1 *A HOLISTIC APPROACH TO THE ENVIRONMENTAL EVALUATION OF FOOD*

2 *WASTE PREVENTION*

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13   **Abbreviations:**

14   GHG, greenhouse gas; LCA, life cycle assessment; AD, anaerobic digestion; N/A,

15   not applicable; MRIO, multi-regional input output; SIC, standard industrial

16   classification; MBS, marginal budget shares; AIDS, Almost Ideal Demand System; RE,

17   rebound effect; FEI, freed effective income; WRAP, The Waste and Resources Action

18   Programme.

19   **Abstract**

20   The environmental evaluation of food waste prevention is considered a

21   challenging task due to the globalised nature of the food supply chain and the

22   limitations of existing evaluation tools. The most significant of these is the rebound

23   effect: the associated environmental burdens of substitutive consumption that arises

24   as a result of economic savings made from food waste prevention. This study

25   introduces a holistic approach to addressing these challenges, with a focus on

26   greenhouse gas (GHG) emissions from household food waste in the UK. It uses a

27   hybrid life-cycle assessment model coupled with a highly detailed multi-regional

28   environmentally extended input output analysis to capture environmental impacts

29   across the global food supply chain. The study also takes into consideration the

30   rebound effect, which was modeled using a linear specification of an almost ideal

31   demand system.

32   The study finds that food waste prevention could lead to substantial reductions in

33   GHG emissions in the order of 706 to 896 kg CO_2-eq. per tonne of food waste, with

34   most of these savings (78%) occurring as a result of avoided food production

35   overseas. The rebound effect may however reduce such GHG savings by up to 80%.

36   These findings provide a deeper insight into our understanding of the environmental

37   impacts of food waste prevention: the study demonstrates the need to adopt a

38   holistic approach when developing food waste prevention policies in order to

39   mitigate the rebound effect and highlight the importance of increasing efficiency

40   across the global food supply chain, particularly in developing countries.

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42   Words count: 229

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1 Introduction

44

45 One third of food produced across the globe is thrown away uneaten, and this waste

46 has a large associated environmental burden (IMechE, 2013). Food waste is

47 responsible for 3.3 Bt-CO_2-eq. yr^{-1}, rendering it equivalent to the world's third largest

48 emitter of carbon after the economies of China and USA (FAO, 2013). In order to

49 reduce the environmental impact of food waste, the food waste hierarchy has been

50 adopted in various forms across different countries, providing guidelines on which

51 disposal technologies are most preferable (Papargyropoulou et al., 2014).

52 Food waste prevention, situated at the top of the food waste hierarchy, is

53 considered to be the most environmentally favorable management option

54 (Papargyropoulou et al., 2014). According to a study published by the European

55 Commission, approximately 44Mt CO_2-eq. yr^{-1} could be avoided by the introduction

56 of a 20% food waste reduction target (EC, 2014). This finding supports the

57 conclusions of other studies that have highlighted the significant environmental

58 benefits of avoiding food waste (Bernstad and Andersson, 2015; Gentil et al., 2011;

59 Martinez-Sanchez, 2016). Nevertheless, reported results are subject to a high level of

60 uncertainty; the reported greenhouse gas (GHG) emissions savings vary widely,

61 ranging from 800 to 4400 kg CO_2-eq. per tonne of food waste (Bernstad and

62 Cánovas, 2015). These variations in literature arise largely due to methodological

63 choices: most studies rely entirely on life cycle assessment approaches, do not

64 consider food imports, and ignore rebound effects. We discuss these three

65 methodological challenges before introducing a new holistic modeling approach to

66 addressing them.

67 Firstly, the majority of studies adopt a conventional process-based Life Cycle

68 Assessment (LCA) approach (Table 1). Excluding Martinez-Sanchez et al's study

69 (2016), all of the reviewed studies adopt a bottom-up LCA approach, and hence

70 inherit the widely-discussed limitations of LCA such as system boundary cut-offs,

71 data inconsistencies, study-specific scenarios and assumptions (Bernstad and la Cour

72 Jansen, 2012; Laurent et al., 2014a, 2014b). These limitations, coupled with the

73 multi-faceted nature of food waste, make the environmental evaluation of food

74 waste prevention practices an arduous task. LCA-based studies are generally

75 product-specific and do not consider variations within the same food category due

76 to differences in the source of food products (e.g., imported vs locally produced),

77 food production systems (e.g., wild caught vs aquaculture fish), and the quality of

78 food products (e.g., conventional vs organic) (Audsley et al., 2009; Bernstad and

79 Cánovas, 2015; Chapagain and James, 2011).

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

Study	Country	Assessment method	International trade included?	Rebound effect included?
Bernstad and Andersson (2015)	Sweden	Consequential 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

82 The second challenge in modeling food waste prevention lies in the globalization

83 of the food supply chain. For example, 48% of the UK's food supply in 2008 was

84 imported from abroad, and these imports accounted for 67% of food-related GHG

85 emissions (Ruiter et al., 2016). It is hence vital to account for the source of food

86 products when estimating environmental benefits associated with food waste

87 prevention. Excluding Bernstad and Andersson's study (2015), all of the studies

88 reviewed assume food production occurs domestically or regionally (Audsley et al.,

89 2009; Martinez-Sanchez, 2016; Matsuda et al., 2012; Venkat, 2011).

90 The final factor that results in substantial variation in estimates of the benefits of

91 reducing food waste is the inclusion, or lack of inclusion, of the rebound effect: the

92 avoidance of food waste in households leads to increased effective income which

93 subsequently results in expenditure on alternative products and services

94 (Binswanger, 2001; Brookes, 1990; Khazzoom, 1980). That is to say, when

95 households avoid food waste, they consequently have more money available that

96 may then be spent on other products and services. As this additional expenditure

97 generates additional GHG emissions, the environmental benefits of reducing food

98 waste can be partially or completely offset. If the economic savings were to be spent

99 on carbon-intensive goods or services (e.g. air travel or domestic heating), it is even

100 plausible for food waste prevention to create higher environmental burdens than if

101 the food waste had not been wasted to begin with (Martinez-Sanchez, 2016).

102 To summarise, conventional approaches used to estimate the environmental

103 benefits of food waste prevention provide only limited insight, in a world where food

104 is internationally traded and financial savings made from waste avoidance often lead

105 to rebound consumer spending. In order to combat these limitations, this study

106 outlines a holistic approach to quantifying the environmental benefits of food waste

107 prevention. To counter the limitations of conventional bottom-up LCAs, a hybrid LCA

108 approach is used, combining conventional process-based LCA and a top-down input-

109 output-based approach. Secondly, the flow of goods and services throughout the

110 global supply chain was modeled using an economic and multi-regional input output

111 method. Finally, the rebound effect was modeled using an econometric-based

112 marginal expenditure model. The United Kingdom was used as a case study.

113 **2 Methodology**

114 Three scenarios for the environmental benefits of food waste prevention were

115 evaluated: a baseline scenario and two food waste prevention scenarios (Figure 1).

116   i. Baseline-scenario: 1 tonne of food is wasted and sent to be processed in an

117   anaerobic digestion (AD) plant. Anaerobic digestion was selected because it is

118   the food waste treatment technology most currently most favoured in the UK

119   (Evangelisti et al., 2014; Salemdeeb and Al-Tabbaa, 2015);

120   ii. A partial-reduction scenario: a 60% reduction in food waste, with the

121   remaining fraction of food waste (400kg) being sent to an AD plant; and

122   iii. A total-reduction scenario: 77% of food waste is prevented and 23% (230kg)

123   is sent to an AD plant.

124 The two food waste prevention scenarios are based on figures from the Waste

125 and Resources Action Programme (WRAP), which estimate that 60% of household

126 food waste in the UK is avoidable whilst a further 17% has the potential to be

127 avoided (WRAP, 2013). The remaining 23% of food waste is unavoidable (e.g. egg

128 shells and tea bags) and thus undergoes a conventional disposal route.

129   Our study adopts a green-consumption approach: households which reduce food

130   waste are assumed to have reduced food purchases, rather than increased

131   consumption. In order to model the environmental benefits of avoiding food waste,

132   we follow Gentil et al.'s approach in considering the quantity of avoided food waste

133   as a virtual waste flow (Gentil et al., 2011). Food waste prevention scenarios

134   therefore also include knock-on savings from food waste avoidance, including

135   avoided household food-related activities (e.g. grocery shopping, storage and

136   preparation). To model these household activities, we used estimates from the

137   literature: shopping is accountable for 70 kg CO_2-eq. per tonne food and the GHG

138   burden associated with home storage and preparation is 420kg CO_2-eq. per tonne

139   (Brook Lyndhurst, 2008; Pretty et al., 2005). This study additionally takes into

140   account the rebound effect and investigates how the economic savings from food

141   waste prevention activities (the purchase of less food products) may be spent on

142   other activities and consequently reduce the net environmental benefits of food

143   waste prevention (Section 2.3).

144   This study includes one environmental indicator, greenhouse gas emissions.

145   These are aggregated and presented as a single mid-point impact category (i.e.,

146   climate change). The global warming potential metric is used to convert greenhouse

147   gases to equivalent amounts of CO_2 on a time horizon of 100 years (IPCC, 2007).

148   <INSERT Figure 1 here>

149   **2.1   Hybrid life cycle assessment: anaerobic digestion**

150   The environmental impacts of the baseline scenario and the unavoided fraction of

151   food waste in other scenarios (i.e., 40% of food waste in the partial-reduction and

152   23% in the total-reduction scenarios) were modeled using a hybrid-LCA waste-

153   related model. First introduced by Salemdeeb and Al-Tabbaa (2015), the hybrid LCA

154   model combines conventional process-based LCA and a top-down input-output

155   analysis in order to reduce truncation error and achieve system completeness, a lack

156   of which is a common limitation associated with conventional LCA tools (Laurent et

157   al., 2014b).

158   Life cycle inventory data and technical parameters related to the AD technology

159   are based on Salemdeeb and his colleagues' study that evaluated the environmental

160   impacts of household food waste management in the UK, including AD (2016) . Food

161   waste collection and transportation are included in the assessment whilst food

162   waste packaging is excluded due to its insignificant impact (Bernstad and Andersson,

163   2015; Lebersorger and Schneider, 2011).

164   **2.2   An environmentally extended multi-regional input output analysis: food**

165   **waste prevention**

166   Input-Output (IO) analysis is a top-down approach to modelling the complex

167   interdependencies of industries within an economy (Leontief, 1936). IO tables are

168   widely applied to link economic sectors with producers and customers to understand

169   the interactions and impacts of economic activities (Leontief, 1951a, 1951b; Miller

170   and Blair, 2009). Exiobase V2 is a high-resolution database used for the Multi-

171   Regional Input-Output (MRIO) model in this study (Wood et al., 2015). The database

172   provides data at an unprecedented level of consistent detail in terms of sectors,

173   products, emissions and resources and covers 43 countries, which together account

174   for approximately 89% of global gross domestic product and 80-90 % of the trade

175   flow by value within Europe (Stadler et al., 2014; Tukker et al., 2014).

176   In order to integrate the monetary value of potential savings made by preventing

177   food waste with the Exiobase database, the following steps were taken: (i) food

178   prices, listed in Table 2, were converted from the British pound (£) to Euro (€) using

179   the purchasing power parity index (World Bank, 2015); [ii] the data was then

180   adjusted to the Exiobase base year (i.e. 2007) in order to take into account inflation

181   using the UK consumer price index (ONS, 2013); [iii] the data reported in purchase

182   prices was then converted into basic prices using a conversion ratio in order to

183   respect margins, taxes and subsidies on products (Appendix A); [iv] a concordance

184   matrix was used to map monetary data onto the Exiobase's structure format

185   (Appendix B); and [v] the data was disaggregated to account for food imports by

186   using existing food import weighting coefficients from Exiobase (Appendix C).

187   Table 2   The functional unit of the study: 1 tonne of UK household food waste
188 (with an approximate economic value of GB £1870) disaggregated into three stream
189 categories (i.e. unavoidable, possibly avoidable and avoidable). The functional unit is
190 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.

191   **2.3   Modelling the rebound effect**

192 The microeconomic rebound effect consists of a direct and indirect effect: the direct

193 effect is related to the additional demand for the product that has been subject to

194 an efficiency improvement (i.e. additional demand for some categories of food,

195 where the efficiency improvement is an increase in the ratio between the food

196 purchased and consumed), whereas the indirect effect refers to the additional

197 demand in all other consumption categories (Font Vivanco et al., 2016). The rebound

198 effect was quantified using a single re-spending model in which all consumption

199 categories were treated equally (Murray, 2013). This approach achieves

200 methodological consistency at the expense of differentiation between the direct and

201 the indirect effect (for examples of the latter, see the works of Freire-González

202 (2011), Thomas and Azevedo (2013) and Font Vivanco and van der Voet (2014)).We

203 specifically estimate how freed effective income (FEI) was spent by calculating the

204 marginal budget shares (MBS) for each consumption category *i*. The MBS were

205   calculated using a linear specification of an Almost Ideal Demand System (AIDS), a

206   demand system model developed by (Deaton and Muellbauer, 1980) with properties

207   that makes it preferable to competing models (Chitnis and Sorrell, 2015; Deaton and

208   Muellbauer, 1980). For instance, compared with other approaches based on

209   expenditure elasticities or Engel curves (Chitnis et al., 2013, 2014; Font Vivanco et

210   al., 2014; Murray, 2013), the AIDS allows for a more accurate estimation of the pure

211   income effect (changes in expenditure due to changes in effective income), as the

212   substitution effect (changes in expenditure due to changes in relative prices) is

213   corrected by means of a price index. In a budget share (w) form, the AIDS model for

214   the ith consumption category and a given time period t is expressed as:

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

215   where n is the number of consumption categories, x is total expenditures, P is

216   defined here as the Stone's price index, p is the price of a given category and α, β

217   and γ are the unknown parameters. The Stone's price index is defined as:

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

218   Additionally, and in order to comply with consumer demand theory, three

219   constraints are imposed: adding-up, homogeneity and symmetry (Deaton and

220   Muellbauer, 1980). The microeconomic rebound effect in demand units (r_d) is

221   defined as:

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

222   where s is the total economic savings.

223   Data on the final consumption expenditure of households and price indices for

224   Classification of Individual Consumption According to Purpose (COICOP) 3 digit

225   categories for the UK and the period 2004-2013 were obtained from Eurostat

226   (2016a, 2016b). In order to harmonise product categories reported by the COICOP 3

227 digit (*i*) and Exiobase databases (*j*), we used the approach from Koning and Xingyu,

228 (2016), which derives transformation tables describing how COICOP categories are

229 distributed over Exiobase categories. We specifically used household expenditure

230 data to give weights to cases where a given COICOP category is distributed over

231 multiple Exiobase categories. The marginal budget shares of UK household

232 expenditure are listed in Appendix H in both Exiobase and COICOP formats.

233 The modelling of the rebound effect entails a high level of uncertainty. When

234 people save money from purchasing less food, it is difficult to determine exactly how

235 they will spend this surplus. We therefore modeled five scenarios of rebound

236 spending, listed in Table 3, that were developed based on a literature review

237 (Appendix D). The first scenario, the behavior-as-usual scenario (R-1), is based on the

238 methodology discussed above to allocate free effective income to all consumption

239 categories.

240 Two sub-scenarios were also considered to investigate the level of uncertainty in

241 MBS estimates. In these scenarios, the re-spend of the FEI is limited to Major

242 Consumption Categories (MCC), a list of 25 expenditure categories which together

243 constitute more than 88% of spending (i.e., categories with the highest MBS, see

244 Table H.3). This approach has been applied in order to obtain more conservative and

245 realistic results than those founded in previous modeling approaches which assume

246 that the FEI is re-spent on services with the highest or lowest GHG-intensities,

247 regardless of the EFI value (e.g., Martinez-Sanchez et al. 2016). In the major

248 spending-high scenario (R-1A), FEI spending occurs within the 15 categories of MCCs

249 with the highest GHG intensities while FEI is re-allocated to the 15 categories of

250 MCCs with the highest MBS in the major spending-low scenario (R-1B). Appendix I

251 lists the 15 categories considered in both scenarios.

252 The second part of the sensitivity analysis is based on the observation made by

253 WRAP, that people tend to spend 50% of FEI on the purchase of higher quality food

254 products (WRAP, 2014). Examples of food up-trade include buying locally-produced

255 organic agricultural products, higher-quality meat or switching between food types

256 (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).

276 Table 4   GHG emissions from food waste management as total food waste (kg
277 CO_2-eq. per tonne food waste) divided on streams and rebound effect. Negative
278 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.

279 Hotspot analysis, depicted in Figure 2, shows that most of the reported

280 environmental benefits are due to the avoidance of food production: 83.5% for the

281 partial reduction scenario and 76% for the total reduction scenario. These findings

282 confirm the results of other studies which recognise the importance of savings made

283 in the production stage (Bernstad and Andersson, 2015; Gentil et al., 2011; Martinez-

284 Sanchez et al., 2016). GHG savings from avoided food production are estimated in all

285 industries across the entire supply chain, from fertilizers to iron and steel inputs

286 (Table 5). Most of the savings result from avoided fertiliser and energy use; N-

287 fertiliser production and coal-based electricity generation contribute to the overall

288 reduction by 25% and 20% respectively.

289 < INSERT Figure 2 here>

290 Table 5   Hotspot analysis for GHG savings from the avoided production of
291 food, as food waste is reduced. Categories reported are Exiobase Industrial
292 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

293   The second largest contributor to GHG savings is food-related household activities

294   (e.g., grocery shopping transportation, food storage and preparation). These

295   activities contribute to GHG reductions by 16.5% and 24% for the partial-reduction

296   and total-reduction scenarios respectively. These estimations are based on limited

297   estimates in literature and are only indicative; the greenhouse gas footprint of food-

298   related household activities is likely to vary substantially. Gruber et al. (2014), for

299   example, estimate that between 0.7 - and 2.1 MJ of electricity is needed to cook 1 kg

300   of rice or potatoes, depending on individual household behaviour.

301   Overall, the combination of GHG savings in food production and related

302   household activities leads to a large potential GHG reduction, ranging from 1138-

303   1419 kg CO_2-eq. per tonne of food waste prevented (Table 4). However, these

304   benefits are reduced by 23-59% due to the impact of the rebound effect, which

305   reduces GHG reductions by between 483 and 1095 kg CO_2-eq. per tonne of food

306   waste. This study quantitatively confirms the significant impact of the rebound effect

307   in reducing environmental benefits associated with food waste prevention

308   (Druckman et al., 2011; Martinez-Sanchez et al., 2016). A further discussion

309   regarding the impact of the rebound effect and the sensitivity of our results is

310   covered in section 3.4.

311   With regards to the baseline-scenario where 1 tonne of food is wasted and sent

312   for anaerobic digestion, -89 kg CO_2-eq. is the net-environmental benefit associated

313   with the treatment of 1 tonne of food waste. The analysis results confirm those of

314   other studies and identify energy recovery and the use of digestate as processes

315   with the highest contribution to these savings (Bernstad Saraiva Schott et al., 2016).

316   Energy recovery and digestate lead to GHG reductions of 185.5 and 4.6 kg CO_2-eq.

317   per tonne of food waste respectively. Contrastingly, the main environmental

318   burdens for AD arise from the digestion process and the use of auxiliary materials

319   required to operate the facility (Salemdeeb et al., 2016), whilst food waste collection

320   and transportation has a less significant impact: 11 kg CO_2-eq. per tonne of food

321   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

351 MRIO model would then combine the advantages of IO analysis to cover the global

352 food supply chain and the advantage of process-based LCA to use up-to-date and

353 high-resolution environmental intensities.

354   Another possible limitation is associated with the approach adopted to convert

355 economic benefits of food waste prevention from purchase prices into basic prices

356 (the format of data in Exiobase). Conversion factors used in this study are derived

357 from the 2010 UK Supply and Use table by deducting both distributors' trading

358 margins and allowing fewer subsidies on products from purchase prices (ONS, 2012).

359 Therefore, the accuracy of conversion factors depends on the quality of the data and

360 methodology used to compile the 2010 UK Supply and Use table. In addition and due

361 to the high level of aggregation in the Supply and Use table, an assumption was

362 made to allocate the same conversion factor into similar food categories: vegetables

363 and fruits, bakery and cakes, and meals and staple food (Appendix A).

364 **3.2   Rebound effect**

365 Results of the sensitivity analysis show a high level of uncertainty associated with the

366 rebound effect, with the reduction in GHG savings ranging from 23-59% (Table 4 and

367 error bars in Figure 5a). The upper limit (R-1A), representing the major spending-

368 high scenario, is a result of re-spending savings on GHG-intensive categories such as

369 wholesale trade, motor gasoline, petroleum and air transport services. The lower

370 limit, representing the major spending-low scenario (R-1B), is a result of re-spending

371 the freed effective income on less GHG intensive categories such as education

372 services, real estate services and communication services.

373   The second part of the sensitivity analysis investigated the effect of switching

374 from conventional to quality-oriented food products (Up-trade scenarios, see Table 3

375 and Figure 5b). The use of the same Exiobase GHG intensities (scenario R-2A) results

376 in a small increase (3.5%). The low increase estimated in scenario R-2A could be

377 explained by two factors: 50% of the re-spending occurs in food product categories

378 that are considered low-GHG categories (Druckman et al., 2011), and the assumption

379 that GHG intensities of quality oriented products increase in the same way as paying

16

380 a higher price per functional unit (Girod and de Haan, 2010; Vringer and Blok, 1996).

381 For example, if the price of a quality-oriented product is twice that of its

382 conventional counterpart, then the environmental burden associated with it would

383 double.

384   The final sensitivity analysis scenario takes into account variations in GHG-

385 intensities between quality oriented and conventional food products as discussed in

386 Appendix D&G. Since up-traded goods often have a higher GHG intensity, we find

387 that switching to quality-oriented products increases the size of the rebound effect

388 by 19.5% and, consequently, reduces food waste prevention benefits (Figure 5b).

389 Examples of higher impact and higher value products include organic products,

390 (which have lower yields than conventional products) boneless meat, (which

391 requires additional energy input in the food production process) and the use of

392 premium packaging.

393   <mark>< INSERT Figure 5 here></mark>

394   Several peer-reviewed studies have investigated the impact of the rebound effect

395 in food waste prevention activities or a similar context (Alfredsson, 2004; Druckman

396 et al., 2011; Martinez-Sanchez et al., 2016). Martinez-Sanchez and her colleagues

397 took an environmental life-cycle costing approach to evaluating the impact of the

398 rebound effect in food waste prevention activities in Denmark. Their study also

399 found a large rebound effect – in fact much larger than that of our study (1528-4367

400 kg CO_2-eq. per tonne of food waste; 2-5 times higher than results reported in this

401 study). Their findings suggest that the rebound effect could even exceed the GHG

402 savings from avoiding food waste, a phenomenon known as "backfire", where

403 reducing food waste might actually increase GHG emissions. The large difference

404 between our estimates and theirs is attributable to various factors: (i) Martinez-

405 Sanchez et al. use a highly aggregated economic model, combining all industrial

406 sectors into 9 categories; (ii) Consumer expenditure surveys are used in Martinez-

407 Sanchez's study to allocate savings from consumption categories; and (iii) Martinez-

408 Sanchez et al. investigate extreme scenarios for the rebound effect, including

409 allocating 100% of the respend to the sector with the highest environmental impact,

410   namely "Household use, Hygiene". Sectorial aggregation is a known source of bias in

411   the input-output literature (Moran and Wood, 2014; Su et al., 2010), and our results

412   may indicate that higher disaggregation leads to lower overall GHG emissions for our

413   case study. Our model of the rebound effect also combines expenditure and cross-

414   price elasticity (section 2.3), which may lend more weight to low GHG-intensive

415   consumption categories compared to simpler models. Finally, our sensitivity analysis

416   for the rebound effect is constrained so that it more closely resembles current

417   household spending. Despite these differences, the potentially large rebound effect

418   reported here as well as in similar studies reveals the limitation of behavioural

419   interventions, such as reducing food waste to reduce greenhouse gas emissions

420   (Martinez-Sanchez et al., 2016). To reduce rebound effects and deliver effective GHG

421   savings, behavioural change must be coupled with economy-wide reductions in GHG

422   intensity (Alfredsson, 2004; Druckman et al., 2011; David Font Vivanco et al., 2016).

423   **3.3   Comparison with previous studies**

424   The results of this study agree with main conclusion of other studies: food waste

425   prevention lead to substantial reductions in GHG. Nevertheless, the magnitude of

426   GHG reduction reported in this study is less than those reported in the literature as

427   shown in Figure (6). Differences arise primarily due to the aggregated nature of the

428   method (as discussed above, see section 3.1). In addition, the study scenarios take

429   into consideration the unavoided fraction of food waste (40% in the partial reduction

430   scenario and 23% in the total reduction scenarios) which is sent to anaerobic

431   digestion, leading to lower GHG reductions than if we had assumed that the total

432   functional unit (1 tonne of food waste) was preventable. More importantly (as

433   discussed in Section 3.2), the inclusion of the rebound effect has also contributed

434   significantly to the reduction in reported results: 25-59% for the partial-reduction

435   scenario and 23-56 for the total-reduction scenario.

436   < INSERT Figure 6 here>

4 Conclusions

437

438 This paper presents a holistic model of food waste prevention, combining

439 conventional process-based LCA and top-down input-output-based approaches that

440 include GHG emissions in the international supply chain and the rebound effect. We

441 find that GHG savings range from 700-888 kg CO_2-eq. per tonne of food waste. These

442 emissions are relatively lower than others reported in the literature, partly due to

443 the inclusion of the rebound effect, which reduces GHG benefits by up to 59%.

444 Overall, our findings indicate that the environmental benefits associated with food

445 waste prevention interventions, such as the "love food hate waste" campaign in the

446 UK (WRAP, 2013), could be partially undermined by rebound spending. Efforts to

447 reduce the impact of food waste must explicitly consider rebound effects as

448 ultimately, to effectively deliver GHG reductions, behavioural change, such as food

449 waste reduction, must be coupled with reductions in GHG emissions across the

450 economy.

451 Furthermore, this study provides the first comprehensive assessment of food

452 waste prevention that includes impacts associated with food imports. It highlights

453 the importance of adopting a top-down, multi-disciplinary, and system-wide

454 approach in order to deal with the complexity of the food supply chain that extends

455 beyond geographical borders and across various industries. The findings of this

456 research have provided a further insight into our understanding of the

457 environmental impacts of globalised food production, particularly in developing

458 countries.

5 Acknowledgements

459

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462

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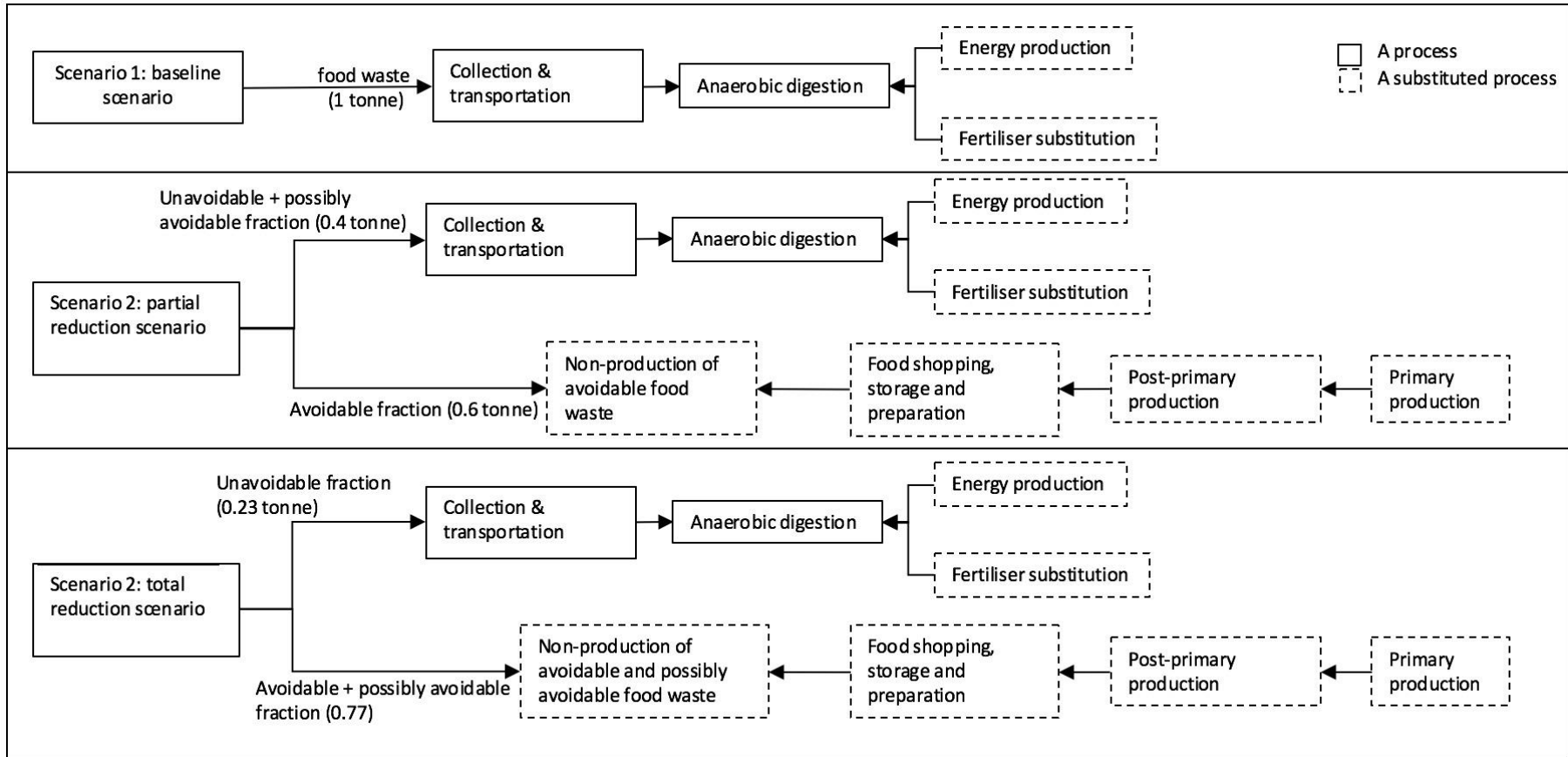633   Resources Action Programme, Banbury, Oxon.

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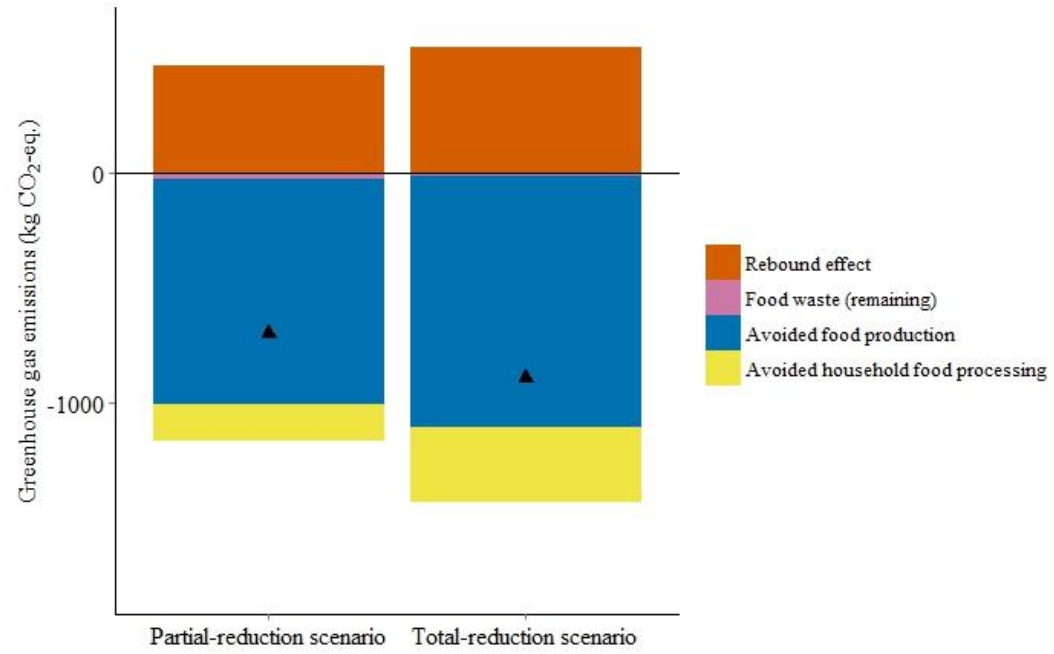
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Figures

639   Figure 1
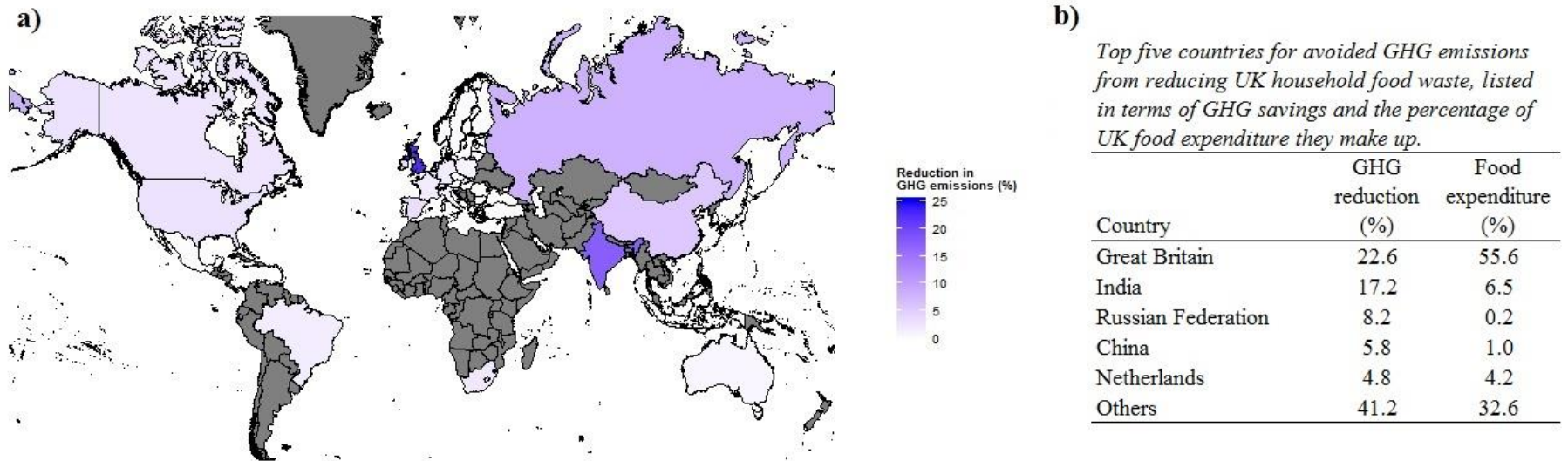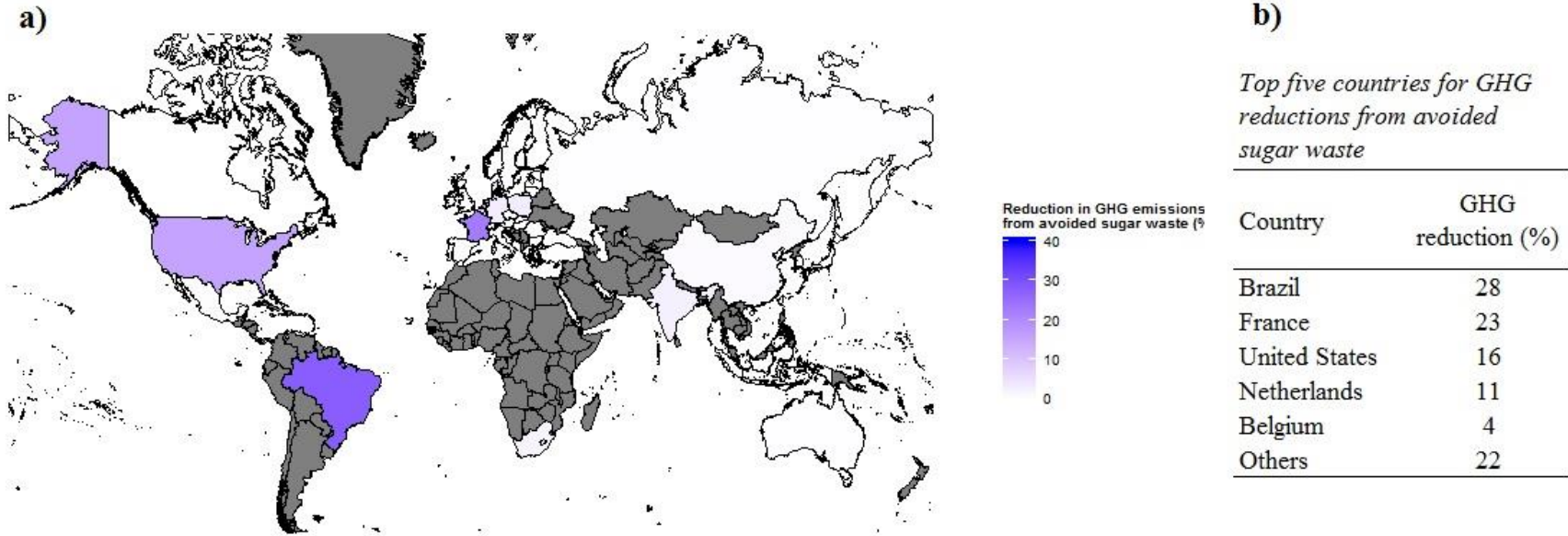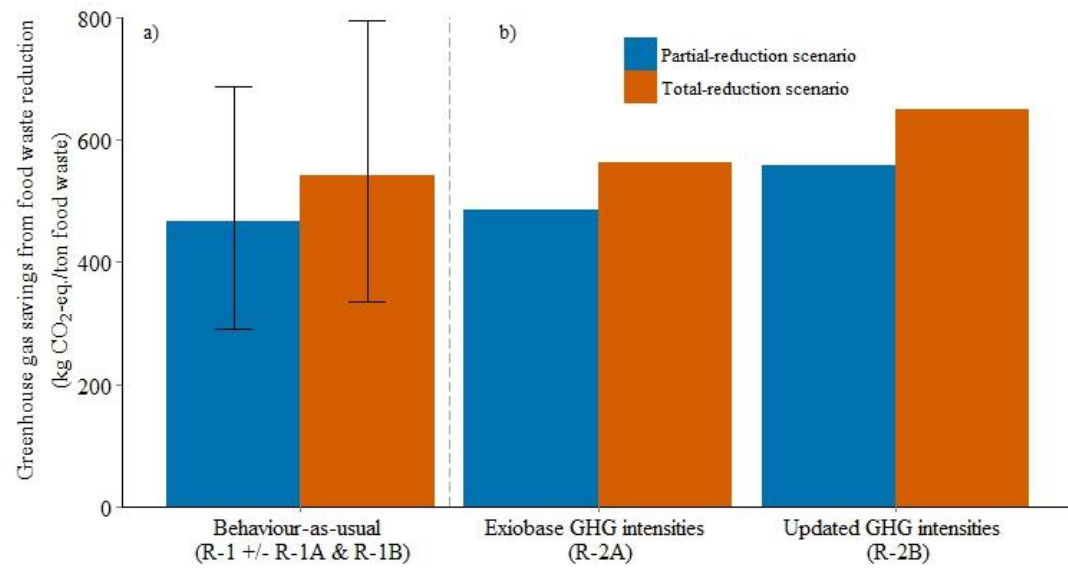
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641

Figure 2

643

a)

Reduction in GHG emissions (%)

- 25
- 20
- 15
- 10
- 5
- 0

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

644

645   Figure 3

a)

Reduction in GHG emissions from avoided sugar waste (%)

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

646

647 Figure 4

648

649

650   Figure 5

651

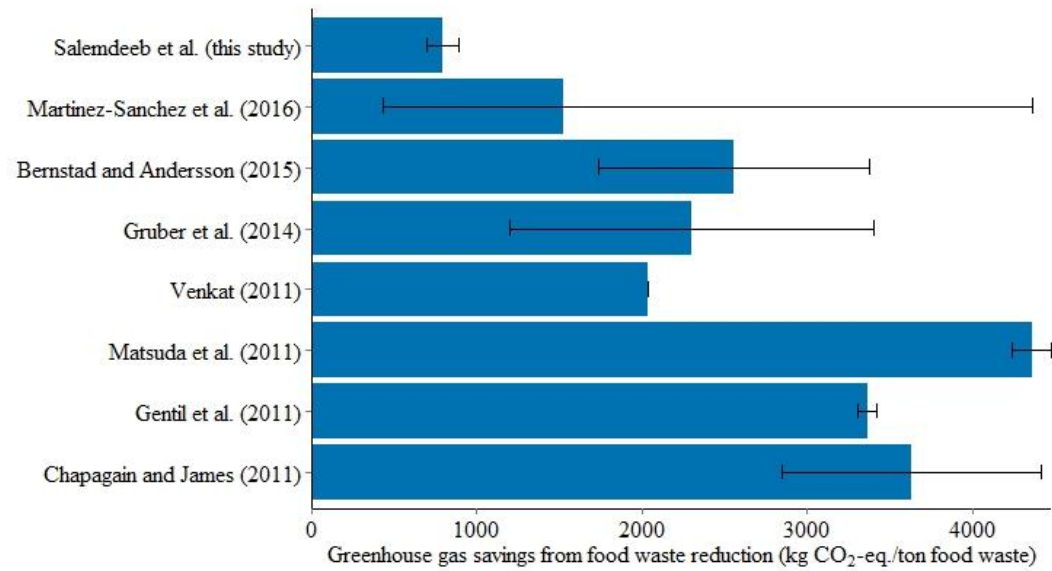Greenhouse gas savings from food waste reduction (kg CO_2-eq./ton food waste)

652

653   Figure 6

654

655   Figures Captions

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

662

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

665

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

671

672   Figure 4 Sources of GHG savings for the avoidance of sugar waste, both from sugar
673   beet and sugar cane. Countries shaded in grey have no data available. A detailed
674   contribution analysis of GHG emissions, disaggregated by industrial sectors and
675   geographical sources, is provided in Appendix J.
676

677

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

685

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

688