ENVIRONMENTAL IMPACTS OF FOOD RETAIL: A FRAMEWORK METHOD AND CASE APPLICATION

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The food retail sector is the gatekeeper between consumers and producers and has substantial influence on consumption and production choices via procurement and provision decisions. Food provision and consumption systems embody huge environmental impacts worldwide. Food retailers as gatekeepers have a key role to play to enable sustainable consumption and provision to become common practice. In this paper, a framework to attribute emissions and water use to individual and all food retail businesses and their products by geographical area and postcode of cities is presented. As far as the current authors are aware, such a framework has not been generated for food retail sector businesses before, primarily due to barriers to input-output modelling of the sector. The scientific value added is that a novel approach to overcome barriers is presented as well as the required framework. The framework is illustrated for Southampton, but can be applied in other regions of the world where similar data exist. The value of a business's product emissions estimates (generated by the framework) is they can be a first step in informing product prioritisation for focusing information searches or more detailed life cycle analysis to make sustainable procurement and choice editing decisions. The approach has value to government, businesses and NGOs in developing strategy and

planning sustainable provision and procurement; by helping benchmark sustainable shopping provision, prioritisation of retail businesses and product categories for sustainable procurement/choice editing.

1. Introduction and Background

Environmental impacts of food products such as CO_2 and water use are a global issue and critical to living within threshold values for key global environmental pressures that society must observe to stay within a safe operating space for humanity (Garnett 2008, Rockström et al 2009, Beddington et al 2011). In the UK and Europe, food provision plays a key role in the generation of greenhouse gases (GHGs). The food chain produces GHG emissions at all stages in the life cycle, including farming and its inputs, manufacture, distribution, refrigeration, retailing, food preparation in the home and waste disposal (Garnett 2011) [1]. Food provision also strongly implicates water use, for example, the total water footprint of the UK is 102 Gm^3 per year, nine times the annual flow of the river Thames, the majority, 74.8 GM^3/yr of this is embodied in agricultural products (WWF 2008).

Food retailers globally have a key role in determining consumption and sustainable production choices in our food systems and therefore associated environmental impacts. On this basis, the aim of this paper is twofold: 1.) To present a method for overcoming barriers in applying input-output to investigate environmental impacts embodied in food product provision by the food retail sector. 2.) To present a framework for enabling comprehensive GHG emissions and water use estimates/accounts for individual and all food retail businesses within a city and with resolution to individual products; this can be used to help prioritise products on which to focus sustainable procurement as well as provision within an area.

Background

Sustainable consumption has the potential to play a key role in reducing GHGs and water use associated with meeting food related needs and wants globally (UNEDSA 2007, Garnett 2008, 2011 Audsley et al 2009). In order to bring about changes in consumption toward lower embodied GHG products, institutions have developed systems for carbon footprint labelling such as PAS2050. It is however, not a given that information and labelling of products available in some shops will give rise to more sustainable products or large scale shifts in consumption towards lower embodied GHG or water products (Sustainable Consumption Roundtable 2006, Vittersø and Tangeland 2014, Akenji 2014 amongst others). Once information is provided, there is a need for consumers to acknowledge information and actively alter consumption towards lower impacting products (Berry et al 2008). The success of labelling in bringing about the transition to lower carbon or lower water food provision rests on the notion that consumer purchasing habits will switch to low impacting alternatives and that these will be available (Gadema et al 2011). In relation to consumer choice however, Clarke et al (2006) identifies that there appears to be a notable degree of stability in many shopping practices over time, and further that attitudinally, the underlying factors determining store choice are broadly the same in 2002 as they were 20 years earlier in 1982. Gadema et al (2011) provide empirical evidence on the attributes that determine consumer choice of products (in stores). They identify that carbon embodied in food is fairly low down the priority list in terms of attributes that determine the consumers decisions within shops, other attributes such as quality, nutrition, price etc. are generally considered more important[2]. The UK Sustainable Development Commission (2007) states that most people expect products brought to be environmentally and socially responsible, similarly as they expect safety of products to be a pre-requisite, research by the Green Alliance (2010) also support this view.

In relation to availability, Clarke et al (2006) also provide challenging information here, they identify the difficulties that consumers can sometimes face in terms of consumer choice, both shop and product availability are affected by locality and geography which are key aspects that effect consumer choice. Jackson et al (2006a) conclude (from their research) that quality and price are crucial attributes of choice ***within*** stores, but importantly also identify the concepts of consumer convenience and accessibility as playing a key role in consumer choice ***between*** stores. This concept/differentiation of ***between*** and ***within*** stores is likely to be important in sustainable consumption and therefore a potential fruitful area for further research. From reading Jackson et al (2006a) it is clear that local shopping provision within a given locality is influenced by the businesses that are available within an area. Due to locality, some consumers have limited choice and in this way their choice is "locked in" to certain shops and available products (often less sustainable) due to the context of their life situation.

[2] Gadema et al (2011) found that free range was the fourth most important attribute after price. Free range is likely to align with emotional concerns over animal welfare and/or health, this is aligned with past research that shows that sustainable consumption has only occurred at scale for products that have emotional resonance or connections to health benefits (Sustainable Consumption Roundtable 2006).

The research above as well as others such as Broken and Allwood (2012) and Vörösmarty et al (2011), suggests a strong role for retail businesses but also government/NGOs in ensuring availability and provision of sustainable products within an area as a pre-requisite. Retailers have a key role to play in monitoring the emissions and water use of the products they choose to sell and actively procuring out or alternatively, warning against the most environmentally damaging products (in their shops). In this way they help ensure more sustainable choices by consumers. In this sense, food retailers have a role as gatekeepers to the environmental sustainability of consumer choices and enablers of sustainable consumption.

In order to help retailers in this role and encourage provision of sustainable products within a local area, perspectives and frameworks that can help retailers efficiently produce proxy benchmarks for their businesses and products are urgently needed. Building on the literature above, frameworks should also provide a comprehensive geographical referenced benchmarking to allow government to estimate impacts (GHGs, water use etc.) and opportunities for sustainable shopping provision within an area. When focusing on estimates to inform sustainable procurement and choice editing, impacts attributable to provision should be identified (as opposed to emissions attributed to consumption or production); see Bradley et al (2013) for a detailed discussion and justification.

Until now, the desired framework discussed above has been missing for the food retail sector therefore leading to one of the aims of this paper. Benchmarks from such a framework can help illustrate impacts and prioritise product categories and areas for monitoring and choice editing, therefore not just leaving all the decisions and action up to consumers. Importantly, such benchmarks need to be efficient and enable a businesses to quickly prioritise the most important products (in terms of environmental impacts) for further attention, for their business, as it is clear from even large food retailers experience that businesses struggle with resource required to estimate their environmental impacts embodied in provision (Guardian 2012). Tesco recently started leading in this area, pledging to label all its products with their carbon footprint. In 2012 however they dropped their carbon label pledge citing that too much work was involved and that other retailers failed to follow their lead (Guardian 2012).

An efficient benchmarking method to apply in estimating 'starting' or 'proxy' business benchmarks is the application of Leontief's input-output analysis (Matthews and Lave 2003, Lenzen 2006). Input-output however, cannot be applied to estimate environmental impacts embodied in provision (using the provision perspective as outlined in Bradley et al 2013) of the food retail sector, due to the way that I-O accounts are constructed in UK and other countries such as Australia and the USA , see Australian Bureau of Statistics (2000) and the USA (BEA

2009). This forms a substantial barrier to efficient environmental estimations for this sector. This is because within the national input-output accounts, food product' transactions for the Retail sector are stripped out and put within the sectors that produce the products. So for Food retail, the product transactions are put within the Manufacturing of food products and beverages sub sectors. This is done when putting together the input-output tables. The transactions in all sub sectors of Manufacturing of food products and beverages, appear as intermediate and final demand. A method is documented in this paper to overcome this issue, addressing the first aim of this paper and enabling environmental I-O modelling to generate provision estimates for the food retail sector, as well as the development of the desired framework for this important sector. The framework is applied to a case study for the UK.

The framework for CLARE is described in Section 2. Section 3 demonstrates the framework for food retail businesses in Southampton (UK). Discussions and conclusions are conducted in Section 4.

2 The framework method

The framework developed to address the aims of this paper is called the Commercial Local Area Resource and Emissions model (CLARE). CLARE is composed of two sub frameworks: CLARE-direct for direct emissions and water use and CLARE-indirect for indirect emissions and water use estimation as seen in Figure 1. In this study direct emissions are the emissions that occur from processes owned, operated or controlled by a business of concern. Indirect emissions are defined as those emissions associated with processes that occur in the life cycle of a product prior to the processes owned, operated or controlled by the business of concern. The indirect definition corresponds with the upstream GHG emissions definition by British Standards Institution, Publicly Available Specification 2050 (BSI, 2008). The development of CLARE-indirect requires an Environmental Input-Output (EIO) model as part of the framework. An outline of CLARE is provided in Figure 1. A version of CLARE was applied for the Hospitality sector in Bradley et al (2013), methods in this paper can be applied for most UK sectors, but unfortunately not for the important food retail sector due to the way that economic accounts are organised and published. A different methodological approach is required for the food retail sector. This is now presented.

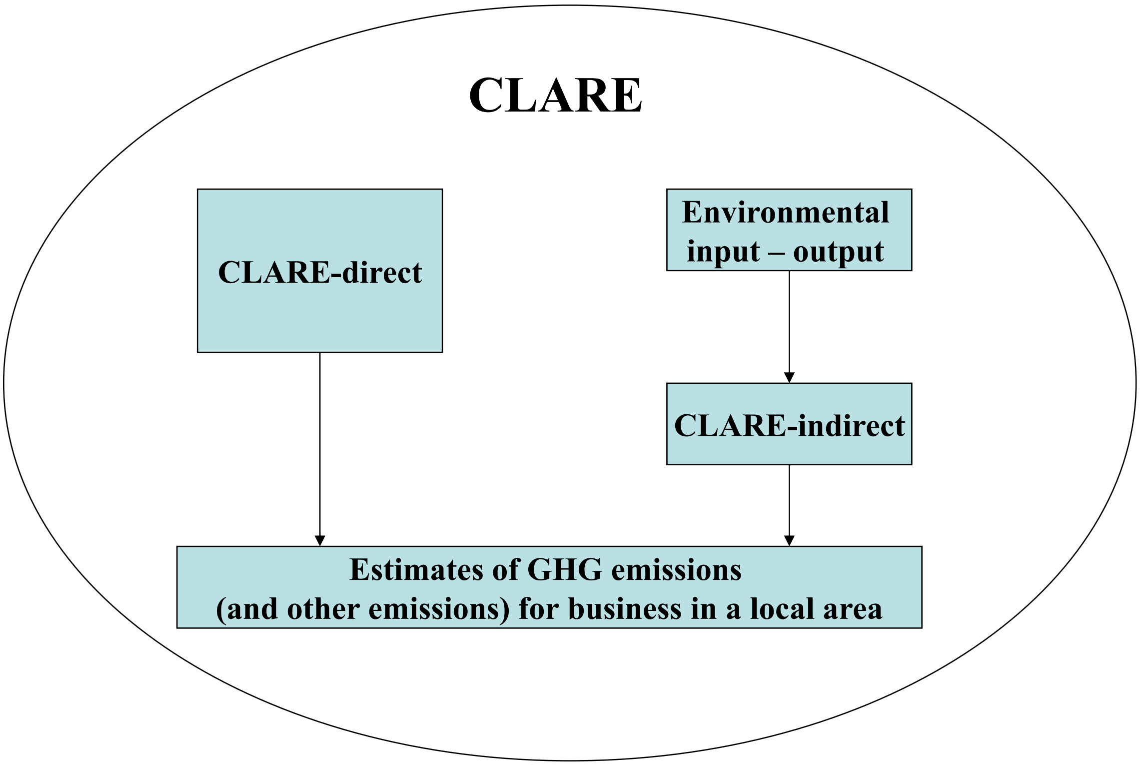

Figure 1: An outline of the Commercial Local Area Resource and Emissions (CLARE) Model.

For CLARE-direct, modelling makes use of sector (macro) and individual business (micro) data but final outputs are produced for businesses (micro level). EIO analysis modelling is done at the sector level (macro). For CLARE-indirect, modelling makes use of sector (macro) and business (micro) data but final outputs are produced for businesses and products (micro level). For simplicity, the term emissions will be used to describe GHG emissions or water use for the remainder of this section. A method and approach for estimation of environmental estimates for individual and all businesses in an area for all other sectors (beyond Retail) was published in Bradley et al (2013) along with an input-output modelling perspective when investigating emissions embodied in provision (consistent with the life cycle analysis/inventory approach applied by businesses); the provision perspective.

2.1 CLARE-direct (production perspective estimation)

The key equation that CLARE-direct applies to estimate direct emissions occurring from a business is quite simple as seen in equation 1. This example is for a single company in sector j.

$$e_o = t_o \bar{u}_j \tag{1}$$

Where:

e_o is the direct emissions occurring from business o (CO_2e for this paper);

t_o is the estimated turnover for the business o; and

$\bar{u}_j$ is the average emissions per unit turnover for the relevant sector (sector j), corresponding with the business;

The challenge in implementing CLARE-direct is to find data to represent a single business, this is illustrated here for a single business in the UK.

Before equation 1 can be applied, both t_o and $\bar{u}_j$ have to be estimated for a business. A range of steps are required to produce t_o and $\bar{u}_j$ using various datasets and equations (datasets can be seen in Figure 2). The first step is to select the specific food retail sector (i) for which one needs to estimate emissions of businesses within a geographic area.

The remaining steps, 2, 3 and 4 are outlined in Figure 2 (equation 1 is conducted lastly at the bottom of the figure). Steps 2 and 3 are applied to estimate t_o. Step 4 is applied to estimate $\bar{u}_j$.

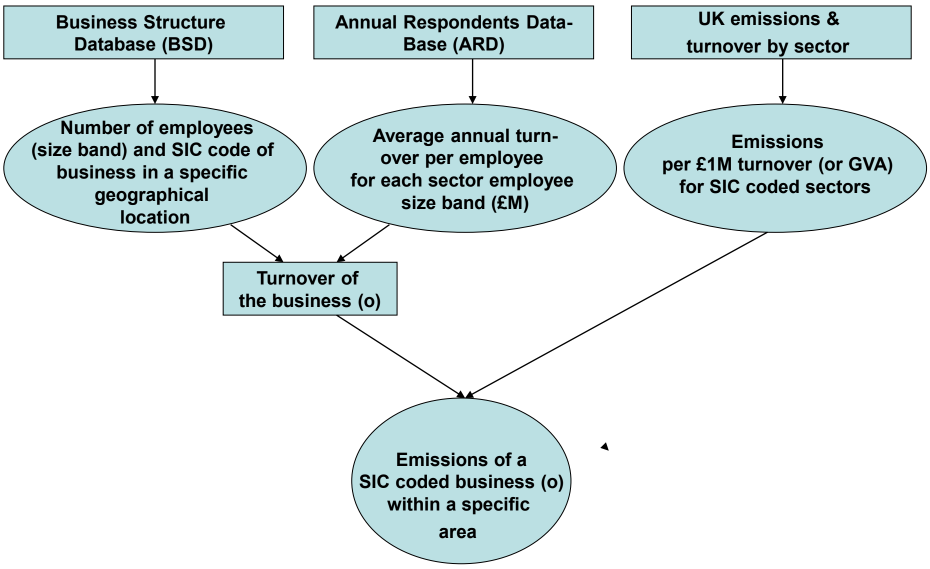

Figure 2: An overview of CLARE–direct.

Once the sector is identified from step 1, the Business Structure Database (BSD) can be searched for all businesses within the sector, within a defined area. Once businesses are found from the BSD it is possible to identify the full 5 digit (most disaggregated level) Standard

Industrial Code (SIC) that each business belongs to, the number of employees[3] and the post code. For each business in the group, the following steps are conducted.

The average annual turnover for the relevant business now needs to be estimated (step two). The Annual Respondents Database (ARD) is used for this. Unlike the BSD, this dataset does not include businesses representing 99% of all UK output, but is a large dataset and has good representation for different business sub sectors (ONS 2008). For the businesses that are within the database however, the number of variables and the 'richness' of the data is much higher than in the BSD. The ARD is searched to find all businesses within the same size band and SIC sector (5 digit) as the relevant business found in the BSD. Businesses found are termed as matching businesses. The key details used to match businesses are the SIC code and number of employees. Once matched retail businesses are found, the calculation of the average turnover per employee for these businesses occurs in step 2 as follows:

$$\overline{f}_j = \frac{1}{n}\sum_{i}^{n}\left[\frac{t_i}{m_i}\right] \quad \text{i = 1 to n where n is the number of businesses in the sample} \qquad (2)$$

Where:

$\overline{f}_j$ is the average turnover per employee for a given size band and SIC code j;

t_i is the turnover for the matching businesses i found in the ARD; and

m_i is the number of employees in business i within the matching sample.

This enables turnover estimation for business (o) isolated from the BSD dataset as shown in equation 3 (step 3):

$$t_o = \overline{f}_j m_o \qquad (3)$$

Where:

t_o is the estimated business turnover for the business o; and

m_o is the number of employees of the business o.

Step four uses various databases to obtain the annual emissions (or water use) data for a sector (and size band if possible) and turnover. Emissions per unit turnover is estimated in equation 4:

$$\overline{u}_j = \frac{e_j}{t_j} \qquad (4)$$

[3] The term employees is used in the current paper to describe the number of people that work in a business, this is equivalent to how employment is defined by Office for National Statistics. The term employees is an easier word to work with linguistically.

Where:

$\bar{u}_j$ is the emissions coefficient for sector j (i.e. emissions per unit of turnover);

e_j are the emissions of sector j; and

t_j is the turnover of sector j.

$\bar{u}_j$ from equation 4 and t_o from equation 3 are used in equation 1 to estimate direct emissions;

Environmental data:

GHG data were predominantly used from ONS (2010) in this study, but BERR Energy Consumption in the United Kingdom: Service Sector Data Tables (BERR 2008), were also used along with knowledge of the Defra carbon dioxide intensity per unit of fuel burnt to provide a more disaggregated figure for direct estimation for the Food retail sector as documented in Bradley (2013). For direct and indirect water use estimation, the most up to date data was the Defra water supply and abstraction data (2006) sent by Harris (2010) on behalf of Defra. Beyond water supplied and abstracted by industry (termed blue water), water (in the form of moisture) stored within UK soil (green water) is used by vegetative plants that the UK agriculture industry sell on to consumers. The environmental impacts associated with the latter water use (green) are generally a lot lower than from those of water supplied by water companies or abstracted (WaterWise 2007) and the focus was blue water. The definitions of blue and green water are from Hoekstra and Chapagain (2007). Environment Agency C&I Waste survey (2002) and (1999) were used for sector wide C&I waste figures. These data were the best sector wide data, robustness checks of these data (due to their age) were performed in Bradley et al (2009), and this work suggests that they estimate reasonably well. This was the only disaggregated and detailed sector wide dataset for C&I waste collected in a consistent way across all sectors and therefore applicable in the environmental input-output model.

2.2 EIO method for the Food retail sector

Leontief first developed input-output analysis and the frameworks that enable this analysis (Millar and Blair, 1985). The basic Leontief input-output model can be extended into an EIO model capable of estimating emissions attributable to consumption in a given region, resulting from final demand expenditure (in sectors).The framework referred to by Miller and Blair (1985) as the limited Leontief EIO system is used to develop the basic EIO framework for this study. See equation (5):

$$\mathbf{e} = \mathbf{u}'(\mathbf{I} - \mathbf{A})^{-1}\mathbf{y} \qquad (5)$$

Where:

$\mathbf{e}$ is a vector of the emissions attributable to final consumption;

$\mathbf{u}$ is a vector of emissions coefficients for a region; and

$\mathbf{u}'$ is the transpose of $\mathbf{u}$.

$\mathbf{I}$ is an identity matrix;

$\mathbf{A}$ is the technical coefficient matrix[4]; and

$\mathbf{y}$ is a vector of final demands.

As mentioned, there is an issue with modelling food retail using input-output, as food products sold by the retail sector are primarily present in producing sectors in I-O tables (not the retail sector). To overcome this issue and enable EIO modelling for the food retail sector, this study takes the approach of generating product by product indirect emissions multipliers for the relevant producing sectors and then apply these to product sales data for relevant food retail businesses (of an area). This allows one to then estimate the indirect emissions embodied in each and every product sold by the food retail sector (all relevant businesses within an area). The EIO modelling used to generate estimates with CLARE-indirect is now presented. In section 2.3, CLARE-indirect is applied in combination with EIO estimates to estimate indirect emissions resulting from food retail product sales.

To be consistent with the data in CLARE-indirect there is a need for emissions to be in the form of emissions per £ of sales to final demand of each of the Manufacturing of food products and beverages sub-sectors. To get to this stage, firstly we need to estimate the emissions embodied in household[5] final demand sales for each of the sub sectors. For this reason EIO modelling of the Food Retail sector, makes use of the following equation:

$$\mathbf{e}_2^{hh} = \mathbf{u}'(\mathbf{I}-\mathbf{A})^{-1}\begin{bmatrix} 0 \\ y_2^{hh} \\ 0 \\ 0 \\ 0 \end{bmatrix} \tag{6}$$

4 A technical coefficient (aij) of the A matrix characterises the inputs from industry i that are required as a result of an increase in one unit of industry j. Such a coefficient is generated by dividing inter-industry sales from sector i to sector j (over e.g. a year) by the output of industry j for the same time frame.

5 Attribution occurs to households as data that enable further disaggregation of sectors' products in CLARE-indirect is household data;

Where:

$\mathbf{e}_2^{hh}$ is a vector of emissions embodied in household final demand of the Manufacturing of food products and beverages sub sector (sector 2); and

y_2^{hh} is the household final demand of the Manufacturing of food products and beverages sub-sector (sector 2);

This method estimates the direct and indirect emissions attributable to household final demand of the Manufacturing of food products and beverages sub-sector (sector 2). In reality there are sixteen sub-sectors within the Manufacturing of food products and beverages sector in the UK input-output accounts; sector 2 only represents one of them. The modelling in this project is carried out for all 16 detailed food producing sub sectors.

Amending the model to avoid double counting for the Food retail sector

The EIO modelling for the Food retail sector in the current study will (as an output) produce figures of direct as well as indirect emissions embodied in product sales. In CLARE-direct however, direct emissions and water use are already estimated, so to use both estimates of CLARE-direct and CLARE-indirect would result in double counting. Therefore in this study EIO is used purely to capture indirect emissions (which are later used by CLARE-indirect). There is therefore a need to develop methods to adjust the EIO model outputs, so that direct emissions of the sector (Food retail sector) are not included within estimates produced. This is done by adjusting the emissions coefficient u of the Food retail sector in the EIO model.

Amendments for the Food retail sector's products

The amendments to equation 5 are as follows in equation 7. Using a 5 sector economy in the example applied here: Sector 2 is the Production, processing and preserving of meat and meat products sector denoted by suffix 2; the third sector is the Retail sector. The Retail sector (SIC 52) is unfortunately the most disaggregated form in which we have the Food retail sector (SIC's 52.1 and 52.2) from input-output tables, and the EIO model. The other three sectors are denoted by suffixes 1, 4 and 5:

$$\mathbf{e}_2^{hh} = \begin{bmatrix} u_1 \\ u_2 \\ 0 \\ u_4 \\ u_5 \end{bmatrix}'(\mathbf{I} - \mathbf{A})^{-1} \begin{bmatrix} 0 \\ y_2^{hh} \\ 0 \\ 0 \\ 0 \end{bmatrix} \tag{7}$$

Where:

u_2 is the emissions coefficient for the Manufacturing of food products and beverages sub-sector. u_1, u_4 and u_5 are the emissions coefficients of sectors 1, 4 and 5. Sector 3 is the Retail sector and so has its emissions coefficient replaced with a zero[6].

For equation 7 there are two first steps in conducting adjustments to the **u** vector before the model can be run:

First obtain the environmental accounts used in making the u vector. Then take out from the environmental accounts the direct emissions for the Retail sector[7]. The change will then be reflected in the emissions coefficient vector (**u**) of the model, as seen in equation 7;

The model (equation 7) is then run. The new outputs from the model will have emissions attributable to the Manufacturing of food products and beverages sub-sector final demand (y_2^{hh}). The emissions estimate will however, exclude any emissions originating from the Food retail sector (so direct emissions of the Food retail sector), thus avoiding double counting.

Adjusting the emissions coefficients u of the EIO model works in avoiding double counting and removing all direct emissions from all Food retail businesses at the sector level (with no international trade), but not at the individual business level with trade. At the individual food retail business level, indirect emissions are potentially occurring from businesses in the same sector and so therefore are not part of a business of concerns direct emissions but perhaps part of its indirect. If this is the case then these

[6] This later step eliminates direct emissions of the Food retail sector from EIO outputs.
[7] The aggregation level of I-O accounts, does not enable disaggregation to the Food retail sector.

indirect emissions should be counted in e_2^{hh}, but from equation 7 they will not be. In this study, the 'small business assumption' is applied: In principle some food retail business indirect emissions may occur from other retail businesses and should technically appear as indirect emissions for the business of concern, but these emissions are very small/minimal and so it is assumed that they can be ignored. From supply and use tables it can be seen that the Retail sector trades very little with itself, and the Manufacturing of food products and beverages sub-sector buys very little from the Retail sector, so this further reduces any error and justifies the 'small business assumption'.

The foreign emissions attributable to household final demand of the Manufacturing of food products and beverages sub-sector, now has to be estimated. In order to account for this, the basic framework is extended to a two region model following Proops et al. (1993) and Jackson et al (2006). The two region model was deemed to be the clearest and best way to ensure transparency and tractability through the framework and estimates produced. Transparency and tractability of any framework that attempts to produce detailed estimates for business are important as business may want to compare their emissions estimates with those of CLARE. To do so would require knowledge of the assumptions and datasets applied. Use of large numbers of datasets for many countries as would occur if a multiregional EIO model was used, would reduce the tractability and transparency of estimates the pros and cons of this decision are discussed in Appendix A. The two region model also enables the study to keep a relatively high level of disaggregation throughout the modelling. Using the two region model of Proops et al (1993) and later Jackson et al (2006), this is conducted as seen in equation 8.

$$\mathbf{e}_{2\beta}^{\mathrm{hh}} = \mathbf{u}^{\alpha\,\prime}(\mathbf{I} - \mathbf{A}^{\alpha})^{-1}\mathbf{B}_{\beta\alpha}(\mathbf{I} - \mathbf{A}^{\alpha})^{-1}\begin{bmatrix} 0 \\ y_2^{\mathrm{hh}} \\ 0 \\ 0 \\ 0 \end{bmatrix} \tag{8}$$

Where:

$\mathbf{e}_{2\beta}^{\mathrm{hh}}$ is a vector of the foreign emissions attributable to UK household final demand of the Manufacturing of food products and beverages sub-sector;

$\mathbf{B}_{\beta\alpha}$ is the imports use coefficients matrix for imports from region β to region α .

Double counting of direct emissions is not an issue when modelling the rest of the world emissions, as the UK business for which modelling in conducted is based in the UK, so the chances of any double counting are very minimal.

Input – output table data

Input-output data and accounts previously used for EIO modelling were from Wiedmann et al (2008). These tables are fairly disaggregated at 123 UK sectors and were the most up to date and robust tables available at the time of PhD. The tables were developed by leading experts in the field, the Department for Environment Food and Rural Affairs commissioned the tables and so these were the most valid tables for use. The PhD project managed to further disaggregate 3 key agriculture sectors further (resulting in a 126 sector model) and this is documented in detail in Bradley (2013), detailed checks were conducted to ensure that the model estimated correctly, these are also provided in the thesis. This was important in ensuring more accurate estimation for food product categories.

2.3 CLARE-indirect (food retail businesses)

Clare-indirect puts businesses at the forefront of attention as opposed to sectors (EIO). For selected businesses, CLARE-indirect estimates the sales of products by businesses (total products) and attributes indirect emissions of products to these business product sales (using estimates from sector level models). A detailed system diagram is provided in Figure 3.

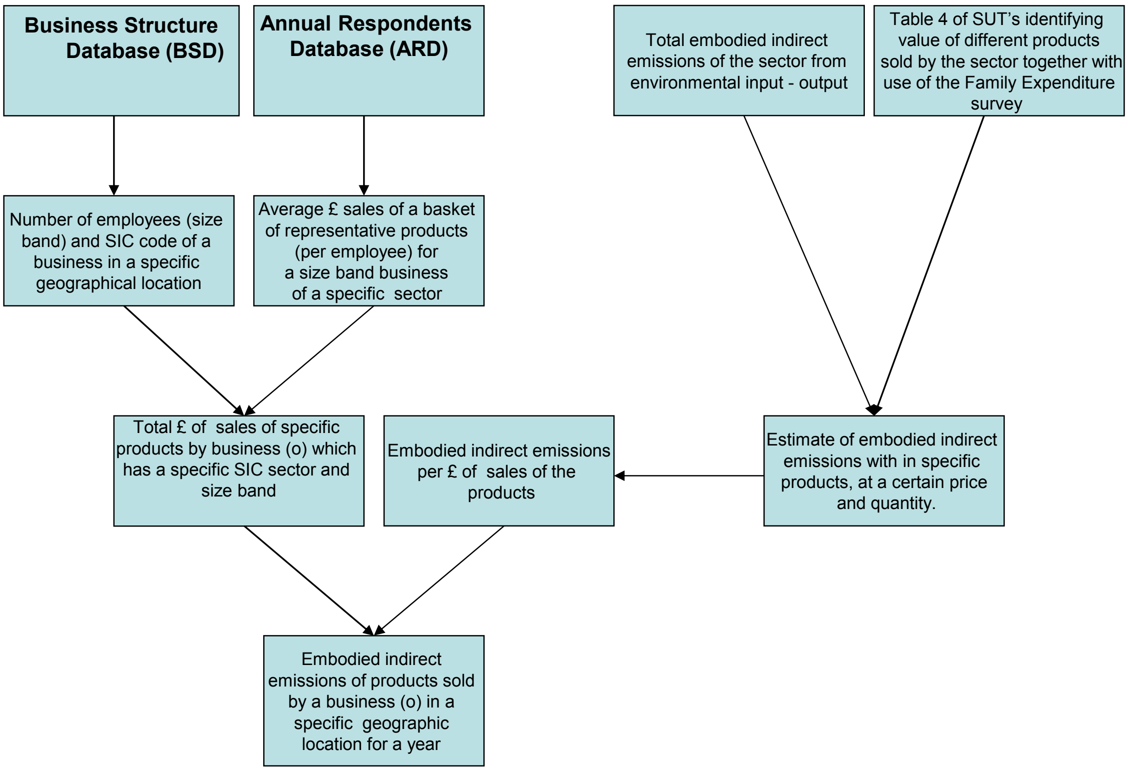

Figure 3: An overview of CLARE-indirect (for Food retail sector businesses).

The first step is to pick the specific retail sector for which one needs to estimate emissions of business or businesses within a geographic area. Once the sector is identified, the BSD can be searched for all retail businesses of the detailed sub sector, within a defined area (all businesses with postcodes within Southampton Unitary authority). Once business(es) are found from the BSD it is possible to reveal the full 5 digit SIC that each business belongs to, the number of employees and the post code of the business. For each business of the group of businesses selected, the following step 2 is conducted (the example business shown in Figure 3 and equation 9, is denoted by subscript (o)).

In step two there is a need to calculate the average sales for a basket of representative products for a specific size band and SIC of the retail business, which matches the SIC and employee profile of the business identified in step one. This is done through searching the Annual Respondents Database to find all retail businesses with matching details. Once matched businesses are found, calculation of the average sales for the range of different products supplied by the business is estimated (per employee). This is shown mathematically for product r in the equation below:

$$\bar{s}_j^r = \frac{1}{n}\sum_i^n \left[\frac{p_i^r}{m_i}\right] \qquad i = 1....n \tag{8}$$

Where:

$\bar{s}_j^r$ is the average sales of a product r per employee for the given size band and SIC code j;

p_i^r is the sales of a product r for matching retail businesses i found in the ARD; and

m_i is the number of employees of the businesses i.

Step three brings together outputs from steps one and two and estimates the total sales of each product type for the retail business of concern (business o), by taking the average sales of products per employee and multiplying this by the number of employees (m is this time taken from the BSD as opposed to the ARD) for the business (o). The procedure can be written out mathematically as follows:

$$p_o^r = \bar{s}_j^r \, m_o \tag{9}$$

Where:

p_o^r is the estimated sales of product r for a specific retail business o; and

m_o is the number of employees of the business o.

Step four estimates the average embodied indirect emissions per unit of expenditure for the given product r. This step firstly requires the estimates of total embodied indirect emissions of sectors' products (from equations 6+7) to be converted to more detailed emissions of individual products of a sector. These estimates are then converted into emissions per unit of expenditure on products. Table 4 of the UK Supply and Use tables (SUTs) allow sector expenditures to be grouped under COICOP product category headings. Using the Family Spending report, which provides very detailed estimates of household expenditure on specific products (COICOP classification), these product categories are further split to specific types of product, again based on expenditure data

(ONS 2005). An assumption of step four is that emissions can be distributed pro-rata to specific types of products in accordance with how the Family Spending report allocate (in a more detailed way) expenditure to products. It is hoped that in future, data will become available that will allow this assumption to be avoided.

Once the amount of embodied indirect emissions for a set of products is known, a set of average embodied indirect emissions intensities can be produced for the products. This is done by dividing total embodied indirect emissions within products by the total household expenditure on products, as seen mathematically in equation 10:

$$\bar{u}^{r} = \frac{e_h^r}{y_h^r} \tag{10}$$

Where:

$\bar{u}^{r}$ is the average embodied indirect emissions per unit of expenditure for a given product r;

e_h^r is the total embodied indirect emissions for the total amount of a product r that households (h) buy; and

y_h^r is the household (h) expenditure for the given same products r.

Finally step five requires the bringing together of steps three and four to estimate the emissions attributable to the product (r) sales of the retail business of concern (business o). This is calculated by applying the following equation:

$$e_o^r = p_o^r \bar{u}^{r} \tag{11}$$

Where**:**

e_o^r is the emissions embodied in retail business o's sales of product r.

3.1 Demonstrating the framework with the case study

In this section a demonstration of the application of the framework to model the food retail sector in Southampton at different scales and different levels of resolution is provided. This can help in answering different questions for businesses and policy makers.

Aggregate results: Southampton Unitary Authority

Results for food retail businesses in Southampton, UK are reported in Figures 4 and 5. Results are primarily for GHGs, water use, but also commercial and industrial (C&I) waste. Clearly from Figures 4 and 5, it can be seen that the Food retail businesses have very high indirect water impacts. Most of this water is extracted for food production by the fish and fish farming and Agriculture sectors[8]. The large amount of indirect GHGs are the result of the food products sold by these businesses, the most important sector where these emissions are actually emitted is Agriculture. With regards to food waste, indirect emissions are also more dominant than direct, production and provision estimates are more even for C&I waste. The general dominance of indirect impacts, flags up the opportunity to retailers to develop strategies and policies for sustainable procurement to reduce emissions and water use embodied in the products that they make available to consumers.

[8] The majority (well over half of the total) of Agriculture's water is from the public water supply (the remainder is directly abstracted), for the fish and fish farming sector most of the water used is directly abstracted fresh water.

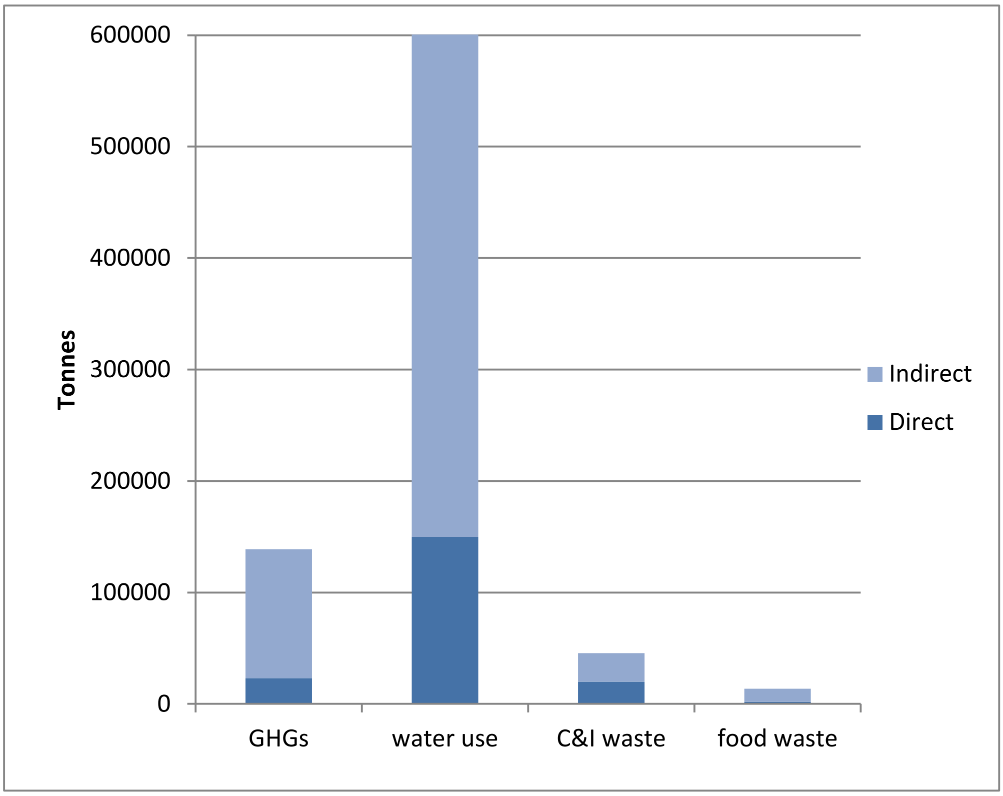

Figure 4: The direct (production perspective) and indirect (provision perspective) GHG emissions, C&I waste, food waste and water use of food retail businesses in Southampton Unitary Authority in 2004.

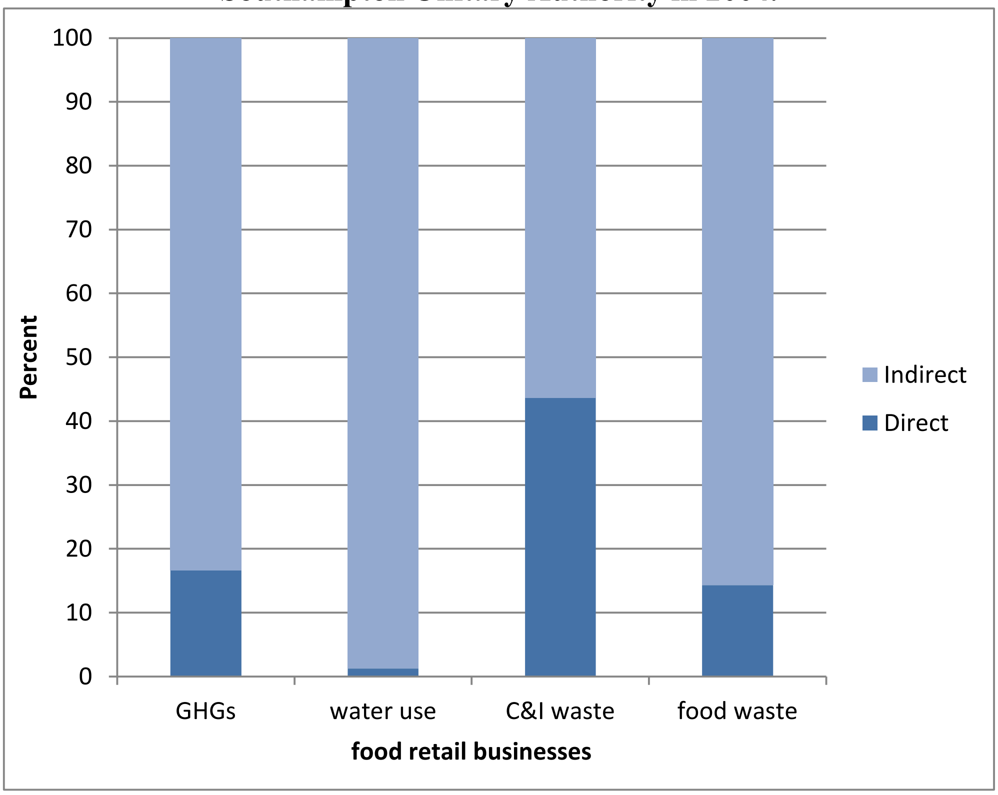

Figure 5: The percentage of direct (production perspective) and indirect (provision perspective) GHG emissions, water use, C&I waste, and food waste for food retail businesses.

3.2 Emissions and water use of businesses

The resolution possible when using CLARE is now demonstrated for different business types. Business types are businesses classified at the most detailed five digit SIC codes. Results for different business types are presented by looking at emissions and water use profiles for typical individual businesses with 10 employees, in Figure 6. These are not actual existing individual businesses as publishing such information would be disclosive, but such estimates are available in in the outputted business estimates stored in the secure environment[9], which can be accessed by any qualified analyst/planners desk top computer.

From Figure 6, it can be seen that businesses can have quite different emissions impacts. Meat retail has the highest GHGs and C&I waste impacts. It is noticeable that the impacts are mainly embodied indirect impacts. Therefore, the focus for these businesses should very much be on assessing how they can reduce their indirect impacts, through sustainable procurement or other mechanisms. Retail of tobacco businesses have comparatively low impacts. For the imported component, see Appendix B.

[9] The secure environment is a lab within ONS, where only authorised and trained researchers are able to access detailed data. Data going into the lab and outside of the lab is checked and assessed for disclosure by ONS staff. Any data or estimates taken out of the lab must be derived from at least 10 observations otherwise data cannot be take outside of the lab.

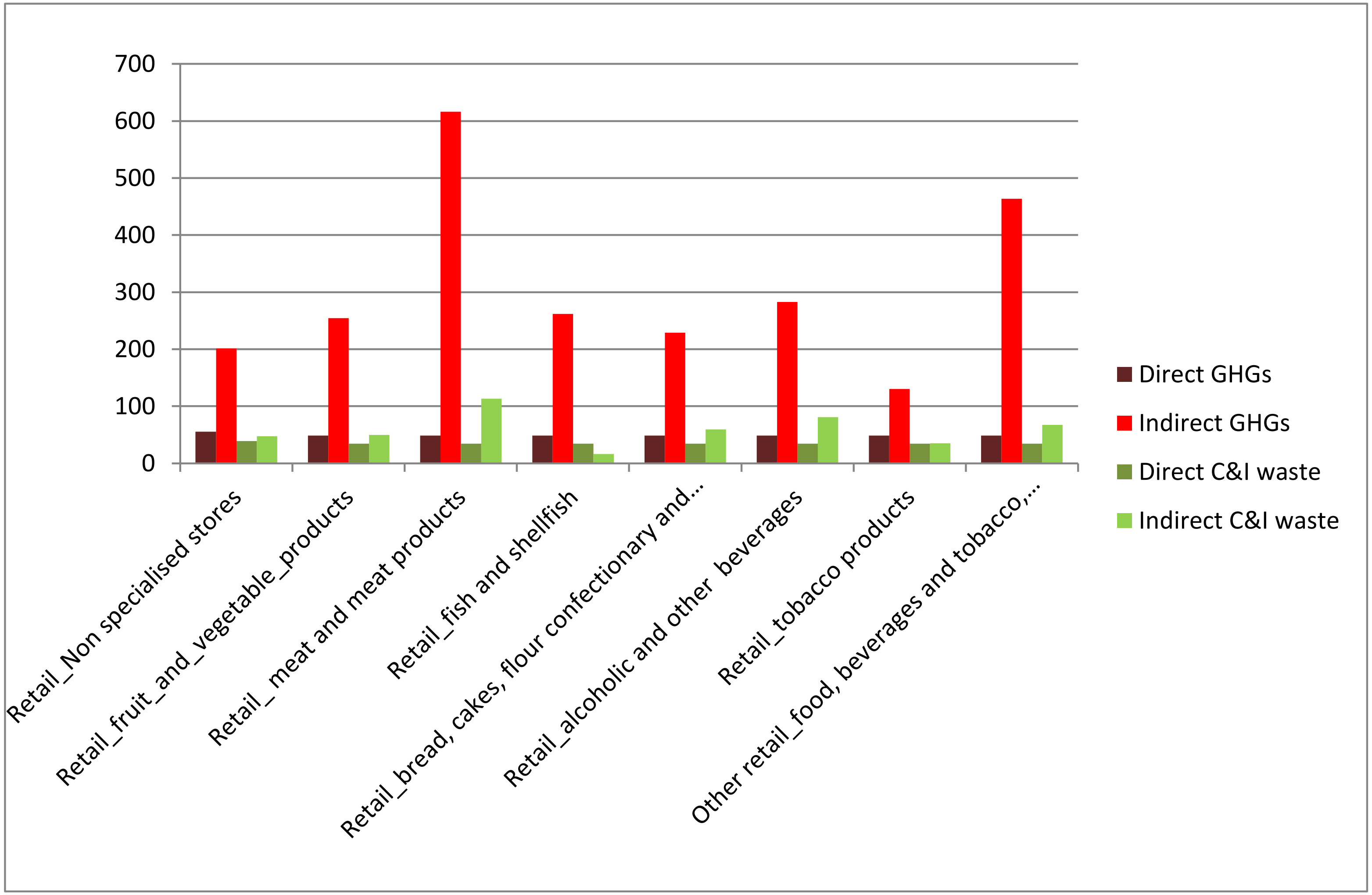

Figure 6: The GHGs and C&I waste profiles for different Food retail and Hospitality business types.

In Figure 7 it can be seen that indirect water use is much larger than direct water use for all businesses. The business with the largest (indirect) water use is the selling fish and shellfish retail business. Indirect water use of Retail fruit and vegetable as well as Other retail (food, beverages and tobacco, specialised) have comparatively high indirect water use requirements. These retail businesses are therefore particularly important in terms of ensuring more sustainable provisioning for water use.

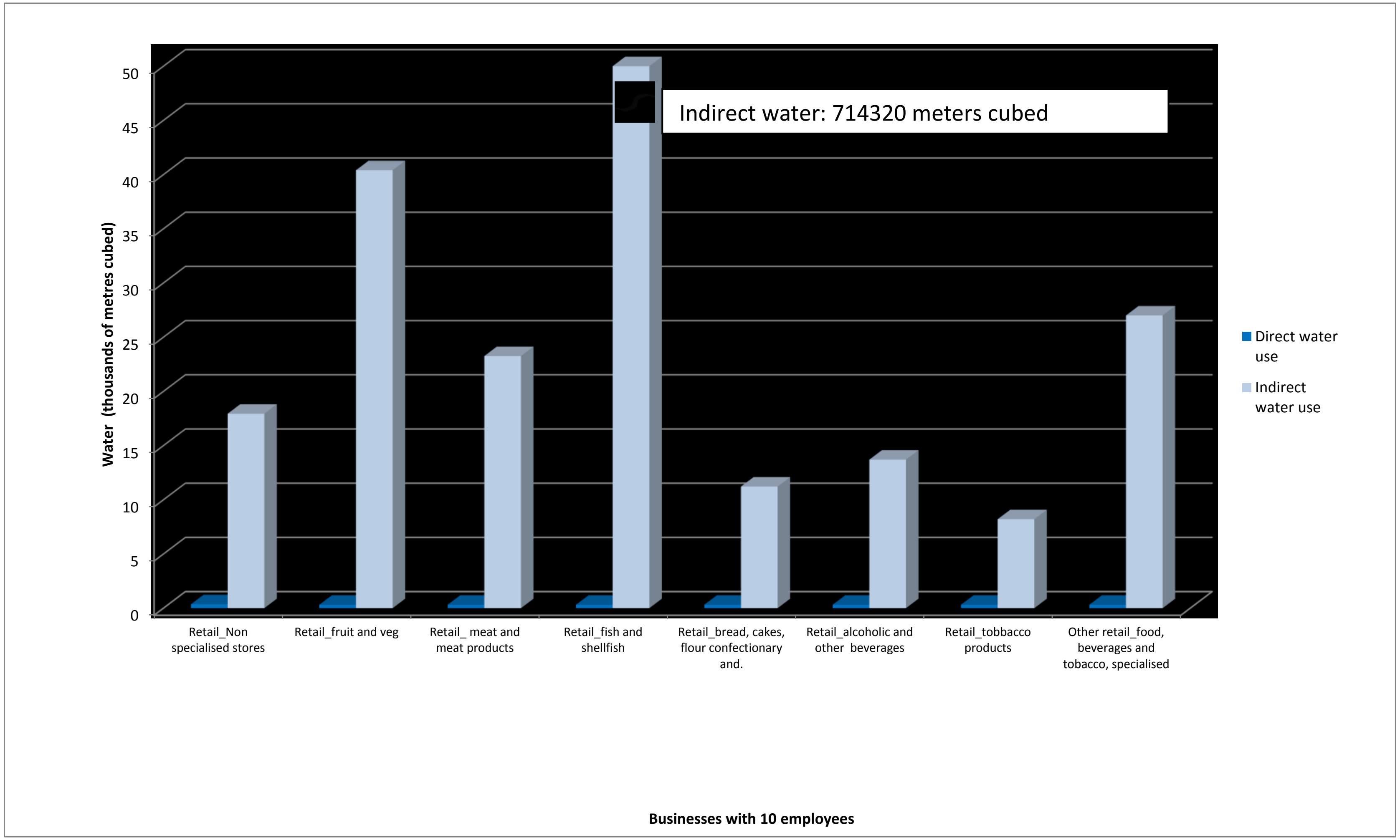

Figure 7: The water use profiles for different Food retail and Hospitality business types.

3.3 Indirect emissions and water use of products

Emissions and water use embodied in products of the businesses provides a further level of resolution for businesses and policy makers and can help prioritise product types for sustainable procurement and choice editing by businesses. Broken and Allwood (2012) identify that choice editing is a key strategy that as yet has been under exploited by companies.

From Figure 8, it can be seen that meat products embody most indirect GHGs of all products sold by various businesses. Businesses classified as other retail (of food, beverages and tobacco specialised) have a lot of GHGs embodied in the dairy products they sell: this is because one of the two forms of businesses in this business category are businesses specialising in dairy produce, eggs and edible oils and fats. Embodied GHGs are also high for fish and shellfish products sold by businesses specialising in retail of fish, crustaceans and molluscs. A number of other products (of various businesses) such as bakery products, alcoholic drinks, fruit and vegetables also embody quite high indirect GHGs. Before a sustainable procurement policy is developed and key products identified for further attention, businesses need to be aware of the environmental impacts of their own business and products (and it is clear from the literature that many are not, see review in Bradley et al 2013), the CLARE model and it's product estimates are particularly good in this respect, as they alert the business to their likely impacts in the first instance. This information can be used in a step by step process, where estimations from CLARE precede measurement, and rough measurement precedes a more refined measurement such as the use of life cycle analysis. As can be seen, the businesses can receive relevant estimations of their environmental impacts attributable to the products they sell, this can raise awareness and then be used to help the business prioritise their investigation, sustainable procurement policy and practice.

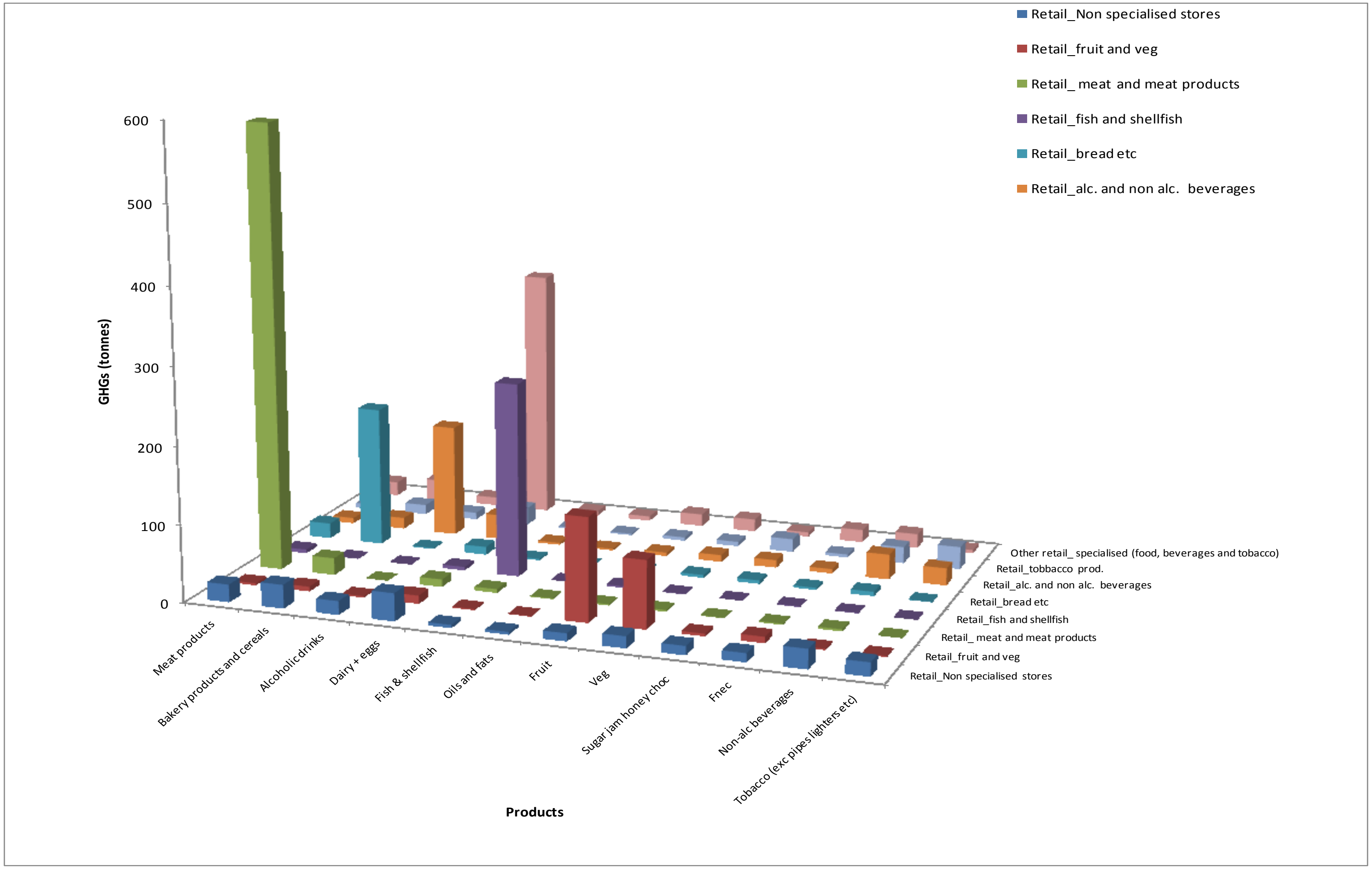

Figure 8: The indirect GHG profiles for different product types for each business (with 10 employees).

Figure 9 presents the indirect water use profiles for different product types by business. One product that comes out high in terms of indirect water use, across many businesses types are fish and shellfish products. This is the result of the large amount of (water industry supplied or abstracted) water use in fish farming, not so much in food manufacturing of the product. This shows that the high indirect water use of different food retail business types in Figure 7, is often the result of sales of fish and shellfish products of each business (and not only fish and shellfish retail businesses) as seen in Figure 9. It should be noted that nearly all of the water associated with fish farming, is water that is directly abstracted as opposed to mains water, industry supplied. This should be taken into account when assessing human and environment welfare impacts. Other products that are high in terms of embodied indirect water use are fruit and vegetable products (sold by specialist fruit and vegetable retail businesses). Quite a lot of indirect water use is also embodied in meat and bakery products, sold by the relevant specialist stores. Such information is useful for businesses that wish to reduce water embodied in their provision. Policy makers may use such information, to make businesses aware of the extent of water use likely to be embodied in their products sold. This can start a dialogue and a step by step process to acquiring better information and discussion with the business on the likely levels of water use embodied in their products, and what actions via choice editing or sustainable procurement (or discussion with suppliers) might move the business towards supplying fish products with lower levels of embodied water use. For example a business might more heavily promote more sustainable alternatives such as mackerel which are generally a more plentiful fish than some other species such as bass and cod (although fisheries vary by location), but also with perhaps lower embodied fresh water use than some inland farmed species such as trout. It may be the case that sometimes promoting another species such as mackerel might result in higher energy use and CO_2 emissions, and in this sense there might be trade-offs between different environmental metrics. These sort of issues should be explored by businesses, once they have identified priority products based on broader product category estimations from CLARE.

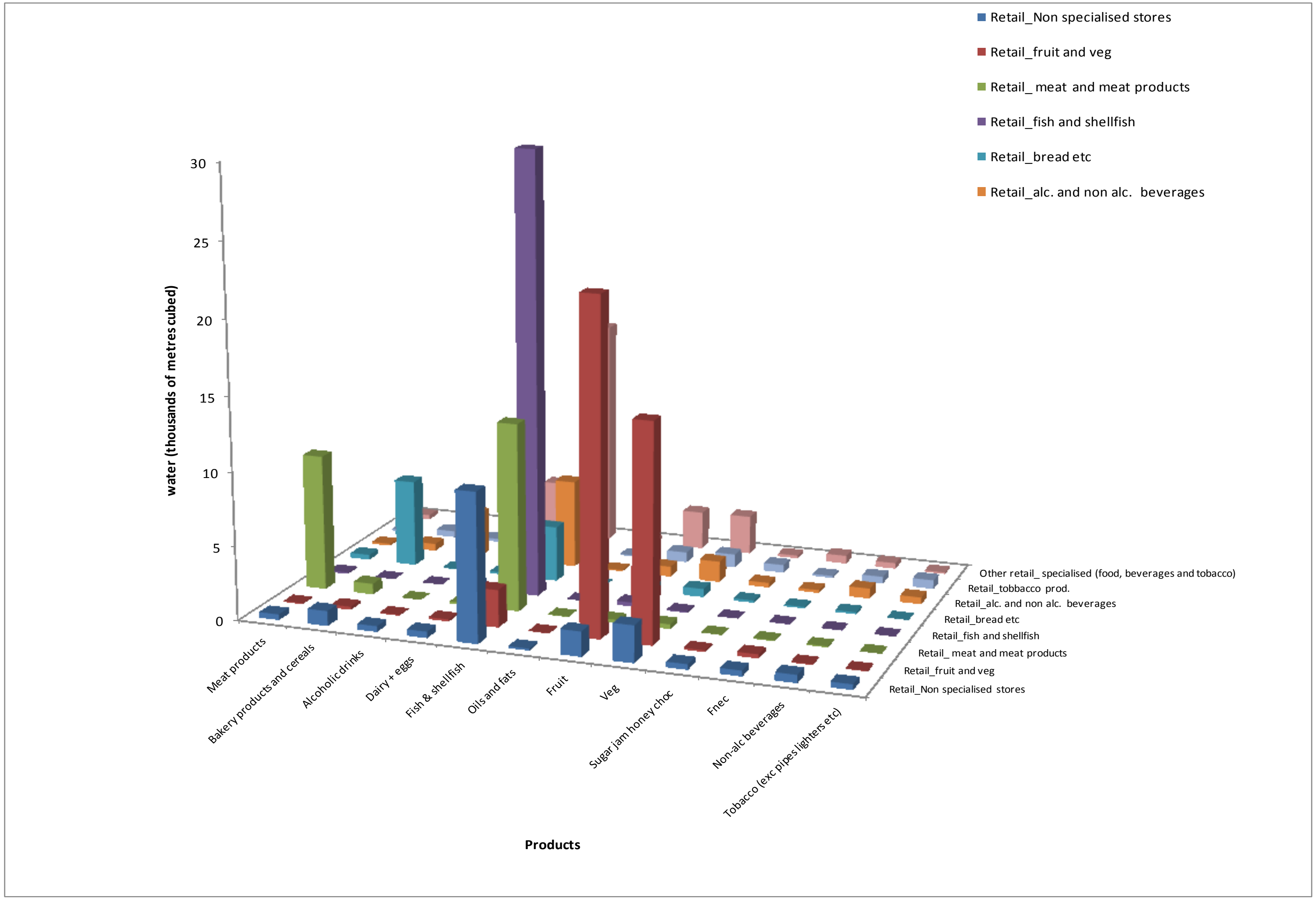

Figure 9: The indirect water use profiles for different product types for each business.

4 Conclusions

This paper identified two barriers to EIO modelling of the food retail sector; one being that the retail sector is often heavily aggregated in I-O tables; the second being due to the way that I-O tables are constructed (in the UK and other countries). This paper presents a method for overcoming these barriers and enables environmental input-output analysis to be conducted for the important food retail sector. Overcoming these barriers and enabling environmental input-output for this key sector is an important contribution of scientific value. The resulting CLARE framework for the food retail sector can be applied for individual and all retail businesses and products of an area by postcode. The generation of such a framework model capable of this has not been presented before and is a key contribution of scientific value. Results and findings from such a framework model can be used by government and businesses to efficiently benchmark important areas for sustainable procurement within business and in terms of benchmarking shopping provision within areas of cities. In these ways, the framework and its estimates can be of value as a first step, to benchmarking environmental impacts of businesses and product provision/shopping provision in a city. The benchmarking allows policy makers to identify likely impacts of retailers and encourage them to prioritise and demonstrate credentials for sustainable procurement as 'gatekeepers' for sustainable consumption. A key value added by the approach, is that it enables policy makers to produce direct and indirect emissions and water use estimates across businesses and areas from the same sectors on a comparable basis with consistent datasets and methods, system boundary and a transparent approach. This addresses issues found in the business reporting literature.

The ability of CLARE to estimate production and provision perspective water use individually and for all businesses by area and across different sectors (as seen in a previous publication), is of particular scientific value to analysts and planners for application in water constrained or water scarce regions, as policy makers can use the model to analyse the extent to which sectors are drawing on available water resources within an area and therefore how different industries growth is impacting water resources. A relevant and novel extension of the model would be in water use forecasting, to estimate or predict future increases in a cities (or local areas) water use as a result economic growth by sector and compare this with available water resources needed to supply these increases (in conjunction with population potable water needs). This could identify paths of development that will lead to greater or lower water use pressures or 'bottle necks' within cities and hence help policy makers guide growth that stays within environmental constraints and ensures civilian population and industry water needs are met. Given key global environmental pressures, this is an urgent application in rapidly developing cities such as Delhi India. The current author advocates and encourages other international researchers to progress and lead this research direction.

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Appendix A

Limitations and assumptions of the modelling approach the CLARE model has a number of assumptions and limitations that should be made clear. CLARE-direct assumes that turnover can be estimated for the business of concern based on knowing a business's employment, and the average turnover per employee for a detailed business employee size band and subsector. In future this assumption can be avoided for some businesses, as the Business Structure Database has enterprise data where actual turnover is recorded and it is thought to be quite accurate to use this in some situations. Monte Carlo simulations carried out as part of the study, show that for many businesses of an area, the application of average turnover per employee is a reasonable way of estimating turnover and the emissions or water use of a business.

More detailed assessment of the assumption is however required. CLARE-direct also assumes that the average direct emissions or water use per unit turnover (for a detailed sector and sometimes employee size band) can be used in conjunction with the estimated turnover of a business to produce the emissions or water use for a business. The extent of inaccuracy caused by this assumption was found to rely very heavily on the extent to which sector and sometimes employee size band emissions data is aggregated, particularly for earlier work on waste. In general it was found that this assumption when making use of heavily aggregated sector data has the most potential to cause inaccuracies in CLARE-direct. CLARE-indirect makes the same assumption when estimating turnover for businesses as used when estimating for CLARE-direct. It is also assumes that average indirect emissions or water use per unit of turnover at a sector level can be used in conjunction with the turnover of a business to produce a correct estimate of the indirect emissions or water use for a business. Again, it was found that detailed environmental data particularly for waste has a strong influence on improved estimation. Disaggregation of economic datasets can also be important, but was not found to be as critical. The assumptions inherent in EIO analysis also apply to the indirect estimates developed in the current study. For more detail on these assumptions and limitations with regards to GHGs see Jackson et al. (2007). See Miller and Blair (1985) for more detail and references on the assumptions of both input-output and EIO.

CLARE-indirect for food retail businesses assumes that a business's employment and average product sales per employee (for detailed employee size band and sub sector) can be multiplied to estimate the sales of products of a business. To estimate emissions, it is then assumed that the emissions intensities for product types from EIO analysis can be applied to matching product types of the business, to estimate the indirect emissions embodied in products sold by the business. A limitation of individual business estimates generated by CLARE is that they must be viewed in a secure environment within ONS by authorised individuals, including vetted researchers. If a business wanted to view its own emissions and water use estimate, this would need agreement with ONS and the business itself, therefore future application of CLARE for single business applications will require agreement and involvement of government, but the potential is clearly there. CLARE makes use of SIC codes, in some situations a business may be classed under two different SIC codes and some may find that SIC codes do not sufficiently describe their activities.

In estimating indirect emissions and water use, the current study made use of a two region model when conducting sector EIO modelling. The two region model applies the domestic technology assumption (see Proops et al 1993 and Jackson et al 2006), this was assumed as we do not generally have $\mathbf{A}^{\beta}$ $\mathbf{u}^{\beta}$ for the rest of the world produced in high disaggregated form, and disaggregation is important when modelling individual sectors consistently for C&I, food waste GHGs and water use. Others such as Jensen (2011) apply such assumptions when modelling waste. The assumption also avoids incorporation of many additional assumptions and unknown uncertainties associated with many foreign databases which would reduce clarity and tractability of estimates of the model, as well as different categorisations in the case of waste. The assumption therefore allows us to move forward with a clear, tractable and transparent disaggregated model. However to enable this, it is assumed that the UK technical coefficient matrix and emissions vector can substitute a technical coefficients matrix for rest of the world production. However, in the case of **A** this assumption may not hold, as although sectors of other countries can be similar in terms of technologies and inputs employed per unit of output, sectors of countries can also employ quite different technology and inputs per unit of output. Additionally, the emissions or water use intensities of sectors in different parts of the world can also be very different. These two assumptions pose key limitations to estimates of the two region model. The assumptions however, do enable clarity and tractability to users in terms of knowledge of datasets used (for which UK data has a certain standard of robustness that statistical agencies provide) and clarity in assumptions and disaggregation used in estimation. Therefore companies using CLARE can make clearer judgment on the extent to which their associated production (direct and indirect) does or does not conform to the assumptions of the model and estimates when conducting investigation. They can also be sure that all datasets used have a level of confidence and disaggregation associated with them. These are key attributes and strengths that the two region model can provide CLARE. Such attributes are much more difficult to attain if using datasets from numerous countries, constructed in different ways from different data with different uncertainties, and with different levels of disaggregation.

A full multi regional model, or a quasi-multi-regional input-output model, as developed by Druckman and Jackson (2009), could be have been used. For a review of various types of models to account for trade effects, see Wiedmann et al (2007). With regards to uncertainties for different types of models see Weber (2008). Weber (2008, p.22) states that: "*It is clear that several large uncertainties exist in the creation and use of environmental MRIO models, though it is also clear that their use is increasing due to the increasing desire to model international trade and differences in production practices across countries. Different modellers choose MRIO for different reasons, and for some uses (such as approximating multidirectional trade for a large number of commodities in countries with less detailed IOTs) the advantages of MRIO models probably outweigh the additional uncertainties in their use. However, as argued here, it is important to remember that MRIO models are no panacea for modelling the impacts of global trade. The necessary aggregation and simplification, along with exchange rate uncertainty, rest-of-world assumptions, and several other unquantifiable uncertainties make MRIO a minefield for practitioners desiring fairly accurate numbers*". He goes on to state that:

"*given the uncertainties, detailed single region models with simplified trade modeling should also be considered, especially if the analysis only requires a few commodities to be modelled and a hybrid analysis using SPA is possible."*

Appendix B

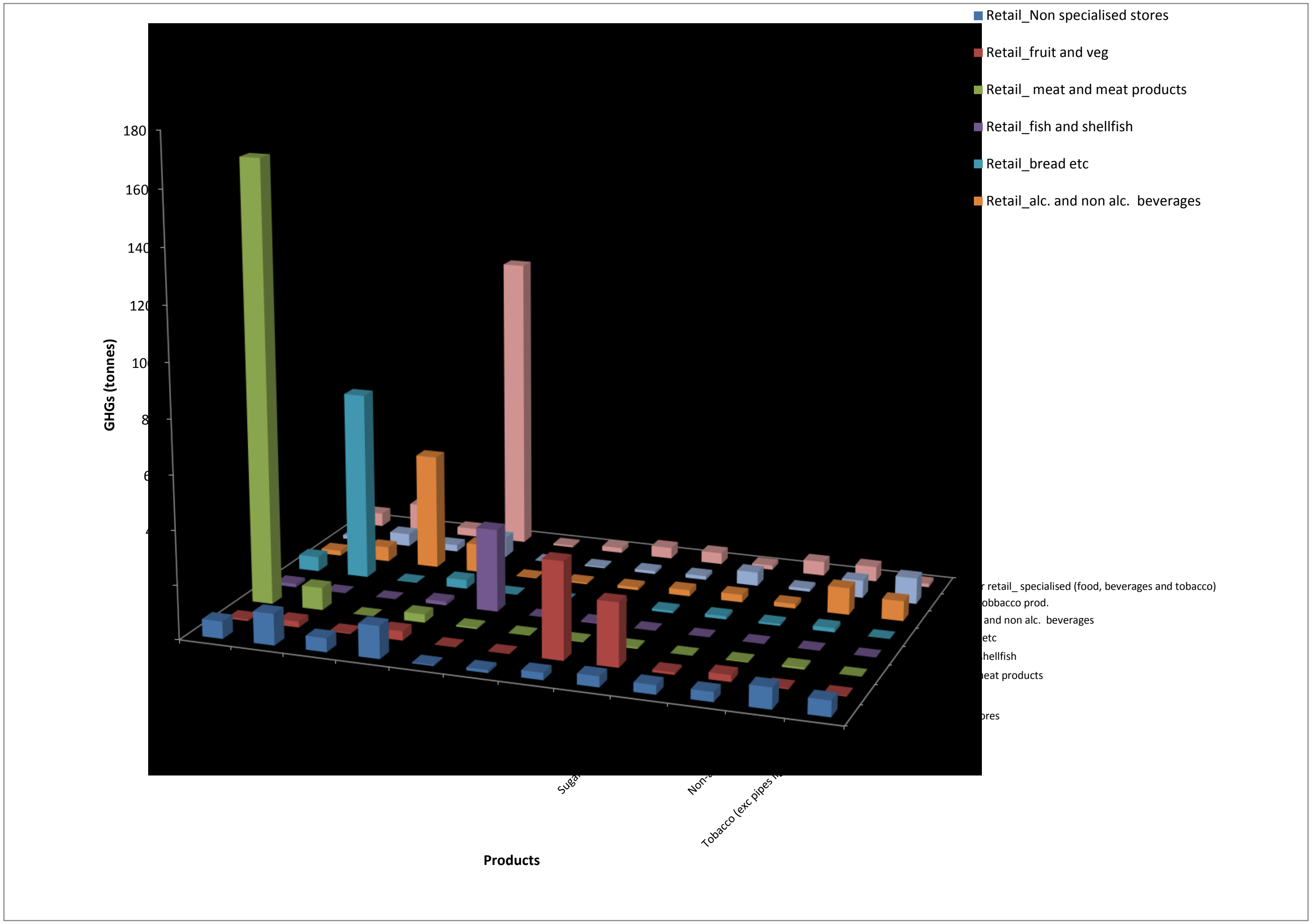

Figure 8b: The imported indirect GHG profiles for different product types for each business (with 10 employees).

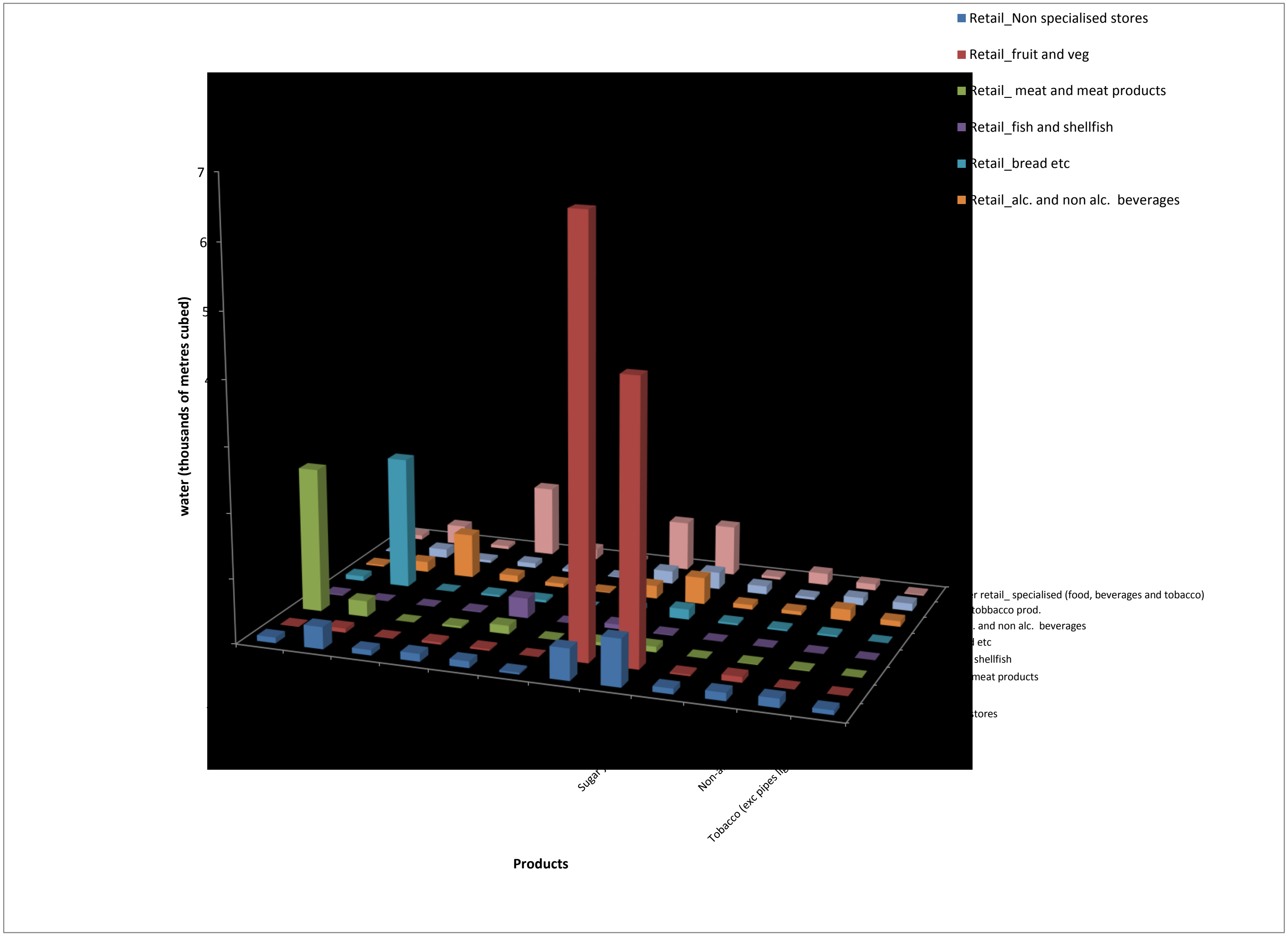

Figure 9b: The imported indirect water use profiles for different product types for each business (with 10 employees).

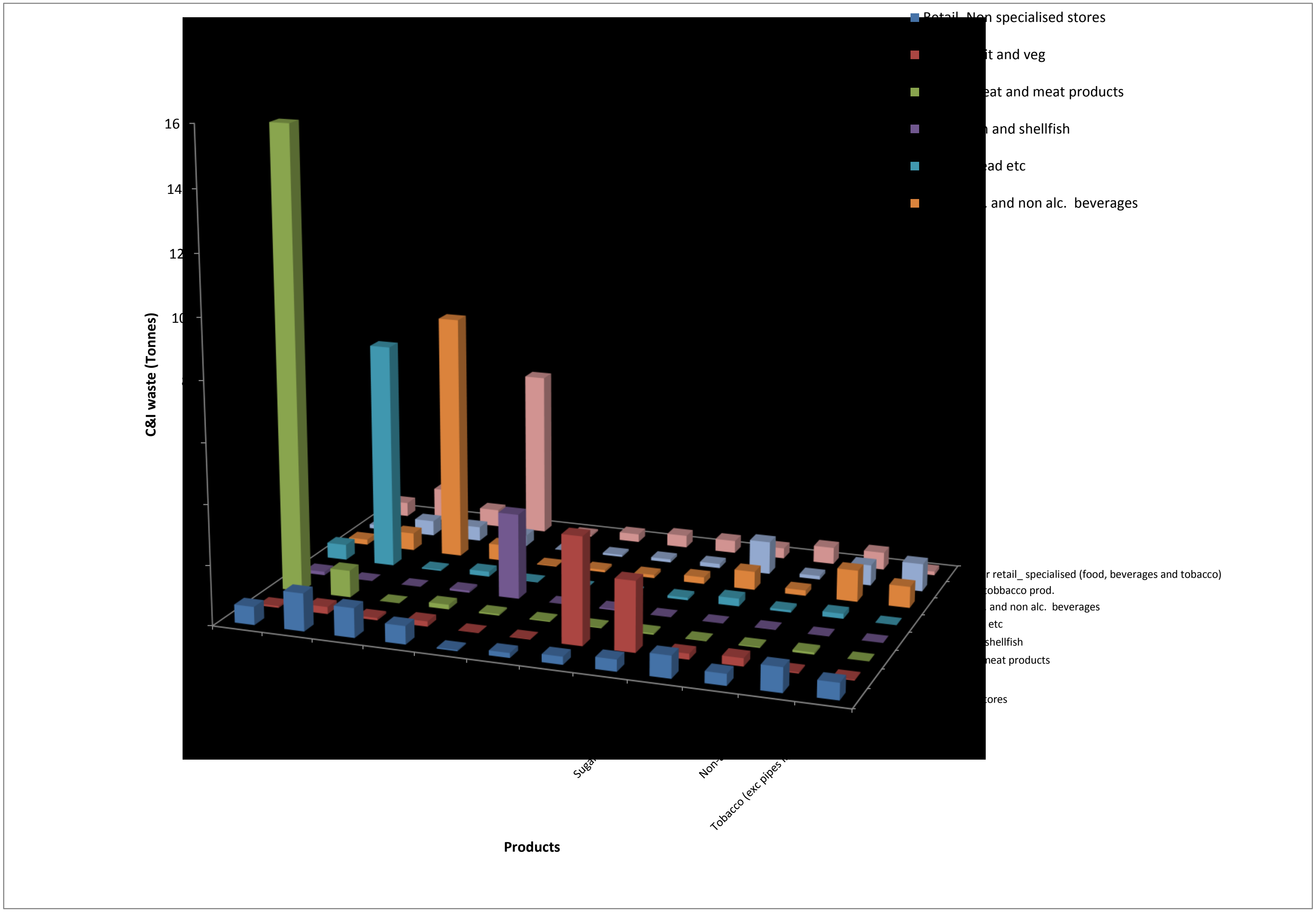

Figure 10b: The imported indirect C&I waste profiles for different product types for each business (with 10 employees).

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