A ranking method for prioritising retail store food waste based on monetary and environmental impacts

Abstract

Food waste has become a major concern globally, leading to high economic, environmental and social awareness, as well as inclusion in international policy documents. In the developed world, the retail stage has the greatest potential for waste reduction as it balances demand with supply, stimulates demand (thus affecting waste at the consumer level) and sets standards to the supply and the products (thus affecting food loss upstream). To precisely direct managerial intervention towards products with high waste-mitigation potential, the waste impact needs to be quantified. Previous studies measuring waste have examined individual metrics exclusive of each other, which affects the ranking of products. The present study proposes a method for prioritising waste based on combined monetary and environmental indicators, and it demonstrates the applicability of the method through empirical data from Scandinavian retail stores. The contribution of the proposed metric is that it results in a unique score comprising economic and environmental impacts for every single product, thus directing the managerial intervention more precisely. In addition, it enables choosing a weight for the economic and the environmental indicators, thus adding to the previous literature that looks at the products either through an economic or environmental perspective, exclusive of each other. Applying the method confirmed the previous research at a product group level that bread, meat and fruits/vegetables are the highest wasters. In addition, for some products, such as meat and fruit, the dependency between economic and environmental impacts is weaker, whereas it is stronger for others (e.g. bread and biscuits), thereby necessitating a method to gauge waste in both dimensions.

Keywords: food waste, retail store, ranking method, monetary impact, environmental impact, managerial intervention

1. Introduction

Food waste is a major concern for the food industry, individual food companies and society due to the considerable negative economic, environmental and social impacts from such waste (Parfitt et al., 2010; Papargyropoulou et al., 2014). In the European Union (EU), about 88 million tonnes of food are wasted annually (Fusions, 2016), and globally, nearly 20%–30% of total food volume is discarded (Gustavsson et al., 2011). Food waste is an indicator of an unsustainable food system (Filimonau and Gherbin, 2017), which is why waste is one of the United Nations' sustainable development goals adopted in 2015 (eu-fusions.org) and part of the European Commission's 'Roadmap to a Resource-Efficient Europe' (EC, 2011).

Research on food waste has been growing consistently during the past decade (Chen et al., 2017). Several studies have raised awareness about the size of various waste fractions (Gustavsson and Stage, 2011; Lebersorger and Schneider, 2014) and the causes of such waste in the food supply chain (Mena et al., 2011, 2014; Papargyropoulou et al., 2014), which calls for managerial interventions for waste prevention (Parfitt et al., 2010; Filimonau and Gherbin, 2017). Waste occurs at all stages in the supply chain, but the retail stage has the greatest potential for waste reduction in the developed world (Parfitt et al., 2010) and is important in terms of waste prevention (Brancoli et al., 2017; Filimonau and Gherbin, 2017; Teller et al., 2018). First, in retail stores, the flexibility to redistribute food for alternative use is limited because little of the products' shelf life is left, and food waste is a net loss on a store's ledger (Kiil et al., 2018). Second, the accumulated environmental (Banasik et al., 2017) and monetary (Alexander and Smaje, 2008; Eriksson et al., 2016) impacts of waste from previous stages are larger in stores compared with earlier supply chain stages. Third, stores act as buffer stocks, where supply meets consumer demand (Eriksson et al., 2012), and managerial interventions are critical to balance product availability (avoiding lost sales and the risk of losing customers) with overstocking (avoiding the risk of causing waste due to products' shelf lives expiring) (Shukla and Jharkharia, 2013; Lee, 2018).

Managerial interventions avoiding waste depend on how waste is measured and analysed (Brancoli et al., 2017). Most waste analyses come from studies ranking waste by mass dimensions based on aggregated data (Gustavsson and Stage, 2011; Katajajuuri et al., 2014), with recent literature considering the monetary (Cicatiello et al., 2016; Brancoli et al., 2017), environmental (Alexander and Smaje, 2008; Papargyropoulou et al., 2014) and social (Cicatiello et al., 2016) impacts of waste. However, the retail sector has received relatively little attention (Filimonau and Gherbin, 2017), with few studies considering multiple indicators of waste exclusive of each other (Scholz et al., 2015; Brancoli et al., 2017), including environmental metrics. Those studies identify products or product groups that are critical from a monetary or an environmental perspective, dividing managerial intervention between different dimensions at a product group level. Corresponding to the triple bottom line perspective (Elkington, 2004), there is a need for identifying products with the highest combined (monetary-environmental-social) waste-mitigation potential. In addition, the existing studies quantify waste in a certain context (country, region, retail chain) without explicitly proposing a generic method for waste prioritisation. Therefore, the present study aims to propose a method for prioritising food waste based on combined monetary and environmental indicators and to propose a tool applicable for waste mitigation by store and warehouse managers.

This paper contributes to knowledge by a multidimensional ranking method and metric for identifying products that take the highest economic and environmental toll on food retailers through waste. The applicability of the method is demonstrated on empirical data covering 211 frequently wasted products from 12 Scandinavian retail stores. Using correlation analysis, the dependency between economic and environmental impacts is shown to be stronger for some products (e.g. bread and biscuits) and weaker for others (e.g. fruits and vegetables), thereby necessitating a method to gauge waste in both dimensions. In contrast with other food-retailing studies (Scholz et al., 2015; Brancoli et al., 2017), the present study does not break down food waste into various single types of secondary waste (e.g. energy and feed) but rather combines economic and environmental factors to generate a waste ranking for making informed and efficient decisions. Contrasting other studies, the aim is not to analyse waste by product type but to identify individual products that should be targeted for waste reduction.

The remainder of this paper is organised as follows: section 2 provides an overview of representative literature dealing with waste quantification in retail stores; the research design is described in section 3; in sections 4 and 5, a ranking method and tool for prioritising food waste is proposed and applied in a case; and in sections 6 and 7, the results are presented and discussed in relation to extant literature.

2. Theoretical background

Striving to generate more precise estimates of retail food waste is a basis for identifying the areas with the largest mitigation potential (Filimonau and Gherbin, 2017). Therefore, this section provides a brief review of representative retail food-waste quantification literature (summarised in Table 1). The previous research, which differed according to the *definition and categorisation of waste*, *data* used in the analysis and *metrics* used for waste quantification and prioritisation, will be further examined.

A common aspect of *waste definitions* is that waste is an object intended for sale and consumption that has been discarded; it is a result of human action or inaction (e.g. incorrect storage or over-purchasing), or of decisions made by consumers, supply chain actors and other stakeholders (Buzby and Hyman, 2012). In contrast, *food loss* (Cicatiello et al., 2016) is a result of natural conditions, such as qualitative drop from decomposition or weather damage. Despite this differentiation, the terms 'waste' and 'loss' often were used interchangeably (Lebersorger and Schneider, 2014), but a distinction between food-waste terms is essential for a more sustainable approach for addressing food waste (Papargyropoulou et al., 2014). Further distinction in food-waste categorisation has been made, such as (a) system boundaries (Eriksson et al., 2012), which defines pre- and in-store waste, respectively; (b) the immediate cause of product discarding (Lebersorger and Schneider, 2014), e.g. 'best before' date expiration; (c) product edibility (Ciciatiello et al., 2016, 2017), e.g. not suited for retail but still edible; and (d) recorded vs. non-recorded waste (Eriksson et al, 2012, 2014; Cicaitello et al., 2017). It should be noted that a

higher specification of waste categories is possible at the expense of additional data collection at the stores. This higher specification will contribute to more reliable data, which is a key foundation for planning, evaluation and identification of well-founded waste prevention (Lebersorger and Scneider, 2014).

The *data* used for waste quantification differs across papers (Table 1) and can be broken down as mass or quantity (kg, tonnes or litres), amount (number of items) and monetary cost (price that the store paid to procure the item). Depending on waste categorisation, most of the data already existed in the companies. In rare cases, data was gathered by the researchers, as when evaluating recorded vs. non-recorded waste in Eriksson et al. (2012). This indicates that the retailers were at some level of awareness by gathering different types of data, such as in-store waste, pre-store waste and even edible fractions of waste. The aggregation level of the basic data differed with the most detailed data reported at stock-keeping unit (SKU)/day. From there, the level of aggregation increased towards the product-group or store-category level and to different time periods (week, month or year). Some studies focused solely on fresh fruits and vegetables (Gustavsson and Stage, 2011; Eriksson et al., 2012), while others expanded their focus to include meat, deli, cheese and dairy, and bread products. Because, in most of the reviewed papers, the purpose of the quantification was to facilitate direction for waste minimisation, the products chosen for the analysis were those with the highest frequency and amounts of waste, covering about 50% of the total waste (Brancoli et al., 2017) or 55% of the total sales area (Cicatiello et al., 2017).

Different waste *metrics* have been used in extant literature, covering quantity-related, monetary, environmental and social impacts from waste (Table 1). Predominant waste analyses focus on waste *quantity*, mass or volume. Some of the papers looked at the mass of waste in proportion to the mass of total sales, i.e. waste quotient (Gustavsson and Stage, 2011; Eriksson et al., 2012; Eriksson et al., 2014; Lebersorger and Schneider, 2014; Mena et al., 2014). The waste quotient alone might not be a sufficient indicator of waste, but Eriksson et al. (2012) additionally considered the quantity of waste per product, finding that products with the largest quantities of waste (e.g. grapes and lettuce) have a much lower waste quotient (2.1) than products such as tamarillos or red currants, which have a very high waste quotient (57) but generate significantly less waste, indicating the impact of the product's relative volume. A group of studies examined a product's (category) share of waste mass out of total waste mass (Scholz et al., 2015; Brancoli et al., 2017) and different products' share of waste mass out of total waste in their own product categories (Scholz et al., 2015). Cicatiello et al. (2016) examined the edible parts of waste and measured it through tonnes of waste recovered in total per month and per product category.

More recent articles focused on exploring the *environmental* impact of store waste, either through greenhouse gas emissions (Scholz et al., 2015; Brancoli et al., 2017) or through the resources used to produce wasted food (Cicatiello et al., 2016). Scholz et al. (2015) defined the carbon footprint (CF) measure of waste as emissions associated with production, distribution and delivery to supermarkets, multiplied by the total mass wasted in stores. This measure was used to analyse the share of product-category waste CF relative to the total waste CF, as well as individual products' waste CF share relative to the total waste CF of the respective category. Scholz et al. (2015) identified a clear difference in prioritisation of products depending on wasted mass vs. carbon-footprint waste, thus suggesting that analysing food waste in terms of both wasted mass and wastage CF is a better basis for identifying priority targets for waste reduction. In addition to CF (expressed through $kgCO_2$ equivalent, or $kgCO_2e$), Brancoli et al. (2017) considered additional environmental indicators, such as ozone depletion, and found that beef affected six of the environmental indicators, while bread heavily impacted three of the indicators. Cicatiello et al. (2016) examined the environmental aspects of recovered products through water and ecological footprints (global square metres) per product category per year. They found that related to quantity, recovery of bread gave the highest positive results, while recovery of meat led to a higher environmental value.

Economic losses caused by waste are important for motivating change in the retail sector (Brancoli et al., 2017). Several studies analysed the relative contribution of the cost of waste to the cost of total products sold (Eriksson et al., 2012; Lebersorger and Schneider, 2014) or to the cost of total waste (Brancoli et al., 2017). These studies point out that reduced economical loss for the retailer (by having a possibility to return the products to the

supplier) actually does not stimulate reduction of waste and increases the environmental loss in the chain, exposing a need for looking jointly at the economic and environmental aspects of the waste.

The *social aspects* of the waste were studied in situations where retailers were recovering the edible fraction of waste for human consumption. Cicatiello et al. (2016) examined the social indicators of waste by measuring the social value of recovered products through the number of portions per dishes per year and the mass of product per dish. Lebersorger and Schneider (2014) analysed the impact of share donations on total food loss.

The studies that examined several waste indicators concurrently ended up with different prioritisation of products, depending on the parameters they examined. For example, when looking at the relative contribution of waste cost per product category compared with the total cost of waste, Brancoli et al. (2017) found that bread had the highest, followed by pork. Bread also had the highest contribution, followed by vegetables, when looking at mass, but concerning environmental factors, beef had the highest contribution, followed by bread. Similarly, Eriksson et al. (2012) found that mass- and economic-based quotients emphasise different kinds of products as critical.

The literature review pointed out that the quantity/mass-related analyses of waste are still dominating, followed by the economic analyses. In response to the external and internal drivers, the grocery retail sector in developed countries is increasingly committing to enhancing its environmental credentials (Filimonau and Gherbin, 2017). Food donation practices could be high on the agenda in some countries, but this practice is still irregular and on an ad hoc basis (Filimonau and Gherbin, 2017), which prevents building a systematic account of this aspect. Even though there is an increasing focus on considering different perspectives on waste impact, and the resulting prioritisation of products highly depends on the focus of the analysis (mass, monetary, environmental or social), there is no existing literature, to the best of our knowledge, that introduces waste measures based on more than one perspective. In addition, no study has proposed a generic method for waste prioritisation.

Table 1
Waste definition, data and metrics for waste analysis

Author	Waste definition/categories	Basic data; period of data; unit of analysis; products considered	Metrics of store food waste			
			Quantity/mass	Economic	Environmental	Social
Brancoli et al. (2017)	In-store products unsaleable due to defects or expired shelf life	Quantity or weight of product/article/day Purchase cost of the wasted product and disposal costs; 1 year; 1 store; 12 product categories with high frequency and large amounts of waste, covering 50% of the total waste (meat, fruits and vegetables, bread)	Relative product-category waste mass [%]	Relative product-category waste cost [%]	Relative product category environmental waste [%] Relative contribution of product's waste fraction on nine environmental impact factors	NA
Cicaitello et al. (2017)	Food waste in stores, edible, inedible, recorded and unrecorded	Quantity discarded and retail cost; 1 year; 1 hypermarket; 11 food departments (covering 55% of total sales area)	Extent of total waste and edible fraction/department [kg] Fraction of edible from the total waste per department [%]	Value of total waste and edible fraction [EUR]	NA	NA
Cicatiello et al. (2016)	Food waste in stores (result of damaged packaging, incorrect storage, etc.) Focus on the edible part of waste	Quantity and buying price of recovered food item daily; 1 year, 1 supermarket; 12 product categories (fruits and vegetables, meat, dairy, etc.)	Quantity of total food recovered/month - Quantity of food recovered/product category/year	Economic value of total food recovered [retail price of recovered items in euro/month]	(Just for meat and bread) Water footprint/product category or/year Ecological footprint per product category or per year	Social value [quantity recovered in kg/dish/year] Social value [nr. of portions/dishes/year]
Eriksson et al. (2016)	Products in store considered unsaleable (expired best-before or use-by date)	Number of items wasted and purchase cost per product (984 products), shelf life, pack size; 2 years; 6 stores; cheese, dairy, deli, meat	Mass of waste per product	NA	CF per products = nr. or wasted items*mass per product*CF value per product	
Scholz et al. (2015)	(In-store waste) Products unsaleable due to passed best-before date, damage or colour change (Pre-store waste) CF of the mass of wasted products from production up to delivery to the store	Wasted mass/product/daily in stores; 3 years; 6 stores; meat, deli, cheese, dairy, fruits and vegetables	Share of wasted mass [%] of product subgroup as a share of product group	NA	Wastage CF = emissions associated with production and distribution * total mass wasted in store/product group/3 years Share of wastage CF per product subgroup [%] as share of department	
Mena et al. (2014)	Any substance or object the holder discards, intends to discard or is required to discard	% of wasted product/year/by product (and by function) Tonnage of wasted product/year/product (and by function) Tonnage of packaging waste Supply network (6 retailers); fruits and vegetables (11 products), meat (4 product groups)	% of waste of total volume (weight)/product group per different stage of supply network	NA	NA	NA
Lebersorger and Schneider (2014)	Food loss (total quantity of articles neither sold nor returned and those transferred to social services)	Mass and cost price per SKU level/per outlet/ per month; 1 year; 612 stores from 1 retail company; fruits and vegetables, dairy, bread and pastry	Food-loss rate by mass [%] = food-loss [quantity]/sales [quantity] per assortment group	Food-loss rate by value [%] = food-loss [cost price]/sales [cost price] per assortment group, per month	NA	Donations (% of food loss by value) [%]

Eriksson et al. 2014	Products subject to rejection on delivery (pre-store), products deteriorated or exceeded best-before date (in store) (recorded and unrecorded)	Total amount of pre-store waste [number of items]/item/year Total in-store waste [number of items]/item/week Total sold[number of items]/item/week; 2 years; 6 stores from1 retail chain; deli, meat, dairy and cheese departments	Waste quotient Q [%] = W/(TW + S) per product or per department (In-store waste mass (W), pre-store and in-store waste mass (TW), mass of sold products (S))	NA	NA	NA
Eriksson et al. 2012	Products subject to rejection on delivery (pre-store), products deteriorated or exceeded best-before date (in store) (recorded and unrecorded)	Mass of waste [mass/article/day]; 1 year; 6 stores from 1 retail chain; fresh fruits and vegetables	Weight of waste; Waste quotient [%] = Waste/amounts delivered	Economical in-store waste quota [%] = value of total waste per year/value of total sold per year	NA	NA
Gustavsson and Stage (2011)	Items considered unsaleable and thus discarded	Annual quantity of waste and sales/product/store; 1 year; 9 stores from 1 retail chain; 16 products (fresh fruits and vegetables)	Waste proportion of total sale/product/year	NA	NA	NA

3. Research design

The present study aims to design a ranking method that can support stores in deciding which products or categories to prioritise based on combined monetary and environmental impacts. Thus, the research design was influenced by design science (Denyer et al., 2008; Holmström et al., 2009) consisting of three components: *design of a ranking method for prioritising food waste* (section 4), *method application (tool) through a case study* (sections 4 and 5), and *results* from deploying the method and tool on waste data (section 6). The method is designed to address the shortcomings of two common approaches for selecting products: *the cut-off limit method* and *the convex-combination method*. The former method has been applied successfully to product classification (Childerhouse et al., 2002), while the latter has proven beneficial for optimising trade-offs between different cost dimensions (Hedenstierna and Disney, 2016, 2018). A case study strategy (Yin, 2009) is preferable because data on food waste may be perceived as proprietary information by many companies, and the access to data through company systems, interviews and observations is critical.

4. Proposing a ranking method to prioritise food waste

The *cut-off limit method* is a conventional method for selecting products according to two features. The data is represented in a scatter plot, where each dimension corresponds to one feature. In the cut-off limit method, a threshold is selected for each of the dimensions, such that the acceptance region has a rectangular shape. This method applies to monetary and environmental waste (specifically $kgCO_2e$ waste in this study) as illustrated in Figure 1 by the upper-right square (region 3). Although intuitive and commonly used, this method only selects products above the predefined limits; it does not rank products or even guarantee that there will be n (any) products above the limit.
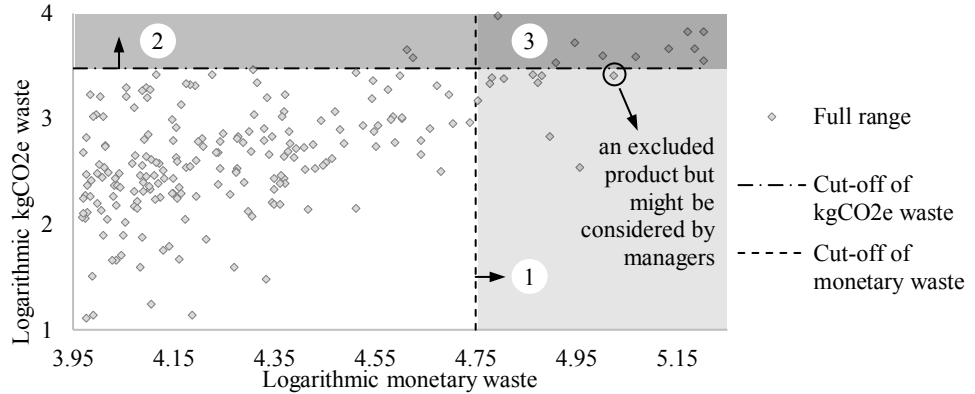

Fig. 1. Cut-off limit method for identifying and selecting heavy-waste products.

As shown in Figure 1, if the aim is to find the top 10 products according to the *cut-off limit method*, the monetary-impact dimension is examined first, a cut-off limit is set to obtain candidates (e.g. 4.75) and then candidates are arranged in descending order to obtain the top 10 waste products. The same procedure is followed for the environmental-impact dimension to identify environmentally impactful products. The two cut-off limits define the top-right square containing the environmental and monetary high-waste products. However, from Figure 1, high-waste products close to the cut-off limit are excluded by this method, but probably should not be ignored by managers because of the high monetary impact (e.g. the circled product in the figure).

The problem with the cut-off limit is that there is no single score to consistently rank the product. This is solved by using *convex combination* (Hedegaard, 2017), which assigns a score to each product and then selects the n most important ones. The score used for convex-combination ranking is

$$\text{Convex score} = \alpha \times \text{Monetary impact} + (1 - \alpha) \times \text{Environmental impact}, \tag{1}$$

in which $0 \leq \alpha \leq 1$ provides a manager's preference for economic savings, with $\alpha = 100\%$ representing purely economic concerns and $\alpha = 0\%$ representing purely environmental concerns. Returning to the scatter-plot

analogy, convex optimisation constrains the top *n* products to being above a line with negative slope. Compared with the previous method, although it does not have a cut-off point in a single dimension, convex combination has the downside of preference variable α being difficult to interpret unless the dimensions are similar in scale.

A major drawback of Eq. (1) is that it does not indicate when the typical values for one of the dimensions are significantly smaller than those for the other dimension. In that case, the score is not sensitive to the changes along dimensions with smaller values. This drawback is addressed by a *scaled ranking method,* where the score is defined as

$$\text{Exponential score} = \text{Monetary impact}^{\alpha} \times \text{Environmental impact}^{(1-\alpha)}. \tag{2}$$

The value of Eq. (2) is affected by both very small values and very large values. Because the products' waste are within a wide range, as shown in Figure 2(b), a logarithmic scale is preferred to visually separate products more clearly, especially to distinguish products with lower waste values. The ranking obtained by an exponential score is identical to the score obtained through convex combination. Thus, the same ranking can be obtained through convex combination after rescaling the variables:

$$\text{Log(Exponential score)} = \alpha \, \text{Log(Economic impact)} + (1-\alpha) \, \text{Log(Environmental impact)}. \tag{3}$$

Having been assigned a score for each product, the *n* products with the highest scores can be selected. Compared with the cut-off limit method, the scaled ranking method produces a hyperbola as the cut-off curve of the top *n* products, as shown in Figure 2(a). The hyperbola becomes a straight line because both the horizontal and vertical axes are in logarithmic scale. The three cut-off lines demonstrate the differences between the considerations of balancing environmental and monetary impact. When environmental impact is a priority, the cut-off line tends towards the horizontal, whereas monetary waste priorities make the cut-off line become more vertical. A balance between waste priorities produces a slope between them. This pattern naturally fits the single-dimension selection and enables users to choose with more flexibility. Compared with the cut-off limit method shown in Figure 1, the scaled ranking method offers a single score. Although the cut-off limit method always results in a rectangular region, here the transition is more flexible. Compared to the convex-score method (Eq. (1)), the proposed method results in a better balance between carbon and monetary waste, as shown in Figure 2(b). With $\alpha = 0.5$, i.e. monetary and environmental waste are considered equally, the convex-score method (dashed line) identifies product B to be outside the cut-off line but includes product A. On the other hand, with the proposed method, product A is outside the cut-off curve, and product B is inside.
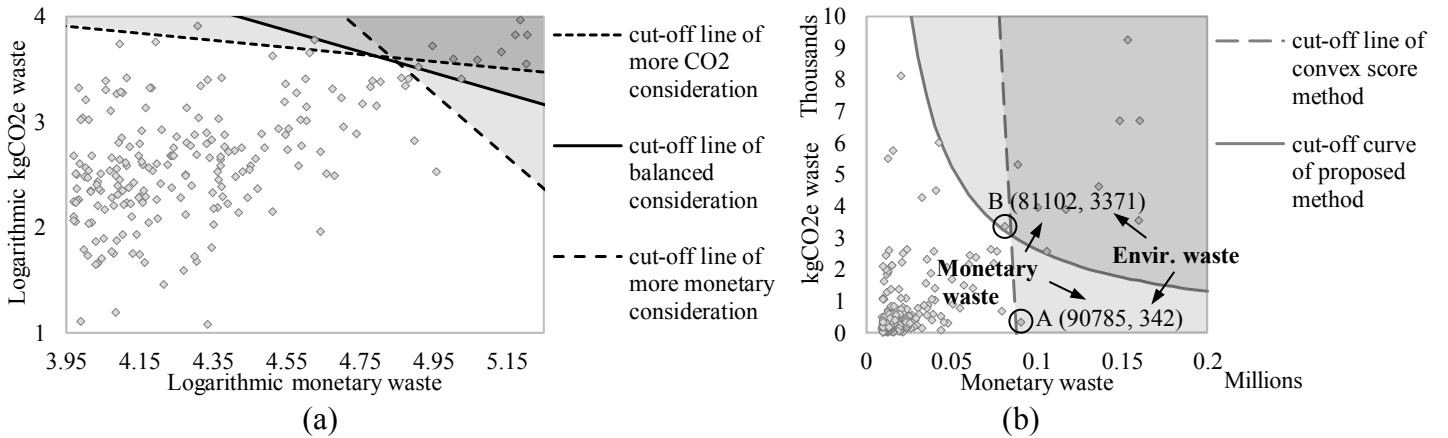

Fig. 2. High-waste product selection (a) based on the proposed method on a logarithmic scale; (b) comparison between the convex-combination method ($\alpha = 0.5$) and the proposed method ($\alpha = 0.5$) on a linear scale.

By the convex score method, $score(A) = 0.5 \times 90785 + 0.5 \times 342 = 45563$ is larger than $score(B) = 0.5 \times 81102 + 0.5 \times 3371 = 42236$, thereby A is prioritised. But by the proposed method, $score(A) = 90785^{0.5} \times 342^{0.5} = 5572$ is less than $score(B) = 81102^{0.5} \times 3371^{0.5} = 16534$, therefore, product B is prioritised.

Furthermore, the convex score method considers the values directly, termed as 'absolute waste' for simplicity. The weighted difference between values affects the product ranking, and the proposed method allows the more extreme values, either higher or lower, to affect the score. In other words, the scaled ranking method is sensitive to the 'relative waste'. In the preceding example, B has a higher score because, although the monetary waste decreases slightly, the environmental waste increases approximately 10 times compared to A.

Without loss of generality, the proposed method can be extended by appending new parameters, which represent new factors and weights, to Eq. (2), e.g.

$$\text{Score} = \left\{ \left[\text{Monetary impact}^{\alpha} \times \text{Environmental impact}^{(1-\alpha)}\right]^{\beta} \times Factor_3^{1-\beta} \right\}^{\gamma} \times Factor_4^{1-\gamma}, \quad (4)$$

where the summation of all weights is still 1, i.e.

$$\underbrace{\alpha\beta\gamma}_{weight_1} + \underbrace{(1-\alpha)\beta\gamma}_{weight_2} + \underbrace{(1-\beta)\gamma}_{weight_3} + \underbrace{(1-\gamma)}_{weight_4} = 1.$$

This allows users to consider more factors according to practical requirements from various perspectives.

Data collection and implementation of the scaled ranking method
Application of the scaled ranking method in a business setting requires a chain of activities to go from waste records in the enterprise resource planning (ERP) system to a useful ranking. Specific problems include data collection and data accuracy, identifying the environmental impact of waste and gaining organisational acceptance for the specific weighting (α) to be used. The process of turning raw data into a ranking is presented in Figure 3, with each step proceeding as follows:

1. *Determine steps for data capture and waste records accuracy.*
   Define standard procedures for registering waste, such as location, time, frequency, what to register and how to upload the data into the ERP system.
2. *Extract and clean information on wasted products from data warehouse.*
   For each SKU, product identifiers, product-group identifiers and waste data are extracted from the ERP system and cleaned to remove inaccuracies.
3. *Calculate the monetary impact of each selected product.*
   The monetary impact of each product is recovered by looking up the product cost (product identifier) and multiplying this by the units wasted.
4. *Calculate the environmental impact of each product with respect to wasted weight.*
   Using the product-group identifier, a lookup operation is used to identify the environmental waste per unit of weight for each product. This is multiplied by the weight to provide the total environmental waste for that product.
5. *Calculate the exponential score of each selected product with a specific α.*
   Calculate scores of products based on the proposed method with an α (0.5 by default) using Eqs.= (2) or (3), based on preference.
6. *Rank the products by score in descending order.*
   Sort the products in descending order based on scores.
7. *Visualise the ranking list for users to view top wasters.*
   Put the sorted products on a ranking table. Map the products in a two-dimensional scatter plot with monetary waste as the x-axis and environmental waste as the y-axis. A hyperbola is plotted as the cut-off limit curve of the top *n* wasters. Products are coloured based on their ranking.
8. *Adjust the α value until the users reach agreement on the monetary-environmental balance.*

Users change the α value to generate a new ranking table according to preferences for balancing monetary and carbon waste.
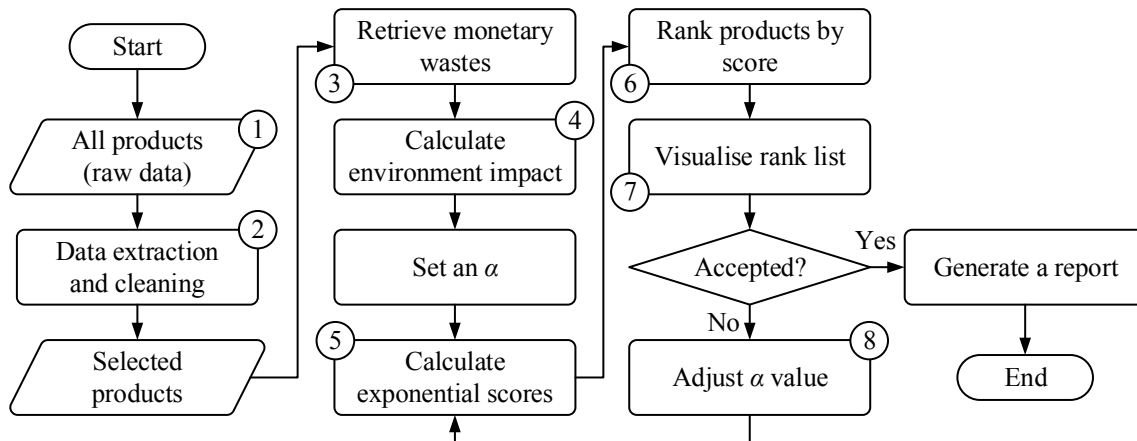

Fig. 3. Flowchart of an Excel-based waste-ranking tool using the proposed ranking method.

5. Method application

The analysis included in-store waste data from 12 stores in a Scandinavian grocery retailer, covering one distribution region. The retailer was selected based on its format and breadth (hundreds of premium stores, supermarkets, discount stores and local markets) and a full range of grocery selections (dry, frozen, chilled and fresh products). The selected stores represent a mix of profiles (four each from discount stores, supermarkets and premium stores) and size, but they have relatively similar distances to the distribution warehouse. Although store profiles varied, the processes are standardised: sales, ordering, stock and shelf management. The stores are considered average in terms of factors such as turnover, profit and percentage waste.

Either store personnel order products manually or a replenishment system orders products automatically. The stores record waste based on products that have passed expiration dates or, because of quality clauses, were registered and scanned into a central information system. For unpacked fruits and vegetables, the estimated mass or total number of items is entered manually. The data collected consist solely of registered in-store waste over a time period of 39 weeks (the first 39 weeks of 2016). The data have been extracted from the company's ERP system, checked and cleaned for errors (e.g. stock-level adjustments) and verified by the company.

For each product, data were obtained on *waste quantity*[1] and *monetary value* of deliveries to stores. The monetary value of waste refers only to the cost of requisition, not to any opportunity costs from lost sales or the cost of return or disposal of unsold products. A Pareto analysis of the 9,175 products revealed that 50% of all monetary waste was generated by 211 food products, which was the sample size selected for further analysis. The products were organised according to how the grocery retailer categorises them (Table 2), which corresponds with previous studies (Brancoli et al., 2017; Lebersorger and Schneider, 2014). Master data provided unit weight per product, which allowed the total weight of waste per product to be calculated. To calculate the environmental impact, CF measures (kgCO2e) were used. The different values of kgCO2e used were extracted from extant Life Cycle Assessment (LCA) literature and are presented in Table 2. The system boundaries in the LCA for the kgCO2e values (Mogensen et al., 2016), covered production, processing and transport until store. The present study has not considered the location of the different suppliers, which affects the final prioritisation. For each product in the sample, the following conversion formula was used:

$$\text{Carbon impact} = \text{Wasted units} \times (\text{weight/unit}) \times (\text{kgCO}_2\text{e emissions/kg}). \tag{5}$$

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[1] Given in kg or an amount converted to kg.

With the LCA measures from extant literature, the level for each item in the product group was calculated based on the share of product-specific waste within each group. For example, in the fresh fish category, most products wasted were salmon filets, and the carbon equivalent for salmon has been calculated accordingly.

Table 2
Carbon equivalent per kg and product group for the 211 products in the sample

Category Group	Sample size (number of SKUs)	Carbon equivalent per kg product (kgCO$_2$e)	Reference
Meat, seafood and dairy	*41*		
Beef, fresh	8	13.9	Mogensen et al., 2016
Lamb, fresh	2	21.4	Mogensen et al., 2016; Clune et al., 2017
Pork, fresh	1	4.6	Nguyen et al., 2011; Mogensen et al., 2016
Poultry, fresh	8	5.5	Nielsen et al., 2003; Mogensen et al., 2016
Seafood, fresh	3	3.0/20.2	Nielsen et al., 2003; Mogensen et al., 2016; Clune et al., 2017
Sausages	2	5.3	Scholz et al., 2015
Milk, fresh	2	1.2	Head et al., 2014; Mogensen et al., 2016, Clune et al., 2017
Cheese	1	8.0	Head et al., 2014; Mogensen et al., 2016; Clune et al., 2017
Fish, fresh	14	3.0	Average measure from Nielsen et al., 2003, and Clune et al., 2017; Mogensen et al., 2016
Bread, biscuits and confectionery	*81*		
Fresh bread	43	0.8	Nielsen et al., 2003; Espinoza et al., 2011; Mogensen et al., 2016
Rolls and cakes	35	0.8	Nielsen et al., 2003; Mogensen et al., 2016
Confectionery	3	2.3	SIK, 2010; Mogensen et al., 2016
Ready-made meals	*7*	27.9/12.4	Scholz et al., 2015; Unilever Food Solution, 2018
Fruits and vegetables	*82*		
Vegetables and potatoes	51	0.5	Hallberg et al., 2006; Davis et al., 2011; Torrellas et al., 2012; Werner, 2013; Saarinen et al., 2012
Fruits and berries	31	0.5	Nilsson and Sonesson, 2007; Beccali et al., 2009; Mordini et al., 2009; Clune et al., 2017
Total	211		

Even if the LCA methodology is ISO standardised (International Organization for Standardization), there is variation in aspects such as the use of emission factors, functional unit and allocation method. Therefore, the results for the same products can vary in different studies, and comparisons between studies should be considered with caution. Measures always bear uncertainties and differences between product groups (Scholz et al., 2015; Clune et al., 2017).

Data analysis and quality
A regression analysis was conducted to investigate any correlation between monetary and carbon waste, which is particularly important for a ranking method consisting of two or more impact measures. The analysis was conducted on an aggregated SKU level to strengthen the sample size. In accordance with Table 2, each product belongs to an aggregated category and a specific product group, with values for monetary and carbon (kgCO$_2$e) impacts derived from mass. A high correlation indicates lower within-product differences in the category. A high waste impact in one of the measures is followed by a high impact in the other measure, which, for the waste-ranking method, means that prioritising to reduce waste in a product category with high covariance will make a positive impact on both monetary and carbon waste. Considering the entire data set without discriminating by category, the linear dependency between the logarithms for monetary and carbon impacts is weak (Figure 4).
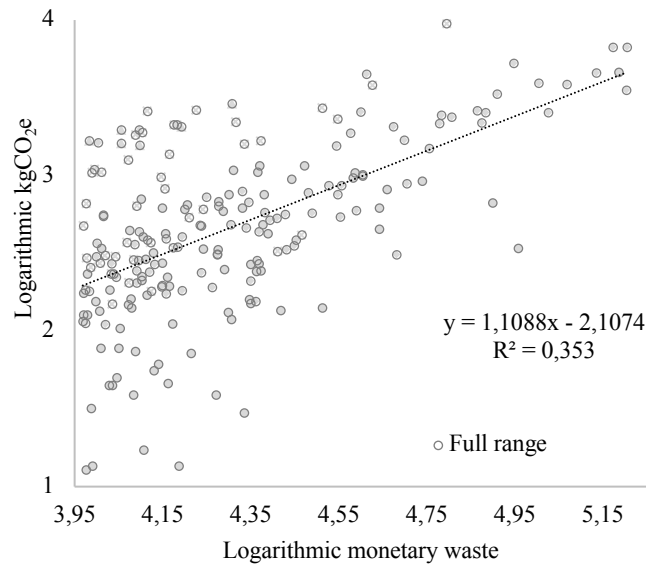
Fig. 4. Regression between kgCO$_2$e and monetary waste.

Doing separate regressions for each category provided a better fit, except for the categories *'Meat, seafood, dairy'* and *'Fruits and vegetables'* (Table 3), which have a weak dependence between monetary and kgCO$_2$e waste. This becomes clear when inspecting Figure 5, in which these two categories show a considerably weaker correlation between monetary and carbon impact.

Table 3
Linear regression of the waste logarithms

Category	LC=	N	R^2	Adj. R^2
Bread, biscuits and confectionery	1.2374 *LM* – 2.6755	81	0.774	0.771
Ready-made meals	2.0658 *LM* – 4.9641	7	0.698	0.638
Meat, seafood, dairy	1.1316 *LM* – 1.8513	41	0.284	0.265
Fruits and vegetables	1.3041 *LM* – 3.3549	82	0.275	0.265
Full range	1.1381 *LM* – 2.2907	211	0.287	0.283

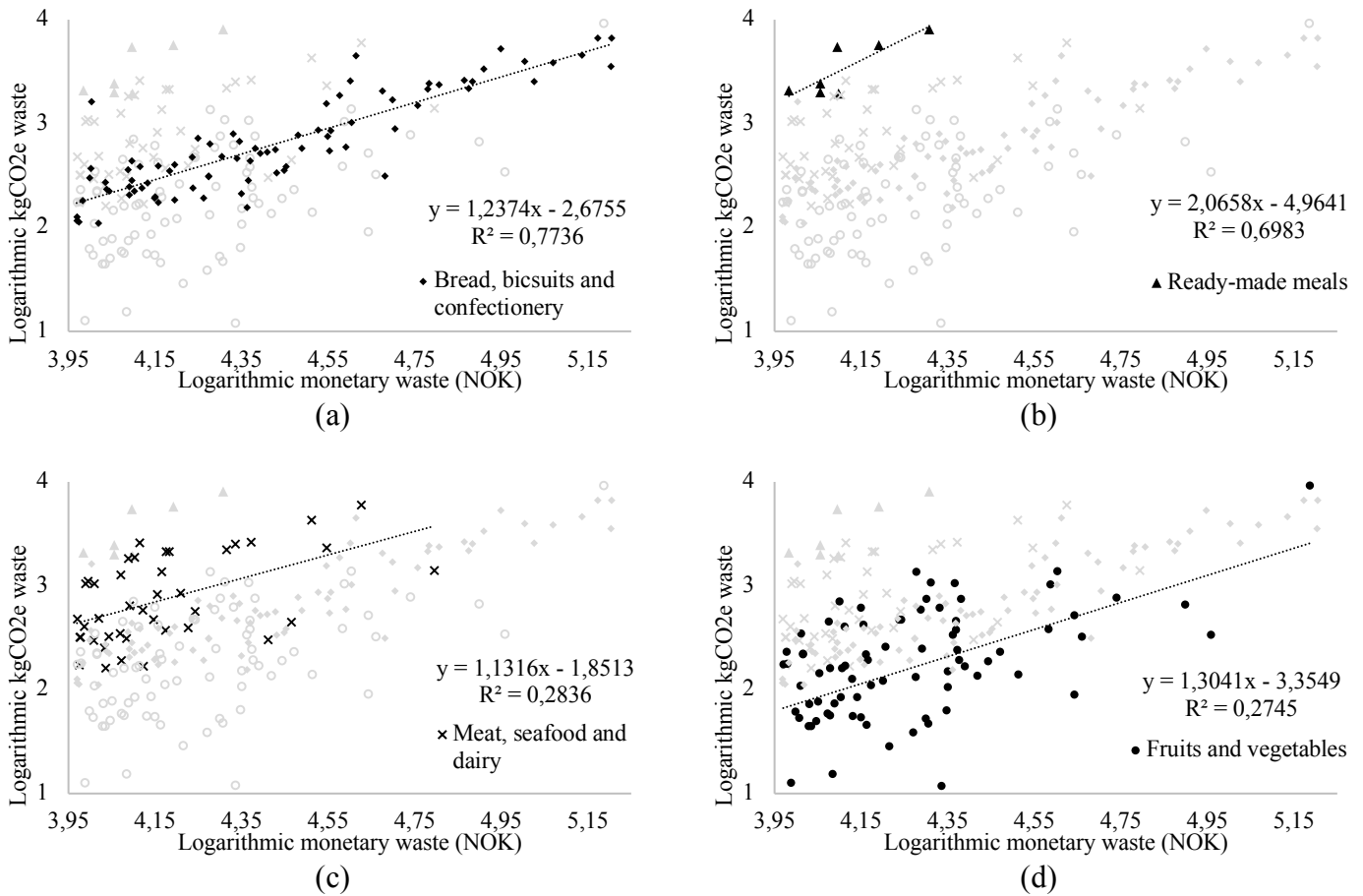*LC* = log kgCO$_2$e impact; *LM* = log monetary impact

Fig. 5. Regression between the carbon and monetary impacts by aggregated categories: (a) Bread, biscuits and confectionery; (b) Ready-made meals; (c) Meat, seafood, dairy; and (d) Fruits and vegetables.

Figure 5 shows *'Bread, biscuits and confectionery'* as the category with the highest covariance between $kgCO_2e$ and monetary waste, with a significant correlation above 60% ($R^2 = 0.774$) (Figure 5a). The second-highest significant correlation between $kgCO_2e$ and monetary waste is found in the *'Ready-made meals'* category ($R^2 = 0.698$) (Figure 5b). However, compared with the sample size of *'Bread, biscuits and confectionery'*, *'Ready-made meals'* has a small sample size, which may increase the risk of having unrepresentative samples. For the *'Fruits and vegetables'* and *'Meat, seafood, dairy'* categories, the analysis shows a weak correlation between $kgCO_2e$ and monetary impacts (Figures 5c and 5d), implying that managers seeking to reduce waste for products in these categories must choose whether to attack the $kgCO_2e$ impact or monetary impact of waste.

To verify that regression on individual categories is preferable, an analysis of covariance (ANCOVA; e.g. Tabachnik and Fidell, 2013) was performed, combining linear regression with analysis of variance (ANOVA). ANCOVA differentiates the grouped data by establishing separate linear-regression models for each group, making the difference between groups more visible because the products are assigned to different categories according to their properties. The output of the ANCOVA appears in Table 4.

Table 4

ANCOVA of products over categories by logarithmic monetary waste (LogMonWaste) and logarithmic $kgCO_2e$ waste

	Degrees of Freedom (DF)	Sum of Squares (SS)	Mean Square (MS)	F-statistic	p-value
Category	3	27.04	9.014	61.19	$<2e \times 10^{-16}$
LogMonWaste	1	23.09	23.087	156.72	$<2e \times 10^{-16}$
Error	206	30.34	0.147		
Total	210	80.47			

$R^2 = 0.6229$; adj. $R^2 = 0.6156$.

For a product randomly selected from the range, the category and the logarithmic dependency between waste types explain over 60% of the variation between CO_2-equivalent waste and monetary waste (because adj. R^2 = 61.2%). Regarding the F-statistic and p-value, the variations are lower within categories than between categories, which means that products belonging to the same category have a higher similarity of monetary-carbon impact than randomly selected products from the full product range. This also validates the necessity to analyse the products by category.

6. Results

This section presents the results from *applying the ranking method* on the data described in section 5. The findings are presented at the product, product-category and product-group levels.

An Excel-based tool was developed to help visualise the findings using the proposed method (Step 7, Figure 3), with its user interface (UI) shown in Figure 6. The UI consists of monetary and carbon indicators to show the spread of products and a ranking table to sort the products according to their scores in descending order. Users enter how many products to extract and then can adjust the α value to balance the consideration between monetary and environmental waste. A splitting curve (based on the convex-combination method) is plotted in real time as the cut-off curve in accordance with the α value. The top wasters are labelled as corresponding with the ranked products. The ranking list on the right is updated dynamically to help users check wasters' details. At a product level, bread is the most frequently wasted product (Figure 6), followed by meat/seafood/dairy (products 10 and 20) and fruits and vegetables (product 3).
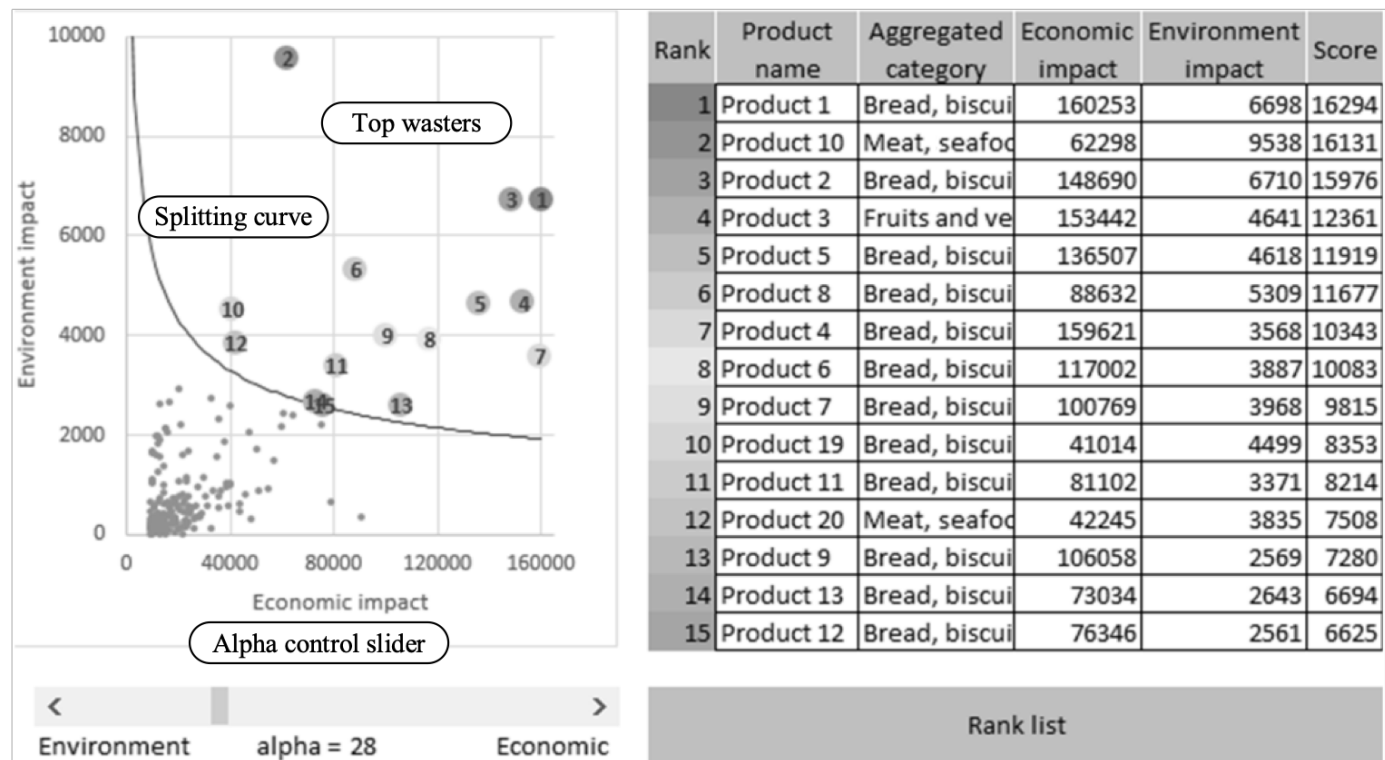

Rank	Product name	Aggregated category	Economic impact	Environment impact	Score
1	Product 1	Bread, biscui	160253	6698	16294
2	Product 10	Meat, seafoo	62298	9538	16131
3	Product 2	Bread, biscui	148690	6710	15976
4	Product 3	Fruits and ve	153442	4641	12361
5	Product 5	Bread, biscui	136507	4618	11919
6	Product 8	Bread, biscui	88632	5309	11677
7	Product 4	Bread, biscui	159621	3568	10343
8	Product 6	Bread, biscui	117002	3887	10083
9	Product 7	Bread, biscui	100769	3968	9815
10	Product 19	Bread, biscui	41014	4499	8353
11	Product 11	Bread, biscui	81102	3371	8214
12	Product 20	Meat, seafoo	42245	3835	7508
13	Product 9	Bread, biscui	106058	2569	7280
14	Product 13	Bread, biscui	73034	2643	6694
15	Product 12	Bread, biscui	76346	2561	6625

Fig. 6. User interface of the ranking tool based on the proposed method.

In Figure 7, the composition of waste fractions from the top 50 most-wasted products is illustrated according to the α coefficient (if $\alpha = 0$, the ranking is based on the kgCO₂e impact only, and if $\alpha = 1$, the ranking is done solely on monetary impact). The volume of the bands in Figure 7 represents the relative size of the waste fractions by illustrating the count composition of the top 50 products in Figure 7a and the score composition of the top 50 products in Figure 7b.
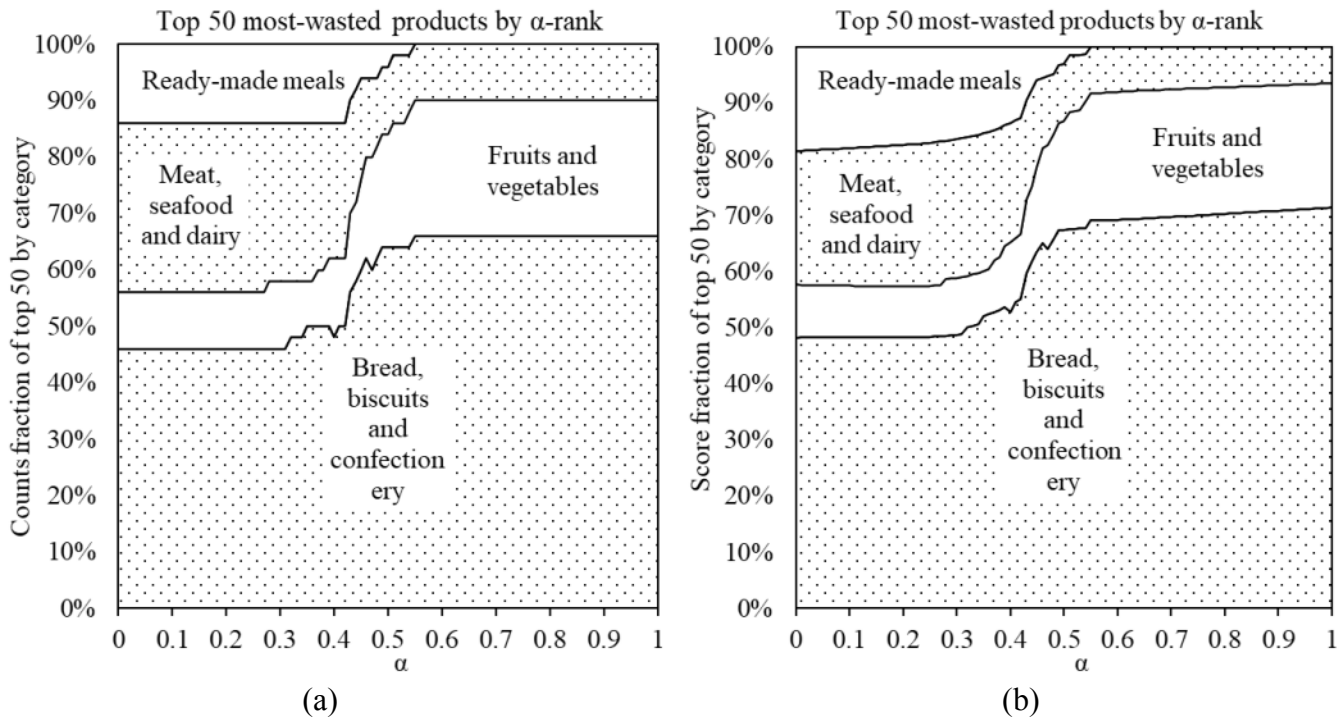
Fig. 7. Count fraction (a) and score fraction (b) of the top 50 most-wasted food products by α-ranking and product category.

Figure 7(a) indicates that the *'Bread, biscuits and confectionery'* category makes the highest impact, according to both $kgCO_2e$ and monetary impact (of the top 50 most-wasted products, the category causes nearly 50% of the carbon impact and over 60% of the monetary impact). The finding is confirmed in Figure 7(b), indicating a higher waste-score fraction for *'Bread, biscuits and confectionery'* than the other product categories, $kgCO_2e$ and monetary-wise. If the α is 0.5 in Figure 7(b), the *'Bread, biscuits and confectionery'* category constitutes over 60% of the top 50 most-wasted products, while the score level of the other product categories ($kgCO_2e$ and monetary-wise) decreases.

The *'Meat, seafood, dairy'* category is the second-highest waste fraction from a $kgCO_2e$ perspective (causing nearly 30% of the carbon impact), followed by *'Ready-made meals'* (causing over 10% of the carbon impact) and *'Fruits and vegetables'* (causing around 10% of the carbon impact). Because the *'Ready-made meals'* category represents a small product sample, conclusions should be considered carefully. From a monetary perspective, the *'Fruits and vegetables'* category (causing over 20% of the monetary impact) follows the *'Bread, biscuits and confectionery'* category and impacts more than *'Meat, seafood, dairy'* (causing around 10% of the monetary impact) and *'Ready-made meals'* (which do not cause any monetary impact, probably because of the very small sample compared with the other categories).

A more-detailed analysis of the waste categories is illustrated at the product-group level in Figure 8 for the top 50 most-wasted products. Generally, the results from the category level are confirmed but with some relevant nuances.

Figure 8 shows that bread and biscuits cause the waste impact in this category. Confectioneries are not among the top 50 most-wasted products with respect to any α value. For the *'Fruits and vegetables'* category, fruits and berries are more dominant than vegetables and potatoes in terms of $kgCO_2e$ and monetary impact, even though the sample size of vegetables and potatoes is higher than fruits and berries (51 vs. 31 products) (Table 2). For both product groups, the monetary waste is higher than the $kgCO_2e$ waste. For the *'Meat, seafood, dairy'*

category, the beef and poultry groups dominate in terms of $kgCO_2e$ impact, followed by seafood, lamb, cheese and pork. Fish does not have any carbon impact. In terms of money, the seafood and poultry group, followed by fish, makes the largest impact. Beef, cheese, lamb and pork do not make any monetary impact. It should be noted that the sample size of the product groups in the '*Meat, seafood, dairy*' category is relatively small, particularly for pork, cheese, lamb, seafood, milk and sausage, with groups such as lamb and seafood having a high carbon equivalent while the opposite is true for fish products (low $kgCO_2e$ per product). The $kgCO_2e$ impact from '*Ready-made meals*' is relatively high but does not cause any monetary impact, as mentioned above. Even though the product sample sizes of the seafood, lamb and '*Ready-made meals*' categories are small, they appear to make a waste impact, making the list of the top 50 most-wasted products.
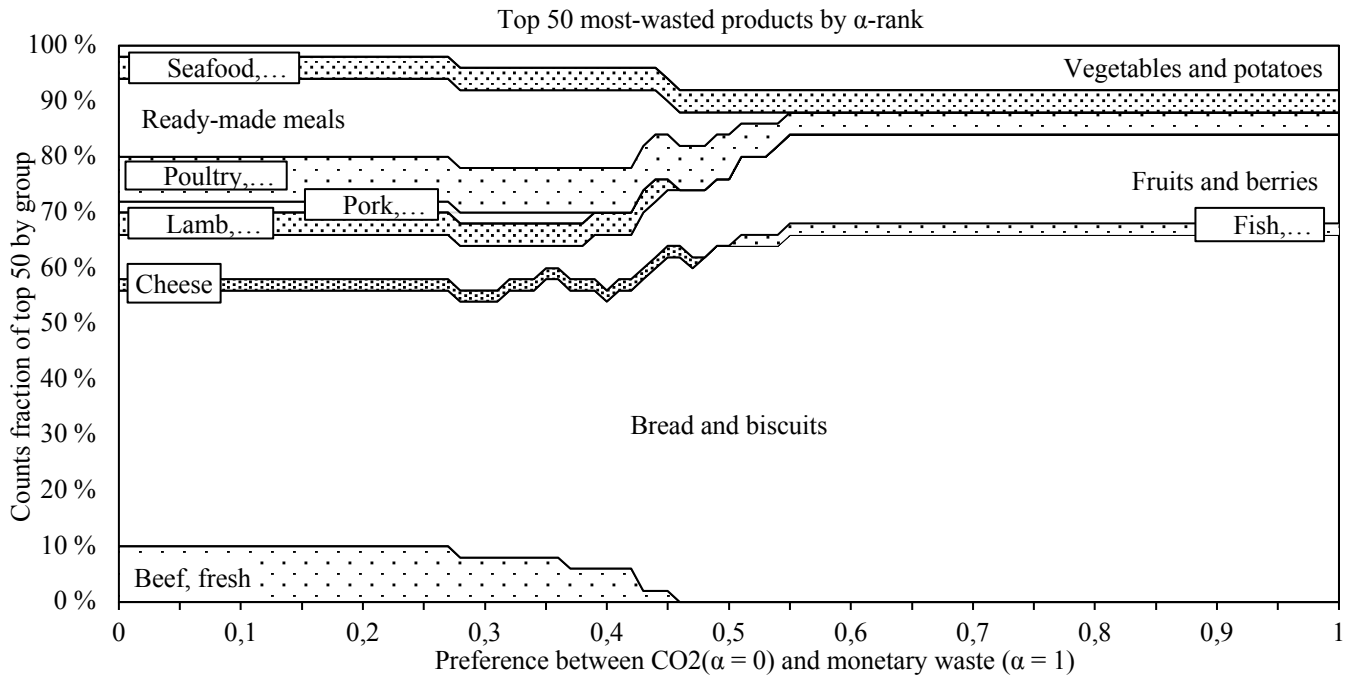

Fig. 8. Top 50 most-wasted products by α-ranking and product group.

Based on the waste impact of the product groups, four clusters are defined: high/low $kgCO_2e$ impact vs. high/low monetary impact (Table 5).

Table 5
Clustering product groups according to $kgCO_2e$ and monetary waste impact

		Monetary impact	
		High	Low
$kgCO_2e$ impact	High	Bread and Biscuits	Ready-Made Meals Beef Poultry Seafood Lamb
	Low	Fruits and berries Vegetables and potatoes	Cheese Fish Pork Confectionery

Table 5 indicates that bread and biscuits should be given high priority when reducing waste, attacking both $kgCO_2e$ and monetary waste, while cheese, fish, pork and confectionery seem to have a lesser impact ($kgCO_2e$ and monetary waste) and should be given less attention. However, if monetary value is a main target for waste

reduction, bread and biscuits, followed by fruits/berries and vegetables/potatoes, should be given attention. If $kgCO_2e$ is the main target, then bread and biscuits are still prioritised, followed by ready-made meals, beef, poultry, seafood and lamb. Because some of the products in this cluster have high CO_2 equivalents, such as ready-made meals, seafood and lamb products, waste levels should be monitored carefully. However, looking at SKU levels (Figure 6), a beef product is the second highest (when more weight is given to the carbon impact, $\alpha = 0.28$). Therefore, even though the bread category has the highest fraction, there could be individual products from other groups that are ranked higher.

7. Discussion

To identify areas with the largest food waste-mitigation potential in retail, many studies focus on quantifying the waste mass, while some others concentrate on the environmental and the social impacts of waste (Table 1). However, the studies either focus on a single metric (Gustavsson and Stage, 2011; Eriksson et al., 2014) or consider several waste-related metrics (Brancoli et al., 2017; Scholz et al., 2015) that lead to different prioritisations of the product categories depending on the metric used (Brancoli et al., 2017). Even though the prioritisations found in the literature might be used as facilitators for directing waste-prevention initiatives, their generalisability is questionable. In addition, it is difficult to get a unified overview due to (1) the different focuses of the analyses (fractions of product category, subcategory, SKU, in relation to total waste, category waste or sales, etc.); (2) different products categories considered in different analyses; and (3) focusing on one country, or one retail chain, having in mind that the food-waste occurrence differs across store formats and is affected by retail (parent) organisation (Teller et al., 2018; Filimonau and Gherbin, 2017).

The metric developed in the present study combines monetary and environmental variables, thus enabling individual SKUs to be ranked into a single scalar score (Figure 6). This is in line with previous research (Scholz et al., 2015) emphasising the importance of not only measuring waste in terms of mass but also relating it to environmental indicators. However, the proposed metric solves the problem of different prioritisations based on solely monetary or environment perspectives (Brancoli et al., 2017; Scholz et al., 2015) by taking the impact of 'relative waste' into consideration. In addition, the metric enables parametrisation by weights that can be selected to fit a certain retail context. For example, depending on the financial situation of the company, a higher or lower weight could be given to the monetary aspect. Or, in a case where there is a policy of returning products to suppliers (pre-store waste) (Eriksson et al., 2012; Lebersorger and Schneider, 2014), the metric can be calculated by using the data for pre-store waste and giving higher weight to the environmental aspect, thus identifying products that could be a focus of waste mitigation and adding to the holistic supply chain sustainability perspective. Meanwhile, the general form of the proposed method enables managers to include more factors as complements to monetary impact and environmental impact by sorting new scores without comparing back and forth.

Even though the main focus of this study was not to precisely quantify the waste, the application of the method resulted in prioritisations that will be discussed in light of previous research, thus presenting the validity of the method. Generally, the present findings correspond to studies pointing to bread, meat and fruits/vegetables as dominating waste fractions (in terms of mass and money, considered separately) (Stensgård and Hanssen, 2015). Bread (in terms of mass and monetary impact) and meat (in terms of CO2eq) is on top in research by Brancoli et al. (2017). Fruits are on top (in terms of mass and monetary) in studies by Lebersorger and Schneider (2014), as well as in terms of mass and carbon in a study by Scholz et al. (2015). The present study deviates from Brancoli et al. (2017), as it was found that in terms of carbon, bread was the dominant waste fraction, not meat. However, on a SKU level, a beef product takes second place on the waste score (Figure 6). The present study did not identify the dairy-product group in the top waste fraction, as identified by Lebersorger and Schneider (2014) and Scholz et al. (2015), although this product group had the lowest share in comparison to the other groups. This could be the result of different criteria for choice of products in which previous studies have focused on product groups leading to 80% of total waste in value, whereas the present study selected the products adding to 50% of the monetary value of waste. Thus, the proposed method extends previous studies (Lebersorger and Schneider, 2014;

Brancoli et al., 2017; Scholz et al., 2015) by demonstrating that waste prioritisations should be made on a SKU level in order to direct managerial interventions more precisely.

Additionally, the study identified a weak correlation between the carbon and monetary waste impacts for meat and fruit, which makes the weighted ranking even more important because it balances the prioritising for these categories across environmental and monetary impacts. Bread has been identified as a category with a strong correlation between dimensions, implying that reduction of its waste will make a positive impact on both monetary and carbon waste.

The proposed method is quite generic in the sense that specific indicators can be operationalised based on the available data by being even more detailed, e.g. if country-specific and SKU-specific measures of $kgCO_2e$ are available, or other measures of environmental impact are sought. However, the reliability of the ranking depends significantly on the values used in calculating the environmental and monetary impacts. Therefore, awareness of data quality is imperative when analysing the results of the ranking.

For retailers, the incentive for focusing on money before carbon will be strong (Brancoli et al., 2017) because it is directly linked to companies' profit-seeking objectives. Carbon is an environmental dimension related to the social responsibility of companies, which makes it easier for store managers to downgrade if managerial interventions and incentives are absent. The identified strong correlation between the two dimensions for some of the products could act as a driver for management attention; by attacking the monetary aspect of waste they actually gain on the environmental aspect as well. For the products with low correlation between the monetary and environmental dimensions, the proposed method could further increase awareness of the critical products and give managers direction regarding where to place their focus.

This was partly observed at the case retailer where the results were discussed with the project team responsible for finding ways to mitigate waste. Today's waste-mitigation and priority decisions typically are made using single mass dimensions at SKU, such as kilo/amount, while the monetary impact is estimated using aggregate total waste figures. Environmental impacts such as carbon were not considered. Demonstrating the method and visualising and discussing the results with the project team created new understanding and awareness about waste and its impact along two dimensions, the ranking of waste fractions and how this could guide managers in deciding what fraction to prioritise. Consequently, the project team started a process for considering how to apply the method as an intervention to mitigate waste in stores.

8. Conclusion

A significantly increasing waste level in the food system calls for managerial interventions at grocery retailing to correct unsustainability. By measuring food waste and striving to generate more precise impact estimates to identify the products with the highest waste-mitigation potential, more exact managerial intervention can be prescribed. However, waste fractions across product groups differ depending on sustainability dimensions used, such as quantity/mass, monetary and environmental, leading to prioritizations on separate metrics.

This paper proposes a ranking method for prioritising food waste with the highest combined monetary and environmental waste-mitigation potential. This facilitates ranking of individual SKUs into a single scalar score for environmental and monetary impact, thus extending existing food waste quantification literature. The metric's parametrisation by weights allows the method to fit into specific context or policies for managerial interventions. Even though the main focus of the study was to propose a ranking method and metric, by applying the method on store data, findings are that at a product group level existing studies are verified pointing out that bread, meat and fruit/vegetables are high wasters. But unlike other studies, the present analysis show that prioritising of products should be made on a SKU level to direct managerial intervention more precisely. Additionally, for some products, such as meat and fruit, there is a weak correlation between carbon and monetary waste impacts, whereas

for bread, the correlation is stronger, making the weighted ranking important because it affects product prioritising.

The study has a number of limitations which provide promising direction for further research. First, the social dimension is not considered in the method provided because the focus in the study is on directing waste prevention, whereas the social perspective on waste is more about using edible waste. Future studies should explore how social aspects impact product ranking, particularly because the social dimension of waste decreases the criticality of the product. These studies should note previous findings about meat and dairy products being more appropriate for donations compared to fruits/vegetables because of the policies of discarding them (before expiry date). Second, the ranking method combines two measures; carbon equivalents that represent the environmental dimension because are accessible in the LCA literature, and monetary value since equivalents are available in business ERP systems. If other measures of environmental and monetary equivalents are available, further studies to express externalities and cost, such as water, land, materials use and cost of lost sales can be done to investigate the effects on prioritization. Third, the presented measure focuses on sole waste indicators but not in relation to the products sold. To improve the precision of scores, the method should include more precise measures of environmental impact (e.g. by considering the closeness and placement of the supplier, etc.) instead of the generic ones found in extant literature and presented in this paper. As evident, the method applicability and reliability depend on available data. Thus, the feasibility of the method is questionable in contexts where there are less robust or accessible records, such as in food service or hospitality sector or geographical regions where IT systems and registration routines could hinder reliable waste data. Therefore, to expand the generalisability of the proposed method and metric, it is important to explore its applicability or adaptations needed in different geographical regions and hospitality sector.

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