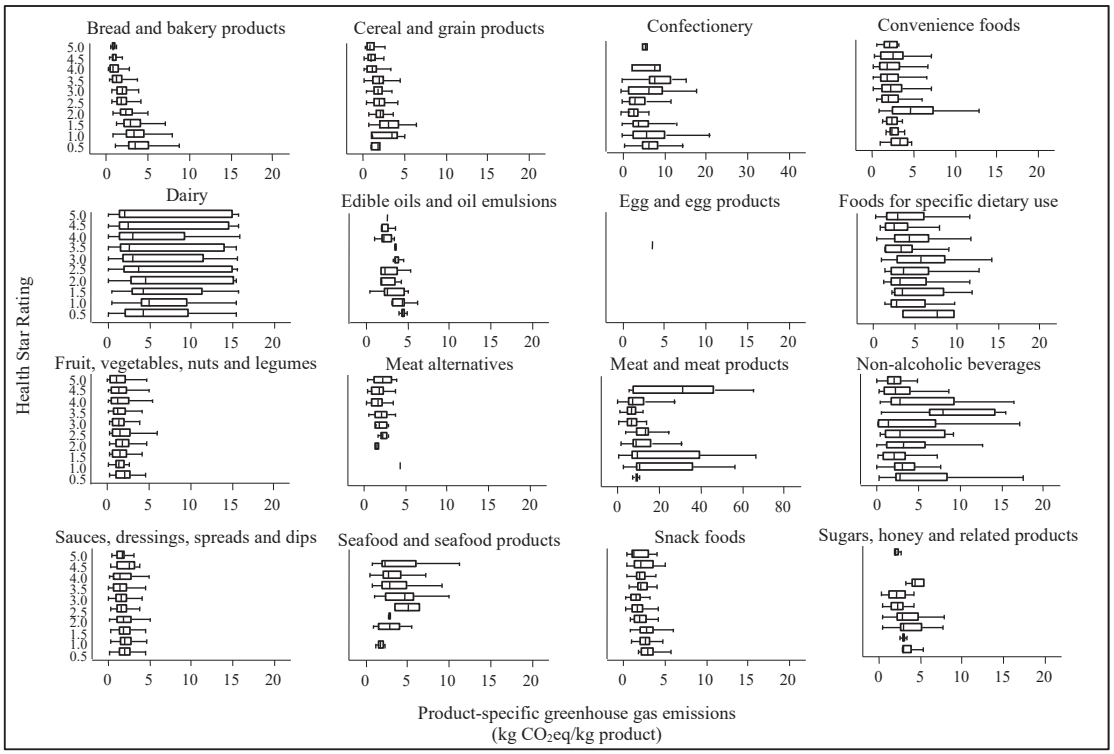
The boxes show the median and the error bars show the 95% uncertainty intervals around the median for the 25th, 50th and 75th percentiles of greenhouse gas emission values for each 'Meat and meat products' subcategory. The shade of the boxes and bars indicate the corresponding percentile, whereby the percentile is derived from the Monte Carlo analysis (i.e., the 25th percentile corresponds with the 25th% of the 1,000 estimated iterations calculated.

Supplementary Figure S4.4. Differences between non-organic and organic greenhouse gas emissions values for 45 ingredients



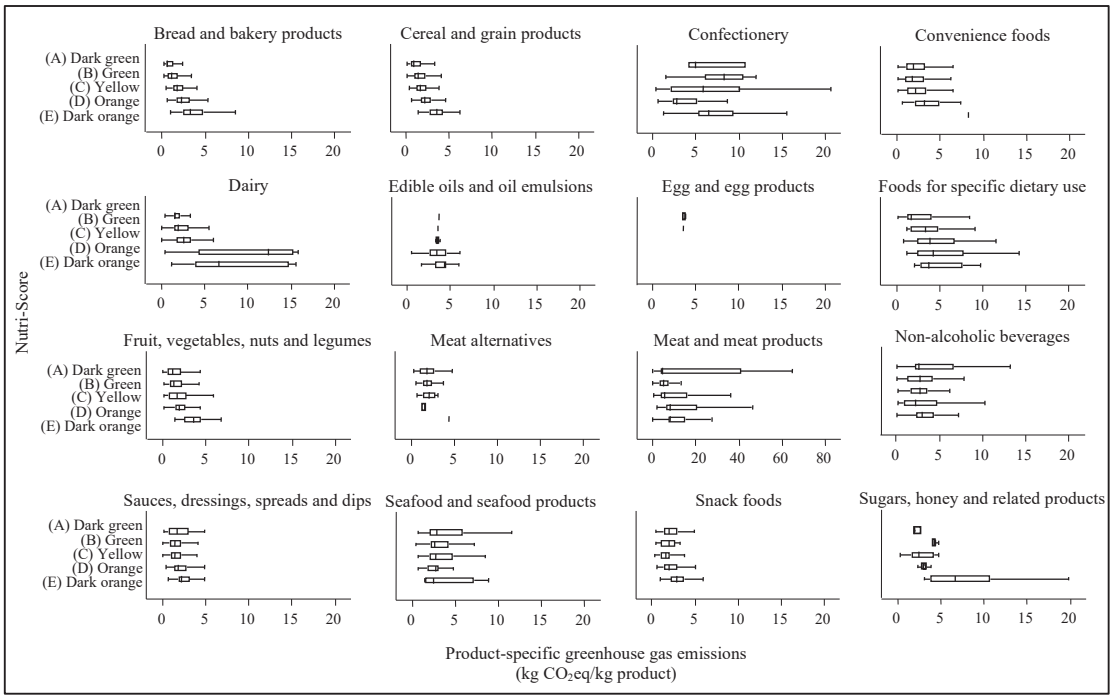
The dot plot represents the difference in median GHGe value derived from the literature search for LCA results for greenhouse gas emissions of food and beverage ingredients. The difference was calculated as (non-organic value) – (organic value). Organic values were only used in the product GHGe estimate if the ingredient was discretely identified as organic in the ingredient list on pack. The impact on results was minimal for the majority of products because most ingredients had very small differences between non-organic and organic values and because ingredients generally make up only a fraction of the final product. Sources with organic ingredient data included: (1) Clune *et al.* 2017, (2) dataFIELD v1.0, (3) CleanMetrics.

Supplementary Figure S5.1. Associations between the Health Star Rating and product-specific greenhouse gas emission estimates by food category



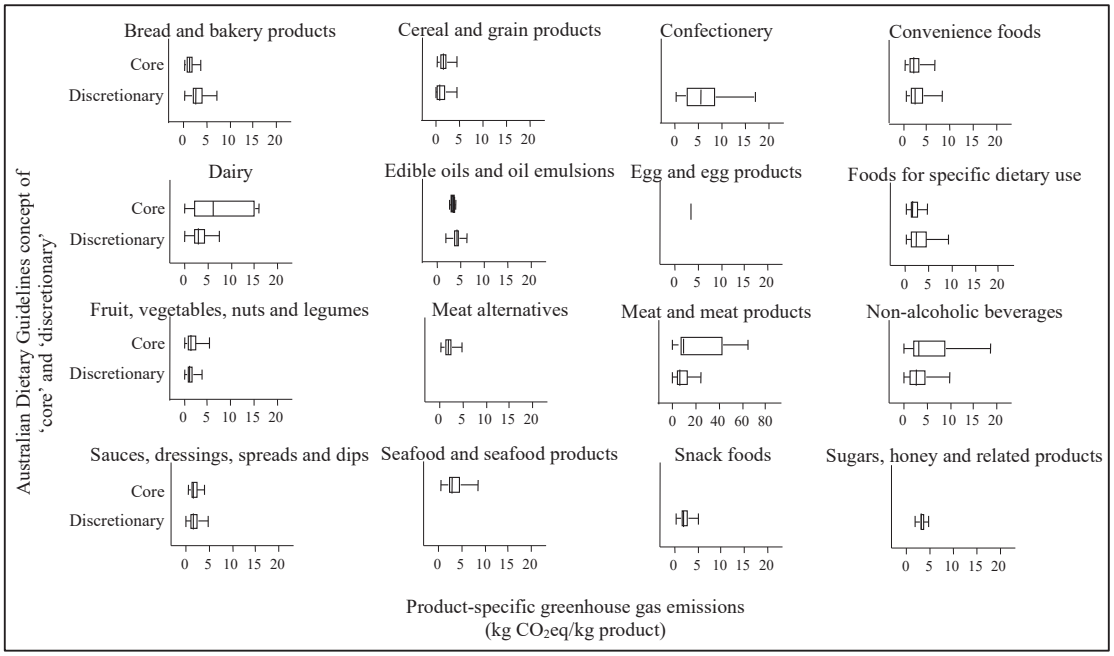
For each Health Star Rating value, these box-and-whisker plots display the interquartile range of greenhouse gas emission values, with the median value marked by the line within the box. The whiskers extend to the lowest datum within 1.5 times the lower quartile and the highest datum within 1.5 times the higher quartile. Outlier values are excluded from the visualisation.

Supplementary Figure S5.2. Associations between the Nutri-Score and product-specific greenhouse gas emission estimates by food category



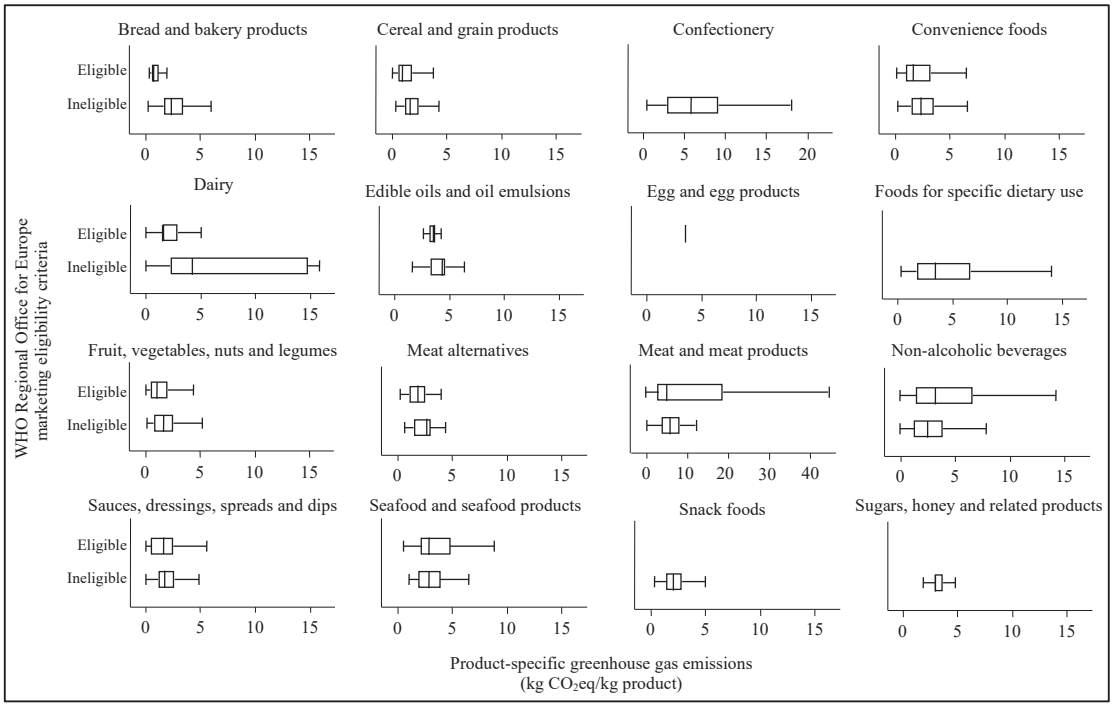
For each Nutri-Score value, these box-and-whisker plots display the interquartile range of greenhouse gas emission values, with the median value marked by the line within the box. The whiskers extend to the lowest datum within 1.5 times the lower quartile and the highest datum within 1.5 times the higher quartile. Outlier values are excluded from the visualisation.

Supplementary Figure S5.3. Associations between the Australian Dietary Guidelines concept of 'core' and 'discretionary' and product-specific greenhouse gas emission estimates by food category



For the Australian Dietary Guideline concept of 'core' and 'discretionary', these box-and-whisker plots display the interquartile range of greenhouse gas emission values, with the median value marked by the line within the box. The whiskers extend to the lowest datum within 1.5 times the lower quartile and the highest datum within 1.5 times the higher quartile. Outlier values are excluded from the visualisation.

Supplementary Figure S5.4. Associations between the WHO Regional Office for Europe marketing eligibility criteria and product-specific greenhouse gas emission estimates by food category



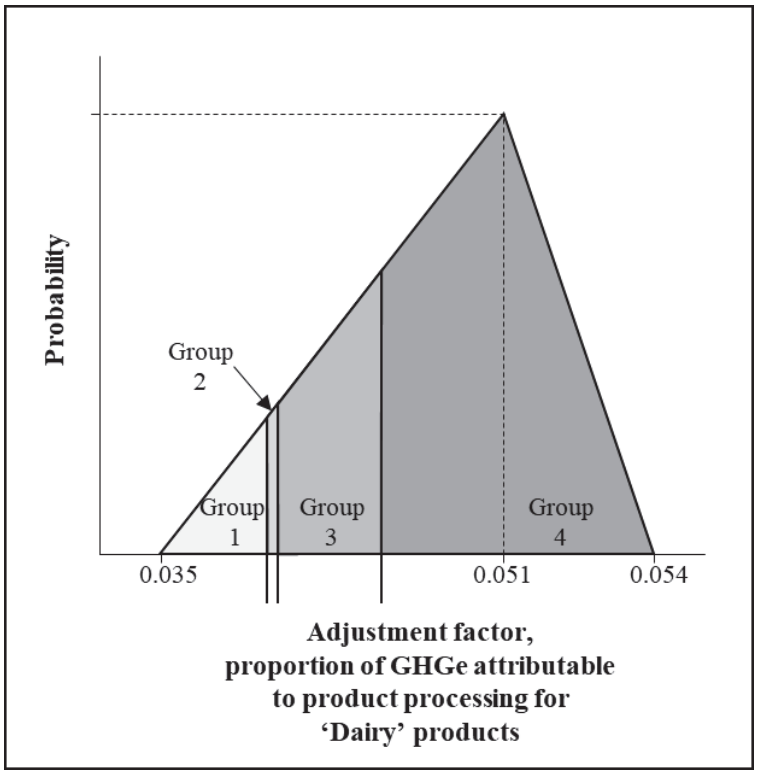
For the WHO Regional Office for Europe marketing eligibility criteria values, these box-and-whisker plots display the interquartile range of greenhouse gas emission values, with the median value marked by the line within the box. The whiskers extend to the lowest datum within 1.5 times the lower quartile and the highest datum within 1.5 times the higher quartile. Outlier values are excluded from the visualisation.

Appendix C. Supplementary information

Supplementary information S4.1. Distribution modes for processing and transport

For each product category, the modes for the processing and transport adjustment factors were assigned as the midpoint percentage contribution of GHGe of the group with the largest number of products, estimated using the corresponding percentile (**Supplementary Tables 4.1 and 4.3**). For example, the distribution of products across NOVA groups 1 through 4 for 'Dairy' was 6.5%, 0.6%, 12.0% and 80.9%, respectively. So, the mode was assigned as percentage contribution at the 90th percentile, which is the approximate midpoint between the minimum percentile (81st) and the maximum percentile (100th) of products in the largest group (Group 4), as depicted in the figure below. This resulted in categories containing more products in Group 1 (associated with less processing and smaller transportation distances) having a right-skewed distribution and categories containing more products in Group 4 (associated with more processing and larger transportation distances) having a left-skewed distribution.

Example distribution and mode selection for processing and transport adjustment factors



Supplementary information 4.2. Impact of uncertainties derived from the Monte Carlo analysis on product greenhouse gas emission estimates

To assess the impact that the variability of ingredient LCAs and processing and transport adjustment factors had on a product's total GHGe estimate based on the Monte Carlo simulation, a sensitivity analysis was performed. This was done by sampling the 10^{th}, 25^{th}, 50^{th}, 75^{th}, and 90^{th} percentile GHGe values for each product in each included category. Products in the lower percentiles represent those with more sustainably sourced ingredients and fewer GHGe associated with product processing and transportation distances. Both the absolute and relative differences in impacts for these percentiles were compared. Absolute differences were calculated by dividing the n^{th} percentile GHGe value by the 50^{th} percentile GHGe value. Relative differences were calculated by subtracting the n^{th} percentile GHGe value from the 50^{th} percentile GHGe value.

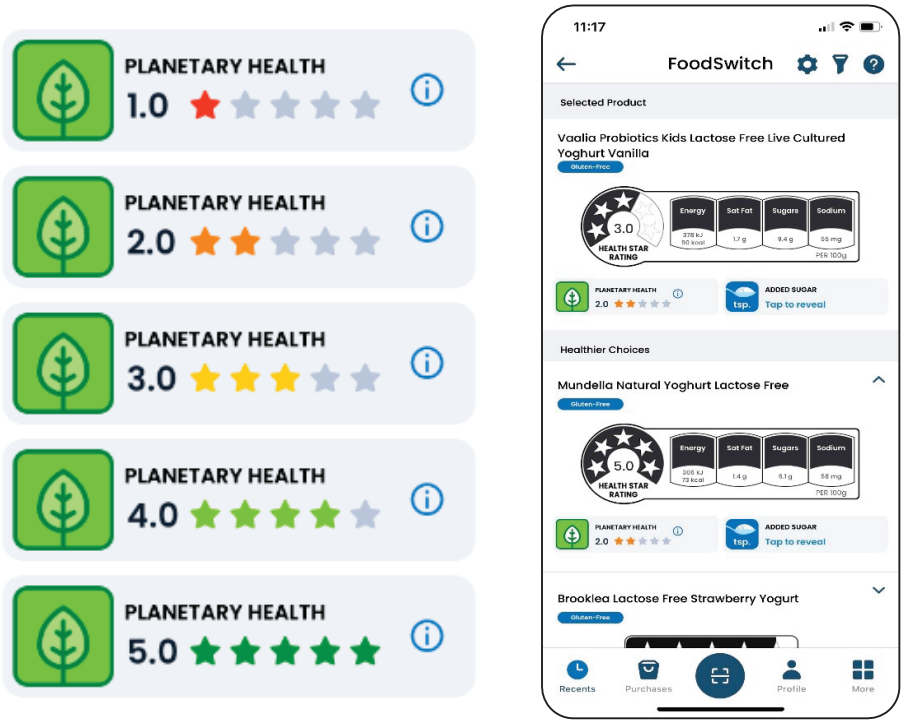
As derived from the Monte Carlo analysis, the estimated product-specific median GHGe was on average 27.2% and 12.6% higher than the 10th and 25th observed percentile GHGe values, respectively. Likewise, the 75th and 90th observed percentile GHGe values were 10.9% and 36.2%% higher than the median GHGe value. The median absolute difference in GHGe was small (0.08 kg CO_2eq/kg product), though in certain cases (i.e., those with larger variability in ingredient GHGe and adjustment factor data) this difference was found to be much larger (more than 5.0 kg CO_2eq/kg product). The products with the largest relative differences between the 10^{th} and 90^{th} percentiles were from the 'Fish and fish product' categories, likely a result of the large differential in GHGe from types of fisheries as seen in the aggregated ingredient GHGe database from included LCAs. Overall, it was found that uncertainty in product-specific GHGe estimates likely did not have major implications for most products. However, for specific use cases such as a comparative analysis of two very similar products, more ingredient, processing and transport GHGe data would be required, whether from producers or from enhanced product and ingredient labelling requirements, in order to determine more precise GHGe estimates.

Supplementary information S7.1. EcoSwitch

Background

FoodSwitch have implemented a Planetary Health Star Rating (PHSR) system in the FoodSwitch mobile phone application. Like the Health Star Rating (HSR), the PHSR displays stars from 0.5 stars up to 5.0 stars. The more stars in the rating means the food is better for planetary health as it is associated with lower greenhouse gas emissions (GHGe). Fewer stars means that the food is worse for planetary health as it is associated with higher GHGe.

Currently, the PHSR icon is displayed against individual products within the FoodSwitch App. However, the app does not currently suggest a 'switch' – i.e., alternative products that are better for the planet.



Aim

The aim is to help consumers make more informed choices about foods based on their climate impact by providing a 'switch' that suggests alternative products that are:

1. Better for planetary health (based on GHGe estimate)
2. Better (or no worse) for human health (based on HSR)

EcoSwitch Planetary Health Star Rating display

The display will be like FoodSwitch, but the PHSR icon will be the focus rather than the Health Star Rating (HSR). The HSR will be displayed as a smaller bar under the PHR icon. This is to ensure the display remains simple and intuitive. In addition, the display page will feature an option to expand the

page to show additional attributes related to both planetary and human health. The attributes to be displayed are listed and example displays are shown below:

- Manufacturer
- GHGe (kg CO_2eq/kg product)
- Country of origin
- Sustainability claims
- Level of processing
- Traffic light labelling

EcoSwitch logic

Healthier choices are qualified by assessing comparable products in the same leaf category as the item scanned. The qualifying logic below seeks to include alternatives that are healthier for the planet (based on GHGe values) and equal or better healthiness (based on the HSR) than the scanned product.

- Healthier choices must have equal or higher HSR
- Healthier choices must have lower GHGe value than the scanned product

Qualifying healthier choices are then ranked from most healthy to least healthy for the planet. This is based on GHGe value – lowest to highest.

Source: FoodSwitch Planetary Health. https://www.georgeinstitute.org/projects/foodswitch

Appendix D. Published papers

Paper 1. Gaines A, Shahid M, Huang L, Davies T, Taylor F, Wu JH and Neal B. Deconstructing the Supermarket: Systematic Ingredient Disaggregation and the Association between Ingredient Usage and Product Health Indicators for 24,229 Australian Foods and Beverages. *Nutrients*. 2021;13(6):1882.

Paper 2. Gaines A, , Davies T, Shahid M, Taylor F, Wu JHY, Hadjikakou M, Pettigrew S, Seferidi P and Neal B. A Novel Approach to Estimate Product-Specific Greenhouse Gas Emissions for 23,550 Australian Packaged Foods and Beverages. *Journal of Cleaner Production*. 2023:138816.

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Article

Deconstructing the Supermarket: Systematic Ingredient Disaggregation and the Association between Ingredient Usage and Product Health Indicators for 24,229 Australian Foods and Beverages

Allison Gaines [1,*], Maria Shahid [2], Liping Huang [2], Tazman Davies [2], Fraser Taylor [2], Jason HY Wu [2] and Bruce Neal [1,2]

[1] Department of Epidemiology and Biostatistics, Faculty of Medicine, School of Public Health, Imperial College London, London SW7 2AZ, UK; bneal@georgeinstitute.org.au
[2] The George Institute for Global Health, University of New South Wales, Sydney, NSW 2042, Australia; mshahid@georgeinstitute.org.au (M.S.); hliping@georgeinstitute.org.au (L.H.); tdavies@georgeinstitute.org.au (T.D.); ftaylor@georgeinstitute.org.au (F.T.); jwu1@georgeinstitute.org.au (J.H.W.)
* Correspondence: a.gaines20@imperial.ac.uk

Abstract: Unhealthy diets are underpinned by the over-consumption of packaged products. Data describing the ingredient composition of these products is limited. We sought to define the ingredients used in Australian packaged foods and beverages and assess associations between the number of ingredients and existing health indicators. Statements of ingredients were disaggregated, creating separate fields for each ingredient and sub-ingredient. Ingredients were categorised and the average number of ingredients per product was calculated. Associations between number of ingredients and both the nutrient-based Health Star Rating (HSR) and the NOVA level-of-processing classification were assessed. A total of 24,229 products, listing 233,113 ingredients, were included. Products had between 1 and 62 ingredients (median (Interquartile range (IQR)): 8 (3–14)). We identified 915 unique ingredients, which we organised into 17 major and 138 minor categories. 'Additives' were contained in the largest proportion of products (64.6%, (15,652/24,229)). The median number of ingredients per product was significantly lower in products with the optimum 5-star HSR (when compared to all other HSR score groups, p-value < 0.001) and significantly higher in products classified as ultra-processed (when compared to all other NOVA classification groups, p-value < 0.001). There is a strong relationship between the number of ingredients in a product and indicators of nutritional quality and level of processing.

Keywords: ingredients; food labelling; health star rating; nutrient profiling; ultra-processing; packaged foods

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Citation: Gaines, A.; Shahid, M.; Huang, L.; Davies, T.; Taylor, F.; Wu, J.H.; Neal, B. Deconstructing the Supermarket: Systematic Ingredient Disaggregation and the Association between Ingredient Usage and Product Health Indicators for 24,229 Australian Foods and Beverages. *Nutrients* **2021**, *13*, 1882. https://doi.org/10.3390/nu13061882

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1. Introduction

Much ill health globally is caused by poor dietary choices [1]. Unhealthy diets are, in turn, underpinned by a food system that tends to promote over-consumption of unhealthy packaged foods and beverages [2,3]. Often these packaged products are high in salt, added sugar and harmful fats which are direct causes of obesity, diabetes and other chronic health conditions [4].

It can be difficult for consumers to pick between more and less healthy packaged food and beverage products. To provide consumers with point-of-sale information that identifies better choices, governments and other organisations are introducing front-of-pack labels. For example, the Health Star Rating (HSR) system [5] developed by the Australian government assigns each food between half a star and five stars using a nutrient profiling

algorithm. The NOVA classification system [6] is another method of distinguishing better-for-you options by defining food and beverage products according to the level of processing involved in manufacturing [7]. A number of studies assessing ultra-processed food intake have found an association between greater consumption of ultra-processed food and increased risks of obesity, cardiovascular disease and mortality [8–10].

Direct assessment of ingredients may be another way to evaluate the healthiness of packaged food products. Ingredient labelling standards and food composition tables in Australia are governed by Food Standards Australia New Zealand (FSANZ). Ingredient labelling is designed to provide consumers with transparency into product composition. FSANZ legislation requires a statement of ingredients to be arranged in descending order by ingoing weight, allowing consumers to discern the primary components of a product's recipe [11]. In addition, explicit percentage labelling is required for 'characterising ingredients' (e.g., strawberry in a strawberry yoghurt) [12]. Food composition tables provide generic reference data describing nutrient content in common foods and can help assess dietary intake [13,14], but do not provide specific information about individual packaged food products.

The numbers and types of ingredients in the packaged food and beverage supply may provide a further means of assessing healthiness [15]. Novel, ingredient-centric work may contribute to improving Australian food composition databases as well as enable studies on ingredient interactions in composite foods [16,17], particularly by better defining ingredient data available on packaged products.

In this study, we sought to define the list of ingredients contained in packaged food and beverage products marketed at major grocery retail outlets in Australia in 2019. We categorised the ingredients identified and explored the associations between the number of ingredients used per product and indicators of product healthiness.

2. Materials and Methods

This was a cross-sectional examination of packaged food and beverage products in the Australian food supply carried out using FoodSwitch, a database developed and operated by the George Institute for Global Health.

2.1. Food and Beverage Product Database

The 2019 FoodSwitch Annual Database, the dataset used in this study, was generated from in-store surveys carried out in Australia at five large supermarkets (IGA, ALDI, Woolworths, Coles and Harris Farm) between August and November 2019 [18]. The dataset represents the majority of supermarket food and beverage products purchased by Australian households [19,20].

The FoodSwitch database holds up to 400 data fields for each included product. Data are obtained direct from packaging (e.g., product name, package size, ingredients, nutritional claims and nutrient content) or derived from data on the packaging (e.g., HSR and NOVA classification). Products held in the FoodSwitch database are classified into a hierarchical categorisation evolved from a system initially developed by the Global Food Monitoring Group [19]. The categorisation system was designed to enable the description and tracking of the nutritional composition of products in groupings meaningful to diverse stakeholders including academic researchers, the food industry, government and consumers [21,22]. There are 18 major food and beverage categories but products are further allocated into hundreds of finer subcategories.

Products were excluded from this analysis if they carried multiple nutrition information panels (e.g., variety packs) or were not in a relevant major food category (i.e., 'Alcohol', 'Vitamins and supplements' or 'Unable to be categorised'). Extensive data cleaning was undertaken but some products were also excluded for having an incomplete or non-standard statement of ingredients.

2.2. Identification of Ingredients

Ingredients were identified from the images of the product label held within the FoodSwitch system and were obtained from either the statement of ingredients or the product name.

For products with a statement of ingredients, data were transcribed into the database as delimited text strings reflecting the form of information provided on pack. The text strings were disaggregated using an automated process creating separate fields for each ingredient and extracting compound ingredient information when present (Table A1 in Appendix A).

Compound ingredients are ingredients made up of two or more sub-ingredients [11]. Sub-ingredients require declaration if they constitute more than 5% of the final food or beverage product or contain a known allergen [23]. There were three forms of compound ingredient presentation: (1) those for which the listed sub-ingredients together made up the entire compound ingredient (complete sub-ingredients), for example, where fortified wheat flour sub-ingredients were listed as wheat flour, thiamine and folic acid; (2) those for which the listed sub-ingredients comprised only the additives or fortificants (incomplete sub-ingredients), for example, where fortified wheat flour sub-ingredients were listed as just thiamine and folic acid; and (3) those for which sub-ingredients were not listed.

Extensive cleaning of the disaggregated ingredient data was done using a semi-automated process (Figure A1). Key elements of the process were the removal of symbols (e.g., reduced-fat milk became reduced fat milk), the correction of spelling errors (e.g., watermellon became watermelon) and the alignment of plurality (e.g., raspberries became raspberry). For ingredients with various common names, a manual process to align terminology was undertaken (e.g., garbanzo bean became chickpea). Descriptive terms were removed from ingredient names (e.g., natural freshly squeezed orange juice became orange juice). When a term relating to an agricultural technique was identified (e.g., organic or free-range) it was removed and stored separately. Approximately 20% of ingredient extractions were manually validated.

For products with ingredients in the product name, a manual ingredient identification and extraction process was performed. The FSANZ Ingredient Labelling of Food standard precludes products from requiring a statement of ingredients in three cases: (1) where the product is labelled with the name of the food and the name of the food includes all ingredients, (2) where the product is water in a packaged form and (3) where the product is contained in a small package (surface area less than 100 cm^2) [11]. For products without a statement of ingredients but whose ingredient information could potentially be determined from the product name, a text-matching algorithm was used to extract ingredient information. For example, the ingredient 'blueberry' was extracted from the product name 'Fresh Blueberries'. In some cases, multiple ingredients were extracted from the product name, for example, the ingredients 'pork mince' and 'veal mince' from the product 'Pork & Veal Mince'.

2.3. Categorisation of Ingredients

Ingredients were categorised into a single, hierarchical structure with each ingredient assigned a major and minor category. Category naming conventions and the category structure were determined by discussion amongst the authors and guided by the terminology used by two specialty ingredient companies: Cargill and ADM [24,25]. Minor categories for 'Sweeteners' were verified against prior publications on sugar types contained in packaged food products [26]. A 'Compound ingredients' category was created to capture any main ingredients which, by name, were clearly composed of multiple sub-ingredients (e.g., chocolate).

Ingredients were flagged depending upon whether they constituted a substantive part of any product (substantive ingredients) or were always a small component of the products (non-substantive ingredients). Non-substantive ingredients were defined as ingredients that are usually less than 2% of a product formula, such as ingredients with

maximum legal usage rates such as certain preservatives, vitamins and minerals; or ingredients that are always used at low levels to provide functional benefits such as gums and other stabilisers [27]. Colours, flavours and most additives were considered non-substantive ingredients.

E numbers were cleaned and listed under the ingredient's common designation, such as the chemical name or additive type. For example, E100 through E199 were listed under the ingredient name colour. Similarly, rare substantive ingredients were grouped under a more common ingredient name where possible (e.g., za'atar was listed as dried herb).

2.4. Analysis

The total number of ingredients was calculated by tallying the number of ingredients at the most granular disaggregation level after the removal of duplicates (e.g., 'canola oil, butter (cream, water, salt), eggs, white vinegar, salt' contains six ingredients since salt was listed twice). Ingredients that were different prior to cleaning but the same after cleaning (e.g., E101 and E102 both classified as colour) were treated as distinct ingredients. Compound ingredients that contained an incomplete or missing sub-ingredient list were considered singular ingredients.

Descriptive statistics were presented for the average number of ingredients per product overall and for main food categories. We assessed the association between the number of ingredients per product and HSR, as well as NOVA classification. Differences in the number of ingredients across HSR scores and NOVA classifications were evaluated using a Kruskal–Wallis H test with post-hoc Dunn pairwise analyses. A subsidiary analysis was done using ingredient numbers based on main ingredients alone (i.e., excluding sub-ingredients). All data preparation and statistical analyses were conducted using Stata IC 15 (StataCorp) and Excel. A two-sided p-value < 0.05 was considered statistically significant. Ethical approval was not required for this study.

3. Results

A total of 27,366 food products were included in the Australian 2019 FoodSwitch Annual Database. Of these, 655 were in excluded product categories or were multi-pack products with more than one nutrition information panel, and 441 had no available means of identifying an ingredient list. A further 2041 products had a disorganised statement of ingredients format so disaggregation of the ingredients was not possible (Figure A2). This left 24,229 products for analysis. Of these, 22,493 (92.8%) displayed the statement of ingredients on pack and 1736 (7.2%) required extraction of ingredients from the product name. The majority of products requiring ingredient extraction from the product name had one ingredient (n = 1732) and the remaining four products had two ingredients.

3.1. Identified Ingredients

The 24,229 products listed a total of 233,113 ingredients, producing a list of 31,934 unique ingredient names. Semi-automated cleaning reduced this number to 915 distinct ingredients (Figure A3). The 915 distinct ingredients were categorised into 17 major categories (Table 1) and 138 minor categories (Tables S1 and S2 in the Supplementary Materials). Of the ingredients, 835 were identified as nutritionally substantive and 80 were identified as nutritionally non-substantive. The majority of unique ingredients belonged to the major category 'Fruit and vegetables' (n = 229), followed by 'Compound ingredients' (n = 128), 'Additives' (n = 86) and 'Liquids' (n = 72).

A total of 9283 (38.3%) products contained at least one compound ingredient with sub-ingredients and 4631 (19.1%) products contained at least one compound ingredient without sub-ingredients. In total, 21,420 compound ingredients were listed. Across all compound ingredient types, 10,650 (49.7%) contained a complete sub-ingredient list, 6139 (28.7%) contained an incomplete sub-ingredient list and 4631 (21.6%) did not contain sub-ingredients which could be disaggregated.

Table 1. Ingredient frequencies by major ingredient category.

Major Ingredient Category	No. of Unique Ingredients	Proportion of UniqueIngredients	No. of Non-Substantive Ingredients [3]	Frequency across All Products [1]	Proportion across All Products [2]
Additives	86	9.4%	67	15,652	64.6%
Herbs and spices	35	3.8%		13,766	56.8%
Sweeteners	30	3.3%	8	12,437	51.3%
Liquids	72	7.9%		11,767	48.6%
Fruits and vegetables	229	25.0%		10,772	44.5%
Oils and fats	33	3.6%		9914	40.9%
Flours and starches	17	1.9%		7245	29.9%
Dairy	56	6.1%	1	7203	29.7%
Compound ingredients	128	14.0%	1	4980	20.6%
Baking ingredients	10	1.1%	1	4977	20.5%
Grains	48	5.2%		4059	16.8%
Nuts and seeds	31	3.4%		2809	11.6%
Meat	60	6.6%		2652	10.9%
Legumes	27	3.0%		2579	10.6%
Eggs	8	0.9%		1699	7.0%
Seafood	41	4.5%		1052	4.3%
Dietary fibres	4	0.4%	2	914	3.8%
	915	100%	80		

[1] Frequency and [2] proportion across all ingredient lists describes the number/proportion of the 24,229 foods for which one or more of the ingredients in each major ingredient category was included in the ingredient list on pack. [3] Non-substantive ingredients were defined as ingredients usually less than 2% of a product formula, such as preservatives, vitamins and minerals, gums and other stabilisers.

3.2. Most Frequently Used Ingredients

As seen in Table 1, at the major ingredient category level, 'Additives' were contained in the largest proportion of products (64.6%, (15,652/24,229)), followed by 'Herbs and spices' (56.8% (13,766/24,229)) and 'Sweetener' (51.3% (12,437/24,229)). A total of 44.5% (10,720/24,229) of products had at least one ingredient categorised under 'Fruits and vegetables' and only 10.6% (2579/24,229) had at least one ingredient under 'Legumes'.

Across all included products, salt (11,182/24,229) and sugar (9872/24,229) were the most frequently used ingredients. 'Additives' (i.e., flavours, colours, emulsifiers, acidity regulators, preservatives and thickeners) represented 6 of the 10 most frequently used ingredients (Table 2).

Table 2. The top 15 ingredients in the 2019 Australian packaged food and beverage supply.

Ingredient Rank [1]	Ingredient	Ingredient Major Category	Substantive Ingredient	Frequency [2]	Proportion[3]
1	Salt	Herbs and spices	N	11,182	46.15%
2	Sugar	Sweeteners	N	9872	40.74%
3	Water	Liquids	N	7971	32.90%
4	Flavour	Additives	Y	7533	31.09%
5	Colour	Additives	Y	4392	18.13%
6	Wheat flour	Flours and starches	N	3780	15.60%
7	Emulsifier	Additives	Y	3771	15.56%
8	Acidity regulator	Additives	Y	3124	12.89%
9	Vegetable oil	Oils and fats	N	3102	12.80%
10	Thickener	Additives	Y	3015	12.44%
11	Preservative	Additives	Y	3013	12.44%
12	Yeast	Baking	N	2763	11.40%
13	Milk powder	Dairy	N	2676	11.04%
14	Dried herbs	Herbs and spices	N	2470	10.19%
15	Vitamins	Additives	Y	1369	5.65%

[1] Rank = ingredients are ranked according to how many of the ingredient lists they are included on out of the 24,229 included packaged food and beverage products. [2] The frequency is the number of products for which the ingredient is listed. [3] The proportion is the percent of the 24,229 total products evaluated.

3.3. Number of Ingredients Per Product across Product Categories

Products had between 1 and 62 ingredients, though about 90% of products had fewer than 20 ingredients and single-ingredient products made up 18.1% (4381/24,229) of the total (Figure 1). The median (interquartile range (IQR)) number of ingredients across all products was 8 (3–14) (Table 3). 'Convenience foods' had the greatest median number of ingredients per product (20 (14–27)), followed by 'Foods for specific dietary use' (12 (7–22)) and 'Bread and bakery products' (13 (9–19)) (Table 3).

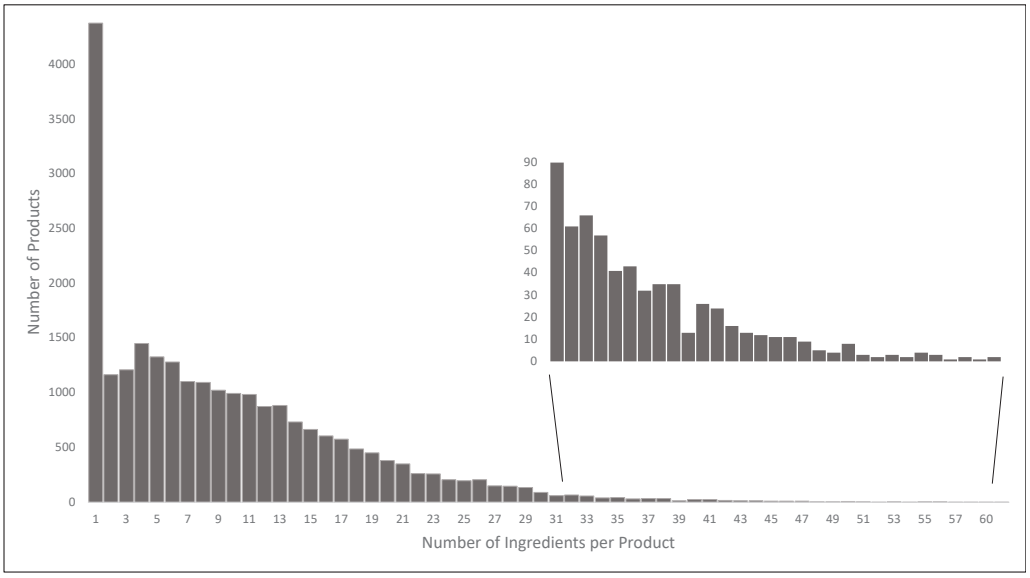


Figure 1. Distribution of the number of ingredients per product. The bar graph displays how many products contain the specified number of disaggregated ingredients in the statement of ingredients. The inset magnified graph displays the number of ingredients per product where product numbers are < 100.

Table 3. The mean number and ranges of ingredients, overall and in major food categories.

	Total Products	Number of Ingredients						
		Mean [1]	SD [2]	Min	25%	50%	75%	Max
All	**24,229**	**9.6**	**8.3**	**1**	**3**	**8**	**14**	**62**
By food category:								
Convenience foods	1425	21.0	10.1	1	14	20	27	61
Foods for specific dietary use	2476	15.0	10.6	1	7	12	22	50
Bread and bakery products	2393	14.6	7.4	1	9	13	19	49
Meat and meat alternatives	726	11.9	9.6	1	1	11	18	53
Snack foods	1930	11.8	6.5	2	6	12	17	38
Sauces, dressings, spreads and dips	685	11.7	6.5	1	7	12	16	43
Confectionery	1351	10.8	6.0	1	7	9	13	62
Cereal and grain products	2556	9.2	8.7	1	1	6	15	58
Dairy	2990	8.3	6.7	1	4	6	11	56
Seafood and seafood products	1978	7.2	6.1	1	3	5	11	41
Non-alcoholic beverages	768	5.5	4.6	1	1	5	8	37
Fruit, vegetables, nuts and legumes	3923	4.2	4.4	1	1	3	6	50
Sugar, honey and related products	441	4.0	4.1	1	1	2	6	26
Edible oils and oil emulsions	498	3.4	3.9	1	1	1	3	16
Egg and egg products	89	1	0	1	1	1	1	1

[1] Mean = the average number of ingredients in products based on the on-pack statement of ingredients. All main and first-level sub-ingredients are included in the total count of ingredients. [2] SD = standard deviation.

Excluding sub-ingredients reduced the total count of ingredients across all products to 165,011. The range in number of ingredients was decreased to 1 to 42, and the median number of main ingredients across all products was decreased to 6 (2–10). The median number of ingredients was reduced across all major food categories and markedly for 'Convenience foods' (from 20 to 10).

3.4. Associations of Number of Ingredients with Healthiness and Level of Processing

The number of ingredients per product was lower in healthier products with higher HSR. Products with 4-star, 4.5-star or 5-star ratings had a significantly lower median ingredient count than all other HSR values (all p-values < 0.001). The highest HSR, a 5-star rating, had the lowest median number of ingredients (1 (1–4)). The association was, however, not linear, with numbers of ingredients across HSR values from 0.5 to 3.5 being approximately similar. A progressive decline in numbers of ingredients used per product was observed across HSR values from 3.5 to 5.0 (Figure 2A).

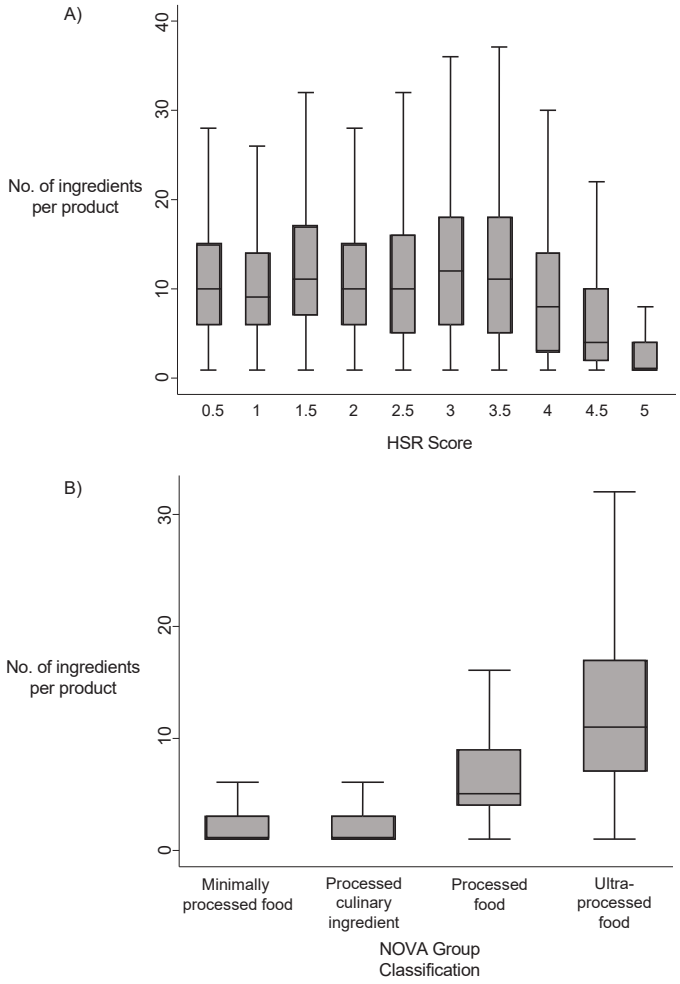


Figure 2. The association of the number of ingredients with (**A**) Health Star Rating and (**B**) NOVA classification. Box plot (**A**) shows the median and interquartile range (IQR) number of ingredients in products assigned different Health Star Rating (HSR) scores. The whiskers are defined as the lower quartile − 1.5 * IQR and the upper quartile + 1.5 * IQR. Outliers are excluded from the graph. Box plot (**B**) shows the median and interquartile range (IQR) number of ingredients in products assigned different NOVA classification groups. The whiskers are defined as the lower quartile − 1.5 * IQR and the upper quartile + 1.5 * IQR. Outliers are excluded from the graph.

A similar pattern was seen across the four NOVA classification groups. Ultra-processed foods (NOVA group 4) used the highest number of ingredients per product (8 (3–14)) while minimally processed foods (NOVA group 1) used the lowest number of ingredients (1 (1–3)). The median number of ingredients per product was significantly higher in ultra-processed products (NOVA group 4) compared to all other NOVA groups (all p-values < 0.001); similarly, the median number of ingredients in processed products (NOVA group 3) was significantly higher compared to NOVA groups 1 and 2 (all p-values < 0.001). The association between number of ingredients per product and NOVA group was non-linear, with similarly low numbers of ingredients in both minimally processed foods (NOVA group 1) and processed culinary ingredients (NOVA group 2) (Figure 2B).

The difference in the number of ingredients used across HSR and NOVA groups was attenuated but the same pattern remained in analyses based on main ingredients alone.

4. Discussion

There are many tens of thousands of packaged food and beverage products available in Australia, but these products are comprised of a much smaller number of ingredients. Of these ingredients, the most commonly used are salt, sugar, flavours, colours and other additives which are widely considered to be indicative of unhealthy foods [28,29]. At the same time, a higher number of ingredients in a product is strongly associated both with lower (i.e., unhealthier) HSR values and NOVA classifications indicating greater degrees of food processing.

The association between the median number of ingredients and nutritional quality was clear, though only apparent for products at the healthier end of the HSR spectrum. At HSR below 3.5 stars, the relationship between the number of ingredients and healthiness plateaued. The reason for this is not clear. A more detailed investigation of the healthiness of individual ingredients in a product with respect to the product HSR was beyond the scope of this initial report but might provide further insights in the future.

Using this large and representative dataset, we ascertained that the median number of ingredients used in products was positively correlated with higher NOVA classifications for levels of processing. More extensive processing done to enhance palatability, convenience and large-scale manufacturing often results in end products comprised of many components that have little in common with the base ingredients. Complex food chemistry may be involved, requiring multiple different additives, albeit usually in small quantities. Extensive processing is also associated with products being less healthy [10] and this correlates well with the observed associations between HSR and number of ingredients using this comprehensive dataset.

The NOVA classification system defines ultra-processed foods as formulations made mostly or entirely from substances derived from foods and additives 'typically with five or more and usually many ingredients' [30]. Thus, as previously suggested, products classified as ultra-processed were expected to contain a larger number of ingredients [6,31]. However, this is not always the case. For example, rice cakes contain only one to two ingredients (rice and, in some cases, salt), yet undergo numerous heat treatments and product modifications to cook, puff and compress the ingredients into the final product. This raises the question of which factors, including chemical, biological and cultural, should be considered when defining foods as ultra-processed. In fact, terminology around food processing and usage in policy making is of growing concern [32,33]. Currently, there is no single, accepted standard for classifying a food product's level of processing [34]. Our results support the need for a more comprehensive classification system as well as further work to understand how processing impacts diet-related research and policy.

The research also identified several inconsistencies in ingredient labelling that may mitigate the goal of providing consumers with transparency into product composition, a pattern which has also been recognised in an analysis of United States product ingredient labelling [35]. The vast range of terms used in ingredient lists as compared to the actual number of different ingredients almost certainly introduces errors in consumer interpre-

tation and understanding. Likewise, the use of compound ingredients, with inconsistent requirements for reporting of sub-ingredients, is another point at which misinterpretation of product ingredients is likely. While the 'Compound ingredients' category had a large number of unique ingredients, the usage of each was small, and it would be relatively little work for the affected companies to disclose those sub-ingredients.

There is a clear opportunity for better standardisation of ingredient reporting to enhance consumer understanding, as well as nutrition research. For example, presently, ingredient naming can be done using common names or generic names—if a product includes pear, apple and peach, a valid statement of ingredients can use either the discrete list of all three ingredients or the generic ingredient fruit [11]. It is also currently permissible for an ingredient to be omitted if it makes up a small proportion of the final product and is not a common allergen, or is a substance used as a processing aid or product flavouring [11]. This may not be a substantial issue in many cases, but in some circumstances it may be important. For example, vitamin and mineral fortification of packaged products, as well as the use of additives, is of increasing interest to consumers and governments around the world [36], and only with full reporting of all ingredients will such data be generally available. There is a strengthening case for both better specification of the regulations governing ingredient reporting as well as their more rigorous enforcement.

The novel ingredient dataset developed for this study enables future research in food composition analysis. Understanding the interactions between food ingredients, particularly when ingredients are processed or cooked in different ways, is of increasing interest in nutrition and food chemistry research [37]. In addition, our enhanced ingredient-level data defining the packaged food and beverage supply can contribute to the new nutrition science concept, which combines biological, environmental and social sciences [38]. For example, our methods can be applied to incorporate ingredient list data into widely used databases to better analyse the packaged food and beverage supply (e.g., FoodEx and LanguaL). There is also potential to address sustainable diets using ingredient breakdowns [39].

A key strength of our study is the size of the dataset on which we have based our analyses. The FoodSwitch platform systematically collects product information from all the main retailers, and these products represent the majority of all packaged food and beverages sold in Australia each year. The extensively cleaned and concise final list of categorised ingredients provides for a unique new description of the main constituents of the Australian packaged food and beverage supply. Future work using ingredient descriptors such as 'organic' and 'free-range' will provide additional opportunities for research and greater insight into the health and environmental characteristics of Australian packaged foods. The large number of carefully defined data points also enabled us to reliably describe the numbers of ingredients in different food categories and how they relate to widely used indicators of healthiness and food processing.

There are also some limitations. For about one-in-ten products, it was not possible to obtain an analysable statement of ingredients, and this was likely a more pronounced issue for products with larger numbers of ingredients. While extensive work was done to standardise ingredient terminology, this work was mostly done by one author and there may be some misclassifications. Workload limitations did not allow us to fully categorise different E numbers, which is a growing area of interest in nutrition research and will be a future task for us [40].

5. Conclusions

The assessment of constituent ingredients provides a novel means of evaluating packaged food and beverage products. Our initial findings related to HSR and NOVA classifications suggest that further exploration of food products based upon their ingredients may provide new insights into their effects on both human health and planetary health.

Supplementary Materials: The following are available online at https://www.mdpi.com/article/10.3390/nu13061882/s1, Table S1: Major and minor ingredient categories and their definitions, Table S2: Final list of 915 ingredients in the 2019 Australian packaged food and beverage supply.

Author Contributions: A.G. and B.N. designed the research; M.S., L.H. and T.D. assisted in developing the data disaggregation and cleaning code and validating the categorisation and results; F.T. and J.H.W. provided essential data and materials; A.G. conducted the research and performed statistical analyses; A.G. and B.N. were responsible for final content. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement: The data presented in this study are available on request from the corresponding author. The data are not publicly available due to privacy policies.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. Formatting requirements for successful disaggregation of a statement of ingredients.

Required Format for Statements of Ingredients	Example Product Name	Example Ingredient List
General		
Statements of ingredients must contain a maximum of one colon (':'), as two or more colons indicate a multi-pack product	Arnott's Sao Biscuits	Biscuits: wheat flour | vegetable oil | salt | yeast | malt extract (from barley) | sugar | baking powder | emulsifier (soy lecitihin) | antioxidant (e307b from soy)
Statements of ingredients must contain an equal number of opening bracket ('[') and/or parentheses ('(') as closing brackets (']') and/or parentheses (')')	Mountain Bread Corn Wraps	Pork | water | cure [salt | sugar | mineral salts (451 | 450) | antioxidant (316) | preservative (250)]
Main ingredients		
Ingredients are separated by a comma (',') or a pipe delimiter (' | ')	McKenzie's Italian Style Soup Mix	Peas | beans | lentils
Ingredient weight percentages are included directly after the ingredient in parentheses ('()')	Val Verde Traditional Pasta Sauce	Tomatoes (96.6%) | onion | salt | onion powder | acidity regulator (citric acid (330))
Sub-ingredients		
Sub-ingredients are indicated using brackets ('[]') or parentheses ('()') directly after the compound ingredient Each sub-ingredient is separated by a comma (',') or a pipe delimiter (' | ')	Mountain Bread Corn Wraps	Corn flour (70%) | wheat flour (flour | folate | thiamin) | filtered water | iodised salt

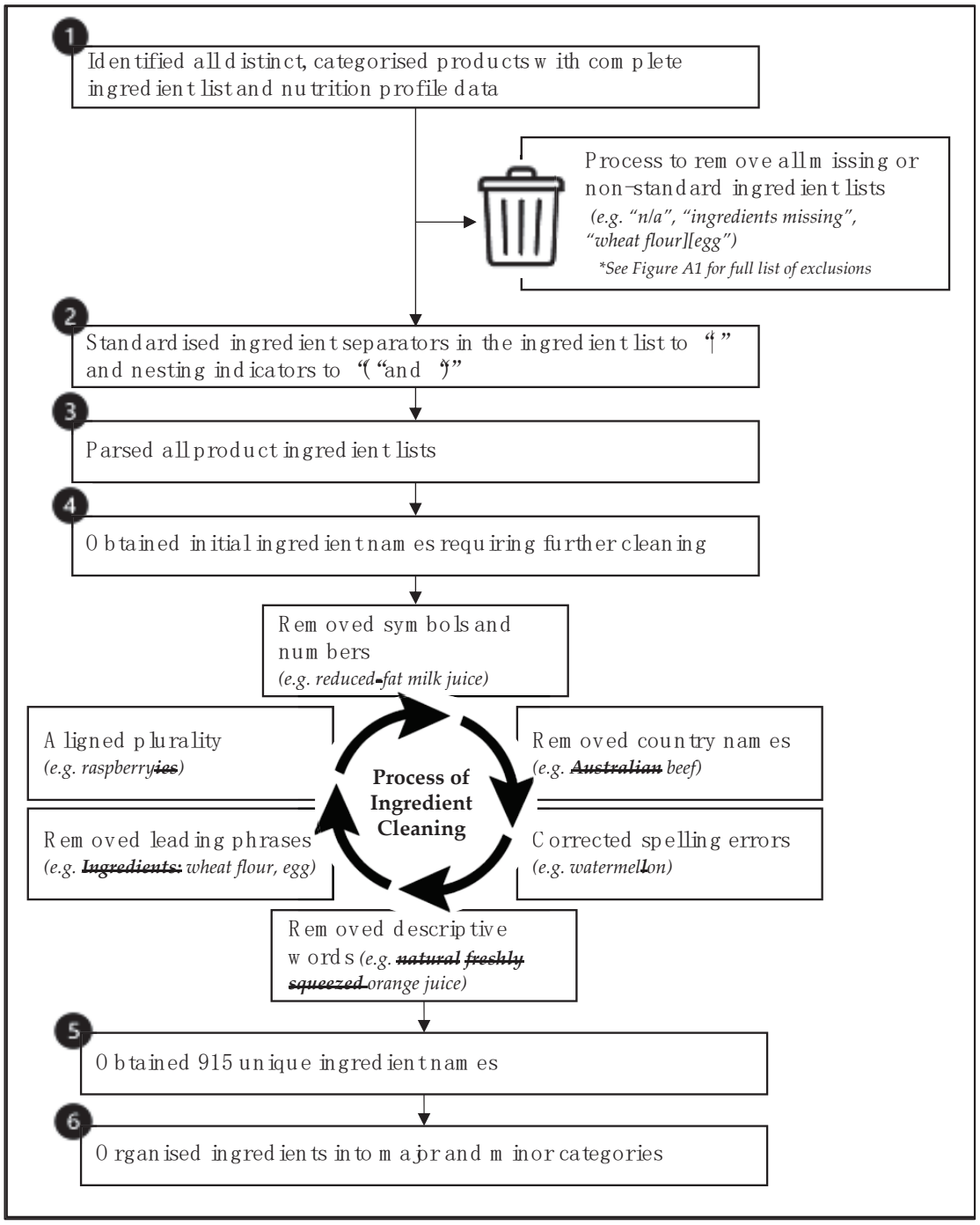


Figure A1. Workflow for developing the list of unique ingredients in Australian food and beverage products. Struck-through words and descriptors that were removed during the process of ingredient cleaning.

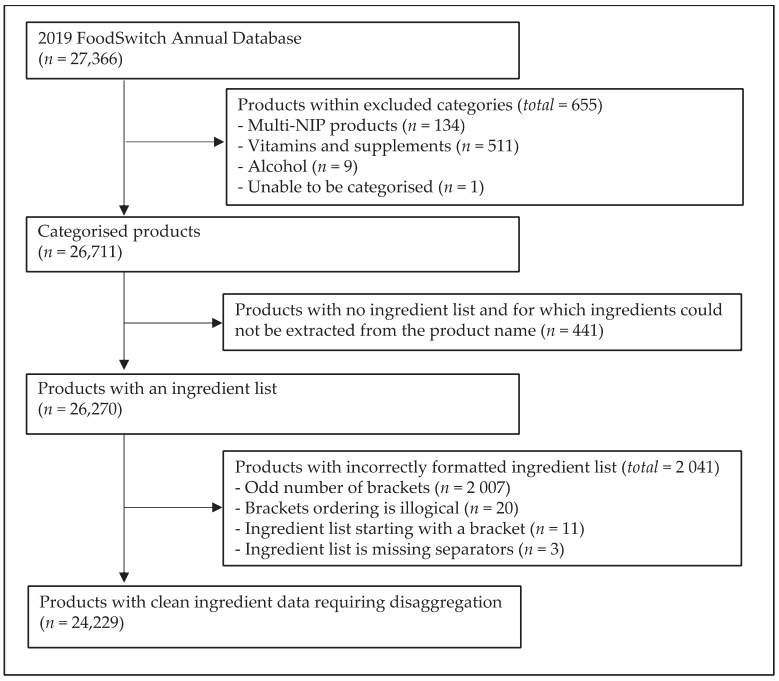


Figure A2. Flowchart describing product inclusion. The 2019 FoodSwitch Annual Database extract is comprised of products scanned during the in-store surveys done between August and November 2019 in Sydney locations of the following large supermarkets: IGA, ALDI, Woolworths, Coles and Harris Farm.

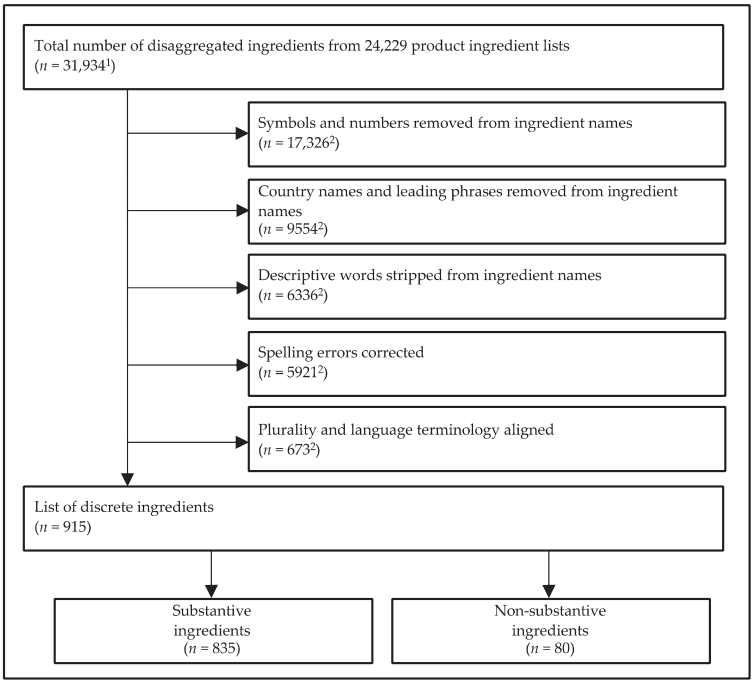


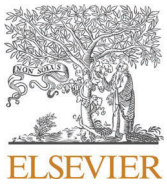
Figure A3. Flowchart describing ingredient cleaning and classifications. [1] The original 31,934 ingredients were a result of the original ingredient disaggregation and consolidation into unique ingredient names. [2] A number of ingredients required multiple cleaning steps, so the number of ingredients cleaned in each step sums to more than the total number of disaggregated ingredients removed.

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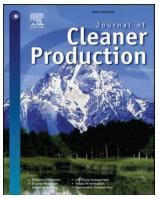
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A novel approach to estimate product-specific greenhouse gas emissions for 23,550 Australian packaged foods and beverages

Allison M. Gaines [a,b,*], Tazman Davies [b], Maria Shahid [b], Fraser Taylor [b], Jason HY. Wu [b], Michalis Hadjikakou [c,d], Simone Pettigrew [b], Paraskevi Seferidi [e], Bruce Neal [a,b]

[a] Department of Epidemiology and Biostatistics, School of Public Health, Imperial College London, Norfolk Place, London, W2 1PG, United Kingdom
[b] The George Institute for Global Health, UNSW, 1 King St, Newtown, NSW, Australia, 2042
[c] Sustainability Assessment Program (SAP), School of Civil and Environmental Engineering, UNSW, Sydney, NSW, 2052, Australia
[d] School of Life and Environmental Sciences, Centre for Integrative Ecology, Deakin University, Melbourne, Burwood, VIC, 3125, Australia
[e] Public Health Policy Evaluation Unit, School of Public Health, Imperial College London, Reynolds Building, St Dunstan's Road, London, W6 8RP, United Kingdom

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ABSTRACT

Greenhouse gas emissions (GHGe) data are predominantly available for agricultural commodities and broad dietary patterns. However, data on commonly consumed, multi-ingredient food products as sold in supermarkets and retail outlets are mostly absent. We developed a novel approach to estimate product-specific GHGe for individual packaged foods and beverages marketed in Australia in 2019. Ingredient lists for 23,550 packaged products were systematically disaggregated and a linear program was used to estimate ingredient proportions in each product. Ingredient-specific, cradle-to-farm gate GHGe values were identified from five life cycle assessment data sources. Weighted GHGe values for each ingredient were summed up to a product-specific GHGe estimate that was then additionally adjusted for processing and transport-related emissions to account for most attributable emissions from cradle-to-retail. To assess validity, GHGe for food categories, estimated as the median of product-specific GHGe estimates, were compared against existing GHGe values for analogous food groups. The included products contained 897 different ingredients for which GHGe values were determined using data from 433 life cycle assessments. The estimated median for cradle-to-retail GHGe for all products was 2.35 kg CO_2eq/kg product (interquartile range, IQR, [1.24, 4.53]). Product-specific GHGe estimates varied substantially within food categories; the 25th and 75th percentile of GHGe values differed by 2-fold or more for most. 'Meat and meat products' had the highest median GHGe value and broadest range of estimates (6.81 kg CO_2eq/kg product, IQR [5.84, 29.2]). 'Fruit, vegetables, nuts and legumes' had the lowest median GHGe (1.20 kg CO_2eq/kg product). Median category values for product-specific GHGe estimates aligned well with values for 34 food groups previously reported ($R^2 = 98.6\%$). Our approach provides a novel method for estimating product-specific GHGe for Australian packaged foods and beverages. The study enabled clear differentiation between products within a given category due to the unique ingredient proportion estimation method, while retaining good comparability against values derived using existing methods. These data have significant potential for driving industry actions and informing government policies.

1. Introduction

Climate change is arguably the greatest environmental and public health risk currently facing the global population (Swinburn et al., 2019; G20 Leaders' Summit, 2021). The food and agriculture sector contributes to over 30% of total anthropogenic greenhouse gas emissions (GHGe) and ranks as the second largest contributor behind energy production (Rosenzweig et al., 2020). If all countries were to adopt a modern Western diet, food-related GHGe would exceed established boundaries by 263% in 2050 (Loken and Declerck). A food system that is environmentally sustainable, nourishing to human health and sufficient for the world's growing population is crucial to mitigating climate change and maintaining wellbeing (Springmann et al., 2018a; Tilman and Clark, 2014; Steffen et al., 2015; Lucas et al., 2021).

* Corresponding author. Department of Epidemiology and Biostatistics, School of Public Health, Imperial College London, Norfolk Place, London, W2 1PG, United Kingdom. Tel.: +44 (0)20 7594 2717
E-mail address: a.gaines20@imperial.ac.uk (A.M. Gaines).

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Over the last decade, a large body of research has emerged describing the environmental impacts of food commodities and different dietary patterns (Clune et al., 2017; Drewnowski, 2014). Life cycle assessment (LCA) protocols have defined the environmental impact of multiple food supply chains around the world (Nemecek et al., 2016). The majority of studies conclude that diets rich in minimally processed fruits, vegetables and grains, and limited in red and processed meat have the lowest carbon footprint (Willett et al., 2019; Fanzo and Davis, 2019). However, packaged and prepared products sold at supermarkets and convenience stores, many of which contain either meat, ultra-processed components or both (Gaines et al., 2021; Crino et al., 2018; Cooper, 2020), have infrequently undergone LCAs. These types of products represent around three-quarters of food purchases in high-income countries (Baldridge et al., 2019; Crino et al., 2018) and already over half in some low- and middle-income countries (Monteiro et al., 2013; Popkin, 2001).

Data describing the environmental impact of individual food products are sparse (Liu et al., 2016; Clark et al., 2022; Fresán et al., 2019) and it is difficult for consumers to make food purchase choices based upon planetary health impacts. Apparently similar packaged products may have markedly different environmental impacts due to different ingredients used or technologies applied during manufacturing (Poore and Nemecek, 2018). Product-specific GHGe values in conjunction with on-pack GHGe labelling would not only enable consumers to make food choices informed by environmental sustainability (Camilleri et al., 2019; Vandenbergh et al., 2011), but might also drive producers, manufacturers and retailers towards actions that reduce their environmental impact (Willett et al., 2019; Potter et al., 2021; Clark et al., 2022).

This research sought to establish a method to calculate GHGe estimates for individual food and beverage products primarily based on ingredients, with the goal of enabling differentiation between GHGe estimates of apparently similar, multi-ingredient products in the packaged food and beverage supply.

2. Material and methods

We developed a novel approach for estimating product-specific GHGe applicable to most Australian foods and beverages available in major Australian supermarkets in 2019 (Fig. 1). We quantified the range of GHGe for product categories and validated our results against the most comprehensive consolidation of GHGe information for main food groups (Poore and Nemecek, 2018).

2.1. Included products

Our analyses used packaged product information included in the 2019 Australian FoodSwitch Annual database (Dunford et al., 2014). Manufacturing and nutritional data (including barcode, product name, package size and ingredient and nutrition information) were captured for each of the Australian FoodSwitch products by trained data collectors who visited five supermarket chains in metropolitan Sydney (Coles, Woolworths, IGA, Aldi and Harris Farms) between August and November 2019. All products were subjected to rigorous checks to ensure data quality and were organised into a category tree based on the system developed by the Global Food Monitoring Group (Dunford et al., 2012, 2014).

2.2. Identification of ingredients in each product and ingredient composition

A method for standardising and categorising the individual ingredients from the product ingredient lists written on the packaging has been described previously (Gaines et al., 2021). For this dataset we

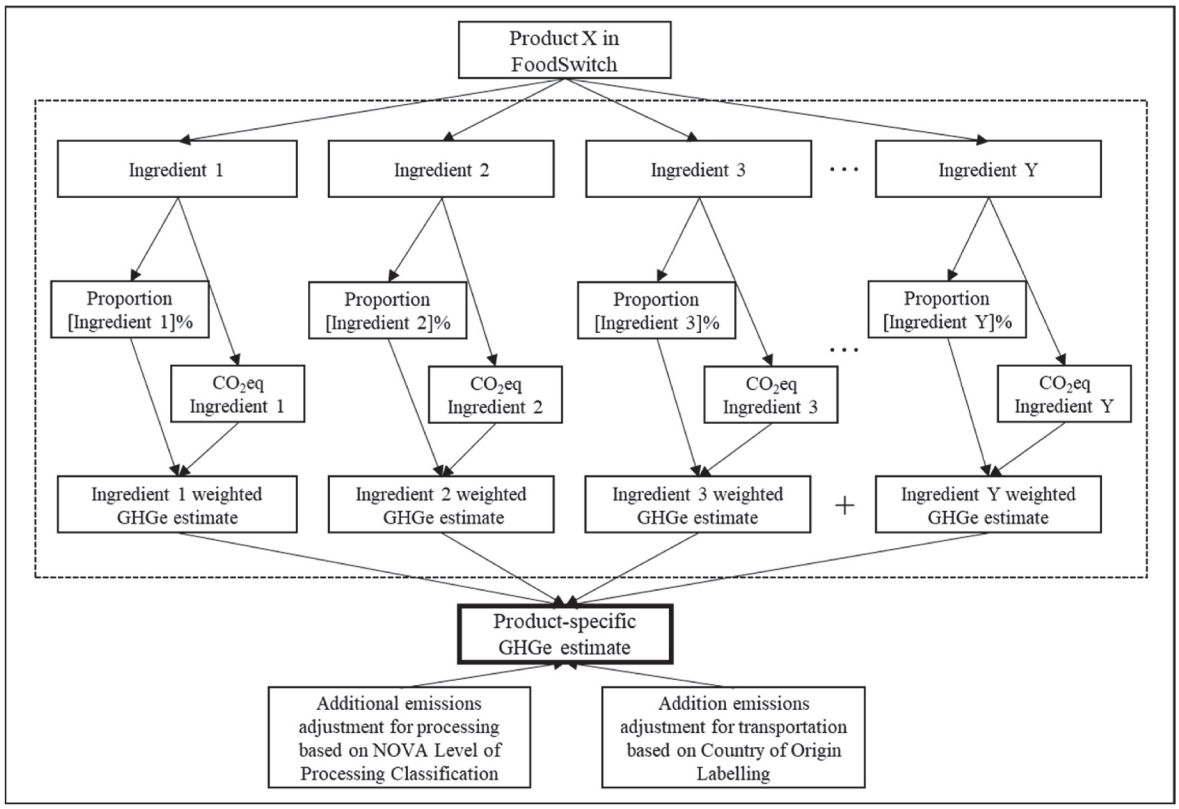


Fig. 1. Ingredient-based approach to product-level greenhouse gas emission estimates
In this visual representation of the product-specific greenhouse gas emission (GHGe) estimation method, the ingredient-based estimate is explained in four steps: ingredient identification, ingredient proportion prediction, ingredient GHGe assignment and weighted ingredient GHGe calculation. The weighted ingredients GHGe estimates are summed to obtain the product-specific GHGe estimate. Adjustments are made to the product-specific estimate for transport and level of processing.

identified 897 unique ingredients and recorded any reported ingredient proportions and indicators of organic farming declared on the packaging. Each ingredient was mapped to a food composition data source to obtain nutrient information (Supplemental Table 1) (Australian Food Composition Database, 2019a; Composition of foods integrated dataset, 2019b; FoodData Central Data Type Documentation,).

2.3. Identification of greenhouse gas emissions applicable to ingredients

We determined GHGe estimates for each ingredient using a two-step process. First, we conducted a structured search for LCA data sources to obtain GHGe values of food ingredients (Supplemental Table 2). We included search results with ingredient LCA data containing Australian data and/or global averages and preferentially used Australian data where possible. System boundaries, which define the activities included in the emissions impact calculation, were aligned to cradle-to-farm gate across each ingredient LCA data source. The functional units were aligned to kilograms of carbon dioxide equivalents per kilogram of ingredient across all data sources. Where GHGe values for an ingredient were available from multiple sources, the median was used. If an exact match did not exist for an ingredient, the closest possible match was used (e.g., 'goji berry' was mapped to 'currants and gooseberries'). Organic ingredients were matched to organic LCA values where possible.

Second, we incorporated additional emissions for selected ingredients using conversion factors identified from commodity trade data sources so that the final functional unit for each ingredient reflected kilograms of carbon dioxide equivalents per kilogram of edible ingredient (kg CO_2eq/kg ingredient). These conversion factors accounted for ingredient mass lost during ingredient processing, preparation and production (e.g., refuse losses including skin and stalks or waste occurring during production) (Bowman et al., 2010; FAO, 1996; Mertens et al., 2019a) and emissions associated with industrial ingredient cooking upstream of retail (e.g., industrial roasting) or other modification (e.g., drying, sweetening or breading) (Frankowska et al., 2020; Mertens et al., 2019a, 2019b). Post-production ingredient losses due to processing occurring after the farm gate (e.g., the evaporation of milk when baked into a cake) were not included in our analysis. We assumed ingredients to be non-organic, raw and unaltered unless otherwise specified on product packaging. Nuances that may further contribute to ingredient GHGe values such as greenhouse-heated vegetable production, beef from dairy herds, industrial processing and storage were not included in our analysis due to limited data availability on product packaging.

The final GHGe estimate for each ingredient listed on the included products was obtained by matching an ingredient-specific GHGe value identified through either the search or after a conversion factor was applied. The ingredient GHGe estimate captured most of the emissions attributable to each ingredient from cradle-to-farm gate (Fig. 2).

2.4. Analysis

2.4.1. Ingredient proportion predictions

A linear programming algorithm was used to estimate ingredient proportions not reported on product packaging (Westrich et al., 1998; Ng et al., 2015). The product nutrition information and the list of ingredients reported on the packaging, along with the nutrient profiles of the ingredients, were used to define the algorithm. The algorithm chose ingredient proportions that minimised the level of discrepancy between the nutrient profile reported on the product packaging versus the nutrient profile derived from possible combinations of ingredient proportions, as expressed in the objective function (OF):

$$OF = \sum_{i=1}^{4} \frac{|C_i - r_i|}{SD_i}$$

where i refers to one of four nutrients (carbohydrates, protein, total fat, sodium). Nutrient values were either obtained from the nutrition information panel on the packaging (r_i) or calculated from the ingredient list and ingredient compositions (C_i). SD_i refers to the standard deviation of the i-th nutrient in the product database (Supplemental Table 3). Dividing by the standard deviation ensured the objective function placed a similar emphasis on nutrients with different units and distributions.

The algorithm was made feasible because Food Standards Australia New Zealand ingredient labelling regulations (FSANZ, 2015, 2018a) require ingredient proportions to descend in value from first-listed to

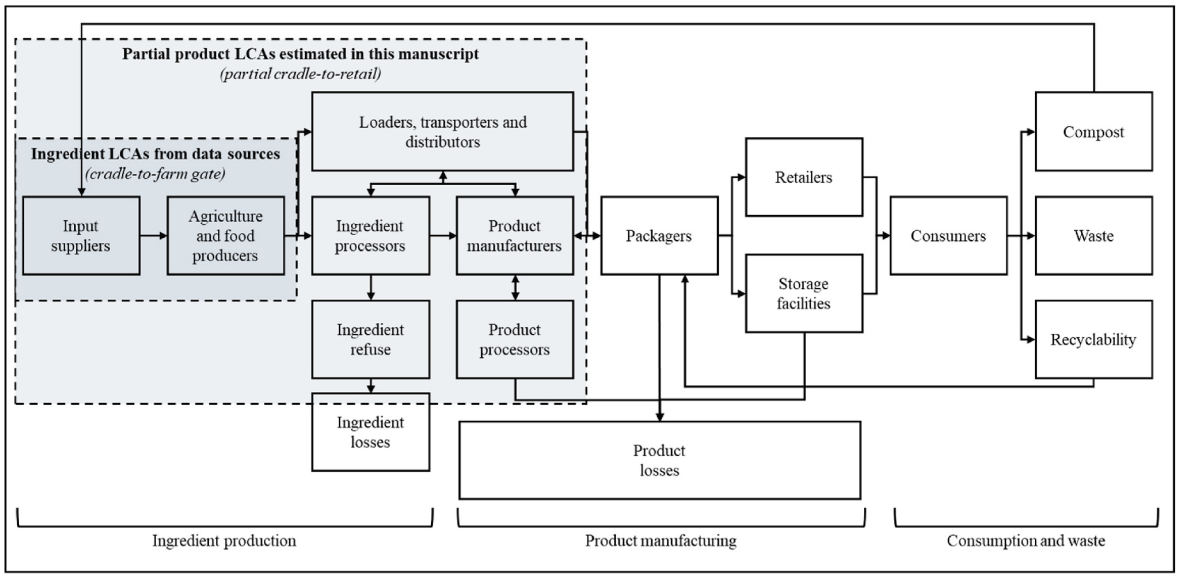


Fig. 2. Life cycle assessment system boundaries used for ingredient and product-specific emissions estimates
In this visual representation of the food system life cycle actors and stages, we have depicted which actors and stages make up (i) the system boundary used for ingredient life cycle assessments as determined from data sources used in analysis and (ii) the system boundary used for the product-specific greenhouse gas emission estimation method in this manuscript. The system boundaries are defined by the dashed-line boxes. The actors and stages that are not included in this analysis are clearly noted, as they are outside of the dashed-line boxes. LCA: Life cycle assessment.

last-listed and to always total 100% (Supplemental Tables 4 and 5). The linear programming was written in *Python 3* using the *Pandas* and *NumPy* libraries. The performance of the algorithm was assessed for a subset of products with a complete set of ingredient proportions reported on product packaging ($n = 2451$) by calculating the overlap coefficient. The overlap coefficient quantified the level of agreement between the reported ingredient proportions and the algorithm's predicted ingredient proportions (Supplemental Table 6).

2.4.2. Calculation of product-specific GHGe with adjustments for processing and transport

A base product-specific GHGe estimate (kg CO_2eq/kg product) was calculated from the ingredient data by summing the GHGe value for each ingredient, weighted by the ingredient proportion in the product. Estimates were further adjusted to account for GHGe attributable to processing and transport. To adjust the base GHGe estimate for processing, we used NOVA classifications available in FoodSwitch (Supplemental Information 1, 2) (Monteiro et al., 2016, 2018, 2019a, 2019b). Adjustments for transport were made using the mandatory Australian country of origin label, which is defined by onshore or offshore acquisition of ingredients and site of processing (Weber and Matthews, 2008; Sandström et al., 2018) (Supplemental Information 3). The magnitude of the adjustment was based on the emission proportions identified as attributable to processing and transport for each food group in the Poore and Nemecek report (Poore and Nemecek, 2018) in combination with the NOVA classification and the country of origin label for the product (Supplemental Table 7).

Though we were not able to capture more granular product-specific processing impacts in this approach, a factor was applied to account for the known mass change when producing cheese from milk (about 10 kg of milk are required to make 1 kg of cheese) (Regulating Victoria's dairy industry - Cheese, 2018b). This was relevant to (1) any cheese product with milk listed as the first ingredient and (2) any main ingredient with milk listed as the first sub-ingredient.

The final product-specific GHGe estimate represents the majority of emissions attributable to product development from cradle-to-retail (i.e., partial cradle-to-retail LCA estimates), including processing and transport upstream from retail (here forth referred to as the product-specific GHGe estimate; Fig. 2). Emissions attributable to post-production product losses, packaging and refrigeration have been excluded from this analysis. Descriptive statistics (median and interquartile range, IQR) of GHGe estimates were calculated for all products combined and for 16 broad FoodSwitch categories. For each category, we estimated GHGe contributed by processing and transport as a proportion of total emissions.

2.5. Food group greenhouse gas emissions data for validation

The Poore and Nemecek (2018) study summarised data from farms, processors, manufacturers and retailers (Poore and Nemecek, 2018) and used meta-analysis to produce cradle-to-retail gate LCA estimates on GHGe and other impact factors for broad food groups. Poore and Nemecek also quantified the contribution of GHGe across production phases including agriculture, processing, transport, packaging and retail. To use the data for validating our product-specific GHGe estimate ranges, we aligned 732 relevant food categorisations available in FoodSwitch with 34 Poore and Nemecek food groups and used GHGe values from the Poore and Nemecek supplemental database, including emissions only from agriculture through to transport for each food group (excluding emissions associated with packaging, retail and product losses).

Validation of GHGe estimates by food category - We compared the medians for 34 food groups derived from our product-specific GHGe estimates against the values for the corresponding the Poore and Nemecek food groups (Poore and Nemecek, 2018). We plotted our median estimates against Poore and Nemecek values and compared the data using the coefficient of determination (R^2) and the Spearman's rank coefficient (ρ).

3. Results

3.1. Included products

The Australian 2019 FoodSwitch Annual Database contains 27,366 food products, 23,550 of which were used in these analyses - 3137 were excluded because the ingredients could not be comprehensively determined from the package labelling and 679 were excluded because product composition or ingredient composition data were inadequate to enable operation of the linear programming algorithm (Supplemental Fig. 1).

3.2. Ingredients and greenhouse gas emission data for ingredients

Five data sources containing LCA data for ingredient GHGe from cradle-to-farm gate were used: Clune et al. (2017), Ecoinvent 3.7.1 (Weidema et al., 2013), dataFIELD v1.0 (Heller et al., 2018), CleanMetrics (Cleanmetrics, 2011) and Agri-footprint 5.0 (Blonk, 2014a, 2014b) (Supplemental Table 8). A total of 433 ingredient GHGe values were identified, including 376 for non-organic ingredients, 45 for organic ingredients and 12 for composite ingredients. The majority of ingredient LCAs (48.3%) were derived from a single GHGe source, 21.9% had two source values and 29.8% had three or more.

For 29.4% of ingredients, there was an exact match to one of the LCA values. For the other 70.6%, the closest possible match was made. One or more conversion factors were applied to 64.3% of ingredients (Table 1). For example, the GHGe value for almond meal was derived from the GHGe value for almond by applying conversion factors of 1.03 for change in mass and 2.00 for ingredient processing. Additives required the largest proportion of matches to the most similar ingredient (60.5%).

3.3. Ingredient proportions

Ingredient proportions were reported on packaging for 2451 (10.8%) products, and we estimated ingredient proportions for the remaining 21,099 (89.2%). For the 2451 products with on-pack ingredient proportions, comparison against the proportions estimated using the linear programming algorithm resulted in a mean overlap coefficient of 85%. The mean overlap coefficients varied from 72% to 90% across food categories and were higher in products with smaller numbers of ingredients (Supplemental Table 9).

3.4. Product-specific greenhouse gas emission estimates

The median product-specific GHGe estimate for all products was 2.35 kg CO_2eq/kg product (range [0.0002, 67.3] and IQR [1.24, 4.53], based on partial cradle-to-retail estimates including processing and transport) (Table 2). Across main categories, the first and third quartiles differed by about 2.5-fold and by up to 7-fold for some subcategories. 'Fruit, vegetables, nuts and legumes' had the lowest median GHGe (1.20 kg CO_2eq/kg product; IQR [0.55, 2.20]). 'Egg and egg products' (IQR [3.54, 3.54]) and 'Edible oils and oil emulsions' (IQR [3.20, 4.21]) had the smallest ranges in values.

'Meat and meat products' had the highest median GHGe value (6.81 kg CO_2eq/kg product) and broadest range in values (IQR [5.84, 29.2]) (Fig. 3A). Median GHGe values for beef, game and lamb products were over four times greater than that of other meat products and 10–20 times greater than that of plant-based meat alternatives (Fig. 3B). 'Poultry products' and 'Meat-based meals' (pre-made foods that contained portions of vegetables and grains alongside meat) had the lowest median GHGe values amongst the 'Meat and meat product' subcategories (5.38 kg CO_2eq/kg product and 5.24 kg CO_2eq/kg product, respectively).

Table 1
Ingredients and greenhouse gas emission data available from life cycle assessments.

Ingredient type	No. of ingredients	Identical match	Match with mass change factor only[a]	Match with modification factor only[b]	Match with mass change and modification factors	Match with most similar ingredient[c]
Additives	*86*	32	1	1	0	52
Baking ingredients	*10*	7	0	1	0	2
Compound ingredients	*118*	44	2	13	6	53
Dairy	*55*	24	2	3	1	25
Dietary fibres	*4*	2	0	0	0	2
Eggs	*8*	5	0	2	0	1
Flours and starches	*17*	4	4	0	6	3
Fruits and vegetables	*227*	10	34	36	138	9
Grains	*48*	25	11	1	2	9
Herbs and spices	*35*	9	4	3	5	14
Legumes	*24*	3	17	0	2	2
Liquids	*72*	31	5	6	11	19
Meat	*56*	12	2	39	0	3
Nuts and seeds	*34*	5	2	9	14	4
Oils and fats	*33*	19	2	2	1	9
Seafood	*40*	19	0	16	0	5
Sweeteners	*30*	13	3	0	0	14
	897	*264*	*89*	*132*	*186*	*226*

We assumed ingredients to be non-organic, raw and unaltered unless otherwise specified. Ingredient emissions data regarding greenhouse-heated vegetable production, beef from dairy herds and industrial storage were not included in our analysis due to limited availability.

[a] Mass change conversion factors account for the removal of seeds, peels, stalks and other excess occurring during ingredient processing (*Source:* Technical Conversion Factors for Agricultural Commodities. Food and Agricultural Organization of the United Nations).

[b] Modification conversion factors account for emissions associated with cooking and other ingredient alterations such as sweetening, breading and drying (*Source:* Bowman et al., 2010. Food Intakes Converted to Retail Commodities Databases: 2003-08: Methodology and User Guide. U.S. Department of Agriculture, Agricultural Research Service).

[c] Similarly matched ingredients are defined as any ingredient for which a proxy was used to determine the suggested GHGe value.

Overall, 90.5% of GHGe were attributable to emissions generated from cradle-to-farm gate, 3.3% to processing and 6.2% to transport. The proportion of emissions attributable to the processing and transport production phases varied greatly by product category; 'Meat and meat products' had the smallest percentage contribution (2.4% by processing and 1.3% by transport) and 'Sugars, honey, and related products' had the largest (7.5% by processing and 29.0% by transport) (Supplemental Fig. 2).

3.5. Validation of GHGe estimates by food category

The median GHGe estimates calculated using product-specific GHGe values largely aligned with data for the 34 food groups previously reported by Poore and Nemecek, (R^2 = 98.6%, ρ = 97.1% and *p*-value<0.001) (Fig. 4). Overall, the product-specific GHGe values showed a slight systematic underestimation when compared to the food group data (2.35 kg CO_2eq/kg product compared to 2.42 kg CO_2eq/kg product). Twenty-one of the 34 product-specific GHGe median values underestimated the food group data. Fish and crustacean products were substantially underestimated by the product-specific calculations (2.76 kg CO_2eq/kg product compared to 5.08 kg CO_2eq/kg product and 8.45 kg CO_2eq/kg product compared to 11.3 kg CO_2eq/kg product, respectively) (Fig. 5).

4. Discussion

The product-specific GHGe values we estimated for foods and beverages sold in Australian supermarkets provided good approximations of corresponding values derived for main food categories reported by the most comprehensive consolidation of food and beverage GHGe information to date (Poore and Nemecek, 2018). Our method used publicly available product information and enabled differentiation in GHGe associated with apparently similar products across a range of foods and beverages available at retail outlets. There were 3-fold or greater differences between the products with the lowest versus highest estimated GHGe in every category, and up to a 20-fold difference in GHGe estimates for products within the 'Convenience foods' and 'Non-alcoholic beverages' categories.

4.1. Strengths and limitations of the methodology

The capacity to differentiate between GHGe for thousands of foods and beverages using only standard information available on a food product's packaging represents a significant step forward because it makes GHGe signposting and comparison of individual products feasible at scale and at low cost. Much of the existing research compares average emissions of broad food categories (Clune et al., 2017; Poore and Nemecek, 2018), ignoring potential differences between multi-ingredient products that currently comprise most of the packaged food supply. These differences provide the opportunity to make more granular, within-category comparisons. For example, the disparity in GHGe associated with pre-packaged sandwiches can be attributed to simple differences in filling ingredients, information which is available on pack, but never with indication of climate impact (Espinoza-Orias and Azapagic, 2018). Therefore, consumers cannot make informed choices regarding sustainability as they can for nutrition. Our approach could enable the implementation of policy needed to develop a widespread, first-generation product-specific climate label. This type of label could be a powerful tool for driving consumers to purchase lower carbon-footprint products (Potter et al., 2021) and supporting other food system actors including producers and processors towards more sustainable practices (Brown et al., 2020, Scarborough et al., 2020; Trieu et al., 2015; Moberg et al., 2020; Springmann et al., 2018b). Only one similar study exists using packaged product data from the United Kingdom and Ireland, which provides an alternative method to estimate the often non-disclosed proportions of ingredients, but concluding with comparable results (Clark et al., 2022).

The Eco-Score, the Eaternity score and SHARP-ID (ADEME, 2022;

Table 2
Median product-specific greenhouse gas emission estimates and corresponding previously reported group-level data for 16 main FoodSwitch categories and 10 meat and meat product sub-categories.

FoodSwitch category	No. of products	Median Poore & Nemecek GHGe*	Median estimated GHGe (This study)	IQR
Overall	*23,550*	*2.42*	*2.35*	*[1.24, 4.53]*
Bread and bakery products	2345	2.55	2.07	[1.22, 3.07]
Cereal and grain products	1952	1.29	1.35	[0.69, 2.23]
Confectionery	1277	5.00	5.56	[2.91, 8.78]
Convenience foods	1418	3.10	1.99	[1.11, 3.32]
Dairy	2956	2.30	4.14	[1.99, 13.7]
Edible oils and oil emulsions	495	3.80	3.53	[3.20, 4.21]
Egg and egg products	89	4.20	3.54	[3.54, 3.54]
Foods for specific dietary use	761	2.30	2.13	[1.21, 4.32]
Fruit, vegetables, nuts and legumes	3766	1.29	1.20	[0.55, 2.20]
Meat alternatives	195	2.42	1.89	[1.19, 2.70]
Meat and meat products	1724	6.80	6.81	[5.84, 29.2]
Beef and game	234	51.7	55.4	[48.0, 55.4]
Beef and game products	76	51.7	42.6	[39.7, 48.0]
Lamb	127	25.0	29.2	[29.2, 33.1]
Lamb products	3	25.0	21.7	[14.7, 23.8]
Meat-based meals	315	6.09	5.24	[4.09, 7.96]
Other meat products	88	25.0	40.3	[6.37, 49.3]
Pork	130	6.80	7.60	[7.01, 7.99]
Pork products	463	6.80	6.57	[5.64, 6.83]
Poultry	213	6.09	6.26	[5.98, 6.37]
Poultry products	75	6.09	5.38	[4.73, 5.94]
Non-alcoholic beverages	2436	2.55	2.92	[1.48, 5.83]
Sauces, dressings, spreads and dips	2327	1.41	1.67	[1.07, 2.56]
Seafood and seafood products	682	5.08	2.84	[2.13, 4.70]
Snack foods	722	2.30	2.03	[1.38, 2.84]
Sugars, honey and related products	405	2.55	2.95	[2.89, 3.67]

GHGe: Greenhouse gas emission estimates, provided in (kg CO_2eq/kg product). IQR: Interquartile range.
*Source: *Poore J, Nemecek T. Reducing food's environmental impacts through producers and consumers. Science. 2018;360(6392):987-92.*

Bunge et al., 2021; Mertens et al., 2019a; Eaternity Score,) have also all attempted to provide product-specific sustainability metrics for foods and beverages at scale. These approaches benefit from including a broader range of sustainability measures such as water use, land use and acidification. However, the Eco-Score and Eaternity score are limited in scope by their reliance on manufacturers providing supplementary data about aspects such as ingredients, processing and packaging. Likewise, SHARP-ID contains less than 200 data points and mostly does not represent products as sold to consumers. A tenet of our approach was to use only data available on packaging, providing the potential to produce an estimate for every product on the supermarket shelf. We elected to focus on GHGe at this time because there were far more ingredient-specific LCA data for GHGe than for other measures of environmental impact, which increased our ability to differentiate between similar products (Poore and Nemecek, 2018). We also found that GHGe was impactful to stakeholder decision-making across a number of reviewed studies (Potter et al., 2021). Including a wider range of sustainability metrics (e.g., water use, land use and acidification) is important and will be considered as this information becomes available for a larger proportion of ingredients.

While our method is a significant advance, it required a series of assumptions and approximations. Although other comprehensive food LCA databases exist (Colomb et al., 2015), we excluded search results containing LCA data pertaining to a specific country other than Australia because a large proportion of products available in Australian supermarkets are produced in Australia (66.7% based on the country of origin label group 1). We also observed that our mean GHGe estimates, both overall and for most food categories, were a slight underestimation compared to the corresponding Poore and Nemecek values. Our method estimates product-specific GHGe based on the quantities of ingredients in the final product, adjusted for the extent of product processing and transportation. However, these adjustment methods and included life-cycle stages are limited by the availability of standardised and regulated product information. There is no standardised system to categorise foods according to their level of processing (Astrup and Monteiro, 2022). We used the NOVA classification (Monteiro et al., 2019a) as it is currently the most commonly employed and has been used in diet-related research (Dicken and Batterham, 2021). Transportation emissions were estimated using country of origin information, contrary to previous research which used distance travelled (often referred to as 'food miles')(Weber and Matthews, 2008) as this information is not available in the FoodSwitch database. However, as transportation only comprises around 5–10% of food system emissions, it would not have a major impact on the final product emissions estimates (Crippa et al., 2021). Our method does not account for emissions upstream of retail such as those attributable to some ingredient losses as well as post-processing product losses, packaging and refrigeration. While we accounted for ingredient refuse, ingredient losses from post-production processing such as mass change during the transformation process from ingredient to product (e.g., the evaporation of milk when baked into a cake) was only addressed in the case of cheese, as the mass change factor is large (approximately 10) when converting milk to cheese. This is likely an issue affecting more food ingredients, albeit with smaller mass change factors, which may have contributed to the slight underestimation of our product-specific GHGe. Additional product losses, packaging and refrigeration-related emissions should be included in future analyses, though the majority of these stages are often projected to make up a small proportion of the overall impacts (Crippa et al., 2021; Poore and Nemecek, 2018).

A second challenge is that the GHGe values for an ingredient can vary depending on the farming technique (e.g. greenhouse versus field grown), year of production and the type of LCA protocol used (Poore and Nemecek, 2018; Clavreul et al., 2017; Heller et al., 2013). Ingredient listings do not require standard reporting of the descriptors required to differentiate these characteristics, and where the information is available there are frequently no GHGe estimates from corresponding or relevant LCAs. While our database of GHGe for ingredients expanded substantially upon the largest compiled to date (Mertens et al., 2019a), a large number of GHGe values assigned to ingredients were still estimated from a generic ingredient, a less-processed version of the same ingredient, or by using estimates for the closest matching ingredient. For some examples, first, our under-estimation of GHGe for fish and crustacean products is likely due to the focus on farmed seafood in the Poore and Nemecek report and the absence of comprehensive LCA data for

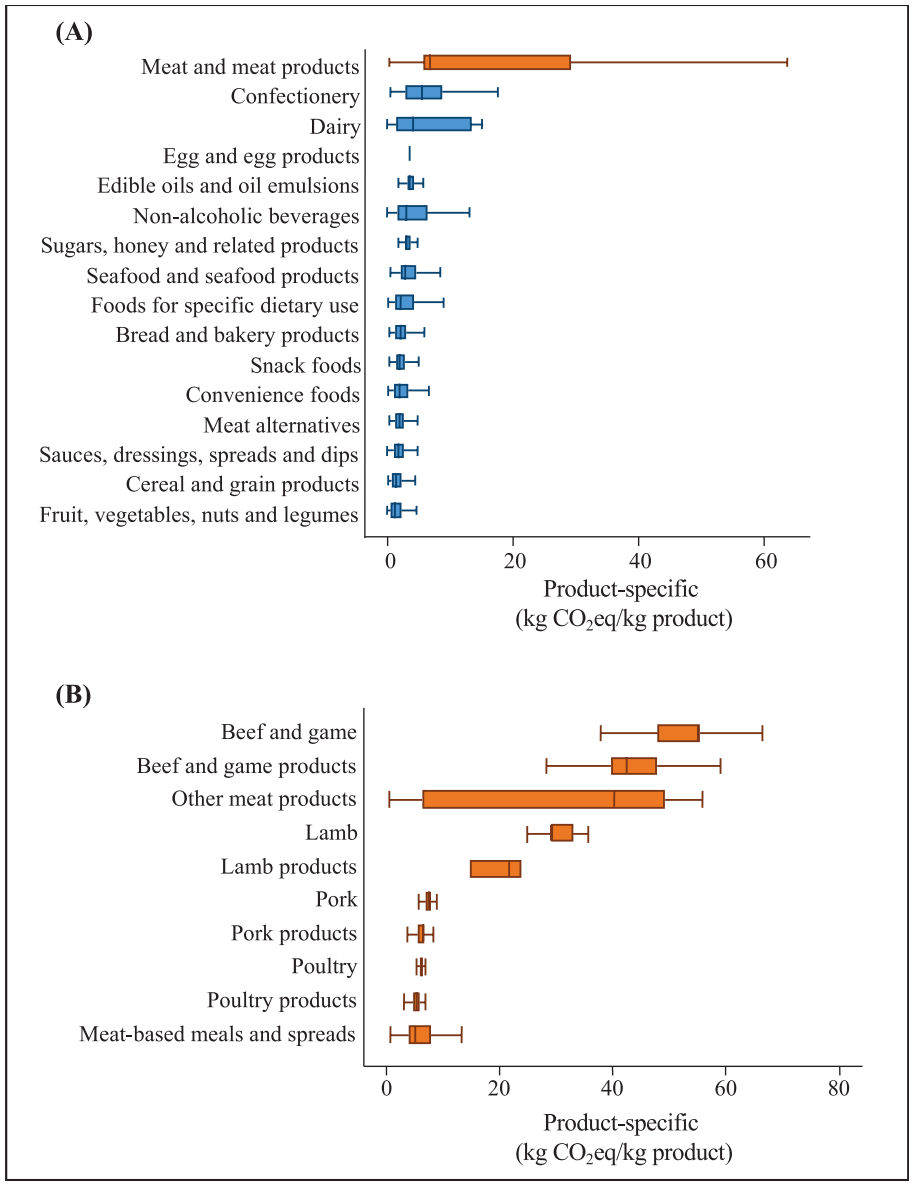


Fig. 3. Product-specific greenhouse gas emission estimates across (A) 16 main food categories and (B) 10 meat and meat product subcategories
This box-and-whisker plot displays the interquartile range of greenhouse gas emission values and the median value is marked by the line within the box. The whiskers extend to the lowest datum within 1.5 times the lower quartile and the highest datum within 1.5 times the higher quartile. Outlier values are excluded from the visualization. The 16 categories are defined within FoodSwitch. "Meat alternatives" are included in part **(A)**. The "Other meat products" category includes dried meats and mixed meat products.

farmed versus wild-caught seafoods (Gephart et al., 2021). Also, the majority of products categorised under 'Egg and egg products' were assigned the same single GHGe value available for eggs, but in practice there are likely to be significant differences between products using eggs from battery versus free-range facilities. Finally, while the data allowed a broad differentiation between organic and conventional production, the level of granularity available to us did not enable comparisons of more subtle differences in production systems (e.g., spatial variability in crop and livestock productivities, or information on the use of renewable energy in the supply chain). As is commonly the case in similar LCA studies (Clark et al., 2022), this compromises the capacity of our approach to discriminate between GHGe estimates for many single- and minimal-ingredient products.

There were several ingredients for which both organic and non-organic forms were specified on product labels and for which separate LCAs for the organic and non-organic ingredient were available. When available, we used these data to explore the potential impact of absent reporting about the organic status of ingredient type and/or the absence of LCA data for organic and non-organic ingredients. We found that inclusion of available organic ingredient GHGe values had minimal impact on product GHGe estimates - the GHGe values for organic versus non-organic ingredients were generally similar (Supplemental Fig. 3). LCA data were particularly sparse for food additives, though this probably had limited overall impact because additives usually constituted only a small proportion of the final product.

4.2. *Recommendations for future research and policy making*

Our method's system boundary included LCA data from cradle-to-farm gate, with additional product adjustments for processing and transport in order to account for the majority of emissions upstream from retail. Emissions attributable to post-processing product losses, packaging, refrigeration and waste were not included because these emissions were beyond the defined system boundary. However, these are recognised as important next steps to consider for future research and lobby to policymakers to make both standard and required (Wohner et al., 2020). The Poore and Nemecek data suggest packaging constitutes on average about 6% of cradle-to-retailer emissions, but it is well established that GHGe attributable to packaging can vary by a large amount between food categories and between otherwise identical products that use optimally sustainable versus least sustainable forms of packaging (Poore and Nemecek, 2018; Crippa et al., 2021). Addressing

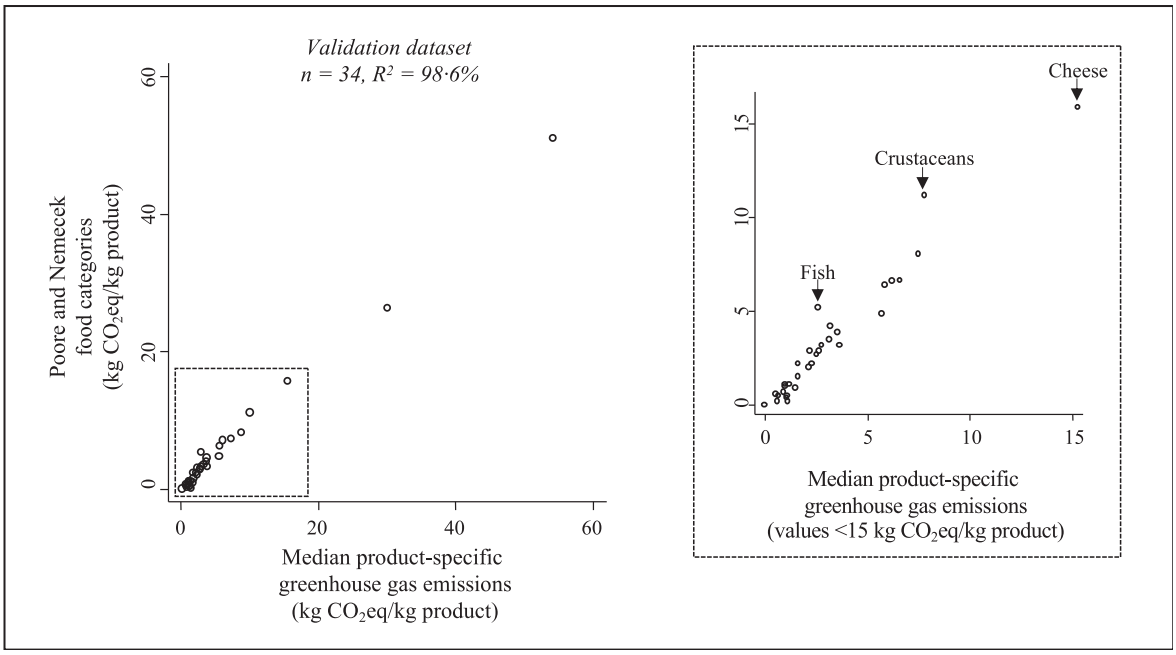


Fig. 4. Validation of median product-specific greenhouse gas emissions estimates against corresponding previously reported data for 34 food groups
This visualization represents the median estimated greenhouse gas emission value for FoodSwitch products mapped to 34 Poore and Nemecek food groups. R^2 is the coefficient of determination, which represents the proportion of variance in greenhouse gas emissions as explained by the estimation methodology, where 100% indicates a perfect fit.

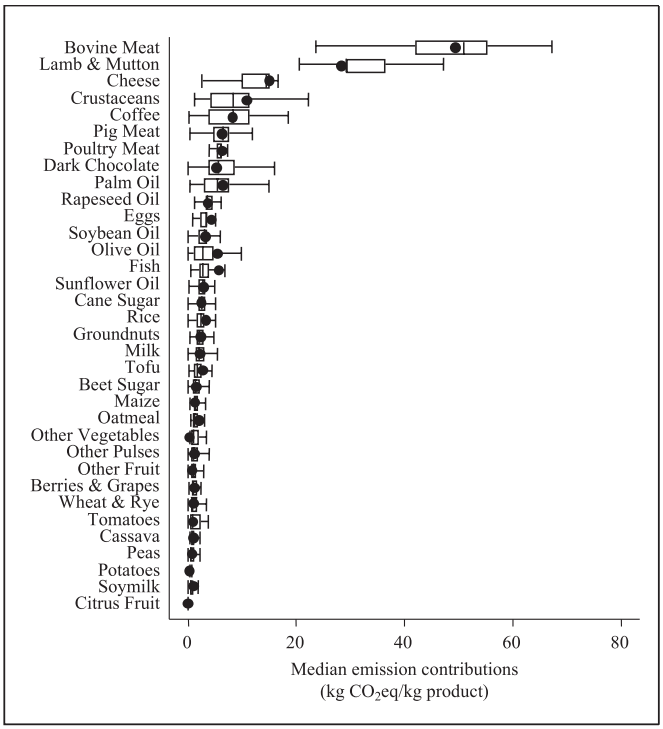


Fig. 5. Validation of range in product-specific greenhouse gas emission estimates against previously reported data for 34 corresponding food groups
This box-and-whisker plot displays the interquartile range of product-specific greenhouse gas emission estimates and the median value is marked by the line within the box. The whiskers extend to the lowest datum within 1.5 times the lower quartile and the highest datum within 1.5 times the higher quartile. Outlier values are excluded from the visualization. The 34 food groups shown are defined in Poore and Nemecek (2018) and the black circles indicate the median greenhouse gas emission values published in the report.

emissions attributable to refrigeration, preparation, loss and waste is also important for evaluating the food system and individual products. Ingredient-specific LCA data were sparse for refrigeration (Poore and Nemecek, 2018) and were not included in the present analyses. In addition to underestimation of product-specific GHGe, the absence of these estimates in our method will likely also have contributed to underestimation of the true variability in GHGe between food products. The implementation of a hybrid LCA and input/output model approach could help to merge the broader, more widely available commodity data with our product-specific data (Yu and Wiedmann, 2018).

The linear programming algorithm used to predict ingredient proportions performed well but was also imperfect. The algorithm relies on nutrient information panels from manufacturers and food composition tables, both of which can vary from truth for a given product, introducing random errors. The adjustments we made for processing and transport were also somewhat crude and will have incompletely captured differences between products. However, the proportion of emissions associated with processing and transport is quite low across the majority of commodities (Poore and Nemecek, 2018). The product-specific adjustments that we did make using the available data helped to discriminate between a number of products that would otherwise have been treated the same, and are thus an important step forward. Improvements in ingredient list terminology (e.g., specifications of ingredient processing methods and ingredient origin) as well as the product's overall extent of processing would enable a more comprehensive and generalisable methodology for estimating product-specific processing and transport emissions. Finally, the absence of a robust gold standard against which to compare our results limits their reliability. There are few publicly available LCA data for individual packaged food and beverage products in Australia, and we therefore compared our results against food category estimates made by Poore and Nemecek. An extensive review of the literature identified these data as the most comprehensive effort to summarise GHGe for foods and beverages to date. We had to group the 23,550 product-specific GHGe estimates to compare against only 34 Poore and Nemecek food categories. However, while the comparator data are imperfect, the broad alignment of our estimates provides significant reassurance about the likely validity of our method.

5. Conclusion

Our novel approach for calculating product-specific GHGe estimates has a sound underpinning rationale and provides plausible estimates across a broad range of food and beverage products. While a series of assumptions and approximations were required, the findings add significantly to the field. These data can be used to empower those seeking to choose foods that have lower carbon footprints and will help policy makers to develop targeted interventions similar to those available for product healthiness.

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Authorship

AG and BN conceptualised and designed the study. AG and TD were involved in the data collection. AG conducted the analyses for the study, with secondary review from MS, FT, PS, and BN. MH verified the accuracy and application of the data. AG, TD, PS, and BN drafted the manuscript. AG, MS, FT, and BN had access to and interpreted the data. All authors read the final manuscript, reviewed it for important intellectual content and approved its submission.

Data sharing

Ingredient and result product-specific greenhouse gas emission data could not be made publicly available because the source data used is blocked by paywalls and/or privacy agreements. We plan to share the results of this research in a publicly available smartphone application by the end of the calendar year.

CRediT authorship contribution statement

Allison M. Gaines: Conceptualization, Methodology, Writing – original draft. **Tazman Davies:** Methodology, Software, Writing – original draft. **Maria Shahid:** Software, Data curation, Writing – review & editing. **Fraser Taylor:** Writing – review & editing, Data curation, Formal analysis, Writing – review & editing. **Jason HY. Wu:** Writing – review & editing, Data curation, Formal analysis, Writing – review & editing. **Michalis Hadjikakou:** Validation, Writing – review & editing. **Simone Pettigrew:** Writing – review & editing. **Paraskevi Seferidi:** Supervision, Conceptualization, Methodology, Writing – review & editing. **Bruce Neal:** Supervision, Conceptualization, Methodology, Writing – review & editing.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Allison Gaines reports financial support was provided by Imperial College London Faculty of Medicine. Maria Shahid reports a relationship with Marlow Foods Ltd that includes: funding grants.

Data availability

Data that exists be shared upon request. Some data that exists behind paywalls cannot be shared.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jclepro.2023.138816.

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