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Identification and modelling of risk factors for food waste generation in school and pre-school catering units

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ABSTRACT

Public sector food service is a major contributor to food waste generation in Sweden, with schools, pre-schools, elderly care homes, hospitals etc., producing approximately 70,000 tons of food waste each year. Sweden has appropriate infrastructure for handling food waste in place, recycling nutrients and energy, but there is still great potential to move upwards in the waste hierarchy and prevent waste. An important step in designing waste reduction measures is to identify and quantify the importance of different risk factors, in order to start by solving the problems with the greatest potential benefit and the lowest cost. This study sought to identify and quantify risk factors for food waste generation in public sector canteens by correlation analyses and statistical modelling. The empirical material comprised food waste quantification data for 177 kitchens in the Swedish municipalities of Falun, Malmö, Sala, Uppsala and Örebro, supplemented with quantifiable information about the kitchens obtained using a questionnaire. According to the findings, plate waste in schools and pre-schools increases with children's age. Schools with older children could potentially reduce plate waste by introducing more structured lunch breaks. Plate waste also increases with dining hall capacity, potentially due to rising stress and noise levels. Both plate waste and serving waste increase with greater overproduction, as indicated by calculated portion size, and could be reduced by schools and pre-schools estimating their daily number of diners and their diners' food intake more accurately. As serving waste was significantly higher in satellite units (which bring in cooked food), due to lack of cooling and storage possibilities, than in production units (which cook, serve and sometimes deliver hot food), satellite units in particular would benefit from more accurate quantification of the food required on a daily basis. These findings were confirmed by multiple linear regression models, which explained >85% of the variation in plate, serving and total waste per portion. When used for quantification after changing the value of different factors, these models confirmed that the main factors influencing serving waste and total waste per portion were type of kitchen and rate of overproduction, while plate waste was mainly influenced by children's age and factors indicating a stressful dining environment.

1. Introduction

Public sector food service is a major contributor to food waste generation in Sweden. According to the Swedish Environmental Protection Agency (SEPA), public food service, including schools, pre-schools, elderly care homes, hospitals etc., generates approximately 70,000 tonnes of food waste per year, which is roughly the same amount as for all other food services such as hotels and restaurants together (SEPA, 2016). Private households waste most food, 717,000 tonnes (SEPA, 2016), which can be explained by the much larger amount of food served in households compared with public catering units. Among all public facilities investigated by SEPA (2016), schools and pre-schools generated most of the total waste (67%), followed by elderly care homes (24%).

Landfilling of organic waste is banned in Sweden (Ministry of the Environment and Energy, 2001) and food waste is mainly managed through incineration (62%) and anaerobic digestion and composting (38%) (SEPA, 2017). In a global perspective, this can be considered fairly advanced waste management, but even the biological recovery options (digestion and composting) are still far from the waste reduction rates stated as the top priority in the EU Waste Framework Directive (EC, 2008). The environmental benefits of producing biogas are also much lower than the potential benefits of preventing waste or using it for higher priority valorisation options (e.g. reuse), thereby substituting for more resource-demanding products and services (Eriksson et al., 2015; Eriksson & Spångberg, 2017).

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Only a few academic studies have examined the food waste generated in public serving units. Eriksson et al. (2017) quantified the food waste from 30 public kitchen units in the Swedish municipality Sala with regard to plate waste and serving waste and found that elderly care homes had the highest waste per portion (90 g), followed by schools (79 g) and pre-schools (51 g). In general, 23% of the food served in Sala's public kitchens was wasted, with 64% being serving waste and 33% plate waste. Production units (facilities which produce food in their own kitchens) had significantly lower waste than satellite units (facilities that receive food produced in another facility and often have few possibilities for cooling and storage of food leftovers). Pre-schools had significantly lower waste than schools. Overall, however, there was great variation between kitchens of the same type (Eriksson et al., 2017).

In a study quantifying the food waste in an American primary school based on a short measurement period of five days, Byker et al. (2014) concluded that portion size, noise levels, time available for food consumption and children's age were possible factors determining food waste in schools. Some other attempts to identify the drivers of food waste in educational establishments have been made, most of which have relied on surveys and have aimed at ensuring that pupils receive sufficient nutrients via their school lunch, rather than at reducing waste. Kinasz et al. (2015) developed a checklist for the prevention of food waste based on the votes of experts, but also concluded that more research is needed to identify the factors controlling food waste generation. In addition to factors concerning management in the service sector, they suggested dining ambiance and knowledge about the diners as potential factors influencing food waste in public facilities. Whitehair et al. (2013) examined whether food waste in universities was reduced when students received information about food waste and found that a reduction of 15% could be achieved. However, only 40% of the students approached agreed to participate in that study and let their trays be weighed. Kuo and Shih (2016) suggest that gender differences might be a factor influencing plate waste, as they found that female plate waste in universities was significantly higher than male plate waste. A significant decrease in plate waste was also found in a study where trays were removed from a university dining hall (Thiagarajah and Getty, 2013).

Statistical approaches examining the drivers of food waste in school kitchens have shown that plate waste increases when sixth graders purchase food outside the dining hall, referred to as competitive food items (Marlette et al., 2005). A study by Niaki et al. (2017) found that children's age is an important factor influencing food waste behaviour in schools which should be taken into account when examining the drivers of plate waste in school kitchens. According to that study, children attending pre-school had significantly higher plate waste than children in higher school years. However, the authors point out that the youngest participants in the study had lunch two hours earlier than the oldest participants. Differences in lunch break procedures should therefore be examined as a factor coupled to food waste behaviour (Niaki et al., 2017). For example, food waste has been shown to decrease by about 10% when primary school children in school years 1 to 3 have their break before eating lunch (Getlinger et al., 1996).

In WRAP (2011), three interventions (improving familiarity and appreciation of school meals; improving the dining experience; children ordering their meals in advance to cooking them) were tested in 39 schools and led to a 4% waste reduction, although this reduction was not statistically significant. Barr et al. (2015) introduced the LEAN philosophy (a systematic method including the elimination of waste within manufacturing) to reduce overproduction, and thereby food waste, in school canteens in Sweden, but was unable to demonstrate any reduction in food waste due to insufficient waste quantification. This highlights the importance of a systematic approach to evaluating food waste reduction measures. An important step is therefore to describe the problem by quantifying waste, but also to correlate this waste to factors that can be improved. Multiple linear regression models have previously been used to quantify risk factors for waste generation in supermarkets (Eriksson et al., 2014) and to simulate the effect of waste-reducing measures (Eriksson et al., 2016a), but this approach has not previously been applied to public sector food services.

The Food and Agricultural Organization FAO (2013) estimates that 1.3 Gtonnes of edible food are lost or wasted along the food supply chain each year, which answers to one third of all food that is intended for human consumption. The consumption stage contributes with 37% to the total carbon footprint generated along the food supply chain, due to food wastage of 3.3 Gtonnes CO_2 equivalents. Annually, the production and post-handling of food that is later wasted together require around 30% of the world's agricultural area. The blue water footprint caused by agricultural products for food waste answers to 250 km^3 of groundwater and surface resources. (FAO, 2013)

Although the agricultural stage has the biggest impact on the environment among all stages in the food supply chain, food consumption has a huge impact on the environment through the energy used for production, packaging, transportation and cooking among others (Schott and Cánovas, 2015). By preventing 1 kg of food waste, up to 29 kg of emitted CO_2 could be saved, depending on the type of food wasted (Eriksson et al., 2015). In addition to decreased greenhouse gas emissions, a 50% reduction in food wastage in developed countries is estimated to result in lowering the global water footprint by 59 Gm^3 according to calculations by Munesue et al. (2014). Furthermore, over 60 million people could be nourished as a result of a 50% reduction. Food waste prevention would save natural resources and diminish negative effects on the environment caused by agricultural economy (Munesue et al., 2014). Knowledge about the implications of food waste and its prevention should be an "urgent priority" according to Thyberg and Tonjes (2015).

This study therefore examined factors influencing food waste in schools and pre-schools, with the objective of identifying and analysing these factors. Another objective was to investigate and model the influence of factors that were significantly related to food waste, in order to create a base for effective measures to reduce food waste in schools and pre-schools.

2. Materials and methods

Risk factors potentially influencing food waste generation were identified from the literature (Section 2.1). Quantitative data that could function as indicators for different potential risk factors were collected, as were food waste data (Sections 2.3 and 2.4). The correlation between food waste and risk factors was then tested for each factor individually. Lastly, the factors were modelled together, in order to calculate their collective impact on food waste generation. The research approach was highly influenced by a previous study conducted by Steen (2017), but with additional analysis and material in order to expand the results.

2.1. Identification and selection of risk factors

Possible risk factors identified from the literature are summarised in Table 1. Although food waste is likely to be influenced by factors such as attitudes and opinions, such factors were excluded from the study due to the associated difficulties in quantification and generalisation. However, for some factors that are difficult to quantify, such as stress, secondary factors such as time available for eating were used as an indicator of how stress was

Table 1
Parameters that have, or might have, an influence on the amount of food waste generated in educational establishments according to the literature and hypotheses concerning the parameters and possibilities to quantify the parameter.

Parameter	Hypothesis according to literature	Quantification
Children's age or differentiation between schools and pre-schools	Food waste increases with age (Byker et al., 2014; Eriksson et al., 2017; Niaki et al., 2017)	School year could be used as a quantitative indicator for children's age
Type of kitchen	Production units generate lower food waste than satellite units (Eriksson et al., 2017)	This factor could be examined in a bivariate analysis
Portion size	Possible factor influencing food waste (Byker et al., 2014; Painter et al., 2016)	Portion size is recorded in grams and therefore quantitative data are available. This factor could be used as an indicator for overproduction and improvable management
Dining ambiance, noise level and pupils' physical or emotional condition	A calm ambiance in the dining hall reduces food waste (SEPA, 2009; Byker et al., 2014; Kinasz et al., 2015; Painter et al., 2016)	Dining ambiance, noise level and conditions evoking stress could be assessed using dining hall capacity and crowdedness as an indicator, quantified as number of seats in the dining space
Time available for lunch and point of time at which lunch is served	To decrease food waste, children should have enough time to eat during their lunch break (Getlinger et al., 1996; SEPA, 2009; Byker et al., 2014; Niaki et al., 2017)	Lunch time could be assessed using dining space capacity in relation to number of children as an indicator, quantified as number of seats in the dining space and number of diners. The longer a lunch break is, the more time is available for pupils' food intake. Time available for lunch is often restricted by schools' dining hall capacity
Management factors and knowledge of diners	Possible factor influencing food waste (Kinasz et al., 2015)	Some management factors and the knowledge of children could be assessed using the number of staff members in the dining facility as an indicator, which is a quantitative measure.
Awareness of food waste as an issue	Possible factor influencing food waste (Whitehair et al., 2013; Painter et al., 2016)	Awareness of food waste can be assessed using education/no education or information about food waste given to staff members and children as an indicator. This factor is quantifiable given suitable data
Distance between classroom and dining space	Possible factor influencing food waste (Painter et al., 2016)	The distance could be quantified as different categorical groups

correlated with food waste generation. Some parameters were also grouped into indicators for which quantification was possible (Table 1).

Other parameters that might have an influence but were not considered for analysis were day of the week (Byker et al., 2014; Eriksson et al., 2017), pairings of meal components (Ishdorj et al., 2015), popularity of meals (Painter et al., 2016), availability of competitive food items (Marlette et al., 2005; Painter et al., 2016) and the children's gender (Kuo and Shih, 2016). These factors were either difficult to quantify or lacked the information required for statistical analysis. As the quantity of food waste varied widely between the public catering facilities included in the analysis, direct statistical analysis was not appropriate for day of the week as a potential factor influencing food waste generation.

2.2. Area of study

Food waste data were available for the municipalities of Sala, Uppsala, Falun, Malmö and Örebro in Sweden, which represent both urban and more rural areas with different numbers of residents. Malmö is located in southern Sweden, while Sala, Uppsala, Falun and Örebro are spread across central Sweden.

Children in Swedish pre-school or "kindergarden" are between the age one and five. After pre-school, pupils can enter school year 0, also referred to as "pre-school class". At the age of seven, pupils start school in the first school year and continue their school path until high school, which contains three different school years. In Sweden, high schools are often separate schools that pupils transfer to after school year 9.

2.3. Food waste quantification

The measurements of food waste were performed by each municipality prior to this study and the data were collected as described by Eriksson et al. (2017), using Excel sheets for recording the waste, number of diners and mass of served food. The waste data were obtained from the municipalities and inserted into the Matomatic platform for food waste data (Matomatic, 2017) in order to achieve a uniform standard of data organisation. The data were aggregated in order to represent the same level of resolution for all municipalities in line with the framework described in Eriksson et al. (2018), which included plate waste and serving waste from lunches served.

Plate waste was defined as all waste scraped from plates handed out to the diners, including inedible parts such as bones or peel. In addition to the weighed plate waste, the number of used plates handed in was counted and used to define the number of portions served per day (Eriksson et al., 2016b)

Serving waste was defined as all food waste generated throughout the preparation and serving process, in both the kitchen and the dining hall, as well as left-overs from the serving trays. Inedible parts discarded during the preparation process were not included.

Some municipalities report a third category, 'other waste', referring to food waste generated through storage or other sources that are not included in the category 'serving waste'. However, this category tends to be insignificantly small compared with the other two and was therefore excluded from the present analysis.

In order to develop comparable values, the variables total waste per portion, plate waste per portion and serving waste per portion, per day, week and semester, were introduced for each school. Total waste per portion was defined as the sum of serving waste and plate waste per portion served. All incomplete measurements were excluded from the calculations. In addition to the three food waste quantities, background data about the number of semesters with food waste measurements, portion size and type of kitchen were included in the original data. As the reported measurements differed in terms of frequency, count and span of time between different kitchen units, the average for all semesters included in each kitchen's reported measurements was used as a comparable measure for analysis. Furthermore, information about the type of kitchen (satellite or production units) was available for 177 kitchens.

2.4. Collection of background data

In order to collect additional information about the dining systems in different preschools and schools in Uppsala, Falun, Sala, Malmö and Örebro, a questionnaire was sent out to the head chefs

Table 2
Information obtained in a survey of kitchen head chefs in Sala, Uppsala, Falun, Malmö and Örebro and included in the present analysis; description of the data by definition, type of data and estimated uncertainty.

Category	Definition	Type of data
Number of pupils	Number of pupils registered at the school in December 2016	Accurate or rounded number (truncation by five pupils)
Number of employees	Number of employees working in the school kitchen in January and February 2017	Accurate number
Number of female and male employees	Number of employees working in the school kitchen in January and February 2017 divided into male and female employees	Accurate number
School years	School years represented in the school	School years as a range of numbers, i.e. 1–9 or KG ("kindergarden"/pre-school) for pre-school with children aged 1 to 5
Dining hall capacity	Number of seats available for diners in the dining hall	Accurate or rounded number (truncation by five seats) or category 'in classroom' when the school had no dining hall and the children ate in their classrooms
Distance between dining space and classroom	Distance between dining space and classroom	As distance in metres or as a description, including whether the dining hall is in the same building as the classrooms; or as "in classroom" for schools with no separate dining hall
Number of meal options	Number of meal options planned by the kitchen staff	Accurate number or as a range, i.e. 2–3

responsible for the kitchens for which food waste data was available. If no response was received, the written questionnaire was followed up by a telephone call. The information collected consisted of quantitative data on number of pupils, dining space capacity, school years, number of meal options, number of employees, number of female and male employees and distance between dining space and classroom. Although some factors, such as number of pupils and dining hall capacity, can fluctuate over time, the fluctuation was assumed to be sufficiently small to allow general trends in the data to be detected (Table 2).

The responses to a question on whether information about food waste was given to children and staff differed widely and contained unacceptable uncertainty, so this information was not considered as a factor for analysis. In response to a question on whether there was a booking system to predict the number of diners, all kitchens replied that the number of diners was calculated based on the number of pupils registered at the school. In most cases, the kitchen required notification to avoid overproduction if pupils were unable to attend lunch in the dining hall, but most kitchens reported that they were often notified late or not at all.

Since none of the kitchens had a serving system with trays, the benefits of a trayless system could not be examined.

2.5. Correlation analysis

Statistical correlation analysis was used to examine the relationship between the factors listed in Table 1 and the amount of food waste generated in pre-schools and schools. In general, correlation analysis uses hypothesis testing to determine how one variable is affected by another. The null hypothesis states that there is no significant correlation between the two variables tested. If the calculated p-value is lower than the assigned significance level, the null hypothesis can be rejected and the two variables influence each other (Helsel and Hirsch, 2002). The significance level for this study was set to $p < 0.05$. Correlation analysis was performed in R (The R Foundation, 2017) and examined whether the data samples were normally distributed according to the Shapiro-Wilk test (Royston, 1991), creating a scatterplot to visualise the relationship between the variables tested and then deciding on a suitable method before performing correlation analysis.

The correlation between two variables can either be positive, meaning that one variable increases as the other increases, or negative, meaning that one variable decreases as the other increases. According to Helsel and Hirsch (2002), the three most common methods for correlation analysis are Pearson's r, Spearman's rho and Kendall's tau. All three methods return a correlation coefficient between −1 and 1, indicating the correlation strength. As the correlation coefficients r, rho and tau are calculated differently, the correlation strength is measured on a different scale depending on the method. It is therefore difficult to compare the strength of correlations with different correlation coefficients. An overall standard states that a correlation coefficient between ±0.1 and ±0.3 indicates a weak relationship, a correlation coefficient between ±0.3 and ±0.5 indicates a moderate relationship and a correlation coefficient higher than 0.5 or lower than −0.5 indicates a strong relationship (Field et al., 2012).

Pearson's r is the most commonly used method for correlation analysis and requires a normally distributed data sample. An exception can be made if one of the variables tested is bivariate and the second variable follows a normal distribution. Otherwise, the method requires the observed variables to be linearly dependent and to fulfil the conditions of interval or ratio data (Field et al., 2012). Outliers, which can be detected in a boxplot, must be excluded from the analysis as the method is not resistant to outliers (Helsel and Hirsch, 2002).

Spearman's rho uses a weighed rank test and requires a monotonic relationship between the two variables tested (Helsel and Hirsch, 2002). As the method depends on a rank test, the data sample is not required to be normally distributed. According to Field et al. (2012), Spearman's rho is not suitable for data samples containing <20 data points or data that do not fulfil the conditions to be ordinal.

In contrast to Pearson's r and Spearman's rho, Kendall's tau is resistant to outliers, as the method is based on a simple rank sum test. However, it demands a monotonic relationship between the observed variables (Helsel and Hirsch, 2002). The method can handle ties in the data sample and does not require the variables tested to be normally distributed. Kendall's tau is suitable for smaller sample sizes, especially if the sample contains many ties (Field et al., 2012).

2.6. Parameters investigated

The following parameters were analysed to determine whether there was a significant correlation between the suggested drivers for food waste in Table 1 and the food waste generated. Correlations between the parameters total waste per portion, serving waste per portion and plate waste per portion were examined. Visual analysis was performed manually on scatterplots before each correlation test, to ensure that only monotonic patterns appeared in the sample examined.

In preparation for multiple linear regression (MLR) and to develop an overview of the interactions between the parameters, a correlation matrix was created using the built-in function "cor" in R. To ensure that the results were not biased by ties or outliers in the data sample, the method was specified as 'Kendall's rank correlation'. The correlation matrix established contained all correlation coefficients between the parameters tested.

2.6.1. Number of pupils

'Number of pupils' was defined as the number of pupils registered at the school or pre-school in December 2016. With a sample size of 141 data points and a discrete range of 10 to 1300 pupils, the data did not contain many ties compared with the sample size. As the data sample had a non-normal distribution (Shapiro-Wilk test, $n = 141$, $p < 0.05$), Spearman's rank correlation was chosen as the most suitable method.

2.6.2. School years

'School years' was defined as the number of academic years represented in a school. Pre-school was counted as one year, since children in pre-school have the same routines and share the same location despite their different ages (1 to 5 years).

The data sample had a discrete range from 1 to 13 different school years and contained 35 data points. As the data were normally distributed (Shapiro-Wilk test, $n = 35$, $p > 0.05$), Pearson's product-moment correlation was chosen as the most suitable method.

2.6.3. Comparable age

In order to develop a relative measure to compare the children's age, 'comparable age' was calculated. It was defined as the sum of all school years represented at a school or pre-school, divided by the range of years. Some schools included a pre-school class. To calculate the sum of all school years represented, each year was assigned a number between 1 and 15, with 1 representing the pre-school class and 15 representing the last year of secondary school. The number 2 represented class 'zero', also named 'pre-school class'.

The data sample had a discrete range from 1 to 13 and consisted of 141 data points. As the data were non-normally distributed (Shapiro-Wilk test, $n = 141$, $p < 0.05$) and contained many ties compared with the sample size, Kendall's rank correlation was chosen as the most suitable method.

2.6.4. Number of employees

'Number of employees' was defined as the number of people working in the dining system's kitchen in January and February 2017. The data sample contained 35 data points with a discrete range from 1 to 11 employees and contained many ties compared with the sample size. As the data were non-normally distributed (Shapiro-Wilk test, $n = 35$, $p < 0.05$), Kendall's rank correlation was chosen as the most suitable method.

2.6.5. Gender of staff (percentage of male employees)

'Gender of staff' (percentage of male employees) was calculated by dividing the number of male kitchen employees by the total number of kitchen employees and multiplying the resulting number by 100. School kitchen staff are commonly dominated by women, and men were therefore chosen as the observed gender percentage. The data sample contained 35 data points on a continuous range from 0 to 100%. As the data were non-normally distributed (Shapiro-Wilk test, $n = 35$, $p < 0.05$) and some ties occurred, Kendall's rank correlation was chosen as the most suitable method.

2.6.6. Employees per pupil

'Employees per pupil' was introduced to develop a comparable measure, since it is likely that the number of employees increases with an increasing number of pupils at the school. The measure was computed by dividing the number of employees by the number of pupils and multiplying the resulting number by 1000 to enhance the scale. The data sample contained 35 data points on a continuous range from 4.55 to 37.04. Visualisation by boxplot showed the presence of one outlier. As the data were non-normally distributed (Shapiro-Wilk test, $n = 35$, $p < 0.05$) and did not contain any ties, Spearman's rank correlation was chosen as the most suitable method. This method is resistant to outliers.

2.6.7. Type of dining space

'Type of dining space' was divided into two categories. Schools in which the pupils ate lunch in their classrooms were assigned to category 1 and schools that offered a separate dining hall were assigned to category 0. The data sample was therefore bivariate and contained 36 data points. As waste per portion, serving waste per portion and plate waste per portion were found to be normally distributed (Shapiro-Wilk test, $n = 36$, $p > 0.05$), Pearson's product-moment correlation was chosen as the most suitable method.

2.6.8. Distance between dining space and classroom

'Distance between dining space and classroom' was divided into three different categories. The resulting data sample contained 34 data points on an ordinal scale with the following categories:

No distance between dining space and classroom, meaning that pupils ate in their classroom.
The dining hall is located in the same building as or within 100 m from the classrooms.
The dining hall and the classrooms are located in separate buildings or are >100 m apart.

As the data sample included many ties due to the categorisation, Kendall's rank correlation was chosen as the most suitable method.

2.6.9. Number of seats in dining space

'Number of seats in dining space' was defined as the total number of chairs in the dining space. For schools without a separate dining hall, the number of seats was assumed to equal the number of pupils per class. According to Skolverket (2014), the average Swedish class has 19 pupils and one teacher, resulting in 20 seats per dining space.

The data sample consisted of 50 data points on a discrete range from 20 to 485 seats. As the data were non-normally distributed (Shapiro-Wilk test, $n = 50$, $p < 0.05$) and contained ties, Kendall's rank correlation was chosen as the most suitable method.

2.6.10. Seats per pupil

'Seats per pupil' was introduced to develop a comparable measure, since dining space capacity is likely to grow with increasing number of pupils. The measure was computed by dividing the number of seats in the dining space by the number of pupils.

The data sample consisted of 50 data points on a continuous range from 0.213 to 1.136. As the data contained ties and were non-normally distributed (Shapiro-Wilk test, $n = 50$, $p < 0.05$), Kendall's rank correlation was chosen as the most suitable method.

2.6.11. Variety of meal options

'Variety of meal options' was used as a measure of the flexibility in a kitchen to change the menu. Greater flexibility could give the kitchen possibilities to include left-overs in new dishes. As an example, a dining system that reported a usual number of 3–6 meal options had a variety of 4 meal options.

The data sample consisted of 33 data points on a discrete range from 1 to 4. As the data contained many ties and were non-normally distributed (Shapiro-Wilk test, $n = 33$, $p < 0.05$), Kendall's rank correlation was chosen as the most suitable method.

2.6.12. Comparable number of dishes

'Comparable number of dishes' was used as a measure of the total number of meal options generally offered at a school. The measure was calculated as average number of meal options offered in each dining system. As an example, a school with a span of 2–3 meal options had a comparable number of 2.5 dishes.

The resulting data sample consisted of 33 data points on a continuous range from 1 to 4.5. As the data were non-normally distributed (Shapiro-Wilk test, $n = 33$, $p < 0.05$) and contained ties, Kendall's rank correlation was chosen as the most suitable method.

2.6.13. Number of semesters with food waste measurements

'Number of school semesters with food waste measurements' varied between 1 and 8 for the different dining systems. As the data sample was non-normally distributed (Shapiro-Wilk test, $n = 177$, $p < 0.05$) and contained many ties compared with the sample size of 177 data points, Kendall's rank correlation was chosen as the most suitable method.

2.6.14. Type of kitchen

'Type of kitchen' was distinguished to be either 0 for production units or 1 for satellite units, resulting in a bivariate data sample with 177 data points. As waste per portion, serving waste per portion and plate waste per portion were normally distributed (Shapiro-Wilk test, $n = 177$, $p > 0.05$), Pearson's product-moment correlation was chosen as the most suitable method.

2.6.15. Portion size

'Portion size' (g) was calculated as the total amount of food served divided by the number of portions served. The data sample consisted of 128 data points on a continuous range from 182.7 to 725 g and contained two outliers at 583.6 g and 725 g. As the data were non-normally distributed (Shapiro-Wilk test, $n = 128$, $p < 0.05$), Spearman's rank correlation was chosen as the most suitable method. The method is resistant to outliers.

2.6.16. Standard deviation (STD) in number of diners

'Standard deviation (STD) in [the daily] number of diners' was calculated for 129 schools and pre-schools and the data sample had a range from 0.98 to 301.43. The data were non-normally distributed (Shapiro-Wilk test, $n = 129$, $p < 0.05$) and did not contain many ties compared with the sample size. Spearman's rank correlation was chosen as the most suitable method.

2.6.17. Comparable STD number of diners

'Comparable standard deviation (STD) in number of diners' was calculated by dividing the standard deviation of the number of diners by the number of pupils. The resulting data sample contained 112 data points on a range from 0.006 to 0.669. As the data were non-normally distributed (Shapiro-Wilk test, $n = 112$, $p < 0.05$) and did not contain any ties, Spearman's rank correlation was chosen as the most suitable method.

2.7. Multiple linear regression (MLR)

2.7.1. Model equation

In order to quantify the impact of significant influential factors on food waste, a multiple linear regression (MLR) model was developed for each food waste quantity. According to Uyanik and Güler (2013), the advantage of using an MLR model instead of diverse correlations is the ability to quantify the total effect from relevant factors on the model outcome.

In general, an MLR model includes an intercept (c0), unscaled model coefficients (c0, c1, c2, ..., cn) and two or more explanatory variables (x1, x2, ..., xn) that together explain the variation in the response variable (y). In most cases some unexplained noise remains, often referred to as the error (ε) in the model. (Eq. (1)); Helsel and Hirsch, 2002). If the model outcome is likely to depend on the interaction between two factors, an interaction term (x1*x2) can be added to the general model equation (Eq. (2); Helsel and Hirsch, 2002).

$$y = c_0 + c_1 * x_1 + c_2 * x_2 + \cdots + c_n * x_n + \varepsilon \quad (1)$$

$$y = c_0 + c_1 * x_1 + c_2 * x_2 + \cdots + c_n * x_n + a_1 * x_1 * x_2 + \cdots + \varepsilon \quad (2)$$

2.7.2. Assumptions and choice of explanatory variables

With respect to the results from the correlation analysis, a number of MLR models based on different factor constellations were tested for each food waste quantity. According to Field et al. (2012), the choice of explanatory variables should be based on theoretical reasons. Only factors that were significantly correlated ($p < 0.05$) or almost significantly correlated ($p < 0.1$) with food waste were therefore used for developing the model. Furthermore, the model outcome should be linearly dependent on all explanatory variables included in the model (Field et al., 2012). The explanatory variables should be independent and randomly distributed, while the response variable is assumed to be normally distributed (Uyanik and Güler, 2013). To allow the MLR model to be generalised beyond the data used for model development, the residuals should be normally distributed and not show any specific pattern (Field et al., 2012).

Since the food waste quantities expressed as plate waste per portion, serving waste per portion and total waste per portion were normally distributed (Shapiro-Wilk test, $n = 35$, $p > 0.05$), three different MLR models (A-C) with food waste quantities as response variables were developed. Graphical analysis confirmed that the assumption about linearity held for all explanatory variables included in the models. To avoid biased models, outliers were removed from the data used for modelling (Uyanik and Güler, 2013) and factors that were likely to cause multi-collinearity (tau > 0.6 according to correlation matrix) were eliminated before model development. Multi-collinearity between factors exists when a factor included in a model is dependent on another factor that is also included in the model. Due to the factors dependence on each other, the model outcome is biased and not representative of the true relationships between the model outcome and the factors included. (Helsel and Hirsch, 2002; Field et al., 2012)

2.7.3. Validation and choice of model

Backwards elimination was used to choose the best performing MLR models. All explanatory variables significantly or almost significantly correlated to the food waste quantity were included in the different models. Explanatory variables that were not significant for the model outcome ($p > 0.05$) were eliminated step by step until all remaining explanatory variables significantly influenced the variation in the response variable ($p < 0.05$) (Helsel and Hirsch, 2002).

To improve model performance, different interaction terms were then added through backwards elimination. The best performing model was chosen with respect to the coefficient of determination, R^2, and the number of explanatory variables. According to Helsel and Hirsch (2002), a good model explains as much of the variation in the response variables with as few explanatory variables as possible. As the R^2-value naturally increases with each explanatory variable included in the model, the adjusted R^2-value, which considers the number of explanatory variables, was used to determine the best performing model (Helsel and Hirsch, 2002). To ensure that the assumptions of linearity, normality and independence held for the chosen models, graphical analysis was performed on a residual and a quantile-quantile plot (Field et al., 2012).

3. Results

3.1. Correlation analysis

The findings from the correlation analysis are summarised in Fig. 1. The analysis showed that the factors 'number of employees', 'number of seats in dining space', 'STD in number of diners' and 'number of pupils' were strongly correlated (tau > 0.7). The strong correlation between these four factors is caused naturally, as a higher number of pupils requires a more generous dining space and a higher number of employees. A higher number of pupils also increases the probability of pupils being absent during lunch time, which increases the standard deviation in the number of diners at a facility. Most likely the number of seats in dining space is the factor directly influencing plate waste per portion, which is discussed in Section 4.2.

In graphical analysis performed on scatterplots before each correlation analysis, only monotonic trends were found when observing the relationship between food waste and the different parameters, verifying Spearman's and Kendall's rank correlations as appropriate methods for analysis. Furthermore, graphical analysis showed that the assumption about a linear relationship between food waste and factors analysed with Pearson product-moment correlation held, verifying the method as appropriate.

3.1.1. Correlations with plate waste per portion

'Plate waste per portion' was significantly positively correlated with 'comparable age', 'portion size', 'number of pupils', 'number of seats in dining space', 'standard deviation in number of diners', 'number of employees' and 'gender of staff' (male employees) (Table 3). The factors 'number of employees', 'number of seats in

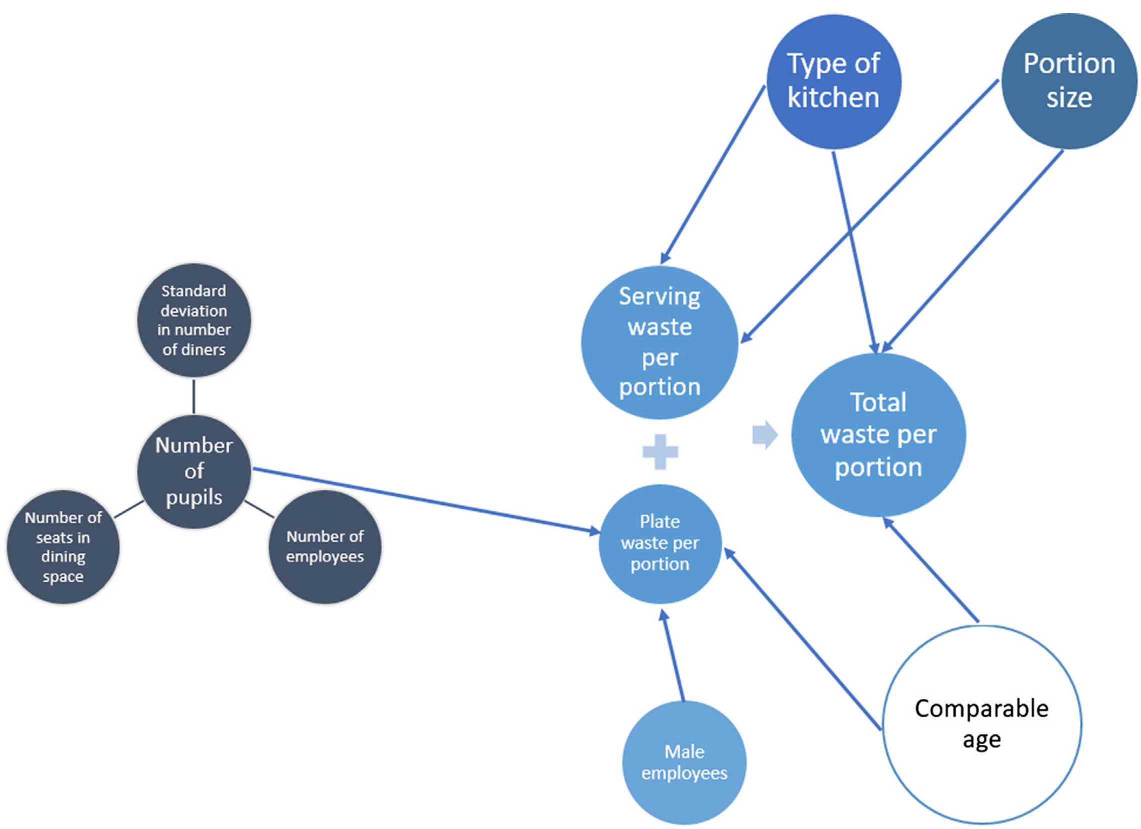

Fig. 1. Schematic model showing the interactions between factors and their influence on food waste quantities. Total waste per portion is the sum of serving waste and plate waste per portion.

Table 3
Significant correlations between different parameters and plate waste per portion; method, number of data points n, p-value and strength of the correlation according to the correlation coefficient; significance level p < 0.05.

Factor	Method	n	p-value	Correlation coefficient
Comparable age	Kendall	141	<0.001	tau = 0.21
Portion size	Spearman	128	<0.001	rho = 0.32
Number of pupils	Spearman	141	<0.0001	rho = 0.38
Number of seats in dining space	Kendall	50	<0.0001	tau = 0.42
STD in number of diners	Spearman	129	<0.01	rho = 0.27
Number of employees	Kendall	35	<0.001	tau = 0.45
Gender of staff (% male employees)	Kendall	35	<0.05	tau = 0.31

Table 4
Significant correlations between different parameters and serving waste per portion; method, number of data points n, p-value and strength of the correlation according to the correlation coefficient; significance level p < 0.05.

Factor	Method	n	p	Correlation coefficient
Portion size	Spearman	128	<0.0001	rho = 0.38
Type of kitchen	Pearson	177	<0.001	r = 0.28

Table 5
Significant correlations between different parameters and total waste per portion; method, number of data points (n), p-value and strength of the correlation according to the correlation coefficient; significance level p < 0.05.

Factor	Method	n	p-value	Correlation coefficient
Comparable age	Kendall	141	<0.05	tau = 0.15
Portion size	Spearman	128	<0.0001	rho = 0.48
Type of kitchen	Pearson	177	<0.01	r = 0.24

dining space' and 'STD in number of diners' were strongly positively influenced by 'number of pupils' (tau > 0.7).

3.1.2. Correlations with serving waste per portion

Serving waste per portion was significantly positively correlated with portion size. Satellite units had significantly higher serving waste than production units (Table 4).

3.1.3. Correlations with total waste per portion

Total waste per portion, i.e. the sum of plate waste and serving waste per portion, was significantly positively correlated with 'portion size' and 'comparable age'. Satellite kitchens had significantly higher waste per portion than primary production units (Table 5).

3.2. Multiple linear regression (MLR)

3.2.1. Plate waste per portion

Among the models tested, the food waste quantity plate waste per portion was best explained by MLR model A including the factors 'comparable age' and 'portion size' (Eq. (3)); Table 6). As a model is always a simplification of reality, the accuracy and robustness of a model decreases with each parameter. Thus, the amount of parameters for this model has been reduced to 'comparable age' and 'portion size' to avoid over-fit. Together, these factors explained 87.1% of the variation in plate waste per portion between the schools used for analysis (n = 121, p < 0.0001, adjusted $R^2 = 0.871$, multiple $R^2 = 0.873$) with a residual standard error of 10.56 g. As the red[1] line in the residuals plot shows (Fig. 2), the residuals for model A were randomly distributed and did not follow a pattern, indicating linearity and homoscedasticity (Fig. 2). Moreover, the standardised residuals in the quantile-quantile plot followed the dashed line and sufficiently satisfied the assumption of linearity (Fig. 3).

$$\begin{aligned} \textit{Plate waste perportion } [g] = {} & 0.952(\pm 0.3176) \\ & * \textit{Comparable age} \\ & + 0.067(\pm 0.0057) \\ & * \textit{Portion size} \pm 10.56 \ g \end{aligned} \tag{3}$$

3.2.2. Serving waste per portion

The food waste quantity serving waste per portion was best explained by MLR model B including 'portion size' and the interaction between 'portion size' and 'type of kitchen' (Eq. (4)); Table 7). Together, these explained 85.1% of the variation in serving waste between the schools used for analysis (n = 120, p < 0.0001, adjusted $R^2 = 0.851$, multiple $R^2 = 0.853$) with a residual standard error of 15.04 g. As the red line in the residuals plot shows (Fig. 4), the residuals for model B were randomly distributed and did not follow a pattern, indicating linearity and homoscedasticity. Moreover, the standardised residuals in the quantile–quantile plot followed the dashed line and sufficiently satisfied the assumption of linearity (Fig. 5).

Table 6
Multiple regression model A for plate waste per portion; significant factors and p-values.

Model A	Factor	p-value
	Comparable age	<0.01
	Portion size	<0.0001

$$\begin{aligned} \textit{Serving waste perportion } [g] = {} & 0.018(\pm 0.0086) \\ & * \textit{Type of kitchen} \\ & * \textit{Portion size} \\ & + 0.101(\pm 0.0050) \\ & * \textit{Portion size} \pm 15.04 \ g \end{aligned} \tag{4}$$

3.2.3. Total waste per portion

Among the models tested, total waste per portion was best explained by MLR model C including the factors 'type of kitchen' and 'portion size' (Eq. (5)); Table 8). Together, these factors explained 92.2% of the variation in total waste per portion between the schools used for analysis (n = 118, adjusted $R^2 = 0.922$, multiple $R^2 = 0.924$, p < 0.0001). As the red line in the residuals plot shows (Fig. 6), the residuals for model C were randomly distributed and the assumptions of linearity and homoscedasticity were fulfilled. Moreover, the standardised residuals in the quantile–quantile plot followed the dashed line, indicating that the assumption about normality was sufficiently fulfilled (Fig. 7).

$$\begin{aligned} \textit{Total waste perportion } [g] = {} & 7.288(\pm 3.516) \\ & * \textit{Type of kitchen} \\ & + 0.180(\pm 0.006) * \textit{Portion size} \\ & \pm 18.11 \ g \end{aligned} \tag{5}$$

4. Discussion

4.1. MLR models for explaining food waste in schools and pre-schools

Among the plate waste models tested, model A had the highest coefficient of determination and can be used to explain 87.1% of

[1] For interpretation of color in Figs. 2, 4, 6, the reader is referred to the web version of this article.

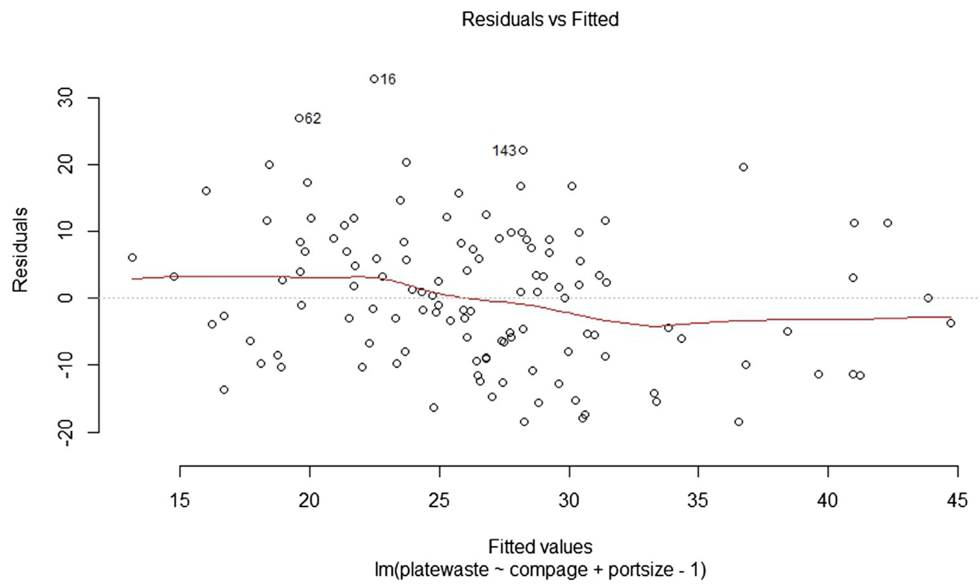

Fig. 2. Residuals plot for multiple linear regression model A for plate waste per portion. Note that the scale on the vertical axis is different from that in Figs. 4 and 6.

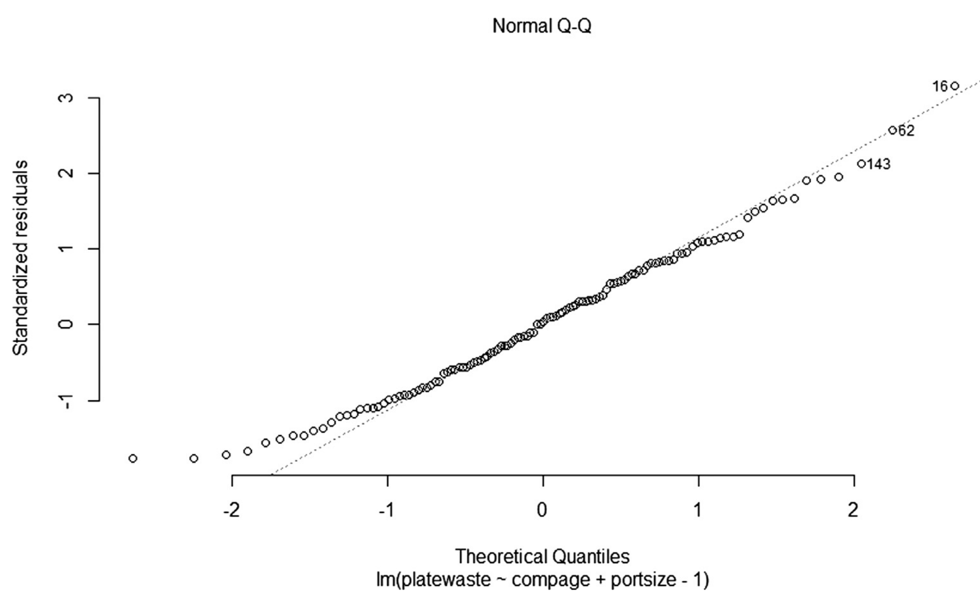

Fig. 3. Quantile-quantile plot for the standardised residuals for model A. The horizontal axis shows the theoretical quantiles and the vertical axis shows the standardised residuals.

Table 7
Multiple linear regression model B for serving waste per portion; significant factors and p-values.

Model B	Factor	p-value
	Type of kitchen: Portion size	<0.05
	Portion size	<0.0001

the plate waste generated in schools and pre-schools. According to this MLR model, the factors comparable age and portion size significantly contribute to plate waste. As the residuals were normally distributed and the assumptions of linearity and homoscedasticity held, model A can be generalised beyond the data range used for developing the model (Field et al., 2012). Thus, the plate waste per portion generated in schools and pre-schools is dependent on children's age and the rate of overproduction, indicated by the portion size, with a residual standard error of about 11 g (Eq. (3)). The finding that plate waste increases with children's age is in line with the results from the correlation analysis. Plate waste was also expected to increase with increasing portion size, which was confirmed by model A.

Among the models tested for serving waste per portion, model B could be generalised beyond the data range used for development, as the assumptions about linearity, homoscedasticity and normality held. The factor portion size and the interaction between type of kitchen and portion size contributed significantly to serving waste per portion and explained 85.1% of the serving waste generated in schools and pre-schools. The effect of the interaction was at its highest when portion size was large in satellite units (Eq. (4)), due to their difficulties in handling and storing food left-overs (Eriksson et al., 2017). Thus satellite units in particular would

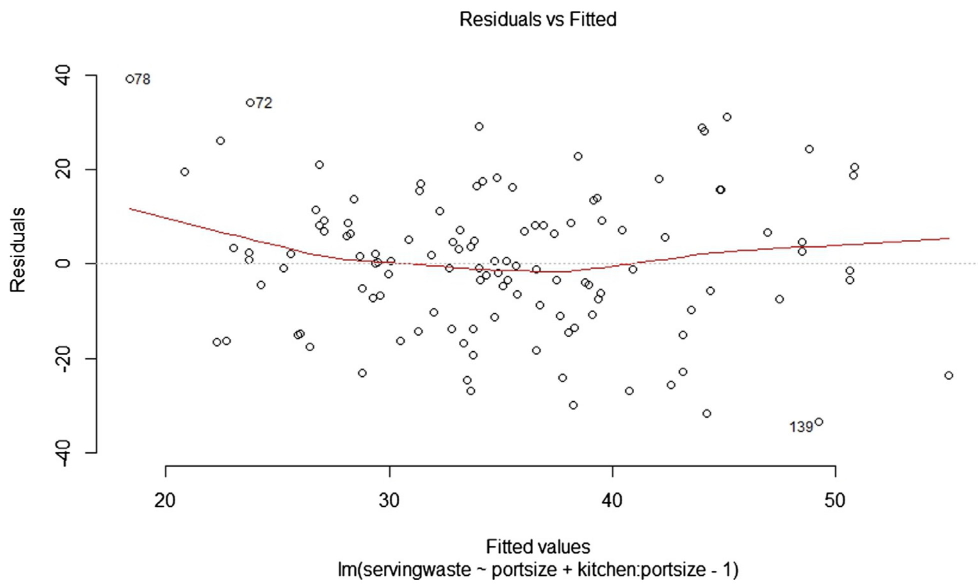

Fig. 4. Residuals plot for multiple linear regression model B for serving waste per portion. Note that the scale on the vertical axis is different from that in Figs. 2 and 6.

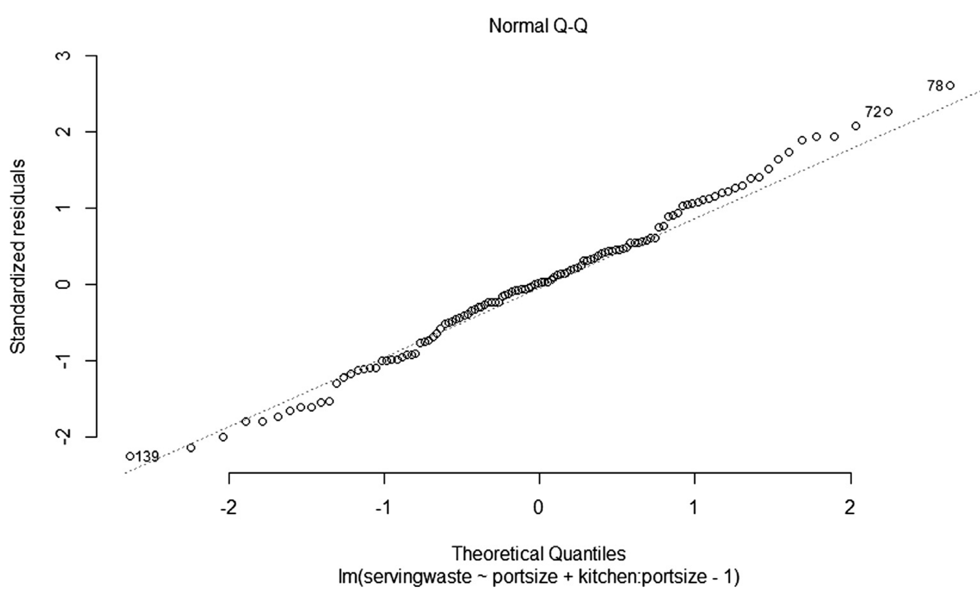

Fig. 5. Quantile-quantile plot for the standardised residuals for model B. The horizontal axis shows the theoretical quantiles and the vertical axis shows the standardised residuals.

Table 8
Multiple linear regression model C; significant factors and p-values.

Model C	Factor	p-value
	Type of kitchen	<0.05
	Portion size	<0.0001

benefit from more accurately planning their diners' intake on a daily basis. Other factors that might explain the variation in serving waste per portion could be management factors or stress (Kinasz et al., 2015), which might require a different approach for quantifying knowledge about diners.

Model C, including the factors type of kitchen and portion size, explained 92.2% of the variation in the total waste per portion for the given dataset, with a residual standard error of approximately 18 g.

Serving waste is reported to contribute two-thirds of the total waste per portion (Eriksson et al., 2016b), which explains the similarities between model B and model C. Since total waste per portion is the sum of both serving and plate waste per portion, the uncertainties in model C are higher regarding the residual standard error compared with those in models A and B.

4.2. Correlation analysis and significant influences on food waste in schools and pre-schools

Plate waste significantly increased with 'comparable age', meaning that children in higher school years produce more plate waste than children in lower years. Children in pre-school had the lowest plate waste, while pupils in secondary school generated the highest amount. In addition to plate waste, the total waste per portion significantly increased with childrens' age. As the correla-

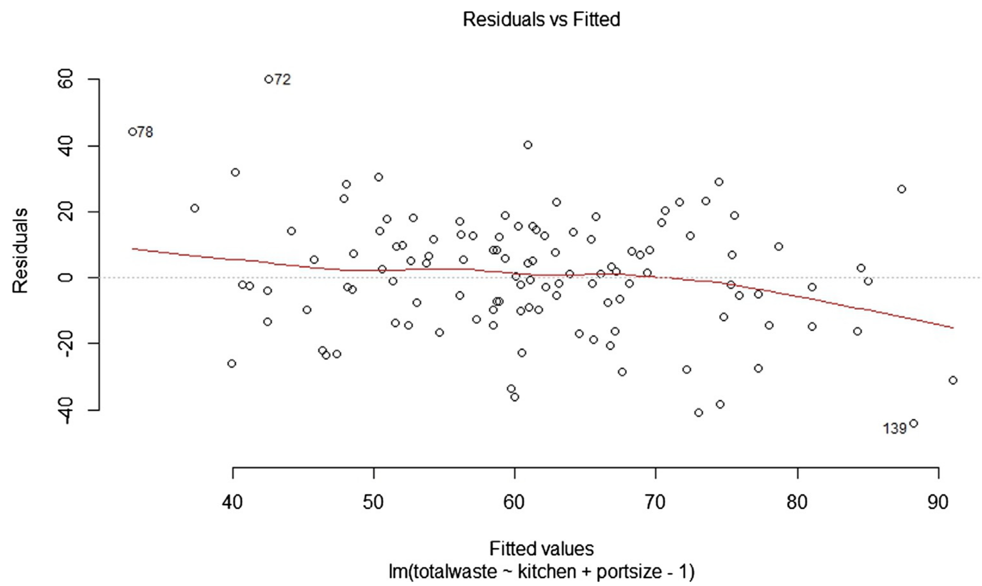

Fig. 6. Residuals plot for multiple linear regression model C for total waste per portion. Note that the scale on the vertical axis is different from that in Figs. 2 and 4.

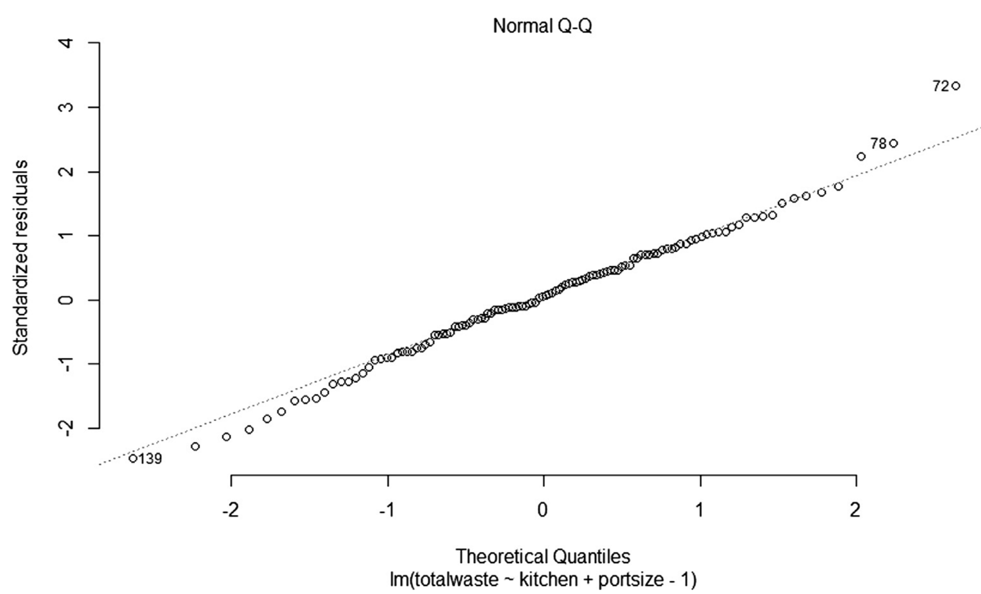

Fig. 7. Quantile-quantile plot for the standardised residuals for model C. The horizontal axis shows the theoretical quantiles and the vertical axis shows the standardised residuals.

tion (tau = 0.15) was weaker than that between plate waste per portion and comparable age (tau = 0.21), it is likely that serving waste per portion does not depend on children's age and that plate waste causes the correlation between total waste and comparable age.

A reason for the correlation between plate waste and comparable age could be that younger children often eat accompanied by their teachers and have more structured lunch breaks than older pupils. For example, pupils at Flogstaskolan in Uppsala eat with their teachers and have "quiet minutes" during their lunch breaks, which lets them eat without any distractions. Another reason for the correlation between children's age and plate waste could be that pupils in higher school years have the possibility to purchase food outside the dining hall, which according to Marlette et al. (2005) increases plate waste.

Schools with pupils in higher school years could most likely lower their plate waste by introducing more structured lunch breaks and should examine whether many of their students purchase food outside school or from the school cafeteria. Since pupils eat lunch for free in Swedish schools, it is unlikely that they tell anyone that they intend to eat elsewhere. Implementation of a booking system like that tested by WRAP (2011), where pupils had to pre-order the meal they intended to eat every day during a test period, could therefore help the kitchen to better plan their production and avoid overproduction.

Both plate and serving waste significantly increased with larger portion size. Since portion size is the total amount of food produced divided by the number of portions that are actually served, portion sizes increase when a facility has fewer diners relative to the amount of food prepared or overestimates its diners' food intake. The factor portion size can therefore be seen as an indicator of food overproduction. According to the municipalities concerned, schools and pre-schools do not plan their food production on a daily basis. Instead, food production follows the number of pupils registered at the school and often neglects knowledge about pupils that are not able to attend the meal due to illness or excursions (Falun, Malmö, Sala and Uppsala municipalities, personal communications, 2017). Due to the lack of information about the daily number of diners, the risk of food overproduction is high. The deviation in the daily amount of diners increases with the number of pupils registered at a school or a pre-school. In large schools, the daily number of diners can deviate by up to 300.

Food overproduction might reduce the staff's urge to balance the children's portion sizes and tempt children to take more food than they intend to eat, which could be an explanation for the correlation between plate waste and portion size.

Serving waste naturally increases with overproduction. According to model B, serving waste reached its peak when portion size was large in a satellite unit. Satellite units in general had significantly higher serving waste than production units, which confirms findings by Eriksson et al. (2017). Production units, rather than satellite units, have possibilities to cool and store left-overs and have a more flexible menu where left-overs can be used, which explains the correlation between type of kitchen and serving waste. For satellite units, the total waste per portion was also higher than the total waste in production units, although the correlation strength ($r = 0.24$) was similar to that of serving waste per portion and type of kitchen ($r = 0.28$), indicating that plate waste per portion is not affected by the type of kitchen.

Given that both serving waste and plate waste could be effectively reduced by preventing overproduction, especially in satellite units, schools and pre-schools would benefit from better data support when estimating the daily amount of diners. Accurate estimates of portion sizes and enhanced planning have also been suggested as solutions for decreasing food waste in schools by Cordingley et al. (2011).

In addition, plate waste was significantly influenced by the number of students, the number of seats in the dining space, the STD in number of diners and the number of employees. As all four factors strongly influenced each other ($tau > 0.7$), it is probable that only one of these four factors directly influences plate waste. Considering that Spearman's rho tends to be higher than Kendall's tau for monotonic relationships (Helsel and Hirsch, 2002) and that the number of data points differed between the factors, no direct conclusion about the strength of the correlations between factors can be drawn. However, the number of seats in the dining space is the parameter most likely to affect plate waste, as increased noise levels in the dining space and a stressful environment probably increase plate waste (SEPA, 2009; Byker et al., 2014; Kinasz et al., 2015; Painter et al., 2016). Considering the fact that Kendall's tau tends to be smaller than Spearman's rho, the correlation between number of seats and plate waste was the strongest among the four factors mentioned, followed by the number of employees, although the latter is not expected to increase plate waste.

The percentage of male staff employed in the kitchen appeared to significantly increase plate waste, but an expanded dataset is required to confirm the presence of male kitchen employees as a factor influencing plate waste. The factor was influenced by the number of pupils ($tau = 0.49$) and comparable age ($tau = 0.50$). Both the number of pupils and comparable age increased generation of plate waste and could therefore have influenced the correlation between the percentage of male employees and plate waste per portion.

A different definition for the number of employees should be considered to quantify knowledge of diners and management factors, as mentioned by Kinasz et al. (2015). Instead of defining the number of employees as the number of staff members in the dining facility, the accumulated number of work hours per week could be used to quantify staff resources, in order to detect theoretically reasonable correlations.

Considering that queue time increases and lunch breaks shorten with a decreased number of seats per pupil, both serving waste and plate waste can be expected to decrease if the number of seats per pupil increases (Getlinger et al., 1996; Byker et al., 2014; Niaki et al., 2017). The dataset used for the present study contained a narrow range and few kitchens with >0.6 seats per pupil. It is therefore likely that a negative relationship between food waste and seats per pupil could be detected in a dataset with a greater range. The same applies for the comparable STD in the number of diners and the number of employees per student.

According to correlation analysis, neither plate waste nor serving waste per portion was significantly influenced by the type of dining space. Whether children eat in their classrooms or in a separate dining hall therefore has no impact on the amount of food waste generated in schools and pre-schools. Other factors without significant correlations with food waste were distance between dining space and classroom, number of semesters with food waste measurements, range of school years, comparable number of dishes and variety of meal options. The latter two factors often vary on a daily basis, which increases uncertainties in the data used for analysis.

4.3. Uncertainties and limitations

Facilities located in different municipalities and different types of educational establishments complicated the collection of unified food waste measurements. The measured food waste data used for analysis and model development in this study therefore contained uncertainties. However, some general trends and associations could be detected with the material used.

Due to the biased opinions caused by public views on dining systems in educational establishments (Persson Osowski, 2012), only quantified factors were used for analysis. The coefficient of determination values obtained showed that over 85% of the food waste generated in schools and pre-schools can be explained using the risk factors analysed in this study, indicating that these factors are likely to explain the majority of food waste generation. However, other factors that are more difficult to quantify could also have a significant impact on food waste generation and including these would help to further improve the models developed here. Such factors could include information about management structures, knowledge about diners, awareness about food waste as an issue and a different definition of the number of employees. A dataset with a wider range regarding the factor seats per pupil should also be analysed. In addition, the variety of meal options should be examined with the aid of a more specific survey.

5. Conclusions

Plate waste in schools and pre-schools increases with children's age and could potentially be reduced by implementing more structured lunch breaks for schools with older pupils. Plate waste also increases with the number of seats in the dining space, probably due to rising noise and stress levels. Both plate waste and serving waste increase with larger portion sizes, indicating overproduction. Total food waste in schools and pre-schools could therefore be effectively reduced by more accurate estimation of the daily number of diners and their food intake. As serving waste is generally higher in satellite units than in production units, satellite units in particular would benefit from better information so that they could more accurately estimate the daily number of diners. There is therefore a need for waste reducing policies in municipalities to not just set goals for food waste reduction, but also to reduce risk factors causing waste. Sometimes there can be goal conflicts if some risk factors also provide benefits and therefore more detailed quantifications of risk factors can build the foundation for efficient and accurate policies and incentives.

Application of multiple linear regression models showed that over 85% of the variation in food waste generated in schools and pre-schools can be explained by children's age, the rate of overproduction and the type of kitchen. However since the age of the children cannot be changed the other parameters could be adjusted in order to compensate for higher age. Especially overproduction is something where the catering units could have the highest benefits by reducing the extra margin. There is also a need to actually test and evaluate interventions with the potential to reduce certain risk factors, since it should not be assumed that just reducing a risk only give the expected outcome.

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