A HOLISTIC APPROACH TO THE ENVIRONMENTAL EVALUATION OF FOOD WASTE PREVENTION

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Abbreviations:

GHG, greenhouse gas; LCA, life cycle assessment; AD, anaerobic digestion; N/A, not applicable; MRIO, multi-regional input output; SIC, standard industrial classification; MBS, marginal budget shares; AIDS, Almost Ideal Demand System; RE, rebound effect; FEI, freed effective income; WRAP, The Waste and Resources Action Programme.

Abstract

The environmental evaluation of food waste prevention is considered a challenging task due to the globalised nature of the food supply chain and the limitations of existing evaluation tools. The most significant of these is the rebound effect: the associated environmental burdens of substitutive consumption that arises as a result of economic savings made from food waste prevention. This study introduces a holistic approach to addressing these challenges, with a focus on greenhouse gas (GHG) emissions from household food waste in the UK. It uses a hybrid life-cycle assessment model coupled with a highly detailed multi-regional environmentally extended input output analysis to capture environmental impacts across the global food supply chain. The study also takes into consideration the rebound effect, which was modeled using a linear specification of an almost ideal demand system.

The study finds that food waste prevention could lead to substantial reductions in GHG emissions in the order of 706 to 896 kg CO_2-eq. per tonne of food waste, with most of these savings (78%) occurring as a result of avoided food production overseas. The rebound effect may however reduce such GHG savings by up to 80%. These findings provide a deeper insight into our understanding of the environmental impacts of food waste prevention: the study demonstrates the need to adopt a holistic approach when developing food waste prevention policies in order to mitigate the rebound effect and highlight the importance of increasing efficiency across the global food supply chain, particularly in developing countries.

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1 Introduction

One third of food produced across the globe is thrown away uneaten, and this waste has a large associated environmental burden (IMechE, 2013). Food waste is responsible for 3.3 Bt-CO_2-eq. yr^{-1}, rendering it equivalent to the world's third largest emitter of carbon after the economies of China and USA (FAO, 2013). In order to reduce the environmental impact of food waste, the food waste hierarchy has been adopted in various forms across different countries, providing guidelines on which disposal technologies are most preferable (Papargyropoulou et al., 2014).

Food waste prevention, situated at the top of the food waste hierarchy, is considered to be the most environmentally favorable management option (Papargyropoulou et al., 2014). According to a study published by the European Commission, approximately 44Mt CO_2-eq. yr^{-1} could be avoided by the introduction of a 20% food waste reduction target (EC, 2014). This finding supports the conclusions of other studies that have highlighted the significant environmental benefits of avoiding food waste (Bernstad and Andersson, 2015; Gentil et al., 2011; Martinez-Sanchez, 2016). Nevertheless, reported results are subject to a high level of uncertainty; the reported greenhouse gas (GHG) emissions savings vary widely, ranging from 800 to 4400 kg CO_2-eq. per tonne of food waste (Bernstad and Cánovas, 2015). These variations in literature arise largely due to methodological choices: most studies rely entirely on life cycle assessment approaches, do not consider food imports, and ignore rebound effects. We discuss these three methodological challenges before introducing a new holistic modeling approach to addressing them.

Firstly, the majority of studies adopt a conventional process-based Life Cycle Assessment (LCA) approach (Table 1). Excluding Martinez-Sanchez et al's study (2016), all of the reviewed studies adopt a bottom-up LCA approach, and hence inherit the widely-discussed limitations of LCA such as system boundary cut-offs, data inconsistencies, study-specific scenarios and assumptions (Bernstad and la Cour Jansen, 2012; Laurent et al., 2014a, 2014b). These limitations, coupled with the multi-faceted nature of food waste, make the environmental evaluation of food waste prevention practices an arduous task. LCA-based studies are generally product-specific and do not consider variations within the same food category due to differences in the source of food products (e.g., imported vs locally produced), food production systems (e.g., wild caught vs aquaculture fish), and the quality of food products (e.g., conventional vs organic) (Audsley et al., 2009; Bernstad and Cánovas, 2015; Chapagain and James, 2011).

Table 1 Quantitative studies evaluating the environmental benefit of food waste prevention.

Study	Country	Assessment method	International trade included?	Rebound effect included?
Bernstad and Andersson (2015)	Sweden	Consequentional LCA	Y	N
Chapagain and James (2011)	UK	LCA	N	N
Matsuda et al. (2012)	Denmark	LCA	N	N
Gentil et al. (2011)	Denmark	LCA	N	N
Venkat (2011)	USA	LCA	N	N
Audsley et al. (2009)	UK	LCA	N	N
Martinez-Sanchez et al. (2016)	Denmark	Life cycle costing	N	Y

The second challenge in modeling food waste prevention lies in the globalization of the food supply chain. For example, 48% of the UK's food supply in 2008 was imported from abroad, and these imports accounted for 67% of food-related GHG emissions (Ruiter et al., 2016). It is hence vital to account for the source of food products when estimating environmental benefits associated with food waste prevention. Excluding Bernstad and Andersson's study (2015), all of the studies reviewed assume food production occurs domestically or regionally (Audsley et al., 2009; Martinez-Sanchez, 2016; Matsuda et al., 2012; Venkat, 2011).

The final factor that results in substantial variation in estimates of the benefits of reducing food waste is the inclusion, or lack of inclusion, of the rebound effect: the avoidance of food waste in households leads to increased effective income which subsequently results in expenditure on alternative products and services (Binswanger, 2001; Brookes, 1990; Khazzoom, 1980). That is to say, when households avoid food waste, they consequently have more money available that may then be spent on other products and services. As this additional expenditure generates additional GHG emissions, the environmental benefits of reducing food waste can be partially or completely offset. If the economic savings were to be spent on carbon-intensive goods or services (e.g. air travel or domestic heating), it is even plausible for food waste prevention to create higher environmental burdens than if the food waste had not been wasted to begin with (Martinez-Sanchez, 2016).

To summarise, conventional approaches used to estimate the environmental benefits of food waste prevention provide only limited insight, in a world where food is internationally traded and financial savings made from waste avoidance often lead to rebound consumer spending. In order to combat these limitations, this study outlines a holistic approach to quantifying the environmental benefits of food waste prevention. To counter the limitations of conventional bottom-up LCAs, a hybrid LCA approach is used, combining conventional process-based LCA and a top-down input-output-based approach. Secondly, the flow of goods and services throughout the global supply chain was modeled using an economic and multi-regional input output method. Finally, the rebound effect was modeled using an econometric-based marginal expenditure model. The United Kingdom was used as a case study.

2 Methodology

Three scenarios for the environmental benefits of food waste prevention were evaluated: a baseline scenario and two food waste prevention scenarios (Figure 1).

i. Baseline-scenario: 1 tonne of food is wasted and sent to be processed in an anaerobic digestion (AD) plant. Anaerobic digestion was selected because it is the food waste treatment technology most currently most favoured in the UK (Evangelisti et al., 2014; Salemdeeb and Al-Tabbaa, 2015);
ii. A partial-reduction scenario: a 60% reduction in food waste, with the remaining fraction of food waste (400kg) being sent to an AD plant; and
iii. A total-reduction scenario: 77% of food waste is prevented and 23% (230kg) is sent to an AD plant.

The two food waste prevention scenarios are based on figures from the Waste and Resources Action Programme (WRAP), which estimate that 60% of household food waste in the UK is avoidable whilst a further 17% has the potential to be avoided (WRAP, 2013). The remaining 23% of food waste is unavoidable (e.g. egg shells and tea bags) and thus undergoes a conventional disposal route.

Our study adopts a green-consumption approach: households which reduce food waste are assumed to have reduced food purchases, rather than increased consumption. In order to model the environmental benefits of avoiding food waste, we follow Gentil et al.'s approach in considering the quantity of avoided food waste as a virtual waste flow (Gentil et al., 2011). Food waste prevention scenarios therefore also include knock-on savings from food waste avoidance, including avoided household food-related activities (e.g. grocery shopping, storage and preparation). To model these household activities, we used estimates from the literature: shopping is accountable for 70 kg CO_2-eq. per tonne food and the GHG burden associated with home storage and preparation is 420kg CO_2-eq. per tonne (Brook Lyndhurst, 2008; Pretty et al., 2005). This study additionally takes into account the rebound effect and investigates how the economic savings from food waste prevention activities (the purchase of less food products) may be spent on other activities and consequently reduce the net environmental benefits of food waste prevention (Section 2.3).

This study includes one environmental indicator, greenhouse gas emissions. These are aggregated and presented as a single mid-point impact category (i.e., climate change). The global warming potential metric is used to convert greenhouse gases to equivalent amounts of CO_2 on a time horizon of 100 years (IPCC, 2007).

<INSERT Figure 1 here>

2.1 Hybrid life cycle assessment: anaerobic digestion

The environmental impacts of the baseline scenario and the unavoided fraction of food waste in other scenarios (i.e., 40% of food waste in the partial-reduction and 23% in the total-reduction scenarios) were modeled using a hybrid-LCA waste-related model. First introduced by Salemdeeb and Al-Tabbaa (2015), the hybrid LCA model combines conventional process-based LCA and a top-down input-output analysis in order to reduce truncation error and achieve system completeness, a lack of which is a common limitation associated with conventional LCA tools (Laurent et al., 2014b).

Life cycle inventory data and technical parameters related to the AD technology are based on Salemdeeb and his colleagues' study that evaluated the environmental impacts of household food waste management in the UK, including AD (2016) . Food waste collection and transportation are included in the assessment whilst food waste packaging is excluded due to its insignificant impact (Bernstad and Andersson, 2015; Lebersorger and Schneider, 2011).

2.2 An environmentally extended multi-regional input output analysis: food waste prevention

Input-Output (IO) analysis is a top-down approach to modelling the complex interdependencies of industries within an economy (Leontief, 1936). IO tables are widely applied to link economic sectors with producers and customers to understand the interactions and impacts of economic activities (Leontief, 1951a, 1951b; Miller and Blair, 2009). Exiobase V2 is a high-resolution database used for the Multi-Regional Input-Output (MRIO) model in this study (Wood et al., 2015). The database provides data at an unprecedented level of consistent detail in terms of sectors, products, emissions and resources and covers 43 countries, which together account for approximately 89% of global gross domestic product and 80-90 % of the trade flow by value within Europe (Stadler et al., 2014; Tukker et al., 2014).

In order to integrate the monetary value of potential savings made by preventing food waste with the Exiobase database, the following steps were taken: (i) food prices, listed in Table 2, were converted from the British pound (£) to Euro (€) using the purchasing power parity index (World Bank, 2015); [ii] the data was then adjusted to the Exiobase base year (i.e. 2007) in order to take into account inflation using the UK consumer price index (ONS, 2013); [iii] the data reported in purchase prices was then converted into basic prices using a conversion ratio in order to respect margins, taxes and subsidies on products (Appendix A); [iv] a concordance matrix was used to map monetary data onto the Exiobase's structure format (Appendix B); and [v] the data was disaggregated to account for food imports by using existing food import weighting coefficients from Exiobase (Appendix C).

Table 2 The functional unit of the study: 1 tonne of UK household food waste (with an approximate economic value of GB £1870) disaggregated into three stream categories (i.e. unavoidable, possibly avoidable and avoidable). The functional unit is presented below using both physical (kg) and monetary (GB£) units (WRAP, 2013).

Food Type	Food waste: Unavoidable		Possibly avoidable		Avoidable	
	Quantity(kg)	EV (£)[1]	Quantity (kg)	EV (£)[1]	Quantity (kg)	EV (£)[1]
Fresh vegetables and salads	39.2	41.7	87.5	95.0	127.1	135.1
Drink	41.5	41.5	0.0	0.0	58.5	58.5
Fresh fruit	82.7	83.8	3.1	3.1	54.9	54.3
Meat and fish	31.4	115.6	10.4	38.2	47.1	173.5
Bakery	0.2	0.2	17.3	26.5	70.6	108.5
Dairy and eggs	9.3	15.0	0.2	0.3	63.9	107.1
Meals (home-made and pre-prepared)	0.2	0.7	0.2	0.7	69.0	329.6
Processed vegetables and salad	0.2	0.4	0.2	0.4	28.2	80.0
Cake and desserts	0.2	0.6	0.2	0.6	25.1	89.5
Staple foods	0.2	0.4	0.2	0.4	23.5	54.9
Condiments, sauces, herbs & spices	0.2	0.7	0.3	1.5	22.0	102.0
Oil and fat	0.2	0.1	8.2	6.2	3.1	2.4
Confectionery and snacks	0.2	1.0	0.2	1.0	9.6	63.3
Processed fruit	0.2	1.4	0.2	1.4	3.3	29.8
Other	0.2	0.0	59.6	4.4	1.7	0.1
Total[2]	**205.7**	**303.4**	**187.4**	**179.8**	**607.8**	**1388.5**

[1] Economic value based on the year 2012
[2] Figures might not sum due to rounding.

2.3 Modelling the rebound effect

The microeconomic rebound effect consists of a direct and indirect effect: the direct effect is related to the additional demand for the product that has been subject to an efficiency improvement (i.e. additional demand for some categories of food, where the efficiency improvement is an increase in the ratio between the food purchased and consumed), whereas the indirect effect refers to the additional demand in all other consumption categories (Font Vivanco et al., 2016). The rebound effect was quantified using a single re-spending model in which all consumption categories were treated equally (Murray, 2013). This approach achieves methodological consistency at the expense of differentiation between the direct and the indirect effect (for examples of the latter, see the works of Freire-González (2011), Thomas and Azevedo (2013) and Font Vivanco and van der Voet (2014)).We specifically estimate how freed effective income (FEI) was spent by calculating the marginal budget shares (MBS) for each consumption category *i*. The MBS were calculated using a linear specification of an Almost Ideal Demand System (AIDS), a demand system model developed by (Deaton and Muellbauer, 1980) with properties that makes it preferable to competing models (Chitnis and Sorrell, 2015; Deaton and Muellbauer, 1980). For instance, compared with other approaches based on expenditure elasticities or Engel curves (Chitnis et al., 2013, 2014; Font Vivanco et al., 2014; Murray, 2013), the AIDS allows for a more accurate estimation of the pure income effect (changes in expenditure due to changes in effective income), as the substitution effect (changes in expenditure due to changes in relative prices) is corrected by means of a price index. In a budget share (*w*) form, the AIDS model for the *i*th consumption category and a given time period *t* is expressed as:

$$w_t^i = \alpha^i + \sum_{j=1,\dots,n} \gamma_s^i \ln p_t^s + \beta^i \ln\left(\frac{x_t^s}{P_t}\right) \qquad (1)$$

where *n* is the number of consumption categories, *x* is total expenditures, *P* is defined here as the Stone's price index, *p* is the price of a given category and *α*, *β* and *γ* are the unknown parameters. The Stone's price index is defined as:

$$\ln P_t = \sum_j w_t^s \ln p_t^s \qquad (2)$$

Additionally, and in order to comply with consumer demand theory, three constraints are imposed: adding-up, homogeneity and symmetry (Deaton and Muellbauer, 1980). The microeconomic rebound effect in demand units (r_d) is defined as:

$$r_d = \sum_j s * w^i \qquad (3)$$

where *s* is the total economic savings.

Data on the final consumption expenditure of households and price indices for Classification of Individual Consumption According to Purpose (COICOP) 3 digit categories for the UK and the period 2004-2013 were obtained from Eurostat (2016a, 2016b). In order to harmonise product categories reported by the COICOP 3 digit (*i*) and Exiobase databases (*j*), we used the approach from Koning and Xingyu, (2016), which derives transformation tables describing how COICOP categories are distributed over Exiobase categories. We specifically used household expenditure data to give weights to cases where a given COICOP category is distributed over multiple Exiobase categories. The marginal budget shares of UK household expenditure are listed in Appendix H in both Exiobase and COICOP formats.

The modelling of the rebound effect entails a high level of uncertainty. When people save money from purchasing less food, it is difficult to determine exactly how they will spend this surplus. We therefore modeled five scenarios of rebound spending, listed in Table 3, that were developed based on a literature review (Appendix D). The first scenario, the behavior-as-usual scenario (R-1), is based on the methodology discussed above to allocate free effective income to all consumption categories.

Two sub-scenarios were also considered to investigate the level of uncertainty in MBS estimates. In these scenarios, the re-spend of the FEI is limited to Major Consumption Categories (MCC), a list of 25 expenditure categories which together constitute more than 88% of spending (i.e., categories with the highest MBS, see Table H.3). This approach has been applied in order to obtain more conservative and realistic results than those founded in previous modeling approaches which assume that the FEI is re-spent on services with the highest or lowest GHG-intensities, regardless of the EFI value (e.g., Martinez-Sanchez et al. 2016). In the major spending-high scenario (R-1A), FEI spending occurs within the 15 categories of MCCs with the highest GHG intensities while FEI is re-allocated to the 15 categories of MCCs with the highest MBS in the major spending-low scenario (R-1B). Appendix I lists the 15 categories considered in both scenarios.

The second part of the sensitivity analysis is based on the observation made by WRAP, that people tend to spend 50% of FEI on the purchase of higher quality food products (WRAP, 2014). Examples of food up-trade include buying locally-produced organic agricultural products, higher-quality meat or switching between food types (e.g., more meat, less staples or more beef, less chicken). Therefore, we also include up-trade scenarios that investigate the impact of re-spending 50% of FEI on purchasing quality oriented food products whilst the remaining 50% of the FEI is spent based on the MBS of the behavior-as-usual scenario. As GHG-intensities can vary largely between quality oriented and conventional food products (Appendix E), we consider two sub-scenarios: (i) Scenario (R-2A) where GHG intensities remain the same for both conventional and quality oriented products, and (ii) Scenario (R-2B) where GHG intensities are updated to reflect the variation between quality oriented and conventional food products; Updated GHG coefficients are provided in Appendix G.

Table 3 Rebound effect scenarios considered in this study.

Scenario	Description
Behaviour-as-usual (R-1)	A reference scenario that assumes the re-spend occurs in line with the methodology discussed in section 2.3. The marginal budget shares (MBS) for each consumption category are listed in Appendix H, in both Exiobase and COICOP formats.
Major spending-high scenario: GHG based (scenario R-1A)	This scenario allocates the re-spend to 15 major consumption categories[1] with the highest CO_2 intensities. MBS were recalculated based on the original weight of MBS values (Appendix I).
Major spending-low scenario: expenditure based (scenario R-1B)	This senario redistributes the re-spend on 15 major consumption categories[1] of the highest MBS. MBS were recalculated based on the original weight of MBS values (Appendix I).
Up-trade scenario: un-updated Exiobase GHG intensities (R-2A)	This scenario assumes that 50% of the re-spend occurs in food-product categories while the remaining 50% follows the same distribution patters on the behaviour-as-usual scenario.
Up-trade scenario: Updated GHG intensities (R-2B)	This scenario uses updated GHG intensities to investigate the variation as a result of purchasing quality oriented products (Scenario R-2A). Conversion factors are derived from literature (Appendix E).

[1] Major consumption categories is a list, presented in Table H.3, of 25 consumption cateogires where more than 88% the re-spend occur (i.e., categories with the highest MBS).

3 Results and discussion

Reducing food waste leads to substantial GHG savings: 706 and 896 kg CO_2-eq. per tonne food waste for the partial and total reduction scenarios respectively. This is a 5-12 times larger greenhouse gas saving than if all food waste were used for bioenergy production (AD, the baseline scenario). Table 4 presents a detailed analysis of the study results; it provides estimates of the environmental benefits associated with the prevention of avoidable food waste and the management of an unavoided fraction of food waste, and shows that the rebound effect may offset these benefits by up to 59% (Section 3.2).

Table 4 GHG emissions from food waste management as total food waste (kg CO_2-eq. per tonne food waste) divided on streams and rebound effect. Negative values are overall GHG savings.

	Food waste treatment (AD)	Food waste prevention	Rebound effect (RE)[1]	Total[1]	RE Reduction rate (%)[2]
Baseline scenario	-89	0	0	-89	NA
Partial-reduction scenario	-36	-1138	467 (290-685)	-706 (-483 to -878)	25-59
Total-reduction scenario	-19	-1419	542 (335-795)	-896(-635 to -1095)	23-56

[1]Range in brackets
[2]The reduction in GHG savings due to the inclusion of rebound spending.

Hotspot analysis, depicted in Figure 2, shows that most of the reported environmental benefits are due to the avoidance of food production: 83.5% for the partial reduction scenario and 76% for the total reduction scenario. These findings confirm the results of other studies which recognise the importance of savings made in the production stage (Bernstad and Andersson, 2015; Gentil et al., 2011; Martinez-Sanchez et al., 2016). GHG savings from avoided food production are estimated in all industries across the entire supply chain, from fertilizers to iron and steel inputs (Table 5). Most of the savings result from avoided fertiliser and energy use; N-fertiliser production and coal-based electricity generation contribute to the overall reduction by 25% and 20% respectively.

< INSERT Figure 2 here>

Table 5 Hotspot analysis for GHG savings from the avoided production of food, as food waste is reduced. Categories reported are Exiobase Industrial categories

Industrial sector	Weight (%)
N-fertiliser	25
Electricity (coal)	20
Vegetables, fruit, nuts	6
Electricity (gas)	5
Crude petroleum and services related to crude oil extraction	5
P- and other fertiliser	3
Basic iron and steel	3
Steam and hot water supply services	2
Chemicals	2
Cereal grains	2
Others	25

The second largest contributor to GHG savings is food-related household activities (e.g., grocery shopping transportation, food storage and preparation). These activities contribute to GHG reductions by 16.5% and 24% for the partial-reduction and total-reduction scenarios respectively. These estimations are based on limited estimates in literature and are only indicative; the greenhouse gas footprint of food-related household activities is likely to vary substantially. Gruber et al. (2014), for example, estimate that between 0.7 - and 2.1 MJ of electricity is needed to cook 1 kg of rice or potatoes, depending on individual household behaviour.

Overall, the combination of GHG savings in food production and related household activities leads to a large potential GHG reduction, ranging from 1138-1419 kg CO_2-eq. per tonne of food waste prevented (Table 4). However, these benefits are reduced by 23-59% due to the impact of the rebound effect, which reduces GHG reductions by between 483 and 1095 kg CO_2-eq. per tonne of food waste. This study quantitatively confirms the significant impact of the rebound effect in reducing environmental benefits associated with food waste prevention (Druckman et al., 2011; Martinez-Sanchez et al., 2016). A further discussion regarding the impact of the rebound effect and the sensitivity of our results is covered in section 3.4.

With regards to the baseline-scenario where 1 tonne of food is wasted and sent for anaerobic digestion, -89 kg CO_2-eq. is the net-environmental benefit associated with the treatment of 1 tonne of food waste. The analysis results confirm those of other studies and identify energy recovery and the use of digestate as processes with the highest contribution to these savings (Bernstad Saraiva Schott et al., 2016). Energy recovery and digestate lead to GHG reductions of 185.5 and 4.6 kg CO_2-eq. per tonne of food waste respectively. Contrastingly, the main environmental burdens for AD arise from the digestion process and the use of auxiliary materials required to operate the facility (Salemdeeb et al., 2016), whilst food waste collection and transportation has a less significant impact: 11 kg CO_2-eq. per tonne of food waste. A hot spot analysis of the baseline-scenario is presented in appendix F.

3.1 The role of the MRIO model

The GHG savings made from the reduction of food waste occur across the international supply chain (Figure 3) with only 22% of these savings occurring within UK borders (Table b in Figure 3). This relatively low percentage is attributed to the UK's dependency on food imports, as well as the reasonably efficient food production systems and low-carbon energy sources of the country. Our results echo results reported in literature and conclude that the majority of the UK food basket's GHG emissions occur abroad (Ruiter et al., 2016), in part due to lower GHG efficiencies in agriculture of developing nations. Whilst only 6.5% of financial savings made from waste avoidance comes from food produced in India, for example, this is equivalent to a 17.5% reduction in food-related GHG emissions (Table b in Figure 3). In this case, the rice products category is the largest contributor to these savings which are made across various industry groups in India, such as coal-based electricity (50%), N-fertiliser (18%), P-fertiliser (4%) and the paddy rice sector (9%).

< INSERT Figure 3 here>

The MRIO approach allows an unprecedented resolution of analysis, including differentiating impacts per food group as well as per country. In the case of sugar, more than half of the GHG savings occur in Brazil and France, the leading suppliers of sugar to the UK (Figure 4); 37% of sugar cane being imported from Brazil and 21% of sugar beet being imported from France (Baker and Morgan, 2012).

< INSERT Figure 4 here>

Despite the analytical strengths of the MRIO method in modelling the global supply chain, the adoption of such an approach is subject to a major limitation. MRIO models use average national data and therefore neglect variation in impacts associated with products aggregated into the same industrial category (for example, this study allocated an average GHG intensity for all dairy products in each country). This shortcoming could in future be addressed by integrating the MRIO model with the World Food LCA database - a comprehensive and international inventory database of 200 food life cycle assessments (Nemecek et al., 2015). The expanded

MRIO model would then combine the advantages of IO analysis to cover the global food supply chain and the advantage of process-based LCA to use up-to-date and high-resolution environmental intensities.

Another possible limitation is associated with the approach adopted to convert economic benefits of food waste prevention from purchase prices into basic prices (the format of data in Exiobase). Conversion factors used in this study are derived from the 2010 UK Supply and Use table by deducting both distributors' trading margins and allowing fewer subsidies on products from purchase prices (ONS, 2012). Therefore, the accuracy of conversion factors depends on the quality of the data and methodology used to compile the 2010 UK Supply and Use table. In addition and due to the high level of aggregation in the Supply and Use table, an assumption was made to allocate the same conversion factor into similar food categories: vegetables and fruits, bakery and cakes, and meals and staple food (Appendix A).

3.2 Rebound effect

Results of the sensitivity analysis show a high level of uncertainty associated with the rebound effect, with the reduction in GHG savings ranging from 23-59% (Table 4 and error bars in Figure 5a). The upper limit (R-1A), representing the major spending-high scenario, is a result of re-spending savings on GHG-intensive categories such as wholesale trade, motor gasoline, petroleum and air transport services. The lower limit, representing the major spending-low scenario (R-1B), is a result of re-spending the freed effective income on less GHG intensive categories such as education services, real estate services and communication services.

The second part of the sensitivity analysis investigated the effect of switching from conventional to quality-oriented food products (Up-trade scenarios, see Table 3 and Figure 5b). The use of the same Exiobase GHG intensities (scenario R-2A) results in a small increase (3.5%). The low increase estimated in scenario R-2A could be explained by two factors: 50% of the re-spending occurs in food product categories that are considered low-GHG categories (Druckman et al., 2011), and the assumption that GHG intensities of quality oriented products increase in the same way as paying a higher price per functional unit (Girod and de Haan, 2010; Vringer and Blok, 1996). For example, if the price of a quality-oriented product is twice that of its conventional counterpart, then the environmental burden associated with it would double.

The final sensitivity analysis scenario takes into account variations in GHG-intensities between quality oriented and conventional food products as discussed in Appendix D&G. Since up-traded goods often have a higher GHG intensity, we find that switching to quality-oriented products increases the size of the rebound effect by 19.5% and, consequently, reduces food waste prevention benefits (Figure 5b). Examples of higher impact and higher value products include organic products, (which have lower yields than conventional products) boneless meat, (which requires additional energy input in the food production process) and the use of premium packaging.

< INSERT Figure 5 here>

Several peer-reviewed studies have investigated the impact of the rebound effect in food waste prevention activities or a similar context (Alfredsson, 2004; Druckman et al., 2011; Martinez-Sanchez et al., 2016). Martinez-Sanchez and her colleagues took an environmental life-cycle costing approach to evaluating the impact of the rebound effect in food waste prevention activities in Denmark. Their study also found a large rebound effect – in fact much larger than that of our study (1528-4367 kg CO_2-eq. per tonne of food waste; 2-5 times higher than results reported in this study). Their findings suggest that the rebound effect could even exceed the GHG savings from avoiding food waste, a phenomenon known as “backfire”, where reducing food waste might actually increase GHG emissions. The large difference between our estimates and theirs is attributable to various factors: (i) Martinez-Sanchez et al. use a highly aggregated economic model, combining all industrial sectors into 9 categories; (ii) Consumer expenditure surveys are used in Martinez-Sanchez’s study to allocate savings from consumption categories; and (iii) Martinez-Sanchez et al. investigate extreme scenarios for the rebound effect, including allocating 100% of the respend to the sector with the highest environmental impact, namely “Household use, Hygiene”. Sectorial aggregation is a known source of bias in the input-output literature (Moran and Wood, 2014; Su et al., 2010), and our results may indicate that higher disaggregation leads to lower overall GHG emissions for our case study. Our model of the rebound effect also combines expenditure and cross-price elasticity (section 2.3), which may lend more weight to low GHG-intensive consumption categories compared to simpler models. Finally, our sensitivity analysis for the rebound effect is constrained so that it more closely resembles current household spending. Despite these differences, the potentially large rebound effect reported here as well as in similar studies reveals the limitation of behavioural interventions, such as reducing food waste to reduce greenhouse gas emissions (Martinez-Sanchez et al., 2016). To reduce rebound effects and deliver effective GHG savings, behavioural change must be coupled with economy-wide reductions in GHG intensity (Alfredsson, 2004; Druckman et al., 2011; David Font Vivanco et al., 2016).

3.3 Comparison with previous studies

The results of this study agree with main conclusion of other studies: food waste prevention lead to substantial reductions in GHG. Nevertheless, the magnitude of GHG reduction reported in this study is less than those reported in the literature as shown in Figure (6). Differences arise primarily due to the aggregated nature of the method (as discussed above, see section 3.1). In addition, the study scenarios take into consideration the unavoided fraction of food waste (40% in the partial reduction scenario and 23% in the total reduction scenarios) which is sent to anaerobic digestion, leading to lower GHG reductions than if we had assumed that the total functional unit (1 tonne of food waste) was preventable. More importantly (as discussed in Section 3.2), the inclusion of the rebound effect has also contributed significantly to the reduction in reported results: 25-59% for the partial-reduction scenario and 23-56 for the total-reduction scenario.

< INSERT Figure 6 here>

4 Conclusions

This paper presents a holistic model of food waste prevention, combining conventional process-based LCA and top-down input-output-based approaches that include GHG emissions in the international supply chain and the rebound effect. We find that GHG savings range from 700-888 kg CO_2-eq. per tonne of food waste. These emissions are relatively lower than others reported in the literature, partly due to the inclusion of the rebound effect, which reduces GHG benefits by up to 59%. Overall, our findings indicate that the environmental benefits associated with food waste prevention interventions, such as the “love food hate waste” campaign in the UK (WRAP, 2013), could be partially undermined by rebound spending. Efforts to reduce the impact of food waste must explicitly consider rebound effects as ultimately, to effectively deliver GHG reductions, behavioural change, such as food waste reduction, must be coupled with reductions in GHG emissions across the economy.

Furthermore, this study provides the first comprehensive assessment of food waste prevention that includes impacts associated with food imports. It highlights the importance of adopting a top-down, multi-disciplinary, and system-wide approach in order to deal with the complexity of the food supply chain that extends beyond geographical borders and across various industries. The findings of this research have provided a further insight into our understanding of the environmental impacts of globalised food production, particularly in developing countries.

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6 References

Alfredsson, E.C., 2004. “Green” consumption—no solution for climate change. Energy 29, 513–524. doi:10.1016/j.energy.2003.10.013

Audsley, E., Brander, M., Chatterton, J., Murphy-Bokern, D., Webster, C., Williams, A., 2009. How Low Can We Go? An Assessment of Greenhouse Gas Emissions from the UK Food System and the Scope to Reduce Them by 2050, WWF and Food Climate Research Network, FCRN-WWF-UK. FCRN-WWF-UK, London.

Baker, P., Morgan, A., 2012. Annex report 4 : UK sugar imports, resilience of the food supply to port distribution. Department for Environment Food and Rural Affairs, London.

Bernstad Saraiva Schott, A., Wenzel, H., la Cour Jansen, J., 2016. Identification of decisive factors for greenhouse gas emissions in comparative lifecycle assessments of food waste management – An analytical review. J. Clean. Prod. 119, 13–24. doi:10.1016/j.jclepro.2016.01.079

Bernstad, A., Andersson, T., 2015. Food waste minimization from a life-cycle perspective. J. Environ. Manage. 147, 219–226. doi:10.1016/j.jenvman.2014.07.048

Bernstad, A., Cánovas, A., 2015. Current practice, challenges and potential methodological improvements in environmental evaluations of food waste prevention – A discussion paper. Resour. Conserv. Recycl. 101, 132–142. doi:10.1016/j.resconrec.2015.05.004

Bernstad, A., la Cour Jansen, J., 2012. Review of comparative LCAs of food waste management systems--current status and potential improvements. Waste Manag. 32, 2439–55. doi:10.1016/j.wasman.2012.07.023

Binswanger, M., 2001. Technological progress and sustainable development: What about the rebound effect? Ecol. Econ. 36, 119–132. doi:10.1016/S0921-8009(00)00214-7

Brook Lyndhurst, 2008. London’s Food Sector Greenhouse Gas Emissions Final Report. Greater London Authority, London.

Brookes, L., 1990. The greenhouse effect: the fallacies in the energy efficiency solution. Energy Policy 18, 199–201. doi:10.1016/0301-4215(90)90145-T

Chapagain, A., James, K., 2011. The Water and Carbon Footprint of Household Food and Drink Waste in the UK. WRAP & WWF, London.

Chitnis, M., Sorrell, S., 2015. Living up to expectations: Estimating direct and indirect rebound effects for UK households. Energy Econ. 52, S100–S116. doi:10.1016/j.eneco.2015.08.026

Deaton, A., Muellbauer, J., 1980. An Almost Ideal Demand System. Am. Econ. Rev. 70, 312–326. doi:10.2307/1805222

Druckman, a, Chitnis, M., Sorrell, S., T., J., 2011. Missing carbon reductions? Exploring rebound and backfire effects in UK households. Energy Policy 39, 3572–3581. doi:10.1016/j.enpol.2011.03.058

EC, 2014. Impact assessment on measures addressing food waste to complete SWD

(2014) regarding the review of EU waste management targets. European Commission, Brussels.

Eurostat, 2016a. Final Consumption Expenditure of Households by Consumption purpose - COICOP 3 digit - Aggregates at Current Prices [WWW Document]. URL http://ec.europa.eu/eurostat/web/main/home

Eurostat, 2016b. Final Consumption Expenditure of Households by Consumption Purpose - COICOP 3 Digit - Price Indices [WWW Document]. URL http://ec.europa.eu/eurostat/web/main/home

Evangelisti, S., Lettieri, P., Borello, D., Clift, R., 2014. Life cycle assessment of energy from waste via anaerobic digestion: a UK case study. Waste Manag. 34, 226–37. doi:10.1016/j.wasman.2013.09.013

FAO, 2013. Food wastage footprint. U.N. Food and Agriculture Organization (FAO), Rome, Italy.

Font Vivanco, D., Kemp, R., van der Voet, E., 2016. How to deal with the rebound effect? A policy-oriented approach. Energy Policy 94, 114–125. doi:10.1016/j.enpol.2016.03.054

Font Vivanco, D., McDowall, W., Freire González, J., Kemp, R., Van der Voet, E., 2016. The foundations of the environmental rebound effect and its contribution towards a general framework. Ecol. Econ. 125, 60–69. doi:The foundations of the environmental rebound effect and its contribution towards a general framework

Font Vivanco, D., van der Voet, E., 2014. The rebound effect through industrial ecology's eyes: a review of LCA-based studies. Int. J. Life Cycle Assess. 19, 1933–1947. doi:10.1007/s11367-014-0802-6

Freire-González, J., 2011. Methods to empirically estimate direct and indirect rebound effect of energy-saving technological changes in households. Ecol. Model. We Break Addict. to Foss. Energy? Spec. Issue, 7th Bienn. Int. Work. Adv. Energy Stud. Barcelona, Spain, 19-21 Oct. 2010.

Gentil, E.C., Gallo, D., Christensen, T.H., 2011. Environmental evaluation of municipal waste prevention. Waste Manag. 31, 2371–9. doi:10.1016/j.wasman.2011.07.030

Girod, B., de Haan, P., 2010. More or better? A model for changes in household greenhouse gas emissions due to higher income. J. Ind. Ecol. 14, 31–49. doi:10.1111/j.1530-9290.2009.00202.x

Gruber, L.M., Brandstetter, C.P., Bos, U., Lindner, J.P., 2014. LCA study of unconsumed food and the influence of consumer behavior, in: Schenck, R., Huizenga, D. (Eds.), The 9th International Conference on Life Cycle Assessment in the Agri-Food Sector. American Center for Life Cycle Assessment, San

Francisco, pp. 489–499.

IMechE, 2013. Global Food Waste Not, Want Not. Institution of Mechanical Engineers, London.

IPCC, 2007. Climate change 2007: Mitigation. Contribution of Working Group III to the Fourth Assessment Report of the Intergovernmetnal Panel on Climate Change. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

Khazzoom, J.D., 1980. Economic implications of mandated efficiency in standards for household appliances. Energy J. 1, 21–40.

Koning, A. d., Xingyu, L., 2016. Disaggregating the household final demand vector into demand by diferent income groups in MRIO. J. Ind. Ecol.

Laurent, A., Christensen, T., Bakas, I., 2014a. Review of LCA studies of solid waste management systems - Part II: Methodological guidance for a better practice. Waste Manag. 34, 589–606. doi:10.1016/j.wasman.2013.12.004

Laurent, A., Clavreul, J., Bernstad, A., Niero, M., Gentil, E., Hauschild, M.Z., Christensen, T.H., 2014b. Review of LCA studies of solid waste management systems - Part I: Lessons learned and perspectives. Waste Manag. 34, 573–588. doi:10.1016/j.wasman.2013.10.045

Lebersorger, S., Schneider, F., 2011. Discussion on the methodology for determining food waste in household waste composition studies. Waste Manag. 31, 1924–1933. doi:10.1016/j.wasman.2011.05.023

Leontief, W., 1951a. Input-Output Economics. Sci. Am. 185, 15–21.

Leontief, W., 1951b. The Structure of American Economy 1919-1939. Oxford University Press, New York, NY, USA.

Leontief, W., 1936. Quantitative input and output relations in the economic systems of the United States. Rev. Econ. Stat. 105-125.

Martinez-Sanchez, V., 2016. SUPP Life-Cycle Costing of Food Waste Management in Denmark: Importance of indirect effects. Environ. Sci. Technol. acs.est.5b03536. doi:10.1021/acs.est.5b03536

Martinez-Sanchez, V., Tonini, D., Møller, F., Astrup, T.F., 2016. Life-Cycle Costing of Food Waste Management in Denmark: Importance of indirect effects. Environ. Sci. Technol. 2016, 4513–4523. doi:10.1021/acs.est.5b03536

Matsuda, T., Yano, J., Hirai, Y., Sakai, S., 2012. Life-cycle greenhouse gas inventory analysis of household waste management and food waste reduction activities in Kyoto, Japan. Int. J. Life Cycle Assess. 17, 743–752. doi:10.1007/s11367-012-0400-4

Miller, R., Blair, P., 2009. Input-Output Analysis: Foundations and Extensions, 2nd ed. Cambridge University Press, New York.

Moran, D., Wood, R., 2014. Convergence Between the EORA,WIOD, EXIOBASE, and OPENEU's Consumption-Based Carbon Accounts. Econ. Syst. Res. 26, 245–261. doi:10.1080/09535314.2014.935298

Murray, C.K., 2013. What if consumers decided to all "go green"? Environmental rebound effects from consumption decisions. Energy Policy 54, 240–256. doi:10.1016/j.enpol.2012.11.025

ONS, 2013. CPI And RPI Reference Tables, January 2013 [WWW Document]. Off. Natl. Stat. URL http://www.ons.gov.uk/ons/rel/cpi/consumer-price-indices/january-2013/cpi-and-rpi-reference-tables.xls (accessed 5.9.14).

ONS, 2012. Input-Output Supply and Use Tables, 2012 Edition [WWW Document]. URL http://www.ons.gov.uk/ (accessed 5.1.16).

Papargyropoulou, E., Lozano, R., K. Steinberger, J., Wright, N., Ujang, Z. Bin, 2014. The food waste hierarchy as a framework for the management of food surplus and food waste. J. Clean. Prod. 76, 106–115. doi:10.1016/j.jclepro.2014.04.020

Pretty, J.N., Ball, A.S., Lang, T., Morison, J.I.L., 2005. Farm costs and food miles: An assessment of the full cost of the UK weekly food basket. Food Policy 30, 1–19. doi:10.1016/j.foodpol.2005.02.001

Ruiter, H. De, Macdiarmid, J.I., Matthews, R.B., Kastner, T., Smith, P., 2016. Global cropland and greenhouse gas impacts of UK food supply are increasingly located overseas. J. R. Soc. Interface 13. doi:rsif.2015.1001

Salemdeeb, R., Al-Tabbaa, A., 2015. A hybrid life cycle assessment of food waste management options: a UK case study, in: The ISWA 2015 World Congress. International Solid Waste Association, Antwerp, Belgium, pp. 334–339. doi:10.13140/RG.2.1.2264.7925

Salemdeeb, R., zu Ermgassen, E.K.H.J., Kim, M.H., Balmford, A., Al-Tabbaa, A., 2016. Environmental and health impacts of using food waste as animal feed: a comparative analysis of food waste management options. J. Clean. Prod. 1–10. doi:10.1016/j.jclepro.2016.05.049

Stadler, K., Steen-Olsen, K., Wood, R., 2014. the "Rest of the World" – Estimating the Economic Structure of Missing Regions in Global Multi-Regional Input–Output Tables. Econ. Syst. Res. 26, 303–326. doi:10.1080/09535314.2014.936831

Su, B., Huang, H.C., Ang, B.W., Zhou, P., 2010. Input-output analysis of CO2 emissions embodied in trade: The effects of sector aggregation. Energy Econ. 32, 166–175. doi:10.1016/j.eneco.2009.07.010

Thomas, B.A., Azevedo, I.L., 2013. Estimating direct and indirect rebound effects for

U.S. households with input-output analysis Part 1: Theoretical framework. Ecol. Econ. - Sustain. Urban. A resilient Futur.

Tukker, A., Bulavskaya, T., Giljum, S., Koning, A. De, 2014. The Global Resource Footprint of Nations The Global Resource Footprint of Nations. The Netherlands Organisation for Applied Scientific Research, Delft.

Venkat, K., 2011. The Climate Change and Economic Impacts of Food Waste in the United States. Int. J. Food Syst. Dyn. 2, 431–446.

Vringer, K., Blok, K., 1996. Assignment of the Energy Requirement of the Retail Trade to Products. STS-UU, Utrecht, The Netherlands.

Wood, R., Stadler, K., Bulavskaya, T., Lutter, S., Giljum, S., de Koning, A., Kuenen, J., Schütz, H., Acosta-Fernández, J., Usubiaga, A., Simas, M., Ivanova, O., Weinzettel, J., Schmidt, J., Merciai, S., Tukker, A., 2015. Global Sustainability Accounting—Developing EXIOBASE for Multi-Regional Footprint Analysis. Sustainability 7, 138–163. doi:10.3390/su7010138

World Bank, 2015. PPP conversion factor, GDP (LCU per international $) [WWW Document]. Int. Comp. Progr. database. URL http://data.worldbank.org/indicator/PA.NUS.PPP (accessed 5.12.15).

WRAP, 2014. Econometric Modelling and Household Food Waste. Waste and Resources Action Programme, Banbury, Oxon.

WRAP, 2013. Household Food and Drink Daste in the United Kingdom 2012. Waste and Resources Action Programme, Banbury, Oxon.

Figures

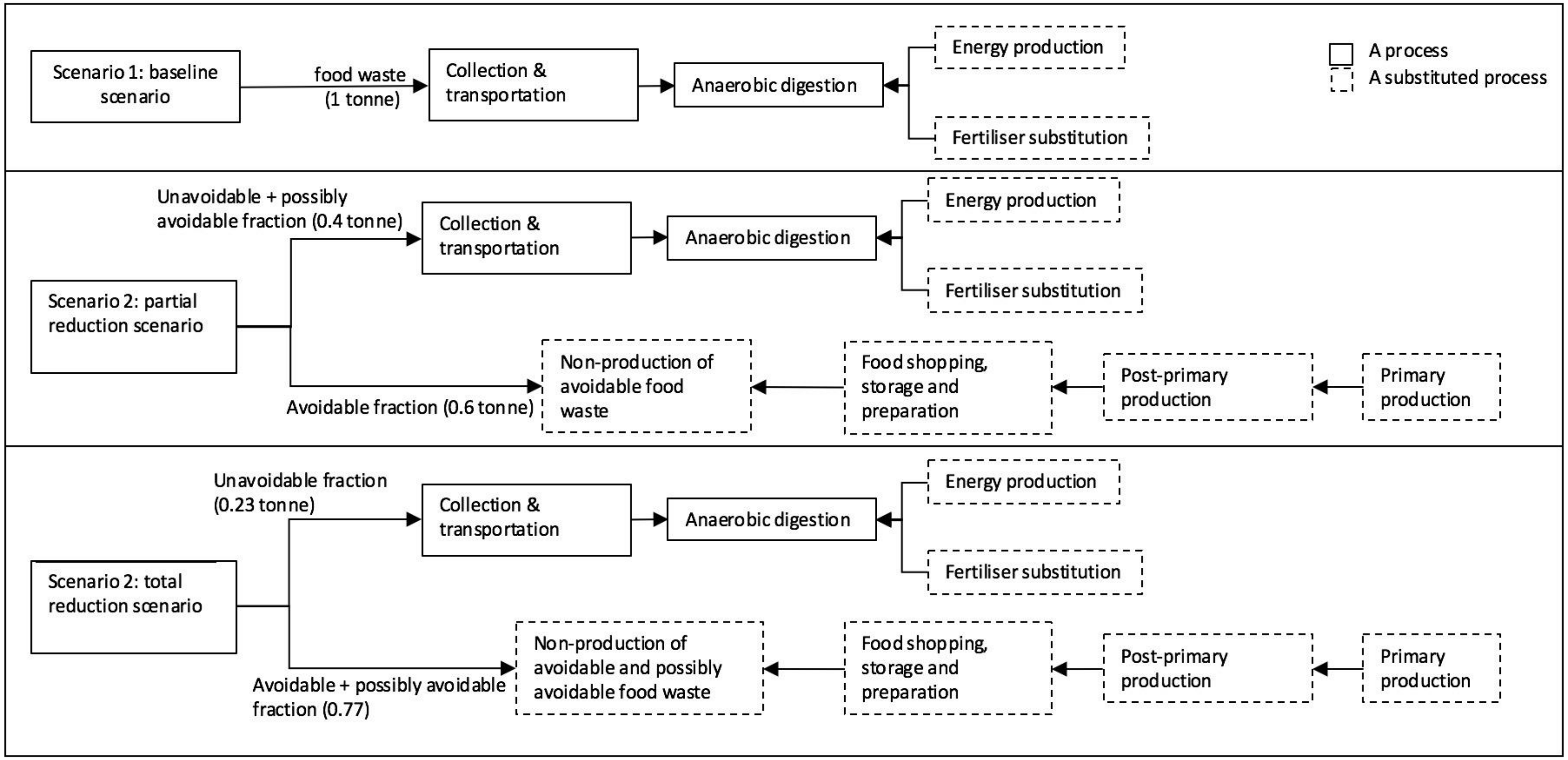


Figure 1

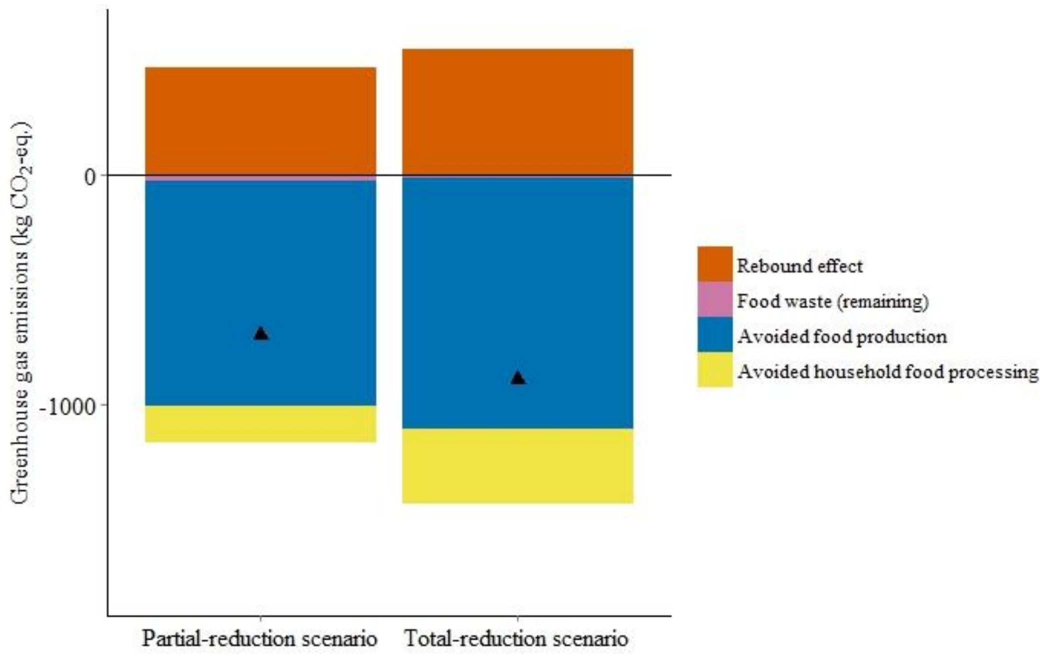
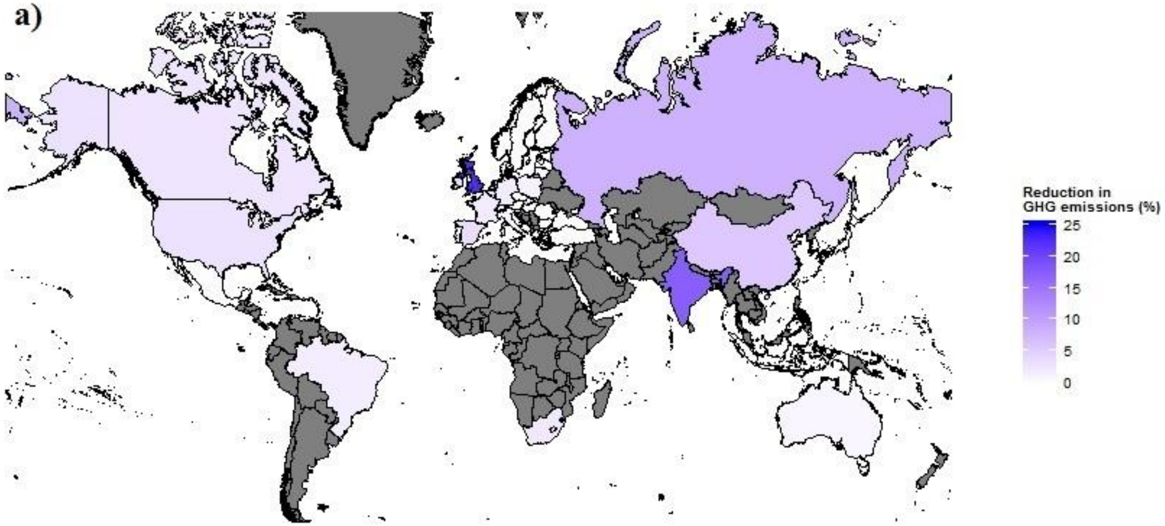

Greenhouse gas emissions (kg CO_2-eq.)
0
-1000
Partial-reduction scenario
Total-reduction scenario
Rebound effect
Food waste (remaining)
Avoided food production
Avoided household food processing

Figure 2

a)



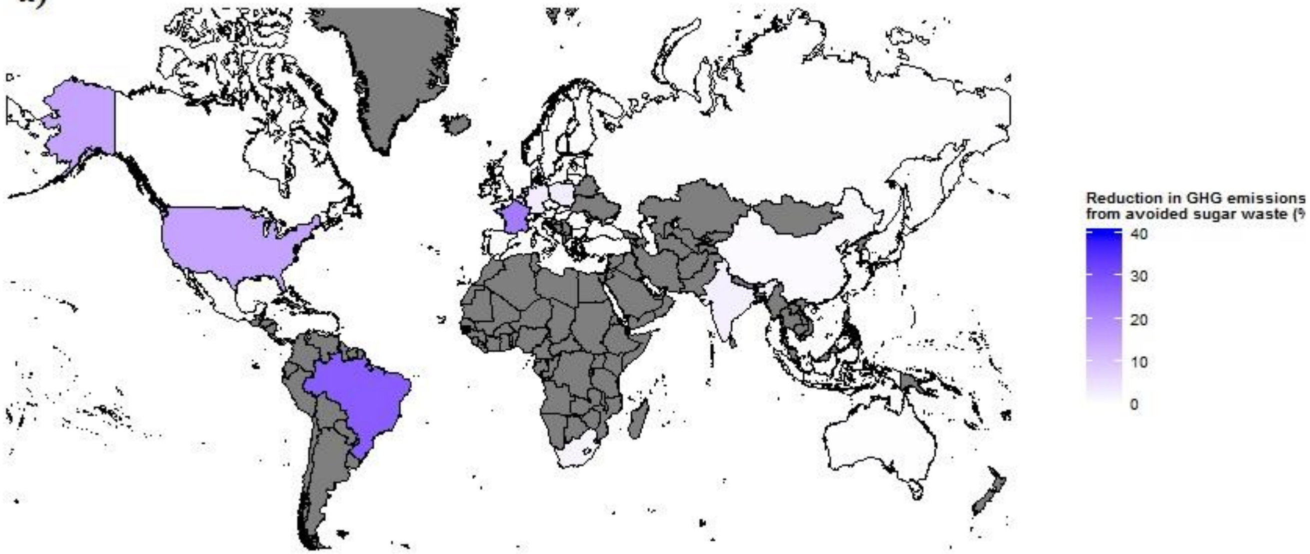
b)

Top five countries for avoided GHG emissions from reducing UK household food waste, listed in terms of GHG savings and the percentage of UK food expenditure they make up.

Country	GHG reduction (%)	Food expenditure (%)
Great Britain	22.6	55.6
India	17.2	6.5
Russian Federation	8.2	0.2
China	5.8	1.0
Netherlands	4.8	4.2
Others	41.2	32.6

Figure 3

a)

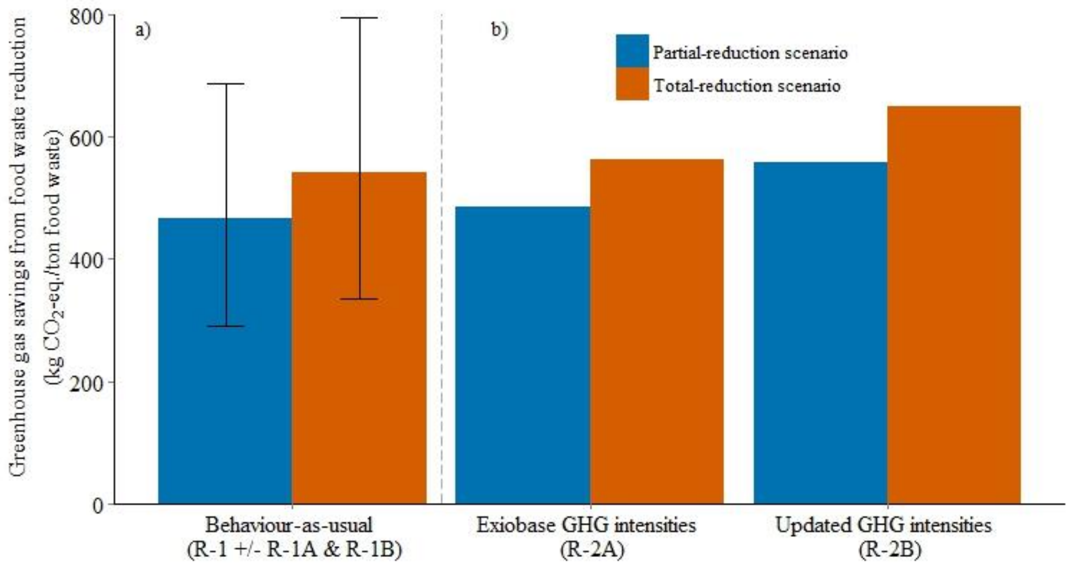


b)

Top five countries for GHG reductions from avoided sugar waste

Country	GHG reduction (%)
Brazil	28
France	23
United States	16
Netherlands	11
Belgium	4
Others	22

Figure 4



800
600
400
200
0
a)
b)
Partial-reduction scenario
Total-reduction scenario
Greenhouse gas savings from food waste reduction
(kg CO2-eq./ton food waste)
Behaviour-as-usual
(R-1 +/- R-1A & R-1B)
Exiobase GHG intensities
(R-2A)
Updated GHG intensities
(R-2B)

Figure 5

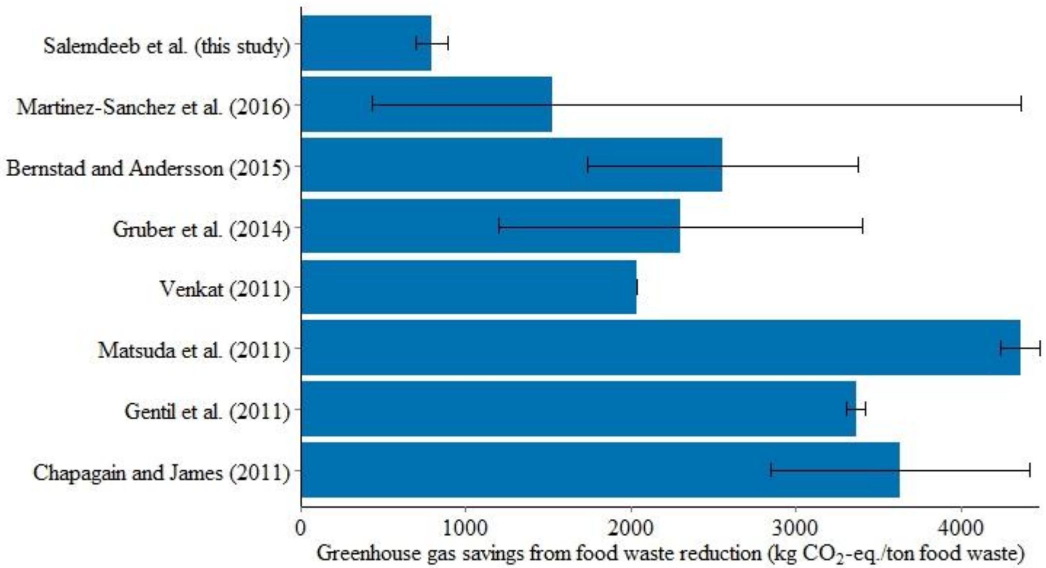

Salemdeeb et al. (this study)
Martinez-Sanchez et al. (2016)
Bernstad and Andersson (2015)
Gruber et al. (2014)
Venkat (2011)
Matsuda et al. (2011)
Gentil et al. (2011)
Chapagain and James (2011)
0
1000
2000
3000
4000
Greenhouse gas savings from food waste reduction (kg CO_2-eq./ton food waste)

Figure 6

Figures Captions

Figure 1 Conceptual diagram of the system investigated in this study. Post-primary production stage includes the processing of primary food products, the distribution and retailing of final products whilst primary production consists of processes required to produce primary food products and transport them to a regional distribution centre. A graphical representation of the system boundary for the AD technology is provided in Appendix F.

Figure 2 Hotspot analysis of GHG savings from food waste prevention. Triangles show the overall avoided GHG emissions.

Figure 3 Preventing food waste in UK households leads to GHG savings internationally, due to savings made throughout the UK's global food supply chain. Countries shaded in grey have no data available. A detailed contribution analysis of GHG emissions, disaggregated by industrial sectors and geographical sources, is provided in Appendix J.

Figure 4 Sources of GHG savings for the avoidance of sugar waste, both from sugar beet and sugar cane. Countries shaded in grey have no data available. A detailed contribution analysis of GHG emissions, disaggregated by industrial sectors and geographical sources, is provided in Appendix J.

Figure 5 Uncertainty in estimates for the rebound effect. The left two bars (a) show the GHG savings assuming that the respend occurs in line with current budget shares (R-1), i.e. behavior-as-usual. The error bars represent the estimates for the GHG savings when spending is assumed to shift across the top 25 consumption categories (scenario R-1A, upper limit & scenario R-1B, lower limit). The bars to the right show (b) the estimated GHG savings, assuming that some of the respend is spent "trading up" to higher quality goods (scenarios R-2A and R-2B).

Figure 6 A comparison of the different estimates of GHG savings from avoiding one tonne of food waste. The error bars illustrate the ranges reported in each study.