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Published in:
Resources, Conservation and Recycling

Link to article, DOI:
[10.1016/j.resconrec.2017.11.013](https://doi.org/10.1016/j.resconrec.2017.11.013)

Publication date:
2018

Document Version
Peer reviewed version

[Link back to DTU Orbit](#)

Citation (APA):
Edjabou, M. E., Boldrin, A., & Astrup, T. F. (2018). Compositional analysis of seasonal variation in Danish residual household waste. *Resources, Conservation and Recycling*, 130, 70-79.
<https://doi.org/10.1016/j.resconrec.2017.11.013>

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Paper is published in Resources, Conservation & Recycling

Compositional analysis of seasonal variation in Danish residual household waste

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Abstract

Seasonal variations are considered one of the key factors affecting the generation and composition of residual waste. Despite this importance, attempts have not been made to characterize residual household waste consistently by accounting for seasonal variations in waste disposal patterns. To assess differences between seasons and within individual households, we collected residual household waste from the same 101 households in summer, autumn and winter. The waste bags were sorted individually, and residual household waste data (mass and composition) were generated for each household. In total, 3 tonnes of waste were collected, weighed and manually sorted into nine (9) waste fractions. The result of mixed linear model indicated that for this study area, seasonal variations may introduce no significant difference to the mass and composition of residual household waste. However, residual waste generation within a household may change significantly between the seasons. The result also showed that while household size may significantly influence the generation of residual household, the difference in residual household waste composition was not significantly different between household sizes.

33	Keywords
34	Seasonal variations
35	Isometric log-ratio
36	Waste composition and generation
37	Repeated measures
38	Multivariate mixed model
39	

1 Introduction

In several countries, the approach to managing waste is changing rapidly. In particular, the transition of municipal solid waste management to circular economy and resource efficiency poses unprecedented challenges in terms of waste management planning, which in turn typically requires comprehensive and reliable data about waste generation and composition. Generally, these data are obtained from sampling, sorting and analysing solid waste streams into desired and pre-defined waste fractions (Edjabou et al., 2015a). To attain reliable data, the seven sampling errors described by Pierre Gy should be avoided: (1) long-range heterogeneity fluctuation, (2) periodic heterogeneity fluctuation, (3) fundamental errors, (4) grouping and segregation, (4) increment and delimitation, (5) increment extraction and (7) preparation errors (Pitard, 1993). Among these errors, tackling periodic heterogeneity fluctuations is particularly challenging, because repeated sampling and analysis is costly and time-consuming (Dahlén and Lagerkvist, 2008).

To address periodic variations (e.g. short-term and seasonal variations), available methods for the determination of waste composition recommend that a waste sample should: (1) cover at least one full week (including weekends), given that the waste generated during weekends may be different to weekdays (Edjabou et al., 2015a), and (2) be stratified based on seasons, which may induce significant variations in the generation and composition of residual household waste (European Commission, 2004). Generally, a full week's data for waste generation and composition are often assumed representative of the whole year (see Edjabou et al., 2015b; Riber et al., 2009). In contrast, a number of other studies have investigated the seasonal generation and composition of household waste (e.g. Denafas et al., 2014; Edjabou et al., 2012; Kamran et al., 2015; Andersen and Larsen, 2012, Aguilar-Virgen et al. 2013). Although these studies concluded that the generation and composition of household waste are affected by seasonal variation, a major drawback of these studies is that the waste was not sampled from the same households for all seasons, thereby introducing

inherent uncertainty related to variations in the households' socio-economic situation.

Besides not addressing fluctuations properly, several of the previously mentioned studies did not deal accurately with the fact that waste composition datasets, by nature, are “closed datasets”, i.e. the relative contribution of waste fractions should always sum up to 100% (Aitchison, 1986). A major problem with closed datasets is that parts of the composition are linked intrinsically to each other (Edjabou et al., 2015c). Consequently, an increase in the percentage of a waste fraction will lead automatically to a decrease in another fraction and vice versa. This natural property of compositional data biases statistical analysis of the relationship between seasonal variations and waste composition. Moreover, results from statistical analysis applied to dataset for waste fraction generation rates (kg waste fraction per week) can neither be necessary generalised nor extrapolated to waste fractional composition dataset (see Edjabou et al., 2017). As a solution, a procedure based on multivariate analysis applied to log-ratio coordinates has been suggested (e.g. Aitchison and Ng, 2005; Egozcue et al., 2003). For this study, an isometric log-ratio transformation (Egozcue et al., 2003) was applied to the waste composition dataset (see SM Table 1), in order to overcome the total sum constraint problem (Aitchison, 1994). Another advantage of the isometric log-ratio transformation is that the same isometric log-ratio coordinates are obtained with either individual waste fraction generation rates (kg waste per week for each waste fraction) or percentage compositions.

The objective of this study was to assess whether the generation and composition of residual household waste are associated with seasonal variations. This was achieved by: (i) collecting waste composition data from 101 households in Denmark, (ii) statistically treating the data using compositional data techniques and (iii) investigating and identifying any significant relationships between seasons and household size.

2 Methods and materials

2.1 Study area

Residual household waste generated in a Copenhagen suburb was sampled and characterized. In this area, paper, board, metal, garden waste, hazardous waste, waste electrical and electronic equipment (WEEE) as well as bulky items were source-segregated. However, some of these fractions are often misplaced in the residual household bins. Thus, misplaced waste fractions are waste fractions that should have been source-sorted by households for recycling purposes. Therefore, residual household waste included food waste, miscellaneous combustible (e.g. diapers, textiles, etc.) plastic packaging and film, tissue paper, wrapping paper and misplaced source-segregated waste (Table 1).

In this study area, the waste bins had volumes of 180-360 l. They are equipped with a throwback lid, which is always closed to protect the waste from weather exposure (rain, snow, sun, etc.). Thus, the weather and seasonal variation cannot influence the physical characteristics of the waste during the storage and the collection from households. As result, any significant changes in generation and composition of waste can be attributed to the households.

2.2 Experimental design

The waste was sampled from the same group of households in autumn, summer and winter, in 2011-2012. Samples from individual households were taken from waste generated during a full week in each of the three seasons, in compliance with existing guidelines, such as European Commission (2004), Nordtest, (1995) and US EPA, (2002). The waste samples were retrieved as part of the ordinary waste collection schedule, to prevent any changes in household waste generation that may lead to biased results. Thus, the municipality department responsible for waste management selected the waste collection route in collaboration with the waste collection company in the study area. The households located in this collection route are assumed to be representative for the study area with regard to the volume of waste bins, household size and socio-economic patterns (e.g. population distribution) (see Edjabou et al.,2015).

In total, 101 randomly selected households were involved in the study. An additional nine households, initially part of the project, were discarded because they missed one or more sampling campaigns. The exclusion was necessary to ensure it was possible to identify any changes in composition and generation rates within individual houses. For each household, the number of occupants for the three seasons was obtained from the local council authorities.

Residual household waste was collected prior to any compaction and sorted into (1) food waste (Food), (2) gardening waste (Garden), (3) paper, (4) board, (5) metal, (6) plastic packaging, (7) plastic films, (8) inert materials and (9) miscellaneous combustible waste (Table 1). Here, the paper fraction included all types of paper, such as kitchen tissue, newsprints, etc. For this study, gardening waste, paper, board, metal and plastic packaging are misplaced waste, whereas food waste, miscellaneous combustible waste are residual household waste.

Waste sorting was conducted within a week after sampling. Neither sieving nor mass reduction was applied prior to waste sorting. Furthermore, waste from individual households was sorted separately, and the data were then recorded and analysed.

The total amount of residual household waste sampled was 3 tonnes, corresponding to about 1 tonne per season (Table 2). The numbers of households as a function of household size (number of occupants per households) and per sampling period are provided in Table 2. For this study, households were split into four groups, according to the number of occupants, namely one person (1p), two persons (2p), three persons (3p) and more than three persons (4p+) (Edjabou et al., 2016).

Table 1

Table 2

2.3 Statistical Analysis

2.3.1 Geometric mean bar plot

We computed geometric mean of data for a fractional solid waste composition as follows:

$$g_{mi}(x) = \exp\left[\frac{1}{n} \sum_{i=1}^n \ln(x_i)\right] \quad \text{Eq. (1)}$$

where $g_{mi}(x)$ is the geometric mean of a waste fraction m for the individual subgroup i (e.g. autumn, winter and summer), n is the number of observations (e.g. 101 households) and $\ln(x_i)$ is the natural logarithm and its inverse $\exp(x_i)$.

To construct the geometric mean bar plot, we used the ratio at a logarithmic scale between geometric means as follows:

$$\log\left(\frac{g_{mi}(x)}{g_i(x)}\right) = X_m \quad \text{Eq. (2)}$$

where $g_i(x)$ is the geometric mean of waste fractions m (e.g. food waste, gardening waste) without subgroups, and X_m is the ratio at a logarithmic scale for the waste fraction m . Based on Eq. (2), geometric means g_{mi} of a waste fraction for each subgroup can be compared consistently and illustrated graphically by means of a geometric mean bar plot. To interpret the bar plot, X_m is back-transformed to a ratio of geometric means (k_m) as follows:

$$k_m = \exp(X_m) = \frac{g_{mi}(x)}{g_i(x)} \quad \text{Eq. (3)}$$

Based on Eq.(3), three possible scenarios are apparent: (1) if $X_m > 0$, then $k_m > 1$ and $k_m = 1 + r_m$. This corresponds to cases where bars are above the x-axis line and is interpreted as the geometric mean (g_{mi}) of a fraction $-m$ for a subgroup i is ($r\%$) higher than the average geometric mean (g_i). (2) if $X_m < 0$, then $k_m < 1$, and $k_m = 1 - r_m$, which occurs in cases where bars are below the x-axis. Here, the geometric mean (g_{mi}) is ($r\%$) lower than the average geometric mean (g_i). (3) if X_m

=0, $k_m=1$ and $r_m=0$, thus $g_i=g_m$. This is shown by non-existent bars. Thus, small bars indicate a small difference between subgroups, whereas large bars highlight major discrepancies.

2.3.2 Mixed linear modelling

For this study, the general mixed linear model has the form:

$$Y_{ijk} = \mu + i_i + v_j + (iv)_{ij} + f_k + \epsilon_{ijk} \quad \text{Eq. (4)}$$

where μ is a general constant, i_i is the contribution of the season i , v_j is the contribution made by household size j , $(iv)_{ij}$ is the contribution of the interaction between season i , household size j , and f_k is the contribution of a random effect k , and Y_{ijk} is a dependent variation. For this study, Y_{ijk} represents waste composition (in percentage) and generation rates (kg/household/week and kg/person/week) and is known as “compositional data with a total” (Pawlowsky-glahn et al., 2015). Noticeably, μ , i_i , v_j , $(iv)_{ij}$ are fixed effects and f_k is a random effect explaining the ‘mixed linear model’ term. Fixed effects analyse the influence of season and household size on the average waste composition and generation rates, whereas a random effect examines the variability in individual houses (Faraway, 2016; Schutz and Gessaroli, 1987). In this sense, it should also be noted that for the waste composition consisting of nine fractions, Y_{ijk} is a compositional random variable (see van den Boogaart et al., 2014, for mathematical specifications and computation). Here, the waste generation rates were analysed in a separate linear mixed model (Kynčlová et al., 2015).

The critical assumption of the mixed linear model applied to the waste composition dataset and waste generation rates, namely (1) homogeneity of variances and covariance and (2) normality distribution of the residuals, were investigated respectively by a Box’s M-test and squared Mahalanobis (Berridge and Crouchley, 2011; Faraway, 2016) and provided in the Supplementary data.

2.3.3 Software

The modelling and analysis of data were carried out in Open Source R statistical programming language and software (R Core Team, 2017) and the freeware CoDaPack (Thió-Henestrosa and Martín-Fernández, 2005). The isometric log-ratio transformation for waste composition was carried out by means of R package compositions (van den Boogaart et al., 2014). We also used other R packages for linear mixed modelling, such as faraway (Faraway and Julian, 2016), pbkrtest (Halekoh and Højsgaard, 2014), lme4 (Bates et al., 2015) and RLRsim (Scheipl et al., 2008). These packages have the advantage to test simultaneously fixed and random effects as well as random effect individually.

3 Results and discussion

3.1 Household waste generation rates

In total, we analysed and modelled data from 303 samples, originating from 101 households over three seasons. The numbers of occupants in these houses are shown in Table 2. On average, the number of occupants per household was 2.4 people, which corresponds to the average Danish household size (Statistics Denmark, 2017).

The average waste generation rates amounted to 9.6 ± 4.5 kg per household per week (or 4.0 ± 2.4 kg per person) in the autumn, 9.9 ± 5.1 kg per household (or 4.0 ± 2.3 kg per person) in the summer and 9.2 ± 5.2 kg per household (3.8 ± 2.5 kg per person) in the winter (Table 3). As a result, the highest waste generation rate was observed in the summer, whereas the lowest was in the winter. The difference between estimates (means and median) is substantial and is linked to the violation of normal distribution assumption and the presence of “outlying” values (see SM Figures 1-3). The arithmetic means were higher than medians suggesting that the data were skewed to the right. Thus, a geometric mean may better compensate data skewness (Reimann et al., 2008). While the arithmetic mean is often used in the literature to represent a central value of a dataset, the results of this study shows that it is important to check the validity of the assumption before estimating arithmetic mean. For this reason, computing geometric mean, median, quartiles, and arithmetic mean provides a

complete information about household waste generation patterns (Edjabou et al., 2017).

Overall, the highest coefficient of variation (CV) was observed in the winter (57 and 66% per household and per week, respectively) and the lowest in the autumn (47 and 53%). The coefficient of variation of waste generation rate ranged from 48 to 57% for waste generation per household and from 53 to 66% for waste generation per person (Table 3). Thus, the dataset of waste per household was less “dispersed” than the mass estimated per person, indicating that mass per household may be preferred over mass per person as a best measure of the waste generation rate, thus confirming previous suggestions by Reimann et al. (2008). However, for this study, we analysed both datasets.

Table 3

The results of the mixed linear model applied to the generation rates do not indicate a significant difference in average waste both per household ($df=2$, $F\text{-value}=1.23$, $p\text{-value}=0.39$) and per person ($df=2$, $F\text{-value}=0.64$, $p\text{-value}=0.75$) between seasons (Table 4). A plausible explanation for this is that fresh food, including imported out-of-season products, is available throughout the whole year in the Danish food supply chain (Edjabou et al., 2016). Additionally, the significant packaging used to preserve and keep food fresh for longer periods during transportation and storage ends up in residual household in all seasons (Edjabou et al., 2015a; Lockrey, 2013).

The results also show there was a significant difference between household sizes in the waste generation per household ($df=3$, mass per household ($F\text{-value}=22.68$, $p\text{-value}<0.001$) and per person ($F\text{-value}=6.42$, $p\text{-value}<0.001$) (see Table 4). Furthermore, the average waste generation rate per household increased significantly in line with the number of occupants, regardless of the season, as shown in Figure 1.I. In contrast, waste generation per person decreased significantly according to the number of occupants in the house (Figure 1.II). Remarkably, similar waste generation patterns were observed in all the seasons, confirming that there was no significant difference in the mass of

household waste between seasons. While these results corroborate the findings of both WRAP (2009) and Edjabou et al. (2016), who suggested that the mass of household waste is affected significantly by household size, they do differ from previously published studies (e.g. Boer et al.2010; Denafas et al., 2014 and Gómez et al., 2009).

Table 4.

The statistical analysis revealed no significant interaction between seasonal variations and household size in the generation of residual waste (df=6, F-value=1.00, p-value=0.43 for kg/household/week and df=6, F-value=0.50, p-value=0.81 for kg/person/week), as shown in Table 5 and in Figure 1.

Figure 1

The random effect analysis shows that the waste generation rates (kg/person/week and kg/household/week) in individual houses were affected significantly by seasonal variations ($\chi^2(1)=39.48$, p-value<0.001) (Table 5). Results for waste generation rate per household are illustrated in Figure 2 (see SM Figure 4for waste generation per person). Here, horizontal lines represent the mean and its 95% confidence interval of mass of waste in each of the 101 households. The 95% confidence intervals excluding zero (vertical line x-axis) correspond to a statistically significant difference between the average waste generation rate in individual house (for the three seasons) and the overall average and vice versa. We deduced that the average generation rate of residual waste in 10% of houses was significantly higher than the overall average. In contrast, average residual waste was significantly lower in 5% of households compared to the overall average. This discrepancy in waste generation within houses may be due to inherent or lifestyle activities in individual households, and it may not necessarily be associated with seasonal variations. These findings may have important implications for planning waste collection systems (collection frequency and volume of waste bin). Whilst there is usually a standard volume of waste bins for all

households, our results suggest that households should be offered the possibility to request an extra bag, in case the volume of their waste exceeds the capacity of their waste bin. This solution is possibly more cost-effective than changing the volume of the waste bin (Nilsson, 2010). Owing to these results, models predicting the mass of household waste should consider random effects, in order to avoid biased estimations.

Table 5

Figure 2:

3.2 Composition of residual household waste

A comparative summary of the composition (percentage wet mass) of residual household waste for the three seasons is presented in Table 6. The descriptive statistics for individual fractions consist of (1) a classical statistics summary, including skewness (measures a distribution's departure from symmetry about its mean), kurtosis (measures the shape of the data), median, arithmetic mean (MEAN), back transformed of log mean (MEAN-log), standard deviation (SD) and coefficient of variation (CV); (2) A compositional data analysis (CoDa) summary involving the geometric mean (Center), the robust geometric mean (Center-R) and the percentage distribution of total variance (clr-variation in%), as suggested by Edjabou et al. (2017). Here, the robust geometric mean deals effectively with the problem of outliers and heavy-tailed distributions (Templ et al., 2016).

Regardless of statistical methods, a clear general pattern is noticeable. First, food waste (40–54%) represents the largest proportion of residual household waste in all three seasons, followed by paper and combustible waste fractions. Second, inert gardening waste and metal have the lowest percentages in all three seasons. Third, the highest percentage of food waste was observed in autumn (45-54%) followed by summer (43-50%).

Overall, misplaced waste fractions (gardening waste, paper, board, metal and plastic package) amounted to 18-30% of residual household waste.

For the three seasons, geometric mean estimates (47-55%) were higher than the arithmetic mean (40-45%) for food waste, while the opposite was found for inert waste (Table 6). This apparent discrepancy is explained by a violation of normal distribution when computing the arithmetic mean. First, the results presented in Table 6 indicate that the compositions of all the waste fractions exhibit a skewed distribution (skewness higher than ± 2), possibly violating the normality assumption (Wilcox, 2012). Second, there is large difference between arithmetic mean and median estimates, signifying that the former might be influenced by extreme values. In contrast, the isometric log-ratio transformation of the waste composition dataset approximates symmetric distribution. Thus, a geometric mean based on the log-ratio addresses the normality assumption and seems more reliable than the arithmetic mean.

Table 6.

Most waste fractions have a high coefficient of variation (above 50%), the highest of which were found for garden waste in winter (269%) and inert in summer (162%). Additionally, these fractions have the highest coefficients of variation in the three seasons. Overall, the coefficients of variation of individual fractions differ among seasons and are hence hardly comparable. The results of the percentage composition of food waste are consistent with the results discussed in Edjabou et al. (2016).

The total variance and its relative distribution (% clr-var) quantify and compare the variability of the percentage for individual waste fractions. The results from the total variance distribution show that inert and gardening waste fractions contributed greatly (i.e. $\sim 70\%$) to total variability in residual waste over the three seasons. On the contrary, the proportions of other waste fractions varied only slightly among households, due to the low contribution made to the total variation (less than 10%). Overall, the contribution of individual waste fractions to the total variance changed slightly over the three seasons. Similar conclusions were reached when comparing residual waste composition

between seasons, using the geometric mean bar plots in Figures 3 and 4. The results indicate that large differences between seasons appear primarily in garden waste. Based on Eq.(2), X_m values for gardening waste were -0.83, -0.56 and 1.39 for autumn, winter and summer, respectively (see Figure3). Given Eq. (3), k_m values for gardening were 0.43, 0.57 and 4.03 for autumn, winter and summer, respectively. The interpretation is that 57% ($r_m = k_m - 1 = 0.43 - 1$) and 43% less gardening waste was generated in autumn and winter compared to average gardening waste. On the other hand, the generation of garden waste in summer was 303% ($r_m = k_m - 1 = 4.03 - 1$) of the average (see SM Tables 2-4). Whilst these results are not surprising, they are in good agreement with those of Boldrin and Christensen (2010), who found that garden waste levels vary substantially during the year, with sizeably large quantities in summer. As mentioned in Boldrin and Christensen (2010), the reason is merely climatic: increased biomass is generated in gardens in summertime because of more insulation, longer days and higher temperatures, which in turn represent more pleasant conditions for gardening activities during which garden waste is collected. Small bars are observed for other misplaced waste fractions (paper, board, plastic packaging and metal), plastic films and combustible waste fractions, indicating that the average proportions of these fractions change slightly throughout the three seasons (Figure 3).

Figure 3

The geometric mean bar plot for residual household waste as a function of household size is shown in Figure 4. Households with one occupant had lower proportions of food waste (-43%), gardening waste (-72%), plastic (-45%), metal (-36%) and inert (-72%) waste fractions than the average (see Figure 4 and SM Tables 6-9); nonetheless, the proportion of paper was 25% higher than the average. Households occupied by three persons had higher proportions of food waste (18%), gardening waste (155%), paper (19%), metal (39%) and inert (199%) waste fractions than the

average. Overall, misplaced waste fractions (gardening waste, paper, board, metal and plastic package) amounted to 18-33% of residual household waste.

Figure 4

The results of the multivariate linear mixed model applied to isometric log-ratio coordinates showed no significant difference in the composition of residual waste between seasons ($df=2$, F -value=0.25, p -value=0.78) or within households $df=3$, F -value=2.04, p -value=0.11) (see Table 4) despite the differences shown in Figures 3 and 4. It should be noted that Table 4 (dataset of waste composition) presents results based on the isometric log-ratio coordinates.

For individual waste fractions, a pairwise comparison between seasons based on bootstrap percentile confidence intervals ($B=1000$) is presented in Figure 5. For example, differences in the proportion of gardening waste were -1.89% (with 95% CI from -4.52 to 0.96) between summer and winter, 0.38% (with 95% CI from -2.73 to 3.34) between autumn and winter and -2.26% (with 95% CI from -4.88 to 0.51) between autumn and summer. Moreover, for the difference in proportions for food waste, we found -0.05% (with 95% CI from -0.41 to 0.28) between summer and winter, -0.12% (with 95% CI from -0.45 to 0.10) between autumn and winter and 0.08% (with 95% CI from -1.16 to 0.034) between autumn and summer. These confidence intervals include zero, suggesting no significant difference in the proportion of garden waste and food waste between seasons, as shown in Figure 5. Overall, large differences were observed for gardening, inert and metal waste for all seasons (longer dashed lines). However, the percentile intervals of all the waste fractions included a zero value (no significance differences). This is illustrated in Figure 5, where all the dashed lines crossed the x-axis (see SM Tables 10).

These findings are contrary to most previous studies, which have suggested that seasonal variations may influence significantly household waste composition (e.g. Boer et al., 2010; Denafas

et al., 2014; Edjabou et al., 2012; Gómez et al., 2009). Several factors may explain these discrepancies. As an example, Boer et al. (2010) found that in Poland, households using a local gas and coal (coke) system generated significantly higher amounts of waste in winter, the composition of which varied significantly throughout the seasons. Moreover, Edjabou et al. (2012) and Gómez et al. (2009) reported significantly higher food waste generation during the rainy season and summer, respectively, in Togo and in Mexico. However, these locations have remarkably different socio-geographic characteristics compared to those in Denmark, making a direct comparison meaningless. Generally, in cases where decentralised heating systems based on coal or biomass are used, ash generation increases considerably, thereby markedly affecting household waste generation and composition during winter. Additionally, most Danish households purchase their food and fresh vegetable on a short-time basis regardless of the season (Edjabou et al., 2016). Another reason is that garden waste (grass clippings, hedge cuttings and soil) generated during summer is disposed of in waste recycling centres (Boldrin and Christensen, 2010). Only indoor flowers that represent a relatively small amount (less than 1% of the residual household waste) are misplaced, usually in residual waste. Moreover, seasonal variations and household sizes did not significantly influence the percentage of other misplaced recyclable materials (i.e. paper, board, plastic and metal) in household waste.

Figure 5

3.3 Limitations and application of these results

The present findings suggest that when waste composition is analysed, sampling should first be performed from all household sizes in the study area. Then, to obtain an average composition, the data should be aggregated (i.e. weighted) according to the distribution of household size in the population (European Commission, 2004). We can conclude that a waste composition dataset

representative of the whole year can be obtained from waste sampled for at least a full week from a representative group of households covering the different socio-economic and geographical conditions of the area. Participation in source-segregating recyclables (i.e. paper, board and plastic packaging and metal) may not be influenced significantly by seasonal variations.

For this study, residual household waste was sorted into nine waste fractions. Analysis of a more detailed waste fraction may not necessarily generate similar results. Additionally, owing to country-specific socio-economic conditions, these data could be applied to countries with important similarities to Denmark.

During the recent years, various software (e.g. CoDaPack, R) and packages (Oksanen, 2015; Templ et al., 2016; van den Boogaart, 2008) for the statistical analysis of compositional data have been developed and freely available. The advantage of these software and packages is that they do not require extensive programming skills. Therefore, we urge practitioners to use compositional data analysis technique to analyse waste composition data.

4 Conclusions and perspectives

To investigate the influence of seasonal variations and household size on the generation rates and composition of residual household waste, the sampling and characterisation of waste were performed for 101 Danish households in summer, autumn and winter. The results of the statistical analysis showed that the generation and composition of residual household waste is not significantly affected by seasonal variations. Therefore, for this study area, seasonal variations do not contribute to the periodic heterogeneity fluctuation error. Conversely, household size does influence significantly the generation rate (mass) of residual household waste, but not the waste composition. Consequently, household size is a critical parameter in sampling residual household waste, in order to estimate the mass of waste generated in a house. Accordingly, it is recommended

that the estimated generation rates of residual household waste are aggregated and based on household size, to avoid fluctuation errors that may be introduced by household size distribution.

Acknowledgments

The authors acknowledge the Danish Environmental Protection Agency (EPA), the municipalities of Gladsaxe and Claus Petersen from ECONET AS for giving us their permission to use these data and for their valuable contributions. Our gratitude goes also to Josep Antoni Martín-Fernández from the Department of Computer Science, Applied Mathematics and Statistics, University of Girona, Campus Montilivi (P4) for his valuable contribution to the statistical analyses employed in this study.

Appendix A. Supplementary data

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3 **Compositional analysis of seasonal variation in Danish**
4 **residual household waste**

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Table 1: List of residual household waste fractions and components included
(based on Edjabou et al., 2015)

Waste fractions	Components
Food waste (Food)	Vegetable and animal derived food waste: Fresh fruit, fresh carrots and potatoes, bread, cereals, residues from fruits, vegetables, coffee grounds, rest of food containing meat
Gardening waste (Garden)	Flowers,
Paper	Advertisements, books & booklets, magazines & Journals, newspapers office paper, phonebooks, miscellaneous paper
Board	Corrugated boxes, beverage cartons, folding boxes, miscellaneous board
Plastic packaging (Plastic)	Packaging plastics, PET/PETE (1), HDPE (2), PVC/V (3), LDPE/LLDPE (4), PP (5) PS (6) non-foamed, PS (6) foamed, Other plastic resins labelled with [1-19] (7), 7) or ABS, Unidentified plastic resin
Plastic film (Plastic foil)	Pure plastic film, composite plastics
Metal packaging (Metal)	Metal packaging containers (ferrous, non-ferrous), and composites
Inert	WEEE, Household hazardous waste, batteries, glass, ashes, cat litter, ceramics, gravel, etc.
Miscellaneous combustible waste	Human hygiene waste, other combustible waste, textile, leather, rubber, vacuum cleaner bags

Table 2: Number of households per sampling period (seasons) as a function
of household size and amount of waste analysed.

Year	Seasons	Number of households as function of household size ^a				Total number of households ^b	Total residual waste kg wet mass ^c
		1p	2p	3p	4p		
2011	Summer	15	45	13	28	101	1005
2011	Autumn	15	45	13	28	101	974
2012	Winter	15	45	13	28	101	932

^aHouseholds containing one (1p), two (2p), three (3p) and more than three (+4p) persons,

Table 3: Descriptive statistics of residual household waste generation rates
as a function of seasonal variations (wet mass): N=101 households per
season. Values are rounded to two decimal places.

Parameters	Mass per household per week			Mass per person per week		
	Summer	Autumn	Winter	Summer	Autumn	Winter
MEDIAN (kg)	9.14	10.28	8.58	3.77	3.42	3.14
MAD ^a (kg)	5.77	5.44	6.10	1.33	1.58	1.83
MEAN-log ^b (kg)	8.34	8.24	7.47	3.52	3.48	3.15
MEAN (kg)	9.95	9.65	9.23	4.03	4.03	3.79
SD (kg) ^c	5.07	4.52	5.25	2.26	2.12	2.51
CV % ^d	50.96	46.88	56.88	56.04	52.55	66.04
Q1 ^e	6.06	5.91	4.99	2.75	2.67	2.18
Q3 ^f	13.86	13.06	13.58	4.59	5.21	4.82

^aMedian absolute deviation, ^bBack-transformed arithmetic mean of the log-transformed data
(equal to geometric mean); ^cStandard deviation; ^dCoefficient of variation; ^e:First quartile;
^f:Third quartile.

38 Table 4: Analysis of variance table of type III for fixed effects of waste
39 generation rates (kg/household/week and kg/person/week) and composition
40 (percentage wet mass) using the R package 'lmerTest'

	DF ^a	Sum Sq ^b	Mean Sq ^c	F.value	Pr(>F)
<i>Dataset^d: kg/household/week</i>					
Seasons	2	26.60	13.30	1.23	0.39
Household size	3	738.80	246.30	22.68	<0.001***
Interaction (seasons and household size)	6	65.00	10.80	1.00	0.43
<i>Dataset^e: kg/person/week</i>					
Seasons	2	3.76	1.88	0.64	0.75
Household size	3	56.93	18.98	6.42	<0.001***
Interaction (seasons and household size)	6	8.79	1.47	0.50	0.81
<i>Dataset^f: waste composition (wet mass) transformed as isometric log-ratio</i>					
Seasons	2	0.56	0.29	0.25	0.78
Household size	3	7.16	2.39	2.04	0.11
Interaction (seasons and household size)	6	5.31	0.89	0.76	0.60

41 ^aDegree of freedom; ^bSum square; ^cmean square;
42 ^dWaste generation rate dataset expressed in kg waste per household per week
43 ^eWaste generation rate dataset expressed in kg waste per person per week
44 ^fWaste composition dataset expressed in percentage wet mass
45 Significance level: High significance probability $p < 0.001$ ***; () no significance-
46 probability higher than 0.05

47 Table 5: Analysis of random effects of the linear mixed effects models for
 48 waste generation rates (kg/household/week and kg/person/week) and
 49 composition (percentage wet mass) using the R package 'lmerTest'

	Variance	Std. Dev ^a	Chi.sp ^b	Chi.DF ^c	P.value
<i>Dataset^d: kg/household/week</i>					
Adresse	6.88	2.62	39.48	1.00	<0.001
Residual	10.86	3.30			
<i>Dataset^e: kg/person/week</i>					
Adresse	1.89	1.38	40.02	1.00	<0.001
Residual	2.96	1.72			
<i>Dataset^f: waste composition (wet mass) transformed as isometric log-ratio</i>					
Adresse	0.00	0.00	00.00	1.00	1.00
Residual	1.17	1.08			

50 ^aStandard deviation^bChi-square^cDegree of freedom of chi-square

51 ^dWaste generation rate dataset expressed in kg waste per household per week

52 ^eWaste generation rate dataset expressed in kg waste per person per week

53 ^fWaste composition dataset expressed in percentage wet mass

54 Significance level: High significance probability $p < 0.001^{***}$; () no significance-
 55 probability higher than 0.05

Table 6: Statistical summary of the residual waste composition (% wet mass basis) as a function of season (N=101 households for each season). Values are rounded to two decimal places. CoDa is compositional data analysis.

		Classical statistics							CoDa-technique ^f		
		skew	kurtosis	MEDIAN	MEAN-log	MEAN	SD ^a	CV % ^b	Center ^c	Center-R ^d	clr-variancee % ^e
Summer	Food	-0.38	-52.00	46.59	35.63	43.35	16.66	38.43	50.44	52.56	2.18
	Garden	2.24	445.00	1.36	0.09	3.47	5.32	153.22	0.13	2.51	30.46
	Paper	2.29	637.00	9.89	8.78	13.27	11.04	83.22	12.42	11.79	4.00
	Board	2.74	1113.00	6.83	6.88	7.99	5.12	64.11	9.75	7.69	1.93
	Plastic	0.94	79.00	4.82	3.93	5.29	3.26	61.62	5.57	5.75	2.58
	Plastic foil	3.09	1436.00	6.09	4.68	6.65	4.47	67.29	6.63	6.84	3.38
	Metal	1.39	223.00	1.72	0.73	2.01	1.65	82.29	1.03	2.18	7.02
	Combustible	2.00	430.00	8.52	9.90	14.61	14.42	98.66	14.02	10.66	3.01
	Inert	2.29	538.00	0.98	0.01	3.36	5.44	161.65	0.01	0.01	45.43
Total						100.00			100.00	100.00	100.00
Autumn	Food	-0.35	-31.00	44.61	40.00	45.31	16.86	37.21	54.56	53.92	1.64
	Garden	2.61	720.00	0.84	0.01	2.91	5.10	175.18	0.01	2.66	37.40
	Paper	2.84	981.00	9.76	8.79	13.89	13.88	99.92	11.99	12.70	3.37
	Board	2.78	1070.00	6.55	6.61	8.44	6.24	73.96	9.02	8.11	2.11
	Plastic	1.11	142.00	4.30	3.63	4.90	2.73	55.82	4.95	5.46	2.35
	Plastic foil	1.73	614.00	5.90	4.94	6.27	3.29	52.49	6.74	6.89	2.94
	Metal	1.49	196.00	1.42	0.95	2.04	1.81	88.92	1.3	2.02	3.78
	Combustible	2.10	410.00	7.70	8.37	12.06	12.33	102.27	11.42	8.22	3.04
	Inert	2.08	438.00	1.39	0.01	4.19	6.19	147.62	0.01	0.02	43.36
Total						100.00			100.00	100.00	100.00
Winter	Food	-0.41	-62.00	43.93	31.76	40.77	17.56	43.06	47.98	50.10	3.22
	Garden	3.94	1592.00	0.73	0.01	4.23	11.39	268.85	0.02	0.05	35.38
	Paper	1.78	348.00	10.19	8.88	13.69	12.22	89.30	13.41	11.58	2.27
	Board	1.44	331.00	7.85	5.22	8.69	5.93	68.21	7.89	8.46	4.82
	Plastic	0.46	-58.00	4.35	2.90	4.84	2.92	60.29	4.38	5.00	3.72
	Plastic foil	1.40	373.00	7.13	5.65	7.41	3.56	48.01	8.53	8.50	3.24
	Metal	1.82	443.00	1.56	0.79	2.39	2.36	98.87	1.19	2.54	4.90
	Combustible	2.18	515.00	10.99	10.97	14.38	12.11	84.23	16.57	10.21	3.77
	Inert	1.79	343.00	1.88	0.02	3.60	4.77	132.58	0.03	3.56	38.69
Total						100.00			100.00	100.00	100.00

58 ^aStandard deviation; ^bCoefficient of variation in percentage ($CV=SD/MEAN*100$); ^cGeometric mean; ^d Robust geometric mean; Centered log-ratio expressed in percentage; Compositional data
59 analysis (Edjabou et al., 2017).

Figures

Figure 1: Household size group means with 95 percent confidence intervals for the three seasons based on: (I) total residual waste generated by a household (kg /household/week), (II) total residual waste expressed per person (kg/person/week).

Figure 2: 95% prediction interval on the random effects in waste generation rate per household (kg/household/week). Horizontal lines represent the mean and 95% confidence intervals of 101 households.

Figure 3: Geometric mean barplot for residual household waste composition dataset (% of wet mass) as function of season. The bars show the log-ratio between geometric mean of a fraction for a subgroup and the geometric mean of overall subgroups (Computation was based on Eqs. (1-3))

Figure 4: Geometric mean barplot for residual household waste composition dataset (% of wet mass) as function of household size. The bars show the log-ratio between geometric mean of a fraction for a subgroup and the geometric mean of overall subgroups (Computation was based on Eqs. (1-3))

Figure 5: Pairwise comparison between seasons of individual waste fractions based bootstrap percentile confidence intervals (B=1000) for log-ratio difference between: (A) summer and winter, (B) summer and autumn, and (C) winter and autumn. The vertical lines represent difference for the means (filled circles) and vertical dashed lines are the percentile intervals (squares show upper and lower limits). The difference is not significant when a vertical dashed line crosses x-axis (upper and lower limits are above and under x-axis respectively). The difference between two groups is positive and significant when the upper and lower limits are above x-axis, the opposite is true for negative and significant difference.

Compositional analysis of seasonal variation in Danish residual household waste

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Supplementary data (SM)

Supplementary materials contain detailed food waste data used for calculations. SMs are divided into tables (Table SM) and figures (Figure SM).

Supplementary materials (SM) –Tables

SM Table 1: Binary partition to compute isometric log-ratio coordinates

	ilr1	ilr2	ilr3	ilr4	ilr5	ilr6	ilr7	ilr8
Food	1	1	1	1	0	0	0	0
Garden	1	1	1	-1	0	0	0	0
Paper	1	1	-1	0	0	0	0	0
Board	1	-1	0	0	1	0	0	0
Plastic	1	-1	0	0	-1	0	0	0
Plastic foil	-1	0	0	0	0	1	1	0
Metal	-1	0	0	0	0	1	-1	0
Combustible	-1	0	0	0	0	-1	0	1
Inert	-1	0	0	0	0	-1	0	-1

SM Table 2: Geometric means of subgroups (g_{mi}) and total average (g_m). Subgroups are **seasons**. These estimates were computed using Eq. 2 and correspond to the values of X

Seasons	Food	Garden	Paper	Board	Plastic	Plastic foil	Metal	Combustible	Inert
Autumn	40.00	0.01	8.79	6.61	3.63	4.94	0.95	8.37	0.01
Winter	31.76	0.01	8.88	5.22	2.90	5.65	0.79	10.97	0.02
Summer	35.63	0.09	8.78	6.88	3.93	4.68	0.73	9.90	0.01
Total average	35.64	0.02	8.82	6.20	3.46	5.07	0.82	9.69	0.01

SM Table 3: Results of log of the ration between geometric mean of subgroups and the average geometric mean. Subgroups are **seasons**. These estimates were computed using Eq. 2 and correspond to the values of X

Seasons	Food	Garden	Paper	Board	Plastic	Plastic foil	Metal	Combustible	Inert
Autumn	0.12	-0.83	0.00	0.06	0.05	-0.03	0.15	-0.15	-0.15
Winter	-0.12	-0.56	0.01	-0.17	-0.18	0.11	-0.04	0.12	0.43
Summer	0.00	1.39	0.00	0.11	0.13	-0.08	-0.12	0.02	-0.28

SM Table 4: Results of back-transformation of log of the ration between geometric mean of subgroups and the average geometric mean. Subgroups are **seasons**. These estimates were computed using Eq. 3 and correspond to the values of k

Seasons	Food	Garden	Paper	Board	Plastic	Plastic foil	Metal	Combustible	Inert
Autumn	1.12	0.43	1.00	1.07	1.05	0.97	1.16	0.86	0.86
Winter	0.89	0.57	1.01	0.84	0.84	1.11	0.96	1.13	1.53
Summer	1.00	4.03	1.00	1.11	1.14	0.92	0.89	1.02	0.76

SM Table 5: Results of back-transformation of log of the ration between geometric mean of subgroups and the average geometric mean. Subgroups are **seasons**. These estimates were computed using Eq. 3 and correspond to the values of ***r in percentage***

Seasons	Food	Garden	Paper	Board	Plastic	Plastic foil	Metal	Combustible	Inert
Autumn	12	-57	0	7	5	-3	16	-14	-14
Winter	-11	-43	1	-16	-16	11	-4	13	53
Summer	0	303	0	11	14	-8	-11	2	-24

SM Table 6: Results of log of the ration between geometric mean of subgroups and the average geometric mean. Subgroups are **household sizes**. These estimates were computed using Eq. 2 and correspond to the values of ***X***

Household sizes	Food	Garden	Paper	Board	Plastic	Plastic foil	Metal	Combustible	Inert
1p	20.29	0.01	10.99	6.82	1.91	3.98	0.52	12.39	0.00
2p	37.62	0.04	8.58	6.10	3.34	5.82	0.91	9.74	0.01
3p	41.90	0.06	10.48	4.43	4.09	5.99	1.13	7.07	0.04
4p	40.98	0.01	7.56	7.05	4.65	4.29	0.75	9.75	0.01
Total average	35.64	0.02	8.82	6.20	3.46	5.07	0.82	9.69	0.01

SM Table 7: Results of log of the ration between geometric mean of subgroups and the average geometric mean. Subgroups are **household sizes**. These estimates were computed using Eq. 2 and correspond to the values of ***X***

Household sizes	Food	Garden	Paper	Board	Plastic	Plastic foil	Metal	Combustible	Inert
1p	-0.56	-1.26	0.22	0.1	-0.59	-0.24	-0.44	0.25	-1.28
2p	0.05	0.58	-0.03	-0.02	-0.03	0.14	0.11	0	0.17
3p	0.16	0.94	0.17	-0.33	0.17	0.17	0.33	-0.32	1.09
4p	0.14	-0.7	-0.15	0.13	0.3	-0.17	-0.09	0.01	-0.09

SM Table 8: Results of back-transformation of log of the ratio between geometric mean of subgroups and the average geometric mean. Subgroups are **household sizes**. These estimates were computed using Eq. 3 and correspond to the values of ***k***

Households sizes	Food	Garden	Paper	Board	Plastic	Plastic foil	Metal	Combustible	Inert
1p	0.57	0.28	1.25	1.10	0.55	0.78	0.64	1.28	0.28
2p	1.06	1.79	0.97	0.98	0.97	1.15	1.12	1.00	1.18
3p	1.18	2.55	1.19	0.72	1.18	1.18	1.39	0.73	2.99
4p	1.15	0.50	0.86	1.14	1.34	0.85	0.91	1.01	0.91

SM Table 9: Results of back-transformation of log of the ratio between geometric mean of subgroups and the average geometric mean. Subgroups are **household sizes**. These estimates were computed using Eq. 3 and correspond to the values of ***r in percentage***

Households sizes	Food	Garden	Paper	Board	Plastic	Plastic foil	Metal	Combustible	Inert
1p	-43	-72	25	10	-45	-22	-36	28	-72
2p	6	79	-3	-2	-3	15	12	0	18
3p	18	155	19	-28	18	18	39	-27	199
4p	15	-50	-14	14	34	-15	-9	1	-9

Pairwise and individual comparison of residual household waste composition between household types:

Here, “original” is the original estimate of the difference between household types for each waste fraction whereas “std. error” is the standard errors or the uncertainty associated to the estimates.

“Basic” and “BCA” are the type of confidence intervals returned from bootstrap.

SM Table 10.1a: 1person and 2 persons: Bootstrap statistics

Waste fractions	original	bias	std. error
Food	0.380	0.014	0.198
Garden	1.600	0.022	1.148
Paper	-0.486	0.031	0.334
Board	-0.350	0.027	0.170
Plastic	0.323	0.010	0.366
Plastic foil	0.143	0.024	0.263
Metal	0.318	0.015	0.454
Combustible	-0.478	0.024	0.202
Inert	1.210	0.048	1.226

SM Table 10.1b: 1person and 2 persons: Bootstrap confidence intervals

Basic	Food	Garden	Paper	Board	Plastic	Plastic foil	Metal	Combustible	Inert
1 person	-0.08	-2.02	-1.46	-0.89	-0.70	-0.52	-0.88	-1.17	-2.67
2 persons	1.3885	5.50	0.73	0.27	1.71	1.28	2.25	0.14	5.20

BCA	Food	Garden	Paper	Board	Plastic	Plastic foil	Metal	Combustible	Inert
1 person	-0.05	-2.02	-1.46	-0.89	-0.70	-0.48	-0.88	-1.17	-2.67
2 persons	1.38	5.50	0.73	0.14	1.71	1.28	2.22	0.14	5.20

SM Table 10.2a: 1person and 3 persons: Bootstrap statistics

Waste fractions	original	bias	std. error
Food	0.45	0.02	0.20
Garden	1.92	0.05	1.50
Paper	-0.33	0.02	0.36
Board	-0.71	0.02	0.27
Plastic	0.48	0.01	0.36
Plastic foil	0.13	0.01	0.27
Metal	0.49	0.01	0.50
Combustible	-0.84	0.02	0.22
Inert	2.09	-0.03	1.53

SM Table 10.2b: 1person and 3 persons: Bootstrap confidence intervals

BASIC	Food	Garden	Paper	Board	Plastic	Plastic foil	Metal	Combustible	Inert
1 person	0.02	-2.59	-1.33	-2.37	-0.51	-0.44	-1.30	-1.46	-2.59
3 persons	1.31	6.52	1.21	0.07	1.94	1.13	2.21	-0.06	7.20

BCA	Food	Garden	Paper	Board	Plastic	Plastic foil	Metal	Combustible	Inert
1 person	0.09	-2.59	-1.12	-2.37	-0.41	-0.37	-1.30	-1.46	-2.59
3 persons	1.31	6.52	1.21	-0.20	1.94	1.13	2.21	-0.19	7.20

SM Table 10.3a: 1person and 4 persons: Bootstrap statistics

Waste fractions	original	bias	std. error
Food	0.43	0.01	0.20
Garden	0.28	-0.05	1.28
Paper	-0.65	0.02	0.34
Board	-0.24	0.03	0.16
Plastic	0.61	0.02	0.37
Plastic foil	-0.20	0.04	0.35
Metal	0.08	0.01	0.49
Combustible	-0.52	0.04	0.21
Inert	0.91	0.02	1.32

SM Table 10.3b: 1person and 4 persons: Bootstrap confidence intervals

Basic	Food	Garden	Paper	Board	Plastic	Plastic foil	Metal	Combustible	Inert
1 person	-0.09	-4.26	-1.39	-0.76	-0.26	-1.20	-1.86	-1.15	-3.19
4 persons	1.28	4.32	0.67	0.28	1.84	1.02	2.06	0.12	5.80

BCA	Food	Garden	Paper	Board	Plastic	Plastic foil	Metal	Combustible	Inert
1 person	0.02	-4.26	-1.34	-0.76	-0.24	-1.20	-1.86	-1.15	-3.19
4 persons	1.28	4.32	0.67	0.22	1.84	0.90	2.06	0.09	5.80

SM Table 10.4a: 2person and 3 persons: Bootstrap statistics

Waste fractions	original	bias	std. error
Food	0.07	0.00	0.07
Garden	0.32	0.06	1.24
Paper	0.16	0.00	0.20
Board	-0.36	-0.02	0.28
Plastic	0.16	0.00	0.14
Plastic foil	-0.01	0.00	0.12
Metal	0.17	-0.01	0.34
Combustible	-0.36	0.00	0.15
Inert	0.89	-0.05	1.33

SM Table 10.4b: 2person and 3 persons: Bootstrap confidence intervals

Basic	Food	Garden	Paper	Board	Plastic	Plastic foil	Metal	Combustible	Inert
2 person	-0.13	-3.15	-0.62	-1.81	-0.30	-0.44	-1.20	-1.00	-3.95
3 persons	0.33	4.02	0.70	0.40	0.63	0.35	1.23	0.16	4.64

BCA	Food	Garden	Paper	Board	Plastic	Plastic foil	Metal	Combustible	Inert
2 person	-0.12	-3.15	-0.60	-1.81	-0.26	-0.43	-1.18	-1.00	-3.95
3 persons	0.33	4.02	0.70	0.40	0.63	0.35	1.23	0.16	4.64

SM Table 10.5a: 2person and 4 persons: Bootstrap statistics

Waste fractions	original	bias	std. error
Food	0.046	-0.01	0.07
Garden	-1.32	0.04	0.94
Paper	-0.17	0.01	0.15
Board	0.11	0.01	0.17
Plastic	0.29	0.00	0.15
Plastic foil	-0.34	0.00	0.24
Metal	-0.24	0.01	0.35
Combustible	-0.04	0.00	0.15
Inert	-0.30	0.02	1.03

SM Table 10.5b: 2person and 4 persons: Bootstrap confidence intervals

BASIC	Food	Garden	Paper	Board	Plastic	Plastic foil	Metal	Combustible	Inert
2 person	-0.23	-4.39	-0.61	-0.36	-0.14	-1.30	-1.51	-0.54	-3.47
4 persons	0.33	1.68	0.32	0.59	0.88	0.25	0.89	0.46	2.91

BCA	Food	Garden	Paper	Board	Plastic	Plastic foil	Metal	Combustible	Inert
2 person	-0.16	-4.39	-0.61	-0.36	-0.12	-1.30	-1.51	-0.54	-3.47
4persons	0.33	1.68	0.32	0.59	0.88	0.23	0.89	0.46	2.91

SM Table 10.6a: 3person and 4 persons: Bootstrap statistics

Waste fractions	original	bias	std. error
Food	-0.02040475	0.000249109	0.06785177
Garden	-1.63	-0.07	1.34
Paper	-0.33	0.00	0.18
Board	0.47	0.00	0.26
Plastic	0.13	0.01	0.14
Plastic foil	-0.33	-0.01	0.27
Metal	-0.42	-0.01	0.43
Combustible	0.32	0.00	0.16
Inert	-1.19	-0.08	1.34

BASIC	Food	Garden	Paper	Board	Plastic	Plastic foil	Metal	Combustible	Inert
3 person	-0.26	-5.52	-0.87	-0.07	-0.33	-1.43	-1.79	-0.14	-5.31
4persons	0.18	3.42	0.42	1.53	0.56	0.29	1.09	0.92	2.34
Slim	bca								
BCA	Food	Garden	Paper	Board	Plastic	Plastic foil	Metal	Combustible	Inert
3 person	-0.26	-5.52	-0.87	-0.05	-0.33	-1.43	-1.79	-0.14	-5.31
4persons	0.18	3.42	0.42	1.53	0.52	0.24	1.09	0.92	2.34

Variance ln(Xi/Xj)										Clr variances
Xi\Xj	Food	Garden	Paper	Board	Plastic	Plastic foil	Metal	Combustible	Inert	
Food		2.3122	0.7788	0.4539	0.7631	0.4713	0.8269	0.8261	2.1608	0.4774
Garden	-3.102		2.0235	1.8036	2.312	2.1085	1.6705	2.3019	3.5006	1.0018
Paper	-1.4962	1.6058		0.657	1.0585	0.7266	0.8999	0.9842	2.1098	0.5132
Board	-1.9027	1.1994	-0.4065		0.6603	0.4321	0.633	0.5882	2.0169	0.4025
Plastic	-2.3895	0.7125	-0.8933	-0.4868		0.6443	0.825	1.0225	2.3439	0.535
Plastic foil	-2.0273	1.0748	-0.5311	-0.1246	0.3622		0.709	0.5154	2.3702	0.4432
Metal	-3.1205	-0.0185	-1.6243	-1.2179	-0.731	-1.0933		1.4412	2.5408	0.5304
Combustible	-1.8135	1.2886	-0.3172	0.0892	0.5761	0.2138	1.3071		2.5286	0.5671
Inert	-2.4951	0.6069	-0.9989	-0.5924	-0.1056	-0.4679	0.6254	-0.6817		1.0873
Mean ln(Xi/Xi)										5.5579

Variance ln(Xi/Xj)										Clr variances
Xi\Xj	Food	Garden	Paper	Board	Plastic	Plastic foil	Metal	Combustible	Inert	
Food		1.7237	1.3643	0.3699	0.3919	0.3777	0.8696	0.6938	3.07	0.4923
Garden	-3.2649		2.3987	1.8217	1.8384	1.5568	2.2281	2.029	5.3487	1.0525
Paper	-1.6433	1.6216		1.1292	1.3437	1.2464	1.5295	1.3903	3.7521	0.7863
Board	-1.9919	1.2731	-0.3485		0.3408	0.3321	0.6511	0.624	2.7425	0.4451
Plastic	-2.3769	0.8881	-0.7335	-0.385		0.3334	1.0729	0.8197	2.7336	0.493
Plastic foil	-2.0779	1.187	-0.4346	-0.0861	0.2989		0.9848	0.5052	3.418	0.4864
Metal	-3.3695	-0.1046	-1.7262	-1.3776	-0.9927	-1.2916		1.3421	2.299	0.6098
Combustible	-1.9305	1.3345	-0.2871	0.0614	0.4464	0.1475	1.439		4.4894	0.6607
Inert	-2.6083	0.6566	-0.965	-0.6165	-0.2315	-0.5304	0.7612	-0.6779		1.5474
Mean ln(Xi/Xi)										6.5736

SM Table 11.C: Variation array for season: **Summer, N=101**

Variance $\ln(X_i/X_j)$										Clr variances
$X_i \backslash X_j$	Food	Garden	Paper	Board	Plastic	Plastic foil	Metal	Combustible	Inert	
Food		2.5496	1.3551	0.6426	0.5619	0.3429	0.8165	0.5624	2.1512	0.499
Garden	-3.1419		2.9087	2.8185	3.2011	2.3028	3.8761	2.4951	3.2275	1.2989
Paper	-1.1522	1.9897		1.1705	1.8249	0.7816	2.4114	1.3171	1.9662	0.7631
Board	-1.7331	1.4088	-0.5809		0.6693	0.2591	1.4926	0.5739	2.2722	0.5499
Plastic	-2.3672	0.7747	-1.215	-0.6341		0.502	0.8872	0.7174	2.5108	0.6041
Plastic foil	-1.7743	1.3677	-0.6221	-0.0412	0.593		1.0963	0.349	1.6368	0.4039
Metal	-2.9515	0.1904	-1.7993	-1.2184	-0.5843	-1.1772		1.2514	2.7415	0.8096
Combustible	-1.5109	1.631	-0.3588	0.2221	0.8563	0.2633	1.4406		2.0055	0.5151
Inert	-2.4826	0.6593	-1.3304	-0.7495	-0.1154	-0.7083	0.4689	-0.9717		1.0284
Mean $\ln(X_i/X_j)$										6.4721

Supplementary data (SM) –Figures

SM Figure 1: Boxplot showing the waste generation rates (a) kg/household/week and (b) kg/person/week as function of seasons (autumn, summer and winter).

SM Figure 2: Boxplot showing the means of waste generation rates as function of household sizes.

SM Figure 3: Boxplots showing waste generates according to season as functions of households size:household containing one (1p), to (2p), tree (3p) and more than tree (3p) persons.

SM Figure 4: 95% prediction interval on the random effects in waste generation rate per person (kg/person/week). Horizontal lines represent the mean and 95% confidence intervals of 101 households.

SM Figure 5: Boxplots showing waste generates according to household size (household containing one (1p), to (2p), tree (3p) and more than tree (3p) persons) as function of seasons (autumn, summer and winter).

SM Figure 6: Illustration of linear mixed model result for waste generation rate (dataset of kg/household/week): results of the contribution of (a) season, (b) interaction seasons and person as well as random effect, and (c) household sizes

SM Figure 7: Illustration of linear mixed model result for waste generation rate (dataset of kg/person/week): results of the contribution of (a) season, (b) interaction seasons and person as well as random effect, and (c) household sizes

SM Figure 8: Results of linear mixed model applied to isometric log-ratio: results of the contribution of (a) season, (b) interaction seasons and person as well as random effect, and (c) household sizes

SM Figure 9: Diagnostic plot for the linear mixed model determining any influence of seasonal variation and household size on the waste generation, dataset of kg/household/week

SM Figure 10: Diagnostic plot for the linear mixed model determining any influence of seasonal variation and household size on the waste generation, dataset of kg/person/week

SM Figure 11: Diagnostic plot for multivariate normality based on qqplot of residuals

SM Figure 12: Diagnostic plot for multivariate normality of residuals based on histogram of residuals and boxplot of raw isometric log coordinates