A HOLISTIC MODEL FOR 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.

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}, which makes it equivalent to the world's third biggest carbon emitter 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 (Papargyropoulou et al., 2014), providing guidelines on which disposal technologies are preferable (EC, 2008).

Food waste prevention, at the top of the food waste hierarchy, is considered to be the most environmentally favorable option (Papargyropoulou et al., 2014). According to a study published by the European Commission, approximately 44Mt CO_2-eq. year could be avoided by introducing a 20% food waste reduction target (EC, 2014). This finding supports other studies highlighting the significant environmental benefits of preventing 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 ton of food waste (Bernstad and Cánovas, 2015). These variations in the 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 modelling approach to addressing them.

Firstly, the majority of studies take a conventional process-based Life cycle assessment (LCA) approach, commonly used in waste management studies (Table 1).

Excluding Martinez-Sanchez et al's study (2016), all of the reviewed studies adopt a bottom-up LCA approach, and therefore 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). LCA is also inadequate for evaluating waste prevention strategies due to its incomplete representation of the food system. For example, LCA studies generally do not consider variations within the same food category due to differences in production systems (e.g. all fish may be assigned the same carbon footprint, rather than distinguishing between different sources and catch methods), quality of the product (e.g. conventional vs organic) and methodological assumptions and approaches (e.g., truncation errors) (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 modelling food waste prevention is the globalization of the food and associated supply chains. For example, 48% of the UK's food supply in 2008 was imported from abroad, and these imports accounted for 67% of the GHG emissions associated with the UK food supply (Ruiter et al., 2016). It is therefore 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 reviewed studies 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 estimated benefits from preventing 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 and additional expenditure on alternative products and services (Binswanger, 2001; Brookes, 1990; Khazzoom, 1980). As this additional expenditure generates additional GHG emissions, the environmental benefits of minimizing 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 disposing of food waste via other waste management alternatives (Martinez-Sanchez, 2016).

To conclude, the limitations discussed above show that conventional approaches to investigating environmental benefits associated with food waste prevention are insufficient in the context of behavioral and systemic effects, as well as a globalized world. In order to combat these limitations, this study outlines a holistic approach to quantifying the environmental benefits of food waste prevention. To counter limitations of conventional bottom-up LCAs, a hybrid LCA approach is used, combining conventional process-based LCA and input-output data (Salemdeeb and Al-Tabbaa, n.d.). Secondly, the flow of goods and services throughout the global supply chain was modelled using economic, top-down multi-regional input output (MRIO) methods. Finally, the rebound effect is modelled using an econometric-based marginal expenditure model. The United Kingdom was used as a case study.

2 Methodology

Three scenarios were modelled for the management of 1 ton of household food waste:

i. Baseline-scenario: 1 ton of food is wasted and all food waste is sent to be processed in an anaerobic digestion (AD) plant. Anaerobic digestion was selected because it is the food waste treatment technology most currently favored 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 being sent to an AD plant; and
iii. A total-reduction scenario: 77% of food waste is prevented and 23% is sent to an AD plant.

Food waste prevention scenarios are based on a study published by the Waste and Resources Action Programme (WRAP), which estimates that 60% of food waste in the UK is avoidable whilst 17% of this total has the potential to be avoided (WRAP, 2013). Possibly avoidable food waste includes leftovers such as bread crusts or potato skins which are eaten by some people, but not others, and unavoidable food waste (the remaining 23% of the total) consists of inedible waste such as egg shells and tea bags (Table 2). Figure 1 shows a schematic diagram illustrating all scenarios and processes.

Our study adopts a green-consumption approach: households which reduce food waste are assumed to have reduced food purchases, rather than increased consumption. Food waste prevention scenarios also include avoided household food-related activities (e.g. grocery shopping, storage and preparation). Literature data was used to model these activities: shopping is accountable for 70 kg CO_2-eq.

per ton food and the GHG burden associated with home storage and preparation is 420kg CO_2-eq. per ton of food waste (Brook Lyndhurst, 2008; Pretty et al., 2005).

Greenhouse gas emissions are presented using a single mid-point impact category: climate change. The global warming potential (GWP) metric is used to convert greenhouse gases to equivalent amounts of CO_2 by weighting their radiative? properties on a time horizon of 100 years (IPCC, 2007).

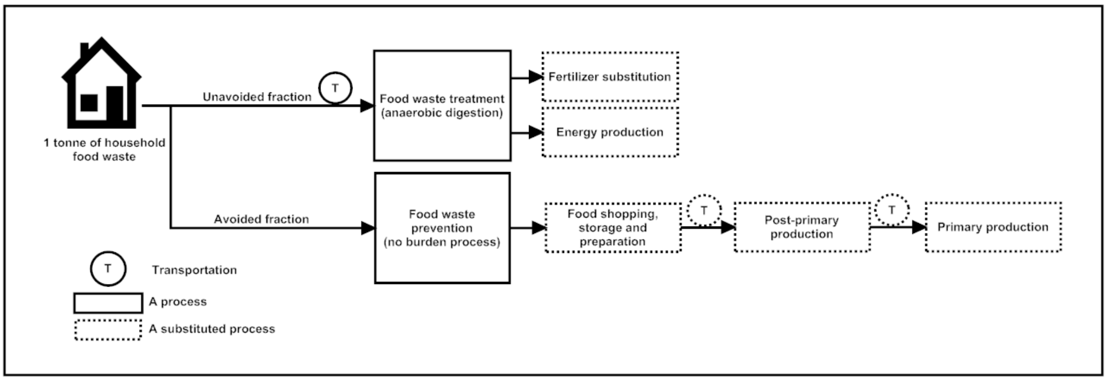


Figure 1 Conceptual diagram of scenarios investigated in this study. Post-primary production stage includes the processing of primary food products, the distribution and retailing of final products whilst primary production consists of processes required to produce primary food products and transport them to a regional distribution centre.

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) was modelled using a hybrid LCA model (Salemdeeb and Al-Tabbaa, (n.d.)) combining conventional process-based LCA and input-output analysis. Life cycle inventory data and technical parameters related to the AD technology are based on a previous study (Salemdeeb et al., 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 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 GB£ 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 to 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 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	89.5	95.0	127.1	135.1
Drink	41.5	41.5	0.0	0.0	58.5	58.5
Fresh fruit	84.7	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	65.9	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]	**207.7**	**303.4**	**189.4**	**179.8**	**609.8**	**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 first 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 latter refers to the additional demand in all other consumption categories (D Font Vivanco et al., 2016). The rebound effect was quantified through 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)). Specifically, we 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 to estimate more accurately 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 (Deaton and Muellbauer, 1980):

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

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 harmonize 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. Specifically, we used household expenditure data to build weights in cases when 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 reducing food waste, it is not certain how they will alternatively spend this surplus. We therefore model 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 (scenarios R-1A and R-1B, see Table 3). In these two scenarios, the profit made from reducing food waste is re-spent on the top 25 consumption categories, which together make up more than 88% of spending (i.e., categories with the highest MBS). Within these 25 categories, the re-spend is divided between the 15 categories with either the highest GHG-intensities (scenario R-1A) or the highest MBS (scenario R-1B). The re-spend is limited to the top 25 consumption categories in order to make the results more conservative and realistic than previous modelling approaches which assume that additional spending may occur on services with the highest or lowest GHG-intensities, regardless of their importance in the household budget (e.g. Martinez-Sanchez et al. 2016).

The second part of the sensitivity analysis is based on the observation made by WRAP that people tend to spend 50% of FEI in buying 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 the freed effective income on purchasing quality oriented food products whilst the remaining 50% of the FEI follow the original expenditure pattern. As GHG-intensities can vary largely between quality oriented and conventional food products (Appendix E), we consider two sub-scenarios: (i) GHG intensities remain the same for both conventional and quality oriented products (scenario R-2A), and (ii) GHG intensities are updated to reflect the variation between quality oriented and conventional food products (scenario R-2B); we model quality orientated food products as organic food products (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 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 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: 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. 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 (Table 4). Emissions are reduced by 700 and 888 kg CO_2-eq. per ton food waste for the scenarios of a partial (60%) and total reduction of avoidable and possibly avoidable food waste (77% with the remaining 23% of unavoidable food waste sent to AD plant), respectively. Hotspot analysis, depicted in *Figure 2*, shows that the avoidance of food production is accountable for the majority of these benefits: 83.5% for the partial reduction scenario and 76% for the total reduction scenario. These findings confirm 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.

Table 4 GHG emissions, expressed in GWP, from food waste management as total food waste (kg CO_2-eq. per ton food waste) divided on streams and rebound effect[1]. 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	-30	-1138	467 (290-685)	-700 (-483 to -878)	25-59
Total-reduction scenario	-11	-1419	542 (335-795)	-888 (-635 to -1095)	23-56

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

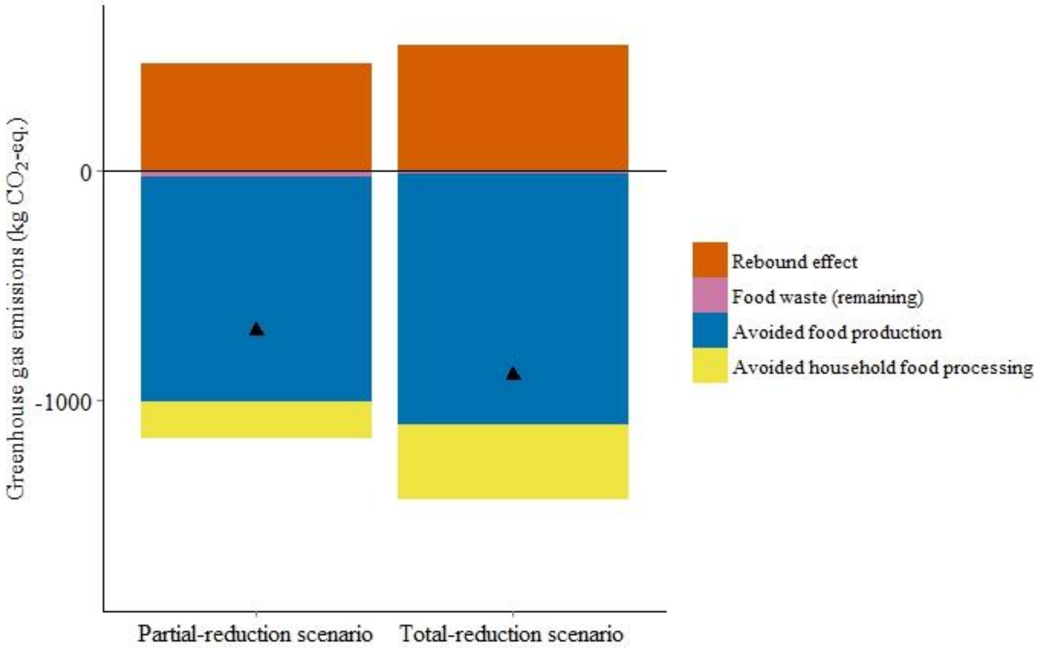


Figure 2 Hotspot analysis of GHG savings from food waste prevention. Triangles show the overall avoided GHG emissions.

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 of 16.5% and 24% for the partial-reduction and total-reduction scenarios respectively. These estimations are based on data obtained from literature and raise questions concerning its reliability. For instance, Gruber et al. (2014) state that between 0.7 - and 2.1 MJ of electricity is needed to cook of 1 kg rice or potatoes, depending on household behaviour.

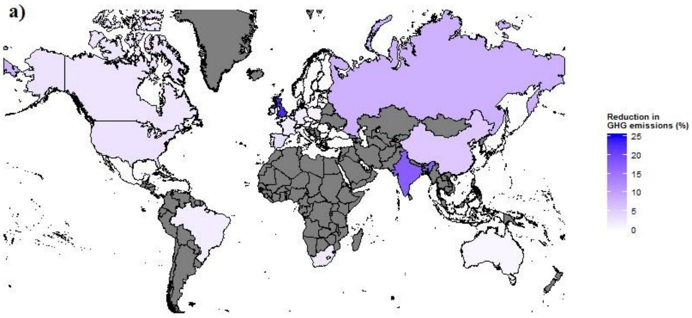
Overall, the combination of GHG savings in food production and related household activities leads to a large potential GHG reduction, ranging from 1138-1419 kg CO_2-eq. per ton of food waste prevented. However, these benefits are reduced by nearly 23-59% due to the impact of the rebound effect, shrinking GHG reductions to between 483 and 1095 kg CO_2-eq. per ton of food waste. Despite the substantial reductions in reported benefits, overall GHG savings remain 5-12 times greater than those reported for anaerobic digestion. The 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 ton of food is wasted and sent for anaerobic digestion, results show an overall GHG reduction of 89 kg CO_2-eq. per ton of food waste. These GHG savings occur mainly due to energy recovery and the displacement of fertiliser, which lead to GHG reductions of 185.5 and 4.6 CO_2-eq. per ton of food waste respectively. Contrastingly, most of the GHG burden of AD is a result of the digestion process itself and the energy input required to operate the system, whilst food waste collection and transportation has a less significant impact: 11 kg CO_2-eq. per ton of food waste (Salemdeeb and Al-Tabbaa, 2015). A hot spot analysis of the baseline-scenario is presented in appendix F.

3.1 The role of the MRIO model

The GHG savings from reducing food waste occur internationally (Figure 3). Only 22% of these savings take place within UK borders (Figure 3b) – this relatively low percentage is attributed to the UK's dependence on food imports, the relatively environmentally efficient food production systems and low-carbon energy sources in the UK. Our results echo recent findings that the majority of the UK food basket's GHG emissions occur abroad (Ruiter et al., 2016), partly due to lower GHG efficiencies in agriculture in 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 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%).

a)



b)

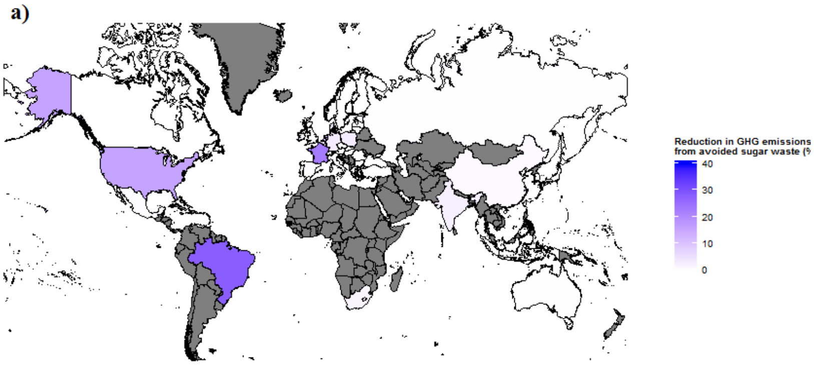
Top five countries for GHG reductions from food waste prevention, listed in terms of GHG savings and the percentage of agricultural expenditure they make up.

Country	GHG reduction (%)	Agricultural 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 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.

The MRIO approach allows an unprecedented resolution of analysis, including differentiating impacts per food group as well as 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).

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 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.

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 improving the quality of data integrated into the MRIO model. This could be done by integrating the World Food LCA database– a comprehensive and international inventory database for 200 food life cycle assessments (Nemecek et al., 2015) - with the MRIO model. This hybrid approach 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.

3.2 Comparison with previous studies

Despite finding substantial GHG benefits of avoiding food waste, our estimates of the GHG savings are more conservative than those reported in previous studies (Figure 5). Differences arise due to the aggregated nature of the method (as discussed above, see section 3.1) and variations in the scenarios evaluated and the data used in each study. The scenarios used in this study assume, for example, that 23% of food waste is unavoidable (40% in the partial reduction scenario and 23% in the total reduction scenarios) and, is therefore sent to anaerobic digestion, leading to lower GHG reductions than if we had assumed that the total functional unit (1 ton of food waste) was preventable.

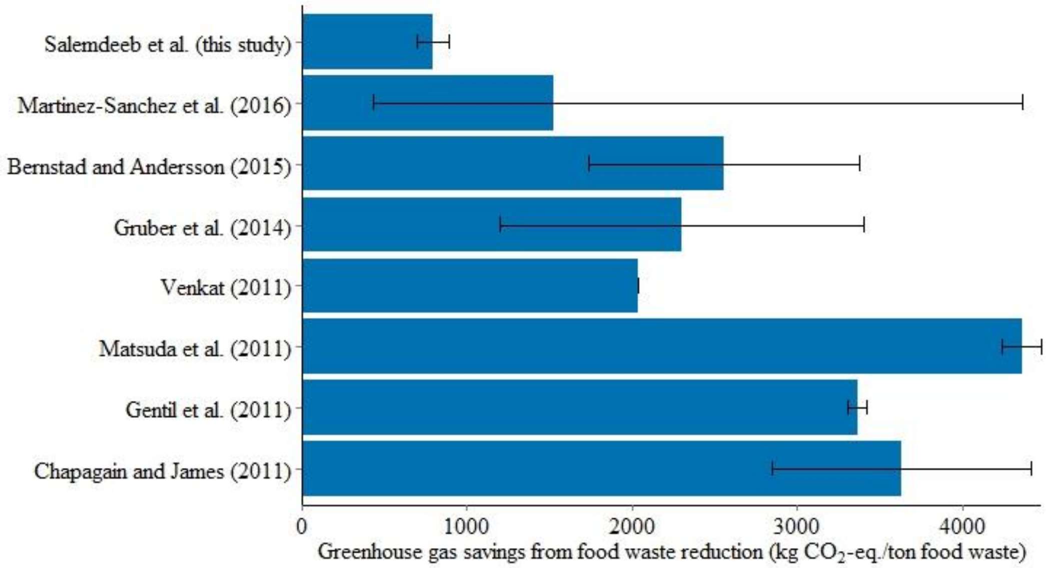


Figure 5 A comparison of the different estimates of GHG savings from avoiding one ton of food waste. The error bars illustrate the ranges reported in each study.

3.3 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 6a). The upper limit (R-1A), representing the GHG-based major spending 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 expenditure-based major spending 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 shifting from conventional to quality-oriented food products (Up-trade scenarios, see Table 3 and Figure 6b). The use of the same Exiobase GHG intensities (scenario R-2A) results in a small 3.5% increase, while using updated GHG intensities increases the size of the rebound effect and, consequently reduces the benefits of food waste prevention by

19.5% (

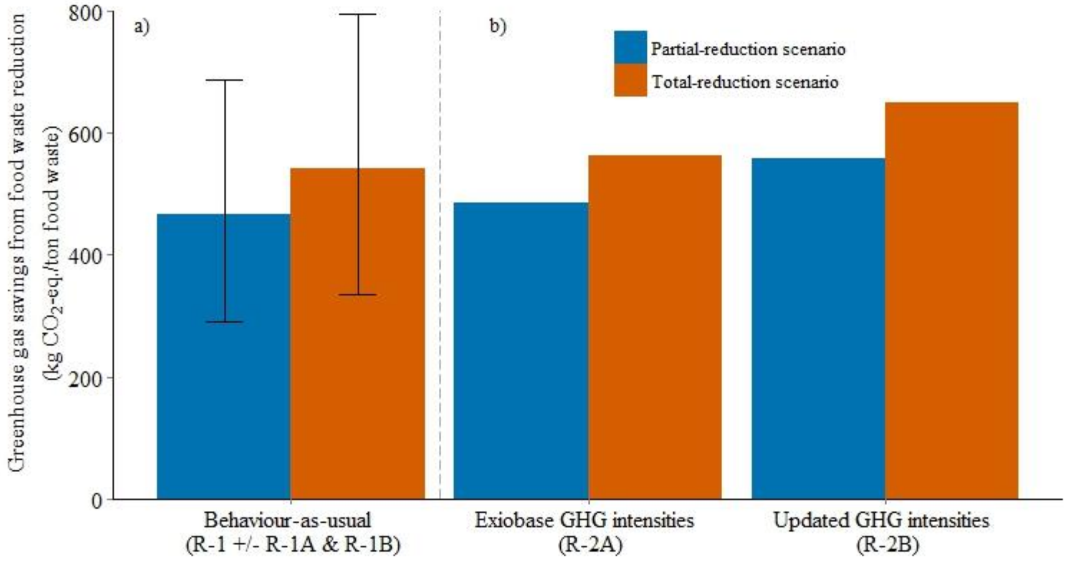


Figure 66b). The low increase estimated using Exiobase GHG intensities could be explained by two factors: 50% of the re-spending occurs in food product categories that are considered low-GHG categories (Druckman et al., 2011), and the assumption that GHG intensities of quality oriented products increase 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 functional unit of a quality-oriented product is twice this of the conventional counterpart, then the environmental burden associated with it would be doubled. Therefore the first scenario of the uptrade option approach may fail to represent the true variation in environmental impacts between conventional and quality-oriented products. The literature review shows that these variations could vary hugely, from -38% for sugar and oil seeds to +27% for pig meat production (Appendix D & G). Updating GHG intensities to reflect these variations (scenario R-2B) show that shifting to quality-oriented products increases the rebound effect and, consequently reduced food waste prevention benefits by 19.5% (

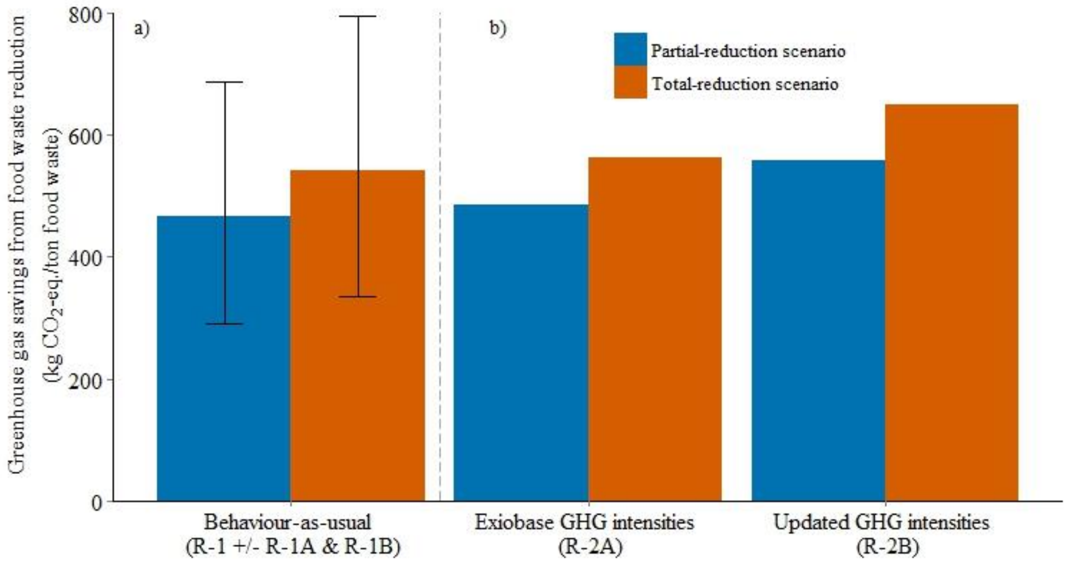


Figure 66b). This is due to the additional environmental burden associated with the production of many quality-oriented food products. Examples of higher impact and higher value products include organic products, (which have lower yields than conventional products) boneless meat, (which requires additional energy input in the food production process) and the use of premium packaging.

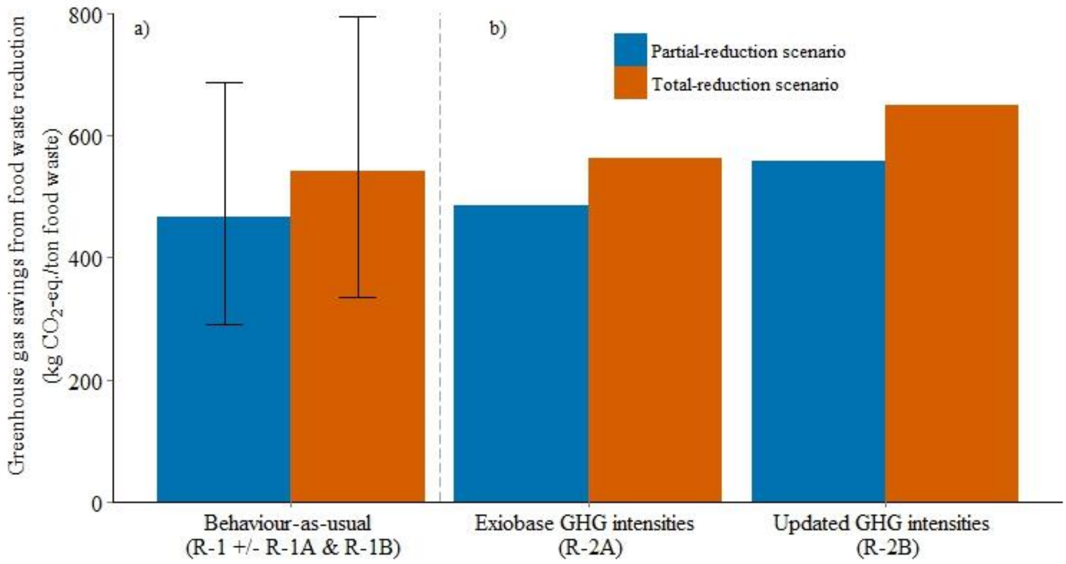


Figure 6 Uncertainty in estimates for the rebound effect. The left two bars (a) show the GHG savings assuming that the respend occurs in line with current budget shares (R-1), i.e. behavior-as-usual. The error bars represent the estimates for the GHG savings when spending is assume to shift between the 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).

A handful of 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 used an environmental life-cycle costing approach to evaluate the impact of the rebound effect in food waste prevention activities in Denmark. Their study's results also found a large rebound effect – in fact much larger than that of our study (1528-4367 kg CO_2 eq/tonne of food waste; 2-5 times higher than results reported in this study). Their findings suggest that the rebound effect could 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 these two estimates are attributable to various factors: (i) Martinez-Sanchez et al. use a highly aggregated economic model, combining all industrial sectors into 9 categories; (ii) they use consumer expenditure surveys to allocate savings on consumption categories; and (iii) they investigate extreme scenarios for the rebound effect, including allocating 100% of the savings 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 rebound effect model 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 in order 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).

4 Conclusions

This paper explores the value of methodological refinements to evaluating the environmental impacts associated with food waste prevention. The quantitative results confirm existing ideas on the environmental benefits of food waste prevention. Concretely, estimated GHG reduction values range between 700 and 888 kg CO_2-eq. per ton of food waste. Nevertheless, these emissions are relatively lower than others reported in the literature, partly due to the impact 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 intervention (e.g., 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; 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 the impacts associated with food imports. It highlights the importance of adopting a top-down multi-disciplinary 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 further insight into our understanding of the environmental impacts of the globalized food production supply chain, particularly in developing countries. The study would consequently help policy makers to develop strategies in order to ensure high efficiency across the global supply chain, especially in developing countries.

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