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DTU Environment
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PhD Thesis
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The synopsis part of this thesis is available as a pdf-file for download from the DTU research database ORBIT: http://www.orbit.dtu.dk

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Preface

The present thesis has been submitted as part of the requirement for the PhD. degree at the Technical University of Denmark. The study was conducted from August 2012 to June 2016, under the supervision of Professor Thomas Frueergaard Astrup and the co-supervision of Professor Charlotte Scheutz. The Danish Strategic Research Council funded this PhD project via the IRMAR (Integrated Resource Management & Recovery) Project (No. 11-116775). The project was carried out in collaboration with ECONET AS.

The thesis is organised in two parts: the first puts into context the findings of the PhD in an introductive review, while the second consists of the papers listed below. These will be referred to in the text by their paper number, written in Roman numerals (e.g. "Edjabou et al. (**I**)").

I **Edjabou, M.E.**, Jensen, M.B., Götze, R., Pivnenko, K., Petersen, C., Scheutz, C., Astrup, T.F.: Municipal solid waste composition: Sampling methodology, statistical analyses, and case study evaluation. *Waste Management 2015,36, 12-23*

II **Edjabou, M.E.,** Boldrin, A., Scheutz, C., Astrup, T.F.: Source segregation of food waste in office area: Factors affecting waste generation rates and quality. *Waste Management 2015,46,94-102*

III **Edjabou, ME.**, Petersen, C., Scheutz, C., Astrup, T.F.: Food waste from Danish households: Generation and composition. *Waste Management.*

IV **Edjabou, ME.**, Martín-Fernández, J.A., Scheutz, C., Astrup, T.F. : Statistical analysis of waste data: comparison of classical and compositional data analysis applied to a household waste case study. Submitted to *Waste Management.*

In this online version of the thesis, paper I-IV are not included but can be obtained from electronic article databases e.g. via www.orbit.dtu.dk or on request from: DTU Environment, Technical University of Denmark, Miljoevej, Building 113, 2800 Kgs. Lyngby, Denmark, info@env.dtu.dk.

In addition, and not included in this thesis, contributions in the proceedings of international conferences were also concluded during this PhD study.

- **Edjabou, M.E.**, Boldrin, A., Scheutz, C., Astrup, T.F.: Generation of organic waste from institutions in Denmark: case study of the Technical University of Denmark, Paper presented at ORBIT 2016- 10th International Conference ORBIT 2016, Crete, Greece.
- **Edjabou, M.E.**, Boldrin, A., Scheutz, C., Astrup, T.F.: Food waste generation in office areas at DTU, Poster session presented at DTU Sustain-DTU Conference 2015.
- **Edjabou, M. E.**, Petersen, C., Scheutz, C., & Astrup, T. F. 2015. Occurrence and temporal variation of Danish household, Paper presented at Sardinia 2015 - 15th International Waste Management and Landfill Symposium, Cagliari, Italy.
- **Edjabou, M. E.**, Pivnenko, K., Petersen, C., Scheutz, C., & Astrup, T. F. 2015. Compositional data analysis of household food waste in Denmark. Poster session presented at CoDa Workshop-6th International Workshop on Compositional Data Analysis, Spain.
- **Edjabou, M. E.**, Petersen, C., Scheutz, C., & Astrup, T. F. 2015. Seasonal variation of household food waste in Denmark, Paper presented at ICSWHK2015- International Conference on Solid Waste 2015, Hong Kong
- **Edjabou, M. E.**, Petersen, C., Scheutz, C., & Astrup, T. F. 2014. Composition of municipal solid waste in Denmark; Poster session presented at DTU Sustain-DTU Conference 2014
- **Edjabou, M. E**., Petersen, C., Scheutz, C., & Astrup, T. F. 2014. Estimating household food waste in Denmark: case study of single-family households, Paper presented at ORBIT 2014- 9th International Conference ORBIT 2014, Gödöllö, Hungary
- **Edjabou, M. E**., Petersen, C., Scheutz, C., & Astrup, T. F. 2013. Characterization of household food waste in Denmark, Paper presented at Sardinia 2013 - 14th International Waste Management and Landfill Symposium, Cagliari, Italy

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I am deeply grateful to CoDaWork (International workshop on Compositional Data analysis) and especially Josep Antoni Martin for agreeing to introduce compositional data analysis to the waste group, for promptly answering my countless mails and for providing R codes.

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Many thanks to my family-in-law for their unconditional support, and I am also grateful to my brother Martin, my cousins (Tom and Gilbert, Laurance and Koufama), my friend Sopa and their respective families for the continuous support. Finally, I would like to thank my family for their love, especially 3L (Louise, Lukas and Leon).

Summary

In response to continuous pressure on resources, and the requirement for secure and sustainable consumption, public authorities are pushing the efficient use of resources. Among other initiatives, the prevention, reduction and recycling of solid waste have been promoted. In this context, reliable data for the material and resource content of waste flows are crucial to establishing baselines, setting targets and tracking progress on waste prevention, reduction and recycling goals. Waste data are also a critical basis for the planning, development and environmental assessment of technologies and waste management. These data are obtained through the characterisation of waste material. In the absence of standardised and commonly accepted waste sampling and sorting procedures, various approaches have been employed, albeit they limit both the comparability and the applicability of results. Thus, waste sampling and sorting procedures, as well as a consistent and transparent waste-naming system, have been developed.

Classical statistics are applied increasingly when analysing waste data, in order to draw conclusions that underpin the development of waste legislation and policy. The existing statistical techniques ignore the inherent properties of waste data, which are "closed data," because the percentage or the mass of individual fractions are positive and add up to a constant. This constant constraint affects statistical analysis seriously and results in erroneous interpretations. Therefore, compositional analysis techniques have been introduced to analyse waste data more appropriately.

Waste was sampled directly from source, in order to attribute the waste data accurately to the geographical areas and types of household generating the waste. Sampling and contamination errors were minimised by avoiding sieving and the mass reduction of waste before manual sorting. Consequently, the waste was collected without compacting. Additionally, the entire sample was manually sorted into 10-50 waste fractions organised according to a three-level approach. This detailed waste fractions list facilitated the comparison of waste data with various objectives.

Analysis revealed that Danish residual household waste constitutes mainly food waste (42 – 45% mass per wet basis). Misplaced recyclable materials in residual waste bins, such as paper, board, glass, metal and plastic, amounted to 20% (mass per wet basis) of residual household waste. Moreover, special waste, such as hazardous waste, batteries and WEEE, was also misplaced in

residual household bins, accounting for 0.4-0.8% of the total. Although the proportion of misplaced special waste was relatively small, these material fractions can have dire impacts on the environment when they are not disposed of appropriately.

Statistical analysis indicated that separating food waste residue from packaging during waste sorting was unnecessary, because this separation did not significantly influence overall waste composition, the percentage of food waste or packaging waste fractions. Furthermore, the difference in waste composition between municipalities was not significant. These results suggest that waste composition data obtained from one municipality could be applied to other municipalities in the same area (provided that municipalities share the same source segregation scheme), although socio-economic aspects between municipalities were not analysed.

Food waste consists of avoidable and unavoidable food waste. Here, "avoidable" food waste is defined as food that could be eaten but instead was thrown away regardless of the reason, whereas "unavoidable" food waste is food that would not be edible under normal circumstances (e.g. bones, banana peel, etc.). Food waste was estimated at 183 kg per household per year (86 kg per person per year), of which 103 kg per household (48 kg per person) per year was avoidable food waste and 80 kg per household (38 kg per person) per year was unavoidable food waste. These food waste fractions occurred in most of Danish households, which suggests that initiatives to reduce *avoidable* food waste should be combined with policies that promote the efficient treatment of *unavoidable* food waste, to ensure plant nutrient and resource recovery.

The mass of avoidable food waste discarded per household increased in line with household size. However, there was no statistical evidence that a household containing one person throws away more avoidable food waste per person than households containing more than one person. This suggests that campaigns and initiatives targeting food waste reduction should particularly aim at households containing more than one person.

Additionally, the mass of avoidable and unavoidable food waste per household and per person discarded in Danish houses was significantly influenced neither by periodic variation nor by geographical variations.

Waste analysis from kitchens in office areas showed that food waste generation amounted to 23 kg per employee per year, of which 20 kg per employee was source-segregated. This suggests that only 11% of food waste was misplaced in residual waste, which itself amounted to 10 kg per employee per year and consisted of 29% paper, 23% plastic and 24% misplaced food waste. Thus, sorting efficiency was estimated at 89% of food waste, accompanied by extremely high purity (99%). These results indicate that the 60% recycling target formulated by the Danish Government for food waste generated by the service sector should be achievable.

Dansk sammenfatning

For at imødegå et stigende pres på klodens ressourcer og ønsket om at sikre bæredygtigt forbrug har effektiv håndtering og udnyttelse af ressourcer stort fokus hos offentlige myndigheder. Blandt initiativer kan nævnes forebyggelse, begrænsning og genanvendelse af affald. Pålidelige data om materialesammensætningen og ressourceindholdet i individuelle affaldsstrømme i samfundet er afgørende for at kunne fastsætte det nuværende udgangspunkt, opsætte fremtidige målsætninger og måle udviklingen i forhold til forebyggelse, reduktion og genanvendelse af affald. Affaldsdata er også et nødvendigt grundlag for at planlægge affaldshåndteringen, udvikle den nødvendige teknologi og udføre miljømæssige vurderinger af affaldssystemet som helhed. Sådanne data kræver karakterisering af affaldet. I mangel af standardiserede og almindeligt accepterede procedurer for prøveudtagning og sortering af affald anvendes forskellige metoder i litteraturen til opgørelse af affaldets sammensætning. Dette begrænser både sammenligneligheden mellem forskellige undersøgelser og anvendeligheden af resultaterne. For at afhjælpe disse begrænsninger i eksisterende metoder til affaldskarakterisering er udviklet specifikke procedurer for prøveudtagning og sortering af affald samt et trinvist system til navngivning af materialefraktioner.

Statistik anvendes i stigende grad til analyse af affaldsdata med henblik på at opnå konklusioner, der understøtter udviklingen af lovgivning og politik på affaldsområdet. De traditionelle statistiske metoder ignorerer dog iboende egenskaber i affaldsdata, som er ”lukkede datasæt” (procentsatserne eller masserne af individuelle materialefraktioner i en affaldsstrøm er f.eks. altid positive og summen af alle fraktioner en konstant). Eksisterende statistisk analyse af affaldsdata tager ikke højde for disse egenskaber, hvilket resulterer i fejlagtig fortolkning af data. Nye procedurer for statistisk analyse af affaldsdata blev derfor introduceret i projektet for at muliggøre en konsistent vurdering af data.

Affald blev udtaget direkte fra kilderne for præcist at fastlægge affaldsdata i forhold til specifikke geografiske områder og typer af husstande. Prøveudtagnings- og sorteringsfejl blev minimeret ved at undlade at sigte og reducere massen af affaldet før manuel sortering. Affaldet blev af samme grund indsamlet uden komprimering. Alle affaldsprøver blev manuelt sorteret i 10-50 affaldsfraktioner samt organiseret og navngivet efter et tre-trins system. Den resulterende liste over affaldsfraktioner øgede muligheden for anvendelse af de indsamlede affaldsdata til forskellige formål.

Affaldsanalyserne viste, at dagrenovationsmængden i Danmark hovedsageligt består af madaffald (42-45 % masse per våd vægt). Fejlplacerede genanvendelige materialer (papir, pap, glas, metal og plast) i dagrenovation udgjorde 20 % masse per våd vægt. Fejlplacering af særlige affaldsfraktioner såsom farligt affald, batterier og WEEE udgjorde 0,4-0,8 % af dagrenovationen. Selv om denne andel var relativ lille, er risikoen for miljøbelastning fra disse materialefraktioner betydelig, hvis fraktionerne ikke håndteres hensigtsmæssigt.

Statistisk analyse af affaldsdata viste, at adskillelsen af madaffald fra emballagen ikke var nødvendig i forbindelse med affaldskarakterisering, fordi denne adskillelse ikke signifikant påvirkede den overordnede sammensætning af affaldet; hverken den procentvise andel af madspild eller emballageaffald såsom papir, pap, metal og plast. Forskellen i affaldssammensætning mellem udvalgte kommuner var ikke signifikant. Dette tyder på, at data for affaldssammensætningen fra én kommune også kan anvendes ved affaldsplanlægning i andre kommuner med tilsvarende affaldsordninger.

Madsaffald består af madspild og øvrigt madaffald. Madspild er betegnelsen for mad, der kunne have været spist, men i stedet er smidt ud uanset årsag. Øvrigt madaffald repræsenterer fødevareaffald, der ikke er beregnet til at spise (f.eks. knogler, bananskræller, m.v.). Madaffald blev estimeret til 183 kg per husstand (86 kg per person) per år. Heraf var 103 kg per husstand (48 kg per person) per år madspild og 80 kg per husstand (38 kg per person) per år øvrigt madaffald. Både madspild og øvrigt madaffald forekom i de fleste af de danske husstande. Dette tyder på, at initiativer til reduktion af madspild bør kombineres med initiativer, der fremmer en effektiv håndtering af det øvrige (og uundgåelige) madaffald for at sikre bedst mulig udnyttelse af ressourcerne i affaldet.

Mængde af madspild per husstand stiger i takt med hussstandens størrelse. Det kunne imidlertid ikke påvises statistisk, at husstande med én person genererer mere madspild per person end husstande bestående af flere personer. Dette indikerer, at kampagner for reduktion af madspild især bør rettes mod husstande med flere end én person.

Desuden var mængden af madspild og øvrigt madaffald per husstand og per person fra danske husholdninger ikke væsentligt påvirket af periodisk eller geografisk variation.

En analyse af affald fra køkkener i kontorarealer viste, at der blev genereret 23 kg madaffald per medarbejder per år; heraf var 20 kg kildesorteret. Dette betyder, at kun 11 % af madaffaldet var fejlplaceret i affaldsspande beregnet til restaffald. Restaffaldet udgjorde 10 kg per medarbejder per år og bestod bl.a. af papir (29 %), plast (23 %) og fejlplaceret madaffald (24 %). Sorteringseffektiviteten for madaffald blev estimeret til 89 % med ekstremt lave urenheder i form af plast osv. (mindre end 0,5 %). Dette indikerer, at målet om 60 % genanvendelse af madaffald fra servicesektoren, som formuleret af den danske regering, bør være opnåeligt.

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Abbreviations

ABS	Acrylonitrile butadiene styrene
CoDa	Compositional data
DTU	Technical University of Denmark
FW	Food waste
HDPE	High Density Polyethylene
LDPE	Low Density Polyethylene
MANOVA	Multivariate analysis of variance
PET	Polyethylene Terephthalate
PP	Polypropylene
PS	Polystyrene
PVC	Polyvinyl chloride
RHW	Residual Household Waste
RW	Residual waste
SSFW	Source-segregated food waste
WEEE	Waste Electrical & Electronic Equipment

1 Introduction

1.1 Solid waste composition

Mounting pressure on resource supply, to satisfy current and future societal needs, requires that we maximise our effective use of available resources (European Commission, 2013). This has led to a growing interest in the concept of a circular economy that promotes a systematic change in the use of resources, which implies, among other initiatives, the recovery of material resources in waste streams through an integrated solid waste management (European Parliament, 2015). However, planning waste management, and the development of waste treatment technologies, requires a detailed and comprehensive quantification of individual material fractions in mixed waste flow. For this reason, without reliable data on the material and resource content of waste flows, and without information about how the waste composition changes according to geography and over time, technology improvement and assessment as well as legislation on waste may end up being based on erroneous data.

Because of the lack of a standardised method for waste characterisation, different protocols are used to obtain waste data. As a result, the quality of these data varies substantially (Dahlén and Lagerkvist, 2008). Additionally, quality can also be affected by the high heterogeneity of solid waste and local conditions, if the waste sample is not representative of the study area (European Commission, 2004). Moreover, the naming of waste fractions is often limited to the aim of the study and is affected by local traditions (Parfitt and Flowerdew, 1997). For example, although organic waste may refer generally to food and gardening waste, paper, plastic, wood and textiles could also be considered as organic materials. Moreover, some name that is given to waste fractions, such as “recyclable paper and board,” “recyclable plastic” and “hard plastic,” are particular to an area and do not necessary refer to the same materials in other areas. These inconsistencies may cause confusion and limit the comparability of waste data between studies (Dahlén et al., 2009; Staley and Barlaz, 2009). Thus, a detailed waste fraction list, organised into different levels, enables a transparent naming system and facilitates the comparison between studies and the use of waste data in different contexts.

Statistical analysis is increasingly applied to assess and compare solid waste data (Wilson et al., 2012) in decision-making processes as well as for policy development in the waste management sector (Dahlén and Lagerkvist, 2008).

Compositional data (wet percentage of individual material fractions) have a limited sample space (e.g. from 0 to 100) along with a constant sum constraint (always summing up to 100). These data are generally ill-suited to classical statistics, due to the fact that they are intrinsically related to each other, as each individual waste fraction is part of the whole composition (Filzmoser and Hron, 2008; Martín-Fernández et al., 2015). To mitigate this limitation, statistical analyses are often applied to the waste generation rate of waste fractions (European Commission, 2004). However, this generation rate (kg waste per person or per household) always equates to the total waste generation rate (e.g. total RHW waste generation rate). Therefore, the generation rates of individual waste fractions also have a limited space and sum up to a constant. These inherent proprieties affect the statistical analysis and interpretations of waste data (Buccianti and Pawlowsky-Glahn, 2011). Nevertheless, municipal solid waste composition data have been analysed often, albeit ignoring sample space. Without the appropriate statistical analysis and interpretation of waste data, technology improvements and assessment, as well as waste regulations, may be based on wrong and poorly documented conclusions from waste data analyses. This study therefore aims at filling these knowledge gaps.

1.2 Research objectives

The overall objective of the PhD project is to provide an improved basis for further technological development, by establishing up-to-date data on the composition of municipal solid waste in Denmark. The specific objectives of this PhD project are to:

- Develop a consistent waste sampling methodology that enables transparent comparison between studies and the flexible application of waste data.
- Perform waste sampling campaigns directed at flows of mixed waste and also determine waste composition.
- Develop and implement an appropriate statistical analysis procedure for waste data.
- Evaluate and interpret selected waste data with respect to variability, including origin, time and geography.

2 Materials and methods

2.1 Waste sampling procedure

In these study areas paper, board, glass, metal, bulky gardening waste, WEEE and household hazardous waste were source-segregated. Thus, the residual waste remained as mixed waste after sorting source-segregated material fractions.

In total, 30 tonnes of residual household waste (RHW) and 2 tonnes from kitchens in an office area were analysed. RHW waste was sampled from 3,137 households in Zealand, Fyn and Jutland (**Table 1**). As shown in Table 1, nine municipalities, eight single-family areas, five multi-family house areas and one office area were involved in the waste sampling campaigns. The waste was sampled directly from individual households and from kitchens, and then it was transported to the sorting area by a non-compaction vehicle following existing waste collection schedules. This allowed for the waste data to be associated with the specific area and/or source and avoided any changes that may potentially lead to changes in waste disposal behaviour (e.g. households and office area), which would have affected the reliability of the data.

Stratification sampling was applied to cover disparities in the study areas (European Commission, 2004). Thus, stratification criteria included housing type (single-family and multi-family), cities and/or municipalities and seasons. However, for waste from kitchens in an office area, we only analysed waste from kitchens at DTU Environment.

2.2 Sorting procedure

Waste sampled from each sub-area (see **Table 1**) was sorted manually, and the entire sample was sorted, to avoid errors from waste splitting. Screening (e.g. sieving) was not applied, in order to reduce contamination and waste material losses (Dahlén and Lagerkvist, 2008).The waste was sorted according to a tiered approach for material fractions (Edjabou et al. **I**). Here, it was subsequently sorted according to three levels, as shown in **Figure 1**.

Food packaging containing food residues was sorted as an extra fraction, and this was also subsequently sorted into the three levels shown in **Figure 1**. This sorting procedure enables the better organisation of sorting activities.

During the sorting campaign, we measured the mass of waste before and after all sorting activities (see **Figure 1**), to quantify mass losses during sorting and storage.

Two sorting methods were applied (see **Table 1** column named "*sorting*"). The first, "single waste bin," consists of sorting the waste separately from each source (e.g. households). This enables one to describe differences in household waste generation (Edjabou et al. **III** and **IV**) and provides waste dataset for each household. The second method, "Batch," consists of sorting mixed waste from a sub-area. Here, one dataset is obtained from a sub-area which may consist of 100 to 200 households (Edjabou et al. **I**).

2.3 Waste fraction classification

We classified waste fractions based on existing literature (Danish EPA, 2014; Dixon and Langer, 2006; Lebersorger and Schneider, 2011; Ojeda-Benítez et al., 2013; Riber et al., 2009; WRAP, 2009), current legislation, such as Waste Electrical and Electronic Equipment (WEEE) (European Commission, 2003), and an identification system for packaging materials (European Commission, 1997).

A tiered fraction classification provides detailed information on each waste fraction and addresses the problem of ambiguous and misleading naming systems. The classification consists of 10 fractions at Level I, 36 fractions at Level II and 56 fractions at Level III (**Table 2**). For example, food waste (Level I) was divided into vegetable and animal-derived food waste (Level II). These latter fractions were further subdivided individually into avoidable processed, avoidable unprocessed and unavoidable food waste (Level III) (detail in Edjabou et al. **I**)).

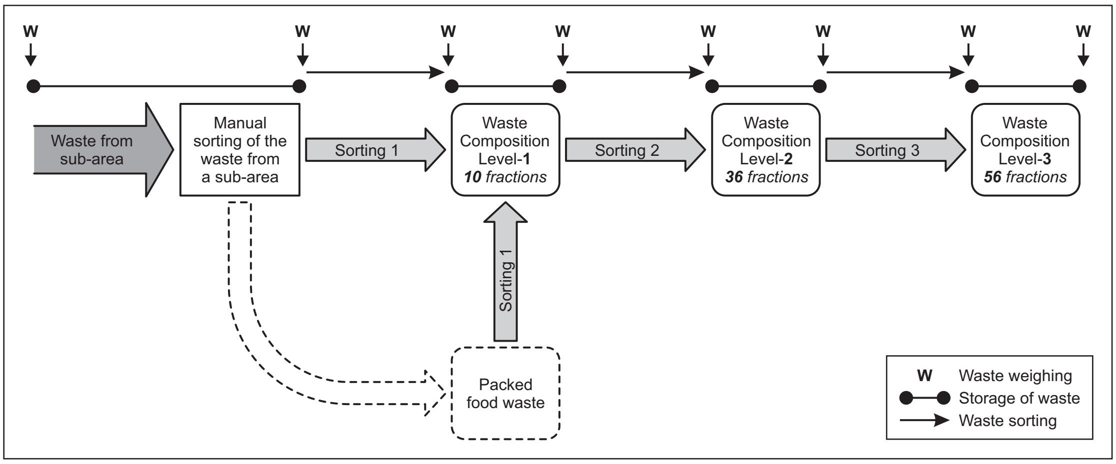


Figure 1. Waste sorting procedure (Edjabou et al. **I**).

Table 1. Sources and types of waste analysed

Sources	Regions[1]	Municipalities	Type of sources[2]	Sub-areas[3]	Number[4]	Mass[5]	Period[6]	Sorting	Studies[7]
Households	Zealand	Gladsaxe	SF	2	209	2,200	1-2	Single waste bin	Edjabou et al. **III, IV, V**
Households	Zealand	Gladsaxe	SF	1	222	1,320	1-2	Single waste bin	Edjabou et al. **V**
Households	Zealand	Gladsaxe	MF	1	319	2,100	1-2	Batch	Edjabou et al. **III**
Households	Zealand	Helsingør	SF	1	189	2,000	1-2	Single waste bin	Edjabou et al. **III, IV**
Households	Jutland	Kolding	SF	2	194	2,000	1-2	Single waste bin	Edjabou et al. **III, IV**
Households	Jutland	Viborg	SF	2	190	2,100	1-2	Single waste bin	Edjabou et al. **III, IV**
Households	Fyn	Odense	MF	1	372	1,800	1-2	Batch	Edjabou et al. **III**
Households	Jutland	Aabenraa	SF	1	100	1,500	1-2	Batch	Edjabou et al. **I**
Households	Jutland	Aabenraa	MF	2	326	1,700	1-2	Batch	Edjabou et al. **I**
Households	Jutland	Haderslev	SF	3	294	5,300	1-2	Batch	Edjabou et al. **I**
Households	Jutland	Haderslev	MF	1	333	3,300	1-2	Batch	Edjabou et al. **I**
Households	Jutland	Sønderborg	SF	2	269	4,400	1-2	Batch	Edjabou et al. **I**
Households	Jutland	Sønderborg	MF	1	120	600	1-2	Batch	Edjabou et al. **I**
Institution	Zealand	Lyngby	Office area	1	90 ±20[8]	1,616[9]	133[10]	Single waste bin	Edjabou et al. **II**
Households[11]	3	8	2	20	3,137	30,320			
Institution[11]	1	1	1	1	90 ±20	1,616			

[1]Administrative regions in Denmark; [2]Single-family (**SF**) and multi-family (**MF**) house areas as well as kitchens in an office area;[3]Sub-areas are number of cities involved in each municipality;[4] Number of households from which the waste was sampled and analysed; [5]Mass of waste sampled in kg wet mass; [6]One to two weeks (1-2) including weekdays and weekend; [7]Data were published in the following paper; [8]Mean and standard deviation of employees working in the office during the sampling period; [9]Kg wet mass of kitchen waste sampled over 133 working days; [10]Number of weekdays. [11]Total.

Table 2. Classification of waste fractions

Level I	Level II	Level III
1-Food waste	1.1 Vegetable food waste; 1.2 Animal-derived food waste	1.i.1 Processed food waste, 1.i.2 Unprocessed food waste; 1.i.3 Unavoidable food waste
2-Gardening waste	2.1 Dead animal and animal excrements (excluding cat litter); 2.2 Garden waste	2.1.1 Dead animals; 2.1.2 Animal excrement bags from animal excrement 2.2.1 Humid soil; 2.2.2 Plant material; 2.2.3 Woody plant material; 2.2.4 Animal straw.
3-Paper	3.1 Advertisements; 3.2 Books & booklets; 3.3 Magazines & Journals; 3.4 Newspapers; 3.5 Office paper; 3.6 Phonebooks; 3.7 Miscellaneous paper.	3.7.1 Envelopes; 3.7.2 Kraft paper; 3.7.3 Other paper; 3.7.4 Receipts; 3.7.5 Self-Adhesives; 3.7.6 Tissue paper; 3.7.7 Wrapping paper
4-Board	4.1 Corrugated boxes; 4.2 Folding boxes; 4.3 Cartons/plates/cups; 4.4 Miscellaneous board.	4.4.1 Beverage cartons; 4.4.2 Paper plates & cups; 4.4.3 Cards & labels; 4.4.4 Egg boxes & alike; 4.4.5 Other board; 4.4.6 Tubes.
5-Plastic	5.1 Packaging plastic; 5.2 Non-packaging plastic; 5.3 Plastic film.	5.i.1 PET/PETE[1] ; 5.i.2 HDPE[2]; 5.i.3 PVC/V[3]; 5.i.4 LDPE/LLDPE[4]; 5.i.5 PP[5]; 5.i.6 PS[6]; 5.i.7 Other plastic resins labelled with[1-19] ABS[7]; 5.i.8 Unidentified plastic resin; 5.3.1 Pure plastic film; 5.3.2 Composite plastic + metal coating.
6-Metal	6.1 Metal packaging containers; 6.2 Non-packaging metals; 6.3 Aluminium wrapping foil	6.i.1 Ferrous; 6.i.2 Non-ferrous (with i=1&2).
7-Glass	7.1 Packaging container glass; 7.2 Table and kitchen ware glass; 7.3 Other/special glass.	7.i.1 Clear; 7.i.2 Brown; 7.i.3 Green.
8-Miscellaneous combustibles	8.1 Composites, human hygiene waste (Diapers, tampons, condoms, etc.); 8.2 textiles, leather and rubber; 8.3 Vacuum cleaner bags; 8.4 Untreated wood; 8.5 Other combustible waste.	8.1.1 Diapers; 8.1.2 Tampons; 8.1.1 Condoms; 8.2.1 Textiles; 8.2.2 Leather; 8.2.3 Rubber;
9-Inert	9.1 Ashes from households; 9.2 Cat litter; 9.3 Ceramics, gravel; 9.4 Stones and sand; 9.5 Household constructions & demolition waste.	-
10-Special waste	10.1 Single Batteries/ non-device specific Batteries; 10.2 WEEE; 10.3 Other household hazardous waste.	10.3.1Large household appliances; 10.3.2 Small household appliances; 10.3.3 IT and telecommunication equipment; 10.3.4 Consumer equipment and photovoltaic panels; 10.3.5 Lighting equipment; 10.3.6 Electrical and electronic tool (no large-scale stationary tools), 10.3.7 Toys, leisure and sports equipment; 10.3.8 Medical devices (except implanted and infected products); 10.3.9 Monitoring and control instruments; 10.3.10 Automatic dispensers.

[1]Polyethylene terephthalate; [2]Density polyethylene; [3]Polyvinyl-chloride; [4]Low-density polyethylene; [5]Polypropylene; [6]Polystyrene; [7]Acrylonitrile/butadiene/styrene;Numbering of waste fractions: n- fractions included in Level I, n.n fractions included in Level II, n.n.n fractions included in Level III (from Edjabou et al., **I**)

2.4 Waste analysis case studies

Residual household waste (RHW) and waste from kitchens in an office area at Technical University of Denmark were analysed.

2.4.1 Mixed waste sampling and “batch” sorting

Waste sampled from single-family (Aabenraa, Haderslev, and Sønderbog, Gladsaxe) and multi-family (Aabenraa, Haderslev, Sønderbog, and Odense) houses in 12 sub-areas was sorted using the “batch” method (see **Table 1**). Therefore, 12 datasets were attained from these sampling campaigns (Edjabou et al. **I** and **III**).

In total, 21 tonnes of residual household waste (RHW) from 2,133 households was manually sorted applying the batch sorting method. These households were selected from 12 sub-areas, six of which were from single-family house areas. However, in the present study, waste datasets from 10 sub-areas in the municipalities of Aabenraa, Haderslev and Sønderbog (**Table 1**) were used to investigate whether the differences in waste composition for Level **I** had been influenced by housing type and the type of municipality. The effect of including food packaging in the food waste fraction during waste sorting was also analysed (Edjabou et al. **I**).

2.4.2 Single waste bin sorting

We sampled RHW in single-family house areas based in the municipalities of Gladsaxe, Helsingør, Viborg and Kolding (**Table 1**) (Edjabou et al. **III** and **IV)**. Approximately 10 tonnes of RHW was sampled from 814 households in single-family house areas. Waste bins were collected and kept separately, following which they were sorted individually and waste data obtained for each household.

The waste was sorted into waste fractions for Level I, and six food waste fractions for level III. The attained data were used to determine the generation and composition of food waste, and the results were interpreted with regard to housing type, household size and geographical and temporal variations (Edjabou et al. **III**).

2.4.3 Waste from kitchens in office area

Residual waste (RW) collected from kitchens in the office area of DTU Environment (2 tonnes) was sampled. In the course of this study, two plastic waste bins of 60 L each were placed in the kitchens, as shown in **Figure 2**: (1) food waste bins were used for source-segregated food (SSFW), such as food leftovers, spent coffee grounds with paper filters, tea bags, etc., and (2) residual waste bins were used for all other waste fractions, except for food waste and source-segregated waste fractions. Here, residual waste included tissue paper, plastic film, food packaging, etc.

Generally, only hot drinks such as coffee and tea are prepared in these kitchens. Employees use kitchens for lunch, coffee breaks and social events, including birthdays, breakfast, etc.

In this study, source-segregated food (SSFW) and residual waste were collected and weighed daily and separately during 133 working days. These waste materials were then sorted manually every two weeks, to measure the purity and misplacement of food waste. We then analysed the influence of (1) monthly, (2) weekday and (3) institutional activity variations on the generation of SSFW and residual waste (Edjabou et al. **II**).

Figure 2. Two 60L plastic waste bins in kitchens, assigned for food waste and residual waste

2.5 Sample size

In the present study, sample size includes the number of households and number of sampling days (for waste from kitchens in office areas) required to attain representative data. We investigated the effect of the sample size by assessing the relationship between confidence intervals and sample size (Crawley, 2005 (see page 45); Sharma and McBean, 2007).

2.6 Statistical modelling and analysis

2.6.1 Classical statistics

Classical statistics consists of applying statistical analysis to "raw" waste data (e.g. kg waste per household per week, kg waste per person per week or wet mass percentage composition) or transformed waste data (e.g. logarithmic, squared root, power, Box-Cox, logit, linear, etc. transformations). Here, "raw" data are data that have not been transformed. Generally, data are transformed to achieve a desired probability distribution (e.g. normal distribution) and/or reduce the influence of unusually high values (e.g. outliers) prior to statistical analysis (Reimann et al., 2008).

2.6.2 Compositional data (CoDa) analysis and modelling

Waste composition (e.g. 41.0% of food waste, 3.5% of gardening waste (Riber et al., 2009)) and individual generation rates of waste material fractions (e.g. 18.0 g/person/day of plastic, 13.4 g/person/day of paper, 238.3 g/person/day of food waste (Thanh et al., 2010)) are typically compositional datasets, because they provide information only on the relative ratio or values of the waste (Aitchison, 1994).

Waste compositional datasets are "closed," because the percentages or mass of individual fractions are positive and add up to a constant. This is known as "sum constraint." Consequently, although these datasets carry the same information, a change of units (e.g. from kg per person to percentage) may influence the outcome of statistical analysis. To overcome this problem, statistical analysis should be applied on log-ratio coordinates, namely the *centered log-ratio* (clr) and the *isometric log-ratio* (ilr)) (Aitchison, 1986; Egozcue et al., 2003).

The centered log-ratio (clr) was calculated as (Aitchison, 1986):

$$v = clr(\mathbf{x}) = \ln\left[\frac{x_1}{g_m(\mathbf{x})}, \frac{x_2}{g_m(\mathbf{x})}, \cdots, \frac{x_D}{g_m(\mathbf{x})}\right] \qquad \text{Equation 1}$$

where D (number of waste fractions) is coefficients, $clr_i(\mathbf{x})=ln(x_i/g_m(\mathbf{x}))$ is log-contrasts and $g_m(\mathbf{x})$ is the geometric mean of the waste composition. Here the geometric mean is:

$$\mathrm{g_m}(\mathrm{x}) = \left(\prod_{i=1}^{D} x_i\right)^{1/D} = \exp\left(\frac{1}{D}\sum_{i=1}^{D}\ln x_i\right) \qquad \text{Equation 2}$$

The isometric log-ratio is formed based on the sequential binary partition (SBP). An SBP consists of selecting which parts contribute to the log-ratio and then deciding if these will appear in the numerator or in the denominator. To create the first ilr coordinate, the complete composition is split into two groups of parts: one for the numerator and the other for the denominator. In the following steps, one of the two groups is split further into two new groups, to create the second ilr coordinate. Thus, in step k, when the $\mathrm{ilr}(\mathbf{x})_k$ coordinate is created, the $\boldsymbol{r}$ parts $(x_{n1},\ldots,x_{nr})$ in the first group are coded as +1 and placed in the numerator, and the $\boldsymbol{s}$ parts $(x_{d1},\ldots,x_{ds})$ in the second group appear in the denominator and are coded as -1. The obtained coordinate, also known as "balance," is a normalised log-ratio of the geometric mean of each group part (Egozcue et al., 2003):

$$b_k = \sqrt{\frac{r_k \cdot s_k}{r_k + s_k}} \ln \frac{\left(x_{n1}\cdots x_{nr}\right)^{1/r_k}}{\left(x_{d1}\cdots x_{ds}\right)^{1/s_k}}, \; k = 1,\cdots,D-1 \quad (12), \qquad \text{Equation 3}$$

where $\sqrt{\frac{r_k \cdot s_k}{r_k + s_k}}$ is the factor that normalises coordinates. A balance is a log-contrast $ilr_k = \sum_{j=1}^{D} a_{kj} \ln \mathbf{x}_j$

where $a_{kj} = \sqrt{\frac{s_k}{r_k \cdot (r_k + s_k)}}$ is waste fractions x_j, which is in the numerator, and $a_{kj} = -\sqrt{\frac{s_k}{r_k \cdot (r_k + s_k)}}$ is waste fractions that appear in the denominator.

Here, from D waste material fractions, we obtain $D\text{-}1$ ilr coordinates.

2.6.3 Overview of the statistical analyses applied

Statistical analysis includes typically descriptive and inferential (hypothesis testing) statistics (Mason et al., 2003), as shown in **Figure 3**.

Prior to statistical analysis, data preparation (first step) involves identifying and handling irregular data such as errors and missing and zero values. This could be done by imputation methods (see Martín-Fernndez et al., 2012).

The second step is descriptive, which summarises data. In this study, for classical statistics, we calculated the arithmetic mean and standard deviation of waste data, as shown in **Table 3**. Here, we assumed that waste data follow a normal distribution. The geometric mean (based on Eq.2) and quartiles were calculated for the CoDa summary, as indicated in **Table 3** and **Figure 3** (Aitchison, 1986; van den Boogaart et al., 2013).

Table 3. Statistical methods used to summarise waste data

Statistics techniques	Central values (mean)	Measures of spread	Sections
Classical[1]	Arithmetic mean	Standard deviation	3.1, 4.2, and 5.1
CoDa[2]	Geometric mean	Quartiles	3.2.3;

[1]Compositional data analysis techniques; [2]Mean and standard deviation calculated based on mass of individual waste fraction: mass per household, per person or percentage (sections 3.1 and 5.1) and per employee (see section 4.2).

The third step involves hypothesis testing. **Table 4** provides a summary of statistical analyses applied to address each question and hypothesis in this study. Hypothesis testing can be illustrated in the formula (Crawley, 2005):

$$\textit{response variable (s)} \sim \textit{explanatory variable (s)} \qquad \text{Equation 4}$$

Response variable is the variable in which we are interested in measuring (e.g. waste composition, mass of RHW, etc.), whereas an *explanatory variable* is a variable that may influence the response variable (e.g. housing type: two samples; household size: four samples).

Two types of statistical analyses are defined based on the number of response variables: (1) univariate analysis is applied when the response variable is a single and independent sample (e.g. total waste generation rates, total food waste generation rates, individual mass of food waste fractions) and (2) multivariable analysis is applied when a response and/or explanatory variables consist of more than one sample (multiple variables) (Randall, 2016). In the present study, multivariate statistics refers to multiple response variables. Although in this case each response variable could be analysed separately, multivariable analysis allows us to examine simultaneously all of the response variables, to ensure that individual "response variable" and their interaction effect are analysed (Brandstätter et al., 2014; Richard and Dean, 2007).

The number of explanatory variable determines the choice of statistical method to test a hypothesis (Crawley, 2007; Dahlén and Lagerkvist, 2008; Kabacoff, 2011).

For univariate analysis (one independent sample), we applied non-parametric methods to investigate differences in waste data, such as permutation tests and bootstrapping regression (Edjabou et al. **I, II** and **III;** Brandstätter et al., 2014). These techniques are resampling methods that assess the accuracy of estimates (mean, median or standard deviation), without making overly restrictive assumptions about the distribution of the data. A permutation test consists of reordering the data (n!), whereas bootstrapping creates samples of any size by randomly sampling from the original data with a replacement (n^n). These methods also have the advantage of being less sensitive to outliers, and they can also be applied to small sample sizes (Kabacoff, 2011, see Chapter 12 page 291).

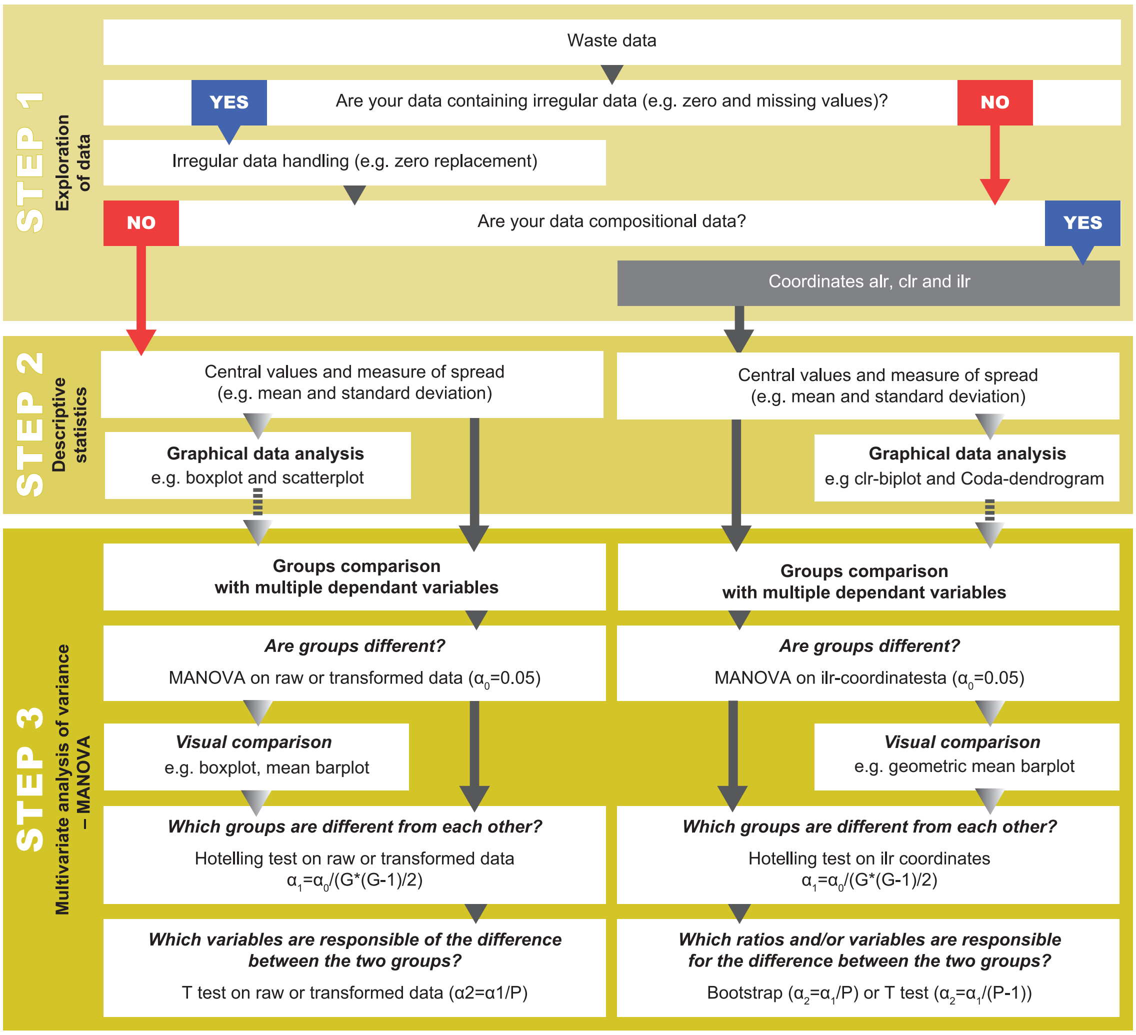
Permutation tests provide a p-value. When this p-value is significant (p-value <0.05), differences are quantified by means of bootstrap confidence intervals. For example, we applied permutation to investigate whether institutional activities would influence the mass of SSFW in the office area at DTU Environment (see **Table 4**).

Contrary to univariate analysis, we applied multivariate statistics to ilr coordinates (**Figure 3** step 3), as described in Section **2.6.2**. The multivariate analysis of waste data was divided into three steps. First, a multivariate analysis of variance (MANOVA) was applied to determine global differences between the datasets. Second, a Hotelling's t-squared test was used to analyse the difference between pairs of datasets, if the MANOVA produced any significant difference. Third, bootstrap confidence intervals or t-tests were used to determine which fraction(s) was/were responsible for the difference (Martín-Fernández et al., 2015).

A MANOVA is used to analyse more than two explanatory variables, whereas the Hotelling's t-squared test is employed to investigate only two (Randall, 2016) (see **Table 4**).

2.7 Statistical software

Modelling and analysis of the data were carried out using the open source R statistical programming language and software (R development core team, 2014) and the freeware CoDaPack (Thió-Henestrosa and Martín-Fernández, 2005). Computer routines implementing the methods can be obtained from http://www.compositionaldata.com.



G is number of groups (e.g. household sizes); P is number of dependent variables (e.g. waste fractions); P-1 is number of ilr coordinates (P=7, see Table 2)

Figure 3. Multivariate analysis procedures for solid waste (from Edjabou et al. **IV**)

Table 4. Questions and statistical method applied in each section

Questions: Determination of difference in:	Variables (samples)		Statistical methods	Type of statistics	Sections
	Responses	Explanatories			
Residual household waste					**3.2**
Including food packaging in FW	10 fractions[1]	2 samples: included or not	Hotelling´s T-squared on ilr coordinates[7]	CoDa	3.2.1
Geographical influence	10 fractions[1]	3 Municipalities: Aabenraa, Haderslev and Sønderborg	MANOVA on ilr coordinates[7]	CoDa	3.2.2
Housing types	10 fractions[1]	2 housing types: Single and multi-families houses	Hotelling´s T-squared on ilr coordinates[7]	CoDa	3.2.2
Household size	8 fractions[2]	4 households sizes: 1, 2, 3, and 4+ persons	(1) MANOVA on ilr coordinates[7]; (2) Hotelling´s T-squared on ilr coordinates[7]; (3) Bootstrap confidence interval (**Figure 3**)	CoDa	3.2.3
Residual waste in office area					**4.3**
Monthly variation	One sample[3]	7 months: from February to August	Permutation test[5] and bootstrapping regression[6]	Classical	4.3
Weekdays	One sample[3]	5 weekdays: from Monday to Friday	Permutation test[5] and bootstrapping regression[6]	Classical	4.3
Institutional activities	One sample[3]	3 periods: lecturing, exams and holidays	Permutation test[5]	Classical	4.3
Household food waste					**5.2**
Housing types	One sample[4]	2 housing types: Single and multi-families houses	Permutation test[5]	Classical	5.2.1
Geographical variation	One sample[4]	4 variables: municipalities of Kolding, Viborg, Helsingør, and Gladsaxe	Permutation test[5]	Classical	5.2.2
Geographical variation	One sample[4]	2 variables: Regions Zealand and Jutland	Permutation test[5]	Classical	5.2.2
Household size	One sample[4]	4 households sizes: 1, 2, 3, and 4+ persons	Permutation test[5] and bootstrapping regression[6]	Classical	5.2.3
Periodic variation	One sample[4]	3 periods: Period1, period 2 and period 3	Permutation test[5]	Classical	5.2.4

[1]Waste fractions at Level **I (Table 2)**; [2]Waste fractions shown in **Table 6**; [3] SSFW and residual waste were analysed individually; [4] Mass per household and per person of the six waste fractions, total food waste, combined avoidable and unavoidable food waste, Processed and unprocessed food waste and vegetable and animal-derived food waste were analysed individually; [5]Permutation test generate p-value; [6]Quantify difference; [7]Isometric log-ratio coordinates calculated based on binary sequential partition in **Table 7** and Eq. (4);[8]Compositional data analysis techniques; [9]Statistical methods applied to mass of individual waste fraction: mass per household, per person (section 5.2) and per employee (see section 4.3).

3 Residual household waste

3.1 Generation and composition

The residual waste generation rate per person per week was 3.4±0.2 in Aabenraa, 4.3 ± 1.5 in Haderslev and 3.5 ± 1.5 in Sønderborg. Aggregated waste generation according to housing type was 3.7 ± 0.8 per person per week in single-family house areas and 4.0 ± 1.5 per person per week in multi-family house areas. The aggregated generation rate of RHW was 3.8 kg per person per week. These results were comparable to those published by the Danish EPA, which estimated 3.4 kg per person per week (Toft et al., 2015).

The detailed RHW composition is shown in **Table 5**. Food waste constituted 41-45% of RHW and consisted of vegetable (31-37%) and animal-derived (7-10%) food waste.

Misplaced material fractions (paper, board, etc.) represented 26% of the RHW. This relatively high percentage of recyclables in RHW indicates that further initiatives are required to increase the source-segregation of recyclables in households.

Riber et al. (2009) found a higher percentage of paper (16%), which comprised advertising flyers, books, magazines and journals, newspapers, office paper and phonebooks. This difference could be explained by factors such as sorting guides and socio-economic patterns (e.g. income levels, demography, etc.).

Detailed RHW composition provides a more transparent and comprehensive waste composition, enabling, to a certain extent, comparison among future and existing studies.

Food packaging with food residues represented 18% of the total RHW. Here, food packaging amounted to nearly 3% of total RHW, and it consisted of plastic (53%), paper and board (34%), glass (13%) and metal (10%).

Table 5. Detailed waste composition (% mass per wet basis) of RWH from Aabenraa, focusing on Level III (Edjabou et al., **I**)

Fractions (Level I)	Fractions (Level II&III)	SF[4] (%w/w[1])	MF[3] (%w/w[1])
Food waste			
	Vegetable food waste	36.6	31.3
	Animal-derived food waste	8.1	9.5
Gardening waste			
	Dead animal and animal excrements[7]	0.5	0.3
	Garden waste etc.		
Paper			
	Other paper[5]	2.5	4.9
	Miscellaneous paper		
	Tissue paper	4.1	3.8
	Envelopes[1]	0.1	0.2
	Kraft paper	0.1	0.0
	Wrapping paper	0.1	0.0
	Other paper	0.2	0.1
Board			
	Other board[6]	6.5	6.0
	Corrugated boxes[1]		
	Egg boxes&alike[1]	0.1	0.1
	Cards&labels[1]	0.1	0.1
	Board tubes[1]	0.3	0.3
	Other board	0.2	0.1
Plastic			
	Non-packaging containers	0.5	0.9
	Packaging plastic[1]		
	1-PET	1.1	0.6
	2-HDPE	0.9	1.1
	3-PVC	0.0	0.5
	4-LDPE	0.0	0.0
	5-PP	1.4	0.4
	6 PS	0.4	1.2
	7-19	0.0	0.0
	Unspecified	1.4	0.8
	Plastic film	9.8	6.7
Metal			
	Metal packaging containers[1]		
	Ferrous	0.8	1.1
	Non-ferrous	0.5	0.8
	Aluminium wrapping foil	0.0	0.0
	Non-packaging metals		
	Ferrous	0.3	0.4
	Non-ferrous	0.3	0.3
Glass			
	Packaging container glass[1]	1.8	2.2
	Table and kitchen ware glass[1]	0.2	0.0
	Other/special glass[1]	0.1	0.1
Miscellaneous combustible	Human hygiene waste	14.1	19.5
	Wood untreated		
	Textiles, leather and rubber		
	Vacuum cleaner bags		
	Other combustible waste		
Inert		1.3	3.2
Special waste[1]		0.7	0.5
Total		100	100

[1]Mis-sorted recyclable material fractions; [2]Mis-sorted other material fractions; [3]Composition of single-family houses areas as % wet weight; [4]Composition of multi-family areas as (% mass per wet basis);[5]Advertising flyers, books & booklets, magazines & journals, newspapers, office paper, phonebook; [6]Corrugated boxes, folding boxes, beverage cartons; [7]Exclude cat litter.

3.2 Factors influencing residual household waste

3.2.1 Inclusion of food packaging in the food waste fraction

We analysed the influence of including food packaging in the food waste fraction by comparing two waste compositional datasets: (1) food packaging was separated from food waste and added to the relevant fractions and (2) a computed dataset where the mass of food packaging was added to the food waste fraction. Here, the 10 waste fractions at Level I were analysed (Edjabou et al. **I**). We found no statistically significant difference between these two datasets (F-statistic=0.08, df=1, p-value=0.8), suggesting that the specific separation of food packaging from food residues during sorting was not critical to the RHW composition.

3.2.2 Geographical variation and housing type

The composition of RHW for Level I fractions from the municipalities of Sønderborg, Haderslev and Aabenraa as a function of housing type (single and multi-family house areas) is shown in **Figure 4**. The compositional datasets between (1) municipalities and (2) housing types were compared in separate MONAVA tests applied to ilr coordinates (CoDa Techniques).

The statistical analyses did not show any significant difference between the compositional datasets of either municipalities or housing type. These results may suggest that for sub-areas with identical household waste source segregation systems, the waste compositional dataset for individual sub-areas (e.g. municipalities) may be statistically representative of all sub-areas. Moreover, although there is a difference in waste management systems between housing type (a shared waste bin in multi-family house areas and an individual waste bin in single-family areas), their compositional waste data were not statistically different, thereby suggesting that housing type may not be a critical stratification criterion for RHW sampling. However, this conclusion is only relevant for aggregated waste fractions at Level I and for the socio-economic and geographical contexts.

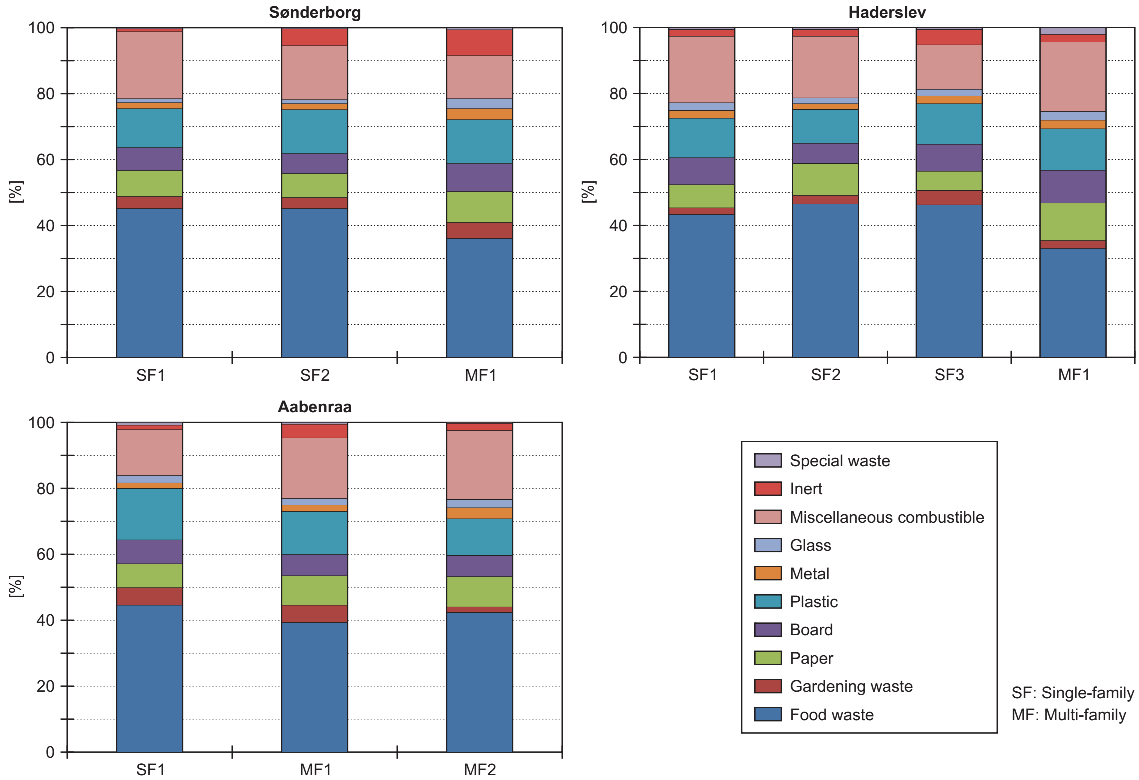


Figure 4. Composition of RHW (% of wet mass) per municipality according to housing type (from Edjabou et al. **I**)

Table 6. Compositional data summary of RHW composition (from Paper **IV**)

Residual household waste	Centre[1]	Quartiles[1]				
		0	25	50	75	100
Avoidable vegetable food waste	13.3	0	7.8	13.9	21.8	72.1
Unavoidable vegetable food waste	15.5	0.1	8.5	15.3	24.0	74.5
Avoidable animal-derived food waste	4.0	0.0	2.0	5.1	9.9	46.9
Unavoidable animal-derived food waste	1.2	0.0	0.4	1.1	2.9	33.5
Paper and board	23.9	2.3	13.5	18.5	25.4	80.6
Metal packaging	1.4	0.0	0.6	1.4	2.7	56.4
Plastic packaging	5.9	0.0	3.3	4.8	6.8	82.4
Other	34.8	5.1	19.2	26.3	38.1	86.7
Total	100	-	-	-	-	-

[1]Percentage of wet waste (from Edjabou et al. IV).

3.2.3 Household size

A descriptive compositional data summary of residual waste (Edjabou et al. **IV**) is presented in **Table 6**. The centre, also known as the geometric mean, is computed using Eq.(2). The spread of distribution was given by quartiles. Similarly to previous studies (Edjabou et al. **I**), RHW consisted predominantly of food waste (combination of the four food waste fractions).

We constructed a CoDa dendrogram to complete a basic description and to enable the exploratory analysis of waste compositional data. This descriptive graph was constructed based on SBP, as shown in **Table 7**. Here, (+1) means that the waste fractions were assigned to the first group, and (-1) indicates that they were assigned to the second group, while (0) means that they were not included in the partition. For example, eight fractions were divided into two groups (food waste and non-food waste) to yield coordinate 1 (b1). Food waste fractions (AVFW, UVFW, AAdFW, UAdFW) coded (+1) were assigned to the first group, and non-food waste fractions coded (-1) (paper, metal, plastic, other) were included in the second group. This partition generated seven coordinates, each corresponding to the number of waste fractions (8) minus 1.

Table 7. Sign codes of the sequential binary partition applied to the RHW composition (from Paper **IV**)

Coordinates	Residual household waste fractions							
	AVFW[1]	UVFW[2]	AAdFW[3]	UAdFW[4]	Paper[5]	Metal[6]	Plastic[7]	Other[8]
b_1	+1	+1	+1	+1	-1	-1	-1	-1
b_2	+1	+1	-1	-1	0	0	0	0
b_3	+1	-1	0	0	0	0	0	0
b_4	0	0	+1	-1	0	0	0	0
b_5	0	0	0	0	+1	+1	-1	-1
b_6	0	0	0	0	+1	-1	0	0
b_7	0	0	0	0	0	0	+1	-1

[1]Avoidable vegetable food waste; [2]Unavoidable vegetable food waste; [3]Avoidable animal-derived food waste; [4]Unavoidable vegetable food waste; [5]Paper and board; [6]Metal; [7]Plastic waste; [8]Other waste fractions (from Edjabou et al. **IV**).

The CoDa dendrogram is shown in **Figure 5** and represents simultaneously (1) SBP, (2) the sample centre, (3) the decomposition of sample variance, (4) the four household sizes associated with each coordinate and (5) a boxplot showing the distribution of individual household size (Egozcue et al., 2003).

The colours of the vertical bar and the boxplots correspond to each household size. The black vertical bars are assigned to the average of the four household sizes.

The centre of the coordinates is indicated where the vertical bar contacts the horizontal bars, and it also provides information on the relative importance between the two groups of waste fractions. The centre of coordinate b_2 is closed to vegetable food waste (AVFW, UVFW), suggesting that most Danish households probably discard more vegetable food waste than animal-derived food waste. However, the coordinate b_3 may indicate that Danish households discard similar amounts of avoidable and unavoidable vegetable food waste, because the centre is situated in the middle of the horizontal bar.

While the length of the vertical bars corresponds to coordinate variance, the distance between them on the same horizontal bar indicates either a similarity (when the vertical bars coincide, e.g. coordinate b_5) or a difference in the mean of household size (large distance between the vertical bars, e.g. coordinate b_1). Thus, the longest vertical bar corresponds to major variability (e.g. a household containing one person (in blue) on the coordinates b_1, b_2 and b_3) and vice versa (e.g. a household of two persons (in green) on coordinate b1). Coordinate b_1 suggests that the ratio between food and non-food waste in households containing one person may vary considerably in relation to other household sizes.

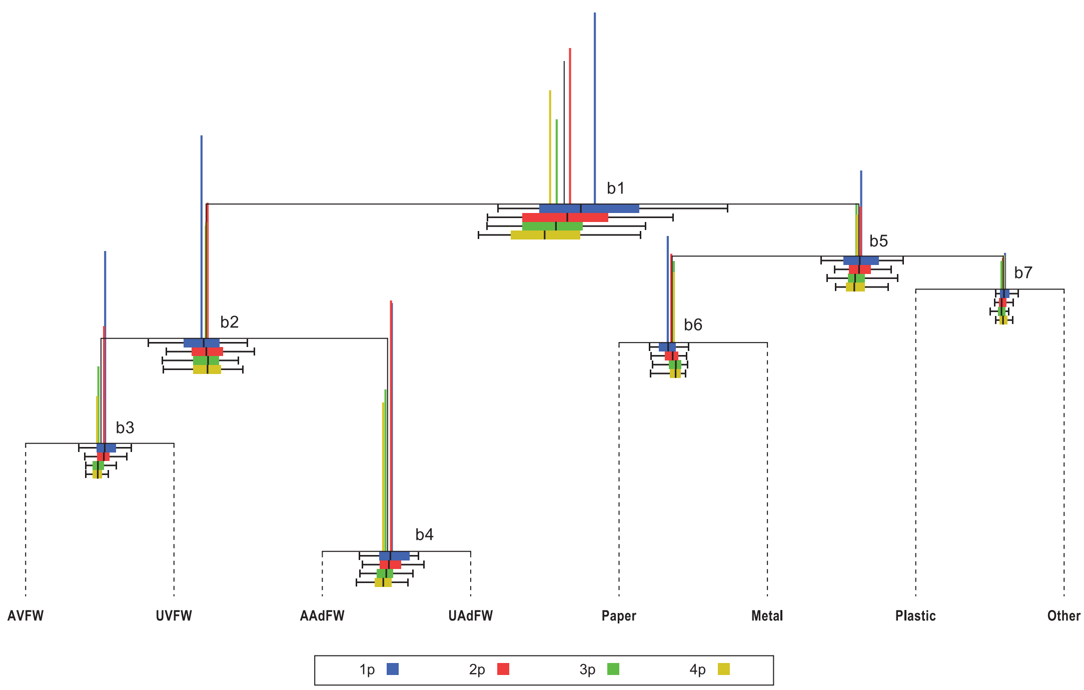


Figure 5. Balance dendrogram representing the eight balances from the SBP applied to the eight waste fractions. Each boxplot refers to one of the four household sizes in the study area (from Edjabou et al. **IV**).

A MANOVA applied to ilr coordinates revealed significant differences (p-value<0.001, df=3) in residual waste between household sizes. These differences are illustrated by means of geometric mean barplots (Martín-Fernández et al., 2015) in **Figure 6**.

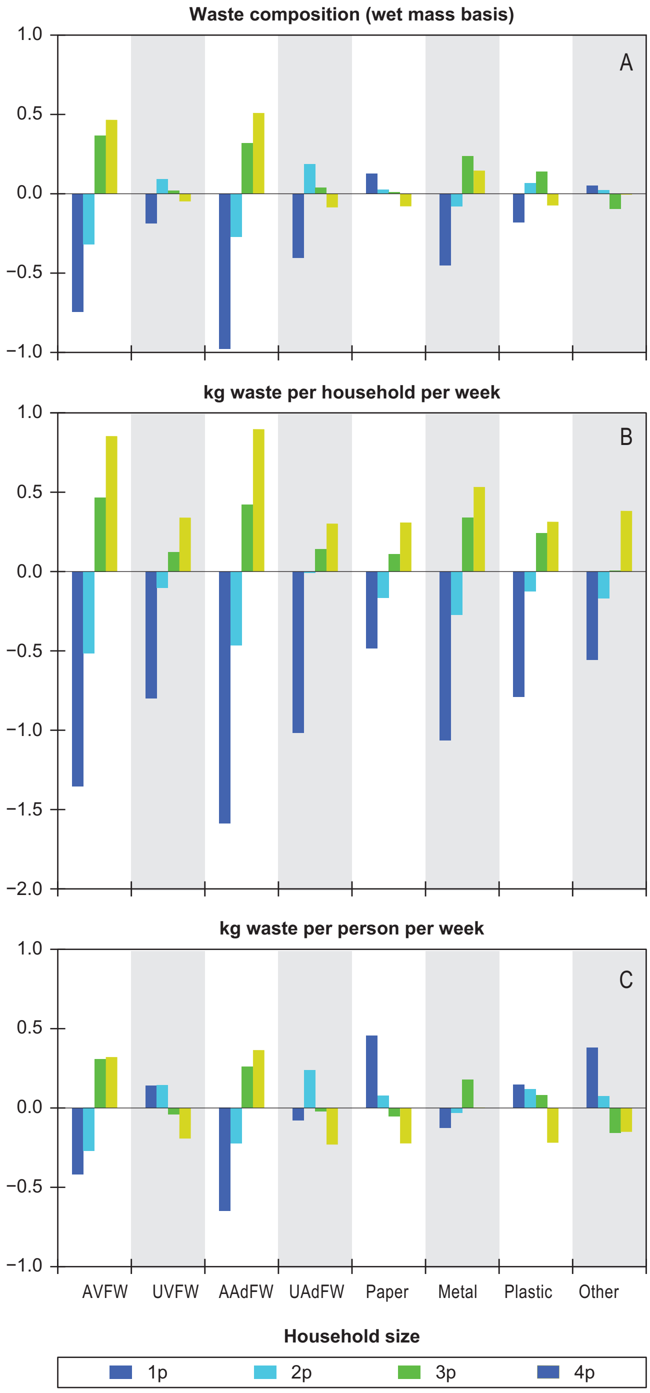


Figure 6. Barplots comparing centre of the RHW compositional datasets as a function of household size (from Edjabou et al. **IV**).

Differences are shown using (1) waste composition as a percentage of wet mass, (2) kg mass per household per week and (3) kg mass per person per week (**Figure 6**). The log-ratio between each group and the whole sample (779 households) is on the **y** axis. For the waste compositional dataset, households of one and two persons may generate individually 52% (100 – (exp (-0.74))*100) and 27% lower avoidable vegetable food waste than average Danish households. In contrast, households containing three and four persons may discard 44% (100 – (exp(0.34))*100) and 59% higher avoidable vegetable food waste than the average Danish household. Moreover, households containing one and two persons may generate less waste mass per household than average households (**Figure 6**: kg waste per household per week). However, no prevailing trend is observed when considering aggregated mass per person of waste fraction (**Figure 6**: kg waste per person per week).

Following the previous results, a Hotelling's t-squared (Martín-Fernández et al., 2015) was applied to the ilr coordinates. The alpha value was adjusted to α_1=0.008, in order to investigate differences between pairs of household sizes. We found significant differences in this regard except for between households of three and more than three persons.

Bootstrap confidence intervals (Martín-Fernández et al., 2015) enable one to quantify uncertainties and indicate the waste fraction that might cause these differences. Bootstrap confidence intervals are shown in **Figure 7** and indicate differences between (A) households of one and two persons, (B) households of one and three persons, (C) households of one and four and more persons, (D) households of two and three persons, (E) households of two and four and more persons and (F) households of three and four and more persons. The vertical bars show the lower and upper and lower confidence bounds of each waste fraction. Waste fraction contribution is significant to the difference when its vertical bar is above or under and does not touch the horizontal bar zero. Here, the α_2 value is adjusted to $\alpha_1/8$ (eight waste fractions as dependent variables), as illustrated in **Figure 3** and Eq. (1).

A bootstrap confidence interval revealed that avoidable food waste (avoidable vegetable and animal-derived food waste) was the common fraction responsible for differences between the following pairs: households of one and three persons (**Figure 7**. B), households of one and four and more persons (**Figure 7**. C), households of two and three persons (**Figure 7**. D) and households of two and four and more persons (**Figure 7**. E).

None of waste fractions was significant between households of three and four and more persons (**Figure 7**. F), as established by the Hotelling's t-squared test. However, neither unavoidable vegetable food waste nor metal packaging contributed to significant differences between household sizes. These results suggest that household size influences significantly the generation and composition of RHW.

The assumptions of the MANOVA, including the homogeneity of variance and covariance and multivariate normality, were tested (Edjabou et al. **IV**).

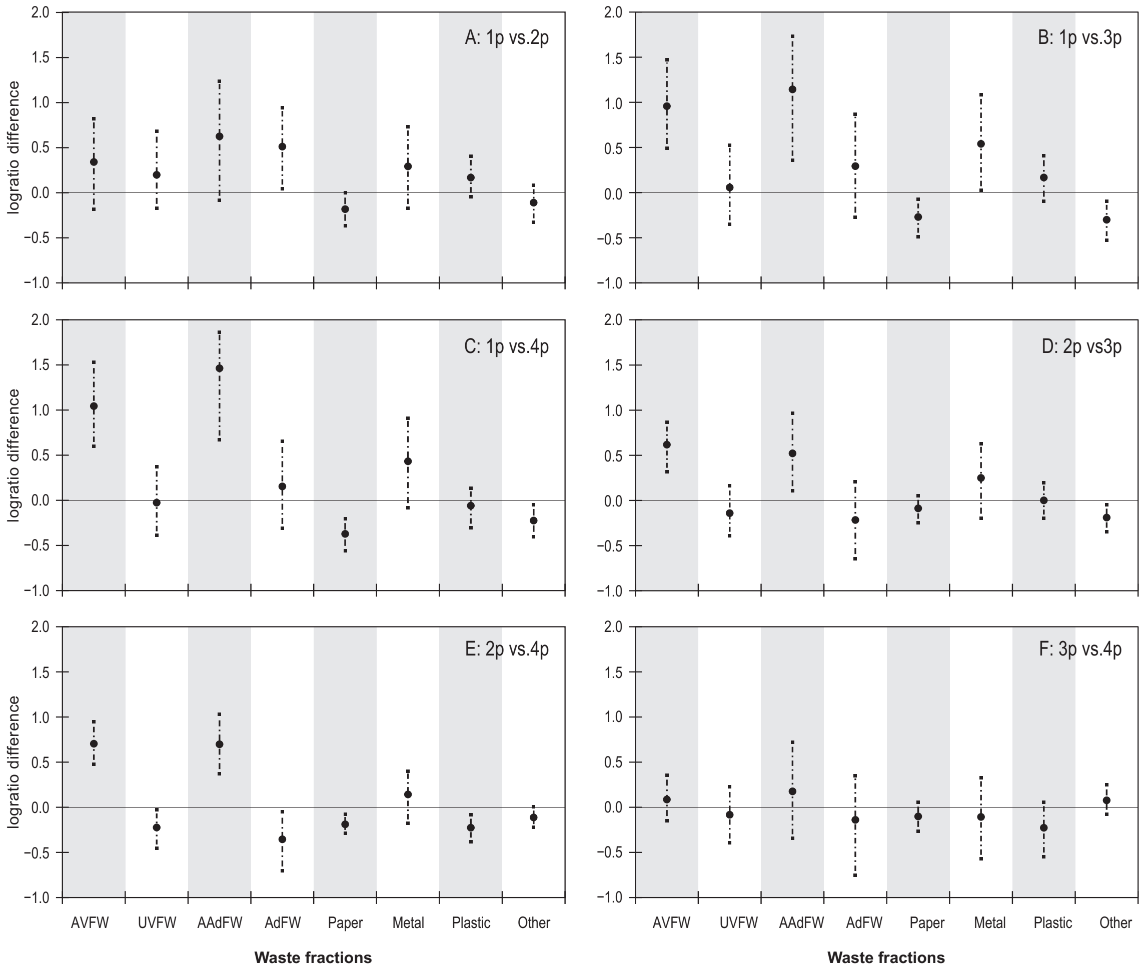


Figure 7. Bootstrap percentile confidence intervals for log-ratio differences between centres of household sizes containing: (A) one and two persons; (B) one and three persons; (C) one and four persons; (E) two and three persons; (F) two and four persons; (D) three and four persons (from Edjabou et al. **IV**)

4 Waste from kitchens in an office area

4.1 Sample size

We investigated the required sample size to obtain reliable estimates of SSFW and residual waste generated from kitchens in the office area. Here, the sample size was the number of days covered by the sampling period. Confidence intervals based on bootstrap, normal distribution and Student's t-distribution are shown in **Figure 8** for SSFW and residual waste. The results indicate that confidence intervals (food waste and residual waste) narrowed rapidly after 20 working days but more slowly thereafter. These results suggest that less than 20 working days is a small sample size, whereas 30 working days could be sufficient to generate reliable estimates.

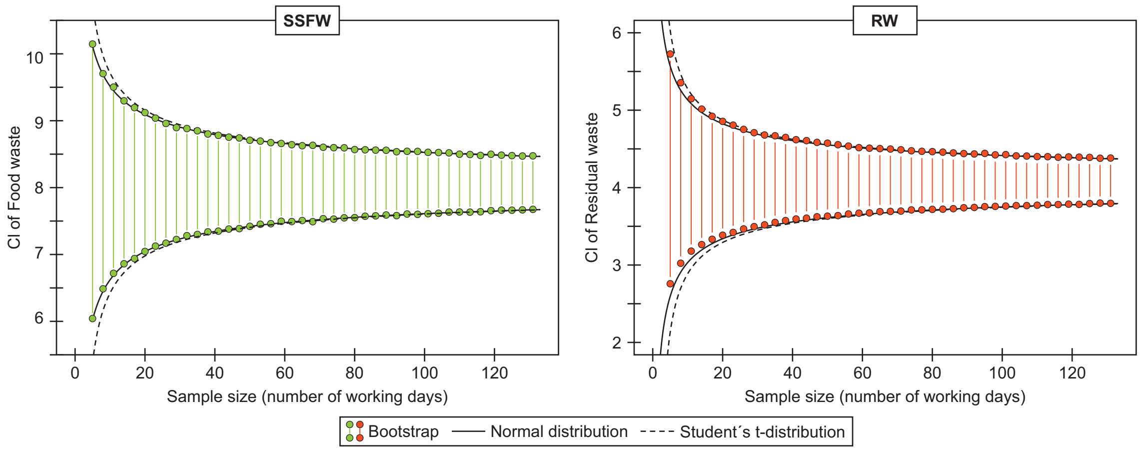


Figure 8. Confidence intervals (based on bootstrap, normal distribution and Student's t-distribution) of source-segregated food waste (SSFW) and residual waste from kitchens in an office area (from Edjabou et al. **II**).

4.2 Waste generation and composition

The mass of SSFW amounted to 20±5 kg per employee per year, whereas the residual waste was 10±4 kg per employee per year (with 250 working days per year). Thus, waste generated in the office area consisted of 67±6% SSFW and 33±6% residual waste.

Waste sorting showed that food waste misplaced in the residual bins represented 24±16% residual waste, whereas less than 1% residual waste was misplaced in the SSFW bins. As a result, only 11% of the total food waste was misplaced, indicating a very high sorting efficiency (89 ± 28%). Moreover, the purity of SSFW was 99±0.01%. These results suggest that a 60% recycling target formulated by the Danish Government for food waste generated by the service sector (Danish Government, 2013) should be achievable.

A comparison of source-sorted food waste between the office area and households suggested that the sorting efficiency and purity of food waste in the office area was higher than in the households, estimated respectively at 25 to 50% and 1 to 9% (Bernstad et al., 2013; Møller et al., 2013). Moreover, although the potential of household food waste (75 kg per person per year (Edjabou et al. **III**)) was higher than in offices areas, the SSFW per office area could be considerably higher than for households, since office areas are usually used by more people (on average 73 employees per office area in Denmark (Statistics Denmark, 2015) than the average household size of 2.2 persons (Statistics Denmark, 2015). Consequently, a significant mass of SSFW could be collected with reasonable logistical ease in office areas.

4.3 Factors influencing waste from kitchens in office areas

The generation rates (in mass per employee per working day, and mass per employee per month) of source-sorted food waste and residual waste as a function of month are shown in **Figure 9**. The highest daily waste generation was in June (21 ± 3 kg/employee/year) for SSFW and in August (19 ± 4 kg/employee/year) for residual waste. However, none of these differences was statistically significant (p-value=0.83, df=6 for SSFW, and p-value=0.25, df=6 for residual waste). These results indicate that the masses per employee per day of SSFW and residual waste were not influenced significantly by monthly variations.

The generation rates of SSFW and residual food waste as a function of weekdays are shown in **Figure 10**. The highest mass for both SSFW and residual waste was observed on Mondays, while the lowest was found on Friday for SSFW and on Tuesdays for residual waste. Statistical analyses showed significant differences in waste generation rates among weekdays, which suggests that waste sampling carried out in office areas should cover all weekdays, in order to attain reliable data.

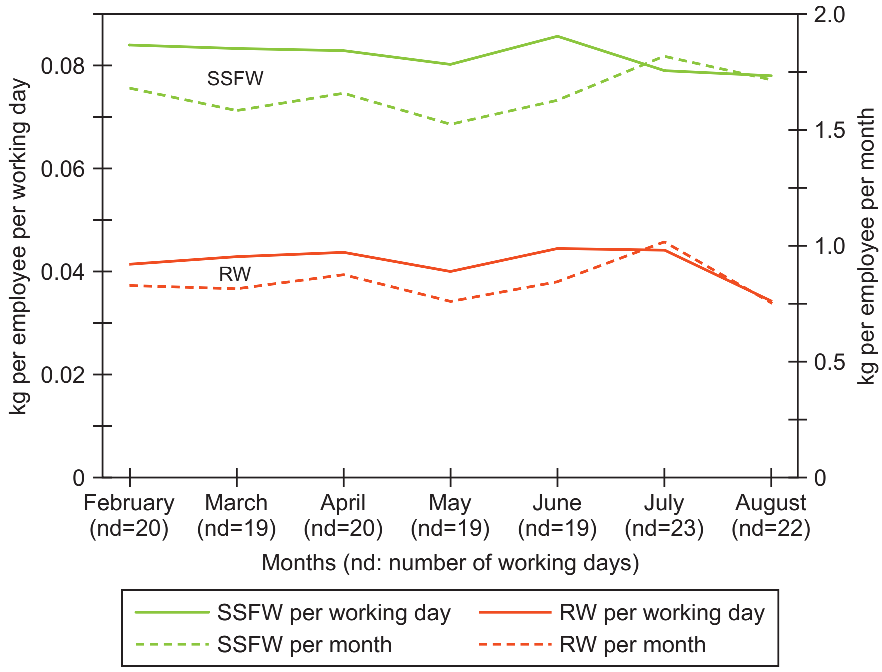


Figure 9. Unit generation rates of source-sorted food waste and residual waste during the waste sampling campaign (kg per employee per working day, and kg per employee per month) (from Edjabou et al. **II**)

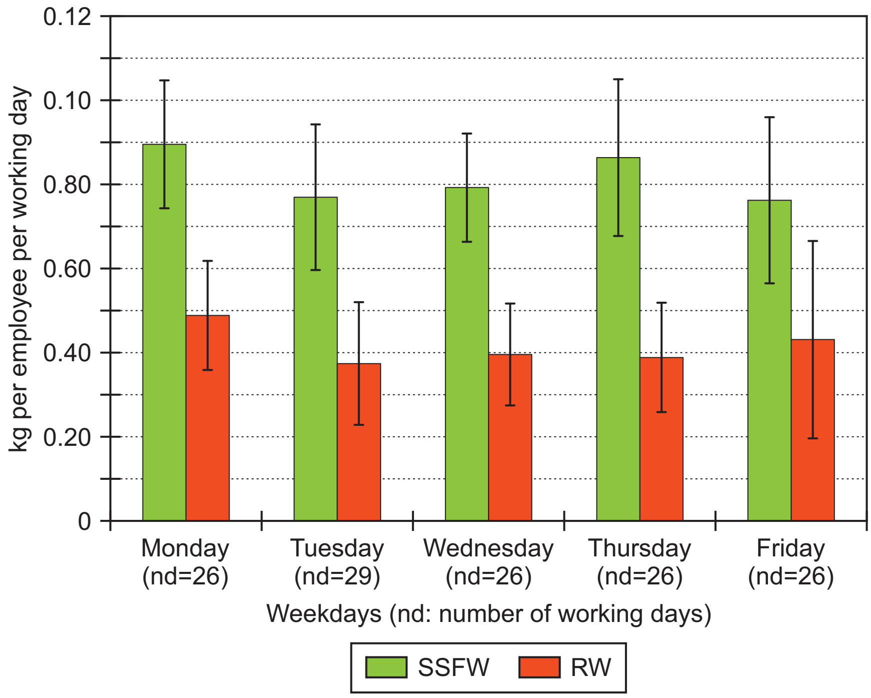


Figure 10. Average unit waste generation rates of source-sorted food waste (SSFW) and residual waste as a function of weekday (from Edjabou et al. **II**)’

Given that employees' kitchens were also open to use by students, we investigated the influence of institutional activities on waste generation rates. The results showed that there was no significant effect of institutional activity on waste generation rates; therefore, the results of these studies could be expanded to other office areas. However, due to the specifications and differences in culture in office areas in different countries, the use of these data should carefully considered the definition of office area in this study.

5 Food waste from Danish households

Residual household waste (RHW) was analysed to quantify food waste mass discarded in Danish houses. Residual waste was collected from single-family house areas (Gladsaxe, Helsingør, Kolding and Viborg) and multi-family house areas (Odense and Gladsaxe). Waste from single-family houses was sorted individually, whereas waste from multi-families was sorted as a "batch" (**Table 1**). Food waste was sorted into six fractions ((1) avoidable processed vegetable food waste, (2) avoidable unprocessed vegetable food waste, (3) unavoidable vegetable food waste, (4) avoidable processed animal-derived food waste, (5) avoidable unprocessed animal-derived food waste, and (6) unavoidable animal-derived food waste) in Level III in **Table 2**.

Here, avoidable food waste is food that could have been eaten but instead was disposed of regardless of the reason (FUSIONS, 2014). On the other hand, unavoidable food waste is defined as 'food that is not and has not been edible under normal circumstances' (WRAP, 2009), such as bones, carcasses, egg shells, peels, fruit skin, etc. Moreover, processed food is food that has been prepared, cooked or served in the home (WRAP, 2009). On the contrary, unprocessed food waste is purchased food that has been discarded without being cooked, prepared or served as a meal (WRAP, 2009).

5.1 Generation and composition

Figure 11 illustrates the total weighted food waste from single and multi-family house areas in Denmark. On average a Danish household discarded 183±18 kg food waste per year (86± kg per person per year), which accounted for 43±1.8% of total RHW. Moreover, food waste consisted of 56.4±3.8% of avoidable food waste and 43.6±2.2% of unavoidable food waste. Avoidable unprocessed food waste constituted 67% of total avoidable food waste. These results indicate that a high proportion of avoidable food waste was purchased, stored (or not) and then discarded.

We also found that 71% of avoidable food waste consisted of vegetable products. This result suggests that Danish households wasted more vegetable food than animal-derived food.

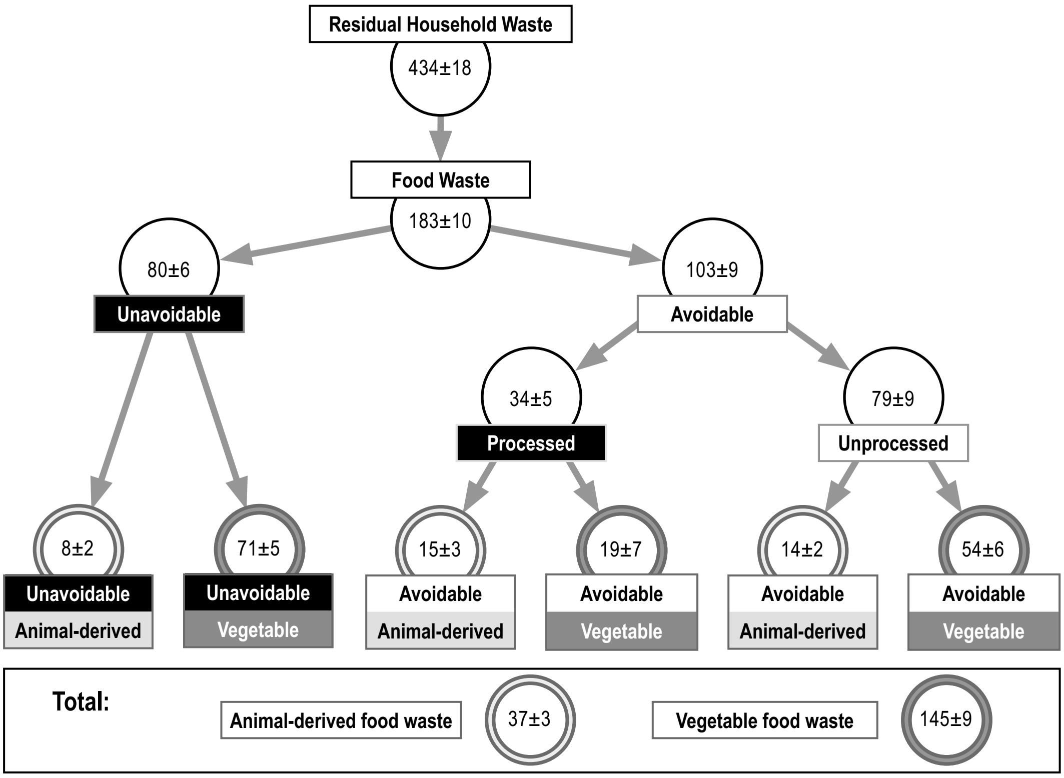


Figure 11. Weighted generation rate of food waste in Danish households in kg wet mass per household (from Edjabou et al. **III**).

5.2 Factors influencing food waste

5.2.1 Housing type (single vs. multi-family house areas)

We investigated differences in the mass of food waste generated from single and multi-family house areas. The results showed that single-family households generated a significantly higher total food waste and avoidable food waste per household than multi-family house areas. However, there was no significant difference between these housing types when we analysed the aggregated mass of waste per person. This may be explained by the difference in the number of persons per household (2.4 for single-family house areas and 1.8 for multi-family house areas (Statistics Denmark, 2015)).

5.2.2 Geographical variation

The distribution of avoidable and unavoidable food waste discarded in single-family house areas as a function of municipalities is shown in **Figure 12**. Statistical analyses revealed that neither regions (Jutland and Zealand) nor municipalities (Gladsaxe, Helsingør, Kolding, and Viborg) introduced significant differences in total avoidable and unavoidable food waste. These results suggest that the quantity of food waste discarded in Danish households was not affected by geographical differences.

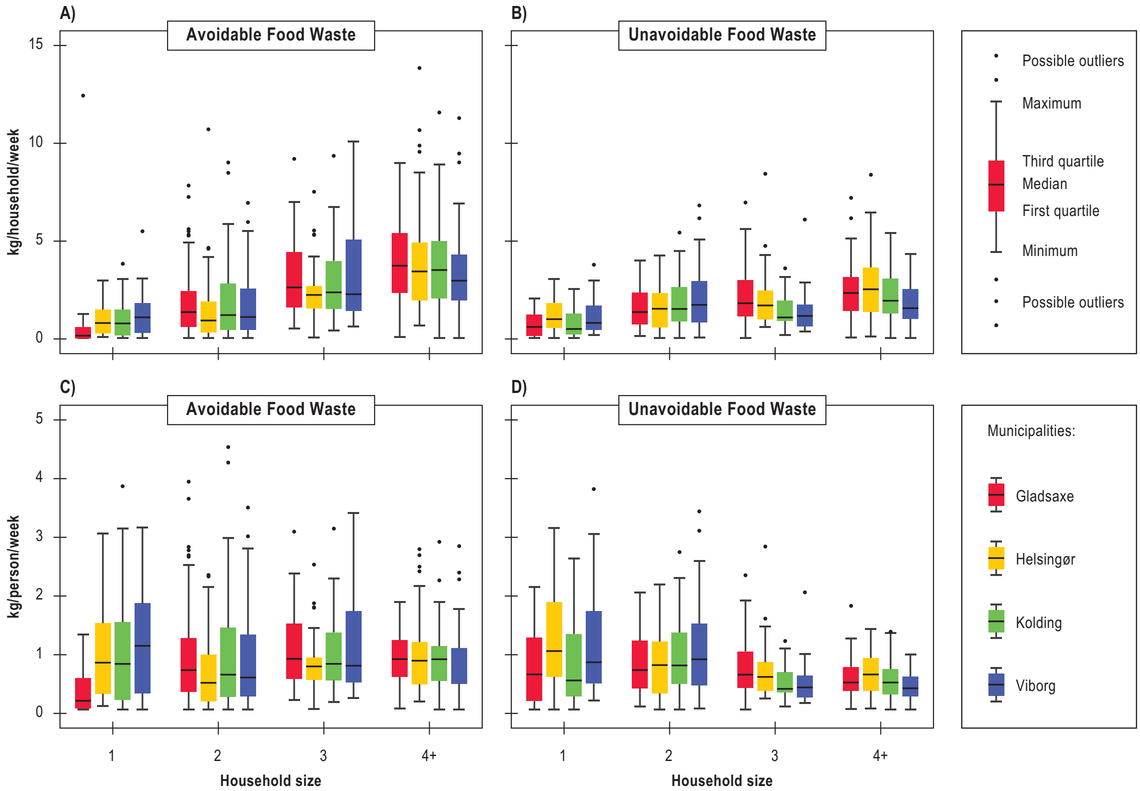


Figure 12. Distribution of the generation of avoidable and unavoidable food waste (box plots are based on a wet mass basis) in single-family house areas as a function of household size for the four municipalities: kg waste per household (A & B) and kg waste per person per week (C&D) (from Edjabou et al. **III**).

5.2.3 Household size

Figure 12 shows that the mass of avoidable and unavoidable food waste per household (**Figure 12**A &B) increased in line with household size. On the other hand, no clear pattern could be observed for aggregated mass per person of avoidable and unavoidable waste (**Figure 12** C & D).

Bootstrap regressing indicated that households containing one person discarded less avoidable food waste than those of two persons (0.66 kg, with a 95% confidence interval of 0.23 to 1.44), three persons (1.85 kg, with a 95% confidence interval of 1.36 to 2.34) and four and more persons (2.75 kg, with a 95% confidence interval of 2.30 to 3.12). Similarly, the mass of unavoidable food waste was also significantly different between household sizes. However, there were no significant differences in mass per person of avoidable food waste discarded in Danish households. While these results differ from those published by Parizeau et al. (2014), they are nevertheless consistent with those of WRAP (2009).

We also analysed the likelihood of generating food waste, by computing the number of households where no food waste, i.e. “zero mass,” was found in the waste bin. The results show that 97% of households involved generated avoidable food waste, suggesting that food waste occurs in most Danish homes.

Logistic regression revealed that only household size affects the generation of avoidable food waste. The results indicate that the likelihood that avoidable food waste is generated increases significantly in line with the number of occupants in a house. Thus, a household containing two and more persons may increase this likelihood by a factor of four, and a household of more than two persons may increase it by a factor of five or more.

These results suggest that an increase in the number of persons per household also increases the likelihood of wasting food. This could be explained by the fact that a person living alone tends to eat “simple meals” or eat at work. On the contrary, a household of more than one person may keep traditional mealtime habits, particularly for dinners, where a warm meal or some form of prepared food is served. Food preparation and serving increase the risk of overestimating food that is purchased or cooked, thus leading to food waste. Additionally, it might be more difficult to plan efficiently the purchasing and cooking of food that satisfies the desire of more than one person, which may cause food leftovers. However, single people may only cook food to satisfy their own desire, or at least less often than in households with more than one person.

5.2.4 Periodic variation of food waste

The periodic variation of avoidable and unavoidable food waste as a function of household size is shown in **Figure 13**. The waste was sampled from the same single-family house in the municipality of Gladsaxe.

The mass per household of avoidable and unavoidable food waste (**Figure 13** A & B) increases in line with household size, whereas the mass per person (**Figure 13**, C & D) shows no clear pattern – as found in 5.2.3. However, the permutation test shows no significant difference in the mass of avoidable and unavoidable food waste per household and per person between these three periods. These results could be explained by the demand and availability of fresh food (e.g. vegetables, fruits, etc.) throughout the whole year, due to the modern food supply chain that enables retailers to import out-of-season produce (HLPE, 2014).

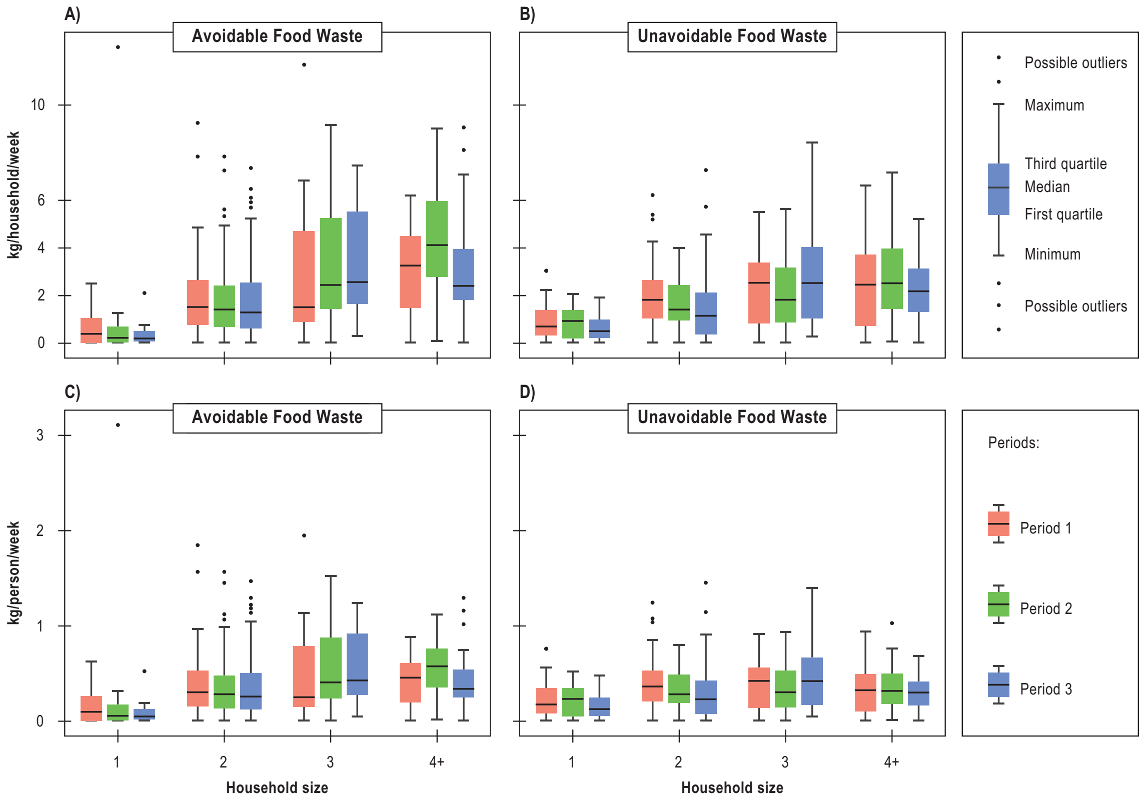


Figure 13. Periodic generation of avoidable and unavoidable food waste (boxplots are based on a wet mass basis) in a single-family house area of Gladsaxe as a function of household size: kg per household (A & B) and kg per person (C & D) (from Edjabou et al. **III**)

5.2.5 Food waste reduction

The waste analysis showed that food waste occurs in most Danish households. This suggests that an initiative to reduce avoidable food waste could be promulgated at national level, even though municipality authorities have the responsibility to manage and prevent solid waste (Halloran et al., 2014).

The mass and likelihood of avoidable food waste increase in line with household size. This implies that awareness programmes to reduce food waste should target all household sizes but more importantly households of more than one person. Shopping planning and the correct storage of vegetables and fruits could reduce substantially the mass of avoidable food waste generated in Danish households (Koivupuro et al., 2012; Lebersorger and Schneider, 2011; WRAP, 2009). Additionally, recipes for food waste leftovers and cooking planning (WRAP, 2009) should be also considered, in order to reduce food waste.

6 Conclusions

In total, 30 tonnes of residual household waste (RHW) and 2 tonnes of waste from kitchens in an office area was sampled and analysed. RHW was collected from 3,137 households in Zealand, Fyn and Jutland. In total, nine municipalities, eight single-family areas and five multi-family house areas and one office area were involved in the waste sampling campaigns.

The waste was sampled at source (e.g. households and institution), thus enabling us to obtain the waste generation rates and the percentage composition of waste fractions. These data were accurately attributed to the source.

We introduced a tiered approach to analyse waste involving three levels of waste fractions. As opposed to a more "linear" waste fraction list, the three-level fraction list allowed a systematic comparison of waste datasets at different levels of complexity, and it is more flexible. Moreover, the naming of waste fractions, by using international legislation (e.g. European legislation), avoids potentially misleading names. Based on these waste sampling campaigns, we provided detailed and comprehensive waste compositional datasets.

CoDa techniques showed to be a robust and suitable method for analysing simultaneous waste composition (percentage or generation rates of individual waste fractions) datasets and generating consistent and comprehensive results.

Statistical analysis showed that including food waste packaging in the food waste fraction did not significantly influence the overall composition of waste or the individual percentage of food waste, plastic, board, glass and metal. This result suggests that the specific separation of food waste packaging from food waste leftovers during sorting was not critical for determining waste composition.

The generation of RHW was estimated at 3.8 kg per person per week and constituted predominantly food waste (41-45% of RHW). Recyclable materials misplaced in RHW bins represented 20-22% of RHW. Statistical analysis showed that the composition and generation rates of RHW were not statistically different between municipalities (given the same source-segregation scheme). However, the composition and generation rates of RHW were significantly different between household sizes. These results suggest that (1) waste data may be transferred from one municipality to another, (2) factor municipality is not a critical stratification parameter (considering a similar source-segregation system scheme) and (3) waste sampling campaigns should include all household sizes, to obtain reliable data.

The analysis of SSFW and residual waste from kitchens in an office area revealed that an employee discarded 20±5 kg per year of SSFW and 10±4 kg per year of residual waste. The sorting efficiency of SSFW was 89±28%. As a result, only 11±9% of food waste was misplaced in the residual bins. This suggests that a 60% recycling target, formulated by the Danish Government for food waste generated by the service sector, including office areas, should be achievable. Statistical analysis revealed a significant difference in SSFW and residual waste between weekdays, thus implying that waste sampling in office areas should include every weekday, in order to obtain reliable data. Moreover, the sampling campaign period should at least cover 20 days in order to obtain reliable waste data.

The analysis of food waste showed that a Danish household discarded 80±6 kg of unavoidable food waste per year and 103±9 kg of avoidable food waste per year, 34±5 kg of which is processed and 79±9 unprocessed. This result indicates that efforts in relation to food waste reduction should also be accompanied by the efficient treatment of unavoidable food waste, to ensure resource recovery, such as through saved plant nutrients.

Avoidable food waste occurred in 97% of the households. Moreover, a Danish household containing one person is less likely to generate avoidable food waste compared to other household sizes. Furthermore, while household size was the only factor influencing significantly the mass of food waste per household, the aggregated mass per person showed no significant differences among household sizes.

7 Perspectives

Based on the findings of this research, and on the experience gained during this PhD, further research may be suggested on the following topics:

- The influence of solid waste fraction water content and its transfer process during collection and storage was not investigated despite the fact that it could affect waste composition. To complete an overview of the physical characteristics of solid waste and documented uncertainties of waste data related to water content, the determination of water content of each material fraction is needed.
- The waste sampled herein was generated over one to two weeks. Thus, uncertainty related to temporal variations in waste generation and composition was not fully investigated. Therefore, sampling waste continuously for a longer period (more than two weeks) and in different seasons of the year might be necessary to quantify uncertainty associated with temporal variation.
- We measured the sorting of food waste from employee kitchens in office areas. To map overall food waste in office areas, sampling in canteens and kitchens, as well as including other types of institutions (apart from a university), should be considered.
- In this study, we estimated total food waste, namely avoidable and unavoidable food waste. However, these fractions include various food products. To develop simple recipes and tips enabling households to reuse their leftovers, an analysis of individual food products (bananas, apples, etc.) may be needed. Moreover, a combined waste stream analysis of household purchasing and consumption patterns should be considered, in order to determine the distribution between foods purchased and unavoidable and avoidable food waste. This could contribute to advising householders on planning shopping. This information may also help retailers and supermarkets in developing new initiatives that could help households reduce their food waste.

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10 Papers

I **Edjabou, M.E.**, Jensen, M.B., Götze, R., Pivnenko, K., Petersen, C., Scheutz, C., Astrup, T.F.: Municipal solid waste composition: Sampling methodology, statistical analyses, and case study evaluation. *Waste Management 2015,36, 12-23*

II **Edjabou, M.E.**, Boldrin, A., Scheutz, C., Astrup, T.F.: Source segregation of food waste in office area: Factors affecting waste generation rates and quality. *Waste Management 2015,46,94-102*

III **Edjabou, ME.**, Petersen, C., Scheutz, C., Astrup, T.F.: Food waste from Danish households: Generation and composition. *Waste Management.*

IV **Edjabou, ME.**, Martín-Fernández, J.A., Scheutz, C., Astrup, T.F. : Statistical analysis of waste data: comparison of classical and compositional data analysis applied to a household waste case study. Submitted to *Waste Management.*

In this online version of the thesis, paper I-IV are not included but can be obtained from electronic article databases e.g. via www.orbit.dtu.dk or on request from.

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The Department of Environmental Engineering (DTU Environment) conducts science-based engineering research within four sections:
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The department dates back to 1865, when Ludvig August Colding, the founder of the department, gave the first lecture on sanitary engineering as response to the cholera epidemics in Copenhagen in the late 1800s.

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