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Modelling Approaches to Food Waste: Discrete Event Simulation; Machine Learning; Bayesian networks; Agent Based Simulation; and Mass Balance estimation

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Abstract:

The generation of food waste at both suppliers' and consumers' levels stems from a complex set of interacting behaviours. Computational and mathematical models provide various methods to simulate, diagnose and predict different aspects within the complex system of food waste generation and prevention. This chapter outlines four different modelling approaches that have been used previously to investigate food waste. Discrete Event Simulation: which has been used to examine how the shelf life of milk and many actions taken around shopping and use of milk within a household influence food waste. Machine Learning and Bayesian networks: which have been used to provide insight into the determinates of household food waste. Agent Based Simulation: which has been used to provide insight into how innovation can reduce retail food waste. Mass Balance estimation which has been used to model and estimate food waste from data related to human metabolism and calories consumed.

Introduction

Food waste is a complex phenomenon. Food gets wasted for a range of different reasons, which are affected by a range of factors: to give a few examples at the household level, how people shop, what they buy, how those items are packaged, the time devoted to food-related activities, skills and capabilities relating to cooking and food management in the home, and attitudes to food safety (Quested et al., 2013). Given this complexity, there are many challenges and questions that need answering for those wishing to prevent food from being wasted or estimating the quantity of food being wasted. Ideally, empirical data would be obtained, but this is currently lacking, mainly due to the monetary and time cost of obtaining such data. Therefore, system-based simulation methods and modelling approaches are being developed using currently available data, as they can incorporate these complexities, and allow these challenging questions to be answered.

Numerous methods have been used to infer the amount of food loss, waste or surplus. This chapter introduces four of the most exciting contemporary food waste prediction and prevention approaches including discrete event simulation (DES), agent based modelling (ABM), Machine Learning and Bayesian Networks, and mass balance estimation (quantification of food waste using food availability, metabolism and calories consumed).

These models are useful for answering different types of question related to food waste. These can include 1) Quantifying the generation of food waste in specific geographies, industries or households. 2) Understanding relationships between different causal factors of food waste, and 3) Assisting with the prioritising of potential initiatives for reducing food waste. For instance, for a research question around "how will the food waste reduction potential compare between providing a longer shelf life for a given product and deploying a behaviour change campaign to encourage people to store foods optimally" different models will produce different insights.

Discrete event simulation (DES)

Discrete event simulation is a system based approach that models a system as a sequence of events over time (Delaney & Vaccari, 1989). In DES, each event marks a change of state in the system. In household food waste simulation, events are specific instances of purchasing, consumption and disposal and each event is controlled by a series of rules that are specified by the user. The fact that the generation of waste (and attempts to prevent this waste) are influenced by decisions relating to purchasing, storage and their use lends itself to modelling the journey of the item through the home and the influence of various decisions.

A key element of DES is the ability to model processes stochastically, i.e. using probabilities to guide decisions, so that the outcome of each decision is not always the same. For example, the amount of milk drunk in a household each day is not constant but varies from day to day (Evans, 2012). DES allows a model to reflect this probabilistic nature. This is achieved by using random numbers to sample from a distribution of realistic values to determine which events happen and their extent. Many instances of food wastage are related to 'unexpected' and 'unusual' events: buying a product with an unusually short shelf life, an unplanned social engagement, or a work commitment leading to dinner being bought and eaten on the way home, rather than in the home (WRAP, 2007). Therefore, to understand the generation of food waste, it is important to model each day as different to the last to understand the impact of this variability. Methods that only include an average level of consumption (e.g. system dynamics) and do not include variation over time would omit an important dynamic within the system and, consequently, the modelling results would be less realistic.

Another aspect of DES models is that they are constructed for a specific system, in this case a single household (rather than an 'average' household). This means that each household modelled has an integer number of people, rather than the national average of people in a household (2.4 people per household). Additionally, different variants of the model can be constructed for different household sizes and other household characteristics.

The successful application of DES to food waste in the home opens up the possibility of using such modelling for other waste streams in the home, and possibly waste generated from businesses. To the best of the authors' knowledge, this has not been done to date, so could be a new area for operational researchers to investigate, leading to many new insights for those working in the area of waste generation and human behaviour.

Milk Model and Key Findings

The initial application of discrete event simulation (DES) to household food waste was *The Milk Model*. This project developed a simulation for one product (milk) and sought to replicate the purchasing, consumption and waste of milk in real homes. The model contains parameters relating to the shelf life of milk and many actions taken around shopping and using the milk (Figure 1). Data from both quantitative and qualitative social research was used as inputs into the milk model. In addition, other survey information relating to milk was included. This included purchasing levels and available shelf life. In such a way, the model acts as a framework in which different types of information are combined to assess waste levels. The model has several inter-dependencies and feedback loops. For example, the number of top-up shops depends on the amount of milk in the fridge, which links back to both consumption and purchasing decisions. This means that the household being modelled can adapt to what is going on in the home in a pseudo-intelligent way.

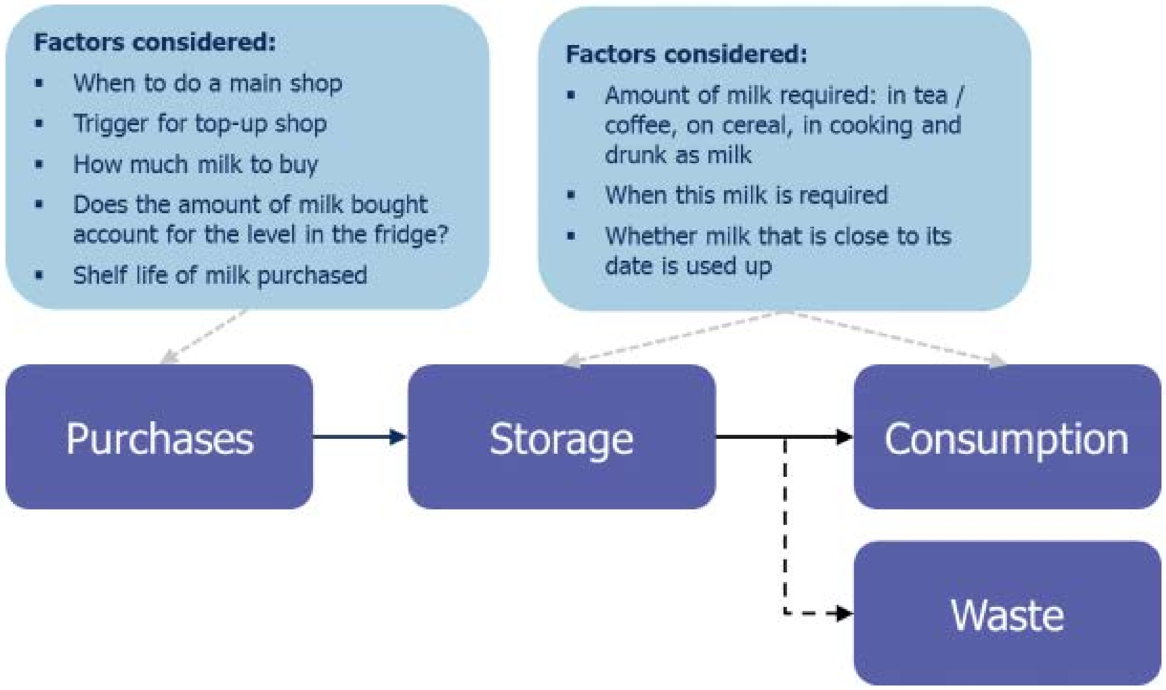


Figure 20.1. Simplified schematic of the system being modelled

The model has been able to replicate many results that have been observed empirically including the trend in milk (and food) waste with household size (Quested, 2013). It also has a similar degree of variation over time than is observed between households in survey work. Both similarities with empirical evidence build confidence in the model.

Table 1 summarises the changes that could lead to lower levels of milk waste, which are grouped into those relating to the product, those relating to purchasing activities and those relating to how the milk is consumed. The table also highlights some unintended consequences of making changes to reduce waste. Some of these consequences are positive: if the shelf life of milk is extended, not only is there less waste but there are also fewer incidents of milk requirements being unfulfilled due to insufficient milk in the fridge. However, some waste-prevention measures involve trade-offs including increased amount of packaging (if a given amount of milk is bought in more bottles) and increased frequency of top-up shops (if less milk is bought in shopping trips). There are also potential impacts – both positive and negative – on the supply chain: for instance, increasing the shelf life of milk for the public may have implications for logistics and storage for milk producers and retailers.

Table 20.2. Changes that could lead to lower milk waste (Quested, 2013)

		Impact on …		
	Change leading to waste reduction	**Waste**	**Unfulfilled milk requirements**	**Notes**
Product	Increasing average shelf life of milk	↓↓	↓	This reduces the number of bottles with a short shelf life
	Decreasing variability in shelf life of milk	↓	↓	This reduces the number of short-shelf life bottles available for purchase
	Increasing time limit in 'once opened use within x days'	↓↓	↓	This has greater impact when milk is bought in large bottles
Purchasing	Checking milk stocks in fridge and adjusting purchases accordingly	↓↓	↑	This has a large waste prevention effect. There is a slight increase in running out of milk if purchases are adjusted by stock levels
	Decreasing the amount of milk purchased in a main or top-up shop	↓↓	↑	This has a direct effect on waste. It can increase the number of top-up shops, which can have an environmental impact.
	Decreasing the amount of milk that triggers a top-up shop	↓	↑	There is a large trade off in when to do a top-up shop between waste and running out of milk
	Buying milk in more smaller bottles	↓	↑↑	Effect on waste is highly context dependent: large effect if milk purchased infrequently and by the households following 'once open, used within x days' advice. However, this could increase total packaging used.
Consumption and Miscellaneous	Using up milk which is approaching its date	↓	→	This could potentially lead to overconsumption
	Decreasing variability in consumption	↓↓	↓	This is dictated by lifestyle. It has more of an impact on waste in smaller households
	Increasing household size	↓↓	↓	Fixed by circumstance

Note – intensity of effect, indicated by arrows, represents author’s view using model results.

Machine Learning and Bayesian Networks

Robust analysis is dependent on multiple methods providing confirmation of results. Two types of analytical method that allow the identification of the "importance" of variables in explaining food waste generation (both self-reported and objectively measured) may be two machine-learning algorithms (Random Forest and Hill-climbing). These methods can be used to develop regression and classification trees as well as Bayesian networks.

Machine Learning is a subfield of computer science that is related to the study of pattern recognition and artificial intelligence. The two algorithms used are designed to recognise relationships between variables and to show how important each variable is to the response (in this case food waste). Random Forests creates many regression and classification trees (minimum 500) where the data are split into different branches of the tree to best explain the response variable. The user can then explore these different branches to examine the relationships between variables.

Bayesian Networks are a graphical representation of a network of variables whereby related variables are joined by an arc (or arrow) and a set of conditional probabilities (where the state of one variable is conditional on the state of another). Machine-learnt Bayesian networks can recognise relationships between variables but not the direction of the relationship so arrow heads are added at random. Machine learning is much more robust to highly correlated variables than previous regression analysis methods.

These different models allow the investigation into relationships that drive food waste in a variety of settings. Below we highlight some examples of Machine Learning and Bayesian Networks being used to investigate household food waste.

The use of systems models to identify food waste drivers - Grainger, M. J. et al. (2018a)

This paper investigated the drivers of household food waste using Bayesian Networks to identify the impact of household characteristics and other variables on self-assessed food waste. Using EU-level Eurobarometer data from 2013, the study confirmed that the country, the age of the respondent, the status (student/non-student), and a belief that the family wastes too much are related to the level of self-assessed food waste. In addition, households from lower-income EU countries (e.g. Portugal, Greece, Bulgaria, Cyprus and Latvia), as well as students and young adults tend to report higher levels of food waste.

However, the analysis found no evidence that food waste behaviours differ between people living in urban and rural areas, and little support of a difference between genders. These geographical and gender differences had been identified in previous literature as potential drivers of food waste (Wenlock & Buss 1977; Sonesson et al. 2005; Barr 2007; Koivupuro et al. 2012; Canali et al. 2014; Parizeau et al. 2015; Stancu et al. 2016; Setti et al. 2016). The additional insight provided by the application of Bayesian Networks provides clarity to the researcher to understand which relationships have evidence within the currently available data. This insight can then be acted upon by the policy maker. In this case, the researchers suggested country-level policy measures targeting different age groups.

Model selection and averaging in the assessment of the drivers of household food waste to reduce the probability of false positives - Grainger, M. J. *et al.* (2018b)

This paper used machine learning algorithms (random forests and "Boruta") along with Generalised Linear Models to identify the key drivers of household food waste, while also reflecting the uncertainty inherent in the analysis of complex observational multidimensional data . The data investigated was household food waste data collected by WRAP (2012) which consisted of face-to-face in-home interview responses (categorical data) on socio-demographic aspects of households and behavioural responses to food waste, along with data on the amount of waste collected from the kerbside for 1,770 households.

As the data set has over 50 variables, there would be over a quadrillion possible Generalised Linear Models to run. To simply this, the “Boruta” and random machine learning algorithms were first used to refine and reduce the variable list. The “Boruta” algorithm adds randomness to the variable set by creating shuffled copies of all variables (these are called “shadow features”). It then runs a random forest classifier on the extended dataset, and assesses the mean decrease in accuracy to evaluate the importance of each variable (higher means are more important). At each iteration, “Boruta” assesses if each variable has a higher Z-score than the maximum Z-score of its shadow features. Variables with scores lower than shadow features are deemed highly unimportant, and removed from the set. The algorithm runs until all variables are confirmed or rejected (or it reaches a specified limit of runs— here, we used 500 trees maximum).The variables retained after applying the “Boruta” algorithm were then processed using a Generalised Linear Model to assess correlations between “avoidable household food waste” and the socio-demographic and behavioural .

The “Boruta” algorithm consistently identified household size, home ownership status, household composition, employment status and the presence of fussy eaters as significant drivers of food waste in all sets of variables. Household size was always the most important variable.

The final model contained household size, local authority, household composition, house type, home ownership status, employment status, the presence of fussy eaters, the presence of children aged between 3 and 11, age of the respondent, social grouping, checking cupboards for tinned food prior to shopping, and discard behaviours related to vegetables, cheese, and food past its sell by date. The variables with the largest positive effect (greater amounts of food waste) included the presence of fussy eaters, household size, and one particular local authority (individual local authority identity was anonymized).Variables with the largest negative effect (reductions in food waste) included discard behaviours interacting with the presence of fussy eaters, employment status interacting with the presence of fussy eaters, four specific local authorities and home ownership status (owning a house outright).

As with Grainger, M. J. et al. (2018a), the application of the machine learning algorithms has enabled new insight into the drivers of household food waste. Again, it is interesting to note that some of the drivers identified as important by previous literature, such as awareness of the food waste problem and shopping habits, here are found as not important.

Agent-based modelling

Agent-Based Models (ABMs) are computational systems that simulate the individual decision-making process of a large number of agents acting and interacting through a set of prescribed rules. The output of an ABM are the emerging phenomena resulting from the interaction among agents’ choice on a large scale, both temporal and dimensional. The characteristics of ABMs lead to several advantages. On the one hand this allows for a large degree of heterogeneity in agents characteristics and interactions rules; on the other hand, it allows the introduction of a well-defined institutional structure. Nevertheless, it is important to constrain the additional complexity to avoid generating models as difficult to understand as the reality studied.

The main tool to analyse ABMs are Monte-Carlo computer simulations, where a set of inputs is provided to the model and the dynamics of the model is iterated many times with different sequences of random numbers. This allows the study of the statistical characteristics of the simulation output (means and standard deviations of the results, their distribution, and the occurrence of rare extreme events), separating random events from proper emerging properties of the simulated system. By modifying the parameter sets, it is possible to *check the robustness* of the results and to assess the implications of a shift in one of the parameters. A well-developed model can be used as a virtual laboratory, as it allows the generation of alternative time-series under controlled "quasi-experimental" conditions. As such, ABMs can also be studied with *regression* techniques, exploring the correlations between different parameters and outcomes and the impact of different types of heterogeneity. Given that many relationships among variables are typically hard-wired, causation structures can be also studied. An alternative method of analysis frequently used to assess ABMs is the *comparison of scenarios*. Within this method, different initialisations and sets of rules are created to simulate specific known cases (such as two countries), or to study the expected impact of a policy intervention. Both the aggregate outcomes and the individual trajectories of the agents are then assessed comparatively. The analysis of the results frequently relies on *graphs*, such as plots and figures.

To design and develop an ABM, it is necessary to specify at least three elements: the *entities* (*agents*); their *interaction rules*; and the *environment and institutions* within which agents interact. The *agents* are the autonomous and discrete decision-making units whose behaviour is modelled. In socio-economic simulations, they are typically persons, companies, or even nations. Their characteristics usually include: *attributes* (idiosyncratic or group-specific properties); *rules of behaviour* (assumptions made about their decision-making processes); *memory* (the possibility of recalling past actions and interactions and their results); and *perception of the environment*. The *interaction rules* are the constraints on how agents can interact. Depending on the type of model, they can be represented in game theoretical form (agents receive a payoff that depends on their actions and on those of other players), as economic exchanges (one or more individuals buy something that someone else sells in exchange for something else), or as exchanges of information. Exchanges typically happen on a defined *interaction space*. Finally, the *environment and institutions* define the external constraints that influence all agents (or groups of them), and their interactions.

Both ABMs were developed in MatLab R2017a, while the BN of consumer food waste generation was developed in R. The integration of the two models was achieved through C++ in DOS, with externally controlled processes in both R and MatLab to allow the sharing of inputs and outputs.

An ABM of retail food waste

The retail ABM aimed at simulating the interaction between the adoption of an innovation reducing food waste by retailers, and resulting food waste levels. The challenge of this setting is represented by the fact that retailers earn a profit from the food wasted at home by consumers, thus profit-maximising retailers are not willing to innovate to reduce it. However, behavioural economics theory points out that additional concerns, such as reputation, can lead to non-trivial outcomes.

The ABM considers the market for a single food commodity, namely fresh fruit and vegetables, due to their high perishability. The introduction of a waste-reducing technology has an impact on the purchasing behaviour of consumers and on retailers' marketing strategies. The market operates in imperfect conditions (e.g. asymmetric information and concentration).

Retail agents are modelled as belonging to three different groups: small shops, discounts, and large-scale companies. Each agent can adopt only one of two different technologies: a baseline that generates a high amount of food waste (initially adopted by all retailers); or an innovative technology which reduces the amount of food waste generated either in store or by customers at home. Retailers decide whether to adopt the low-waste innovation based on a utility function which includes three main elements: (1) the profit earned, which depends on selling prices, innovation costs, and the share of food wasted in store and by consumers after purchase; (2) environmental concerns, and reputational concerns linked to pro-environmental behaviours; (3) other retailers' decisions.

To reduce model complexity, consumers are modelled as homogeneous masses with shared attributes, or with attributes varying within a certain range, who at the onset of each simulation purchase from the same typology of retailers. Three groups of consumers are considered: (1) quality-oriented ones, who purchase from small shops, characterised by a low price elasticity; (2) unsophisticated ones, who purchase from large-scale companies, characterised by an average elasticity; (3) convenience-seeking consumers, who purchase from discounts, characterised by a high elasticity. Consumers choose the retailer from which to purchase based on a set of parameters which do not vary *inside* groups, but may change *between* groups: elasticity to price; environmental concerns; their state of information about the existence of retailers which adopted the low-waste technology; and a satiation quantity, which is the same for all of the consumers and is technology-dependent (the quantity of food necessary to achieve satiation is lower if the retailers adopted the low-waste technology).

Within the model, time is divided in periods during which decisions are assumed to be taken parallelly by all agents according to a set of steps. The intra-period steps of the retail model are the following:

1. Each retailer (with a given probability) can decide to change the technology adopted, maximizing its utility function;
2. Given the previous decision, each retailer can change its selling price (small shops base the pricing decision on the behaviour of similar companies in their network, large and discount companies on the market share of adopting retailers);
3. The consumers purchasing from a retailer that changes technology are assigned to the same retailer;
4. A share of consumers becomes informed about the existence of the low-waste technology – according to the studies on innovation diffusion (Rogers 2010), this share results from information from external sources (e.g. advertising from retailers) and information circulating among consumers (e.g. word of mouth);
5. A mass of consumers with similar characteristics decides to move to a different retailer based on the parameters listed previously, including their utility and information status;
6. The market shares of each retailer are recalculated, and a new step can start.

Outputs and applications

The final output consists in the market shares of retailers and consumers that adopted the low food waste technology, as well as in the total food waste generated in the market. Examples of technologies whose adoption can be simulated are a storage system prolonging the shelf-life of fruits and vegetables, a bag allowing consumers to reduce the exposure of the products to external conditions in the way home, etc. The data to calibrate the model can be obtained from the literature (e.g. retailers' and consumers' behavioural patterns) and from statistical datasets (e.g. market shares of each retailer type).

An ABM of consumer food waste

The integrated consumer ABM-BN simulates the effects of behavioural factors and social interactions on the evolution of individual opinions and actions regarding food waste, and thus on food waste generation at household level. Its structure is based on the Food Waste Model developed within REFRESH by Van Geffen, van Herpen and van Trijp (2017). Also the data for calibrating the model come from a questionnaire developed within REFRESH. The questionnaire, inspired by the Motivation, Ability and Opportunity theoretical model (Rothschild 1999; Thøgersen and Ølander 1995), tried to measure a set of fixed features and food-related behaviours and to quantify food waste within a sample of consumer households from four pilot countries (the Netherlands, Germany, Hungary, and Spain).

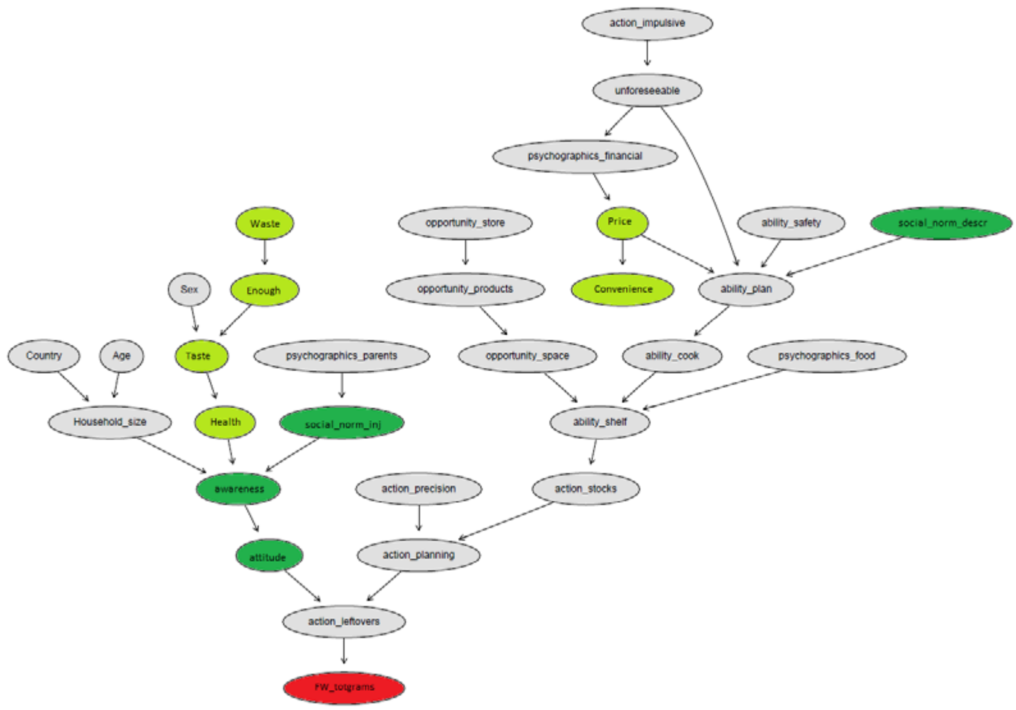
The features detected by the questionnaires can be grouped into six categories: (1) socio-demographics; (2) motivations (awareness of food waste consequences, attitudes towards wasting food, injunctive social norms, and descriptive social norms); (3) competing goals with respect to food (health, taste, preparing time, price, having enough food, and not having too much food); (4) households' food related practices (planning, buying, overviewing stocks, cooking, storing, and leftovers management); (5) opportunities (availability of products, accessibility of stores, availability of space and storage equipment, etc.); (6) abilities (difficulty with accurate planning, creative cooking, and assessing food safety; and knowledge of how to prolong shelf life); (7) psychographics (awareness of parents, perceived financial control, and involvement in food preparation). The data from the questionnaires were expressed probabilistically in a consumer BN.

As a first step, simulated populations are generated with a process based on data from the REFRESH consumer questionnaire. Then, the ABM evolves according to the following intra-step dynamics:

1. For each agent, one of the six competing goals related to food is selected for discussion;
2. For each agent, the agents within her individual social network whose average opinion on the six competing goals is closer than a given threshold are selected for discussion;
3. The agent changes her opinion on the competing goal selected by averaging it with the average of her neighbours, with weights represented by the relative salience of that goal;
4. The opinions of the agent on all other goals change accordingly, following empirically observed statistical correlations between opinions;
5. The agent selected changes her *awareness* of food waste consequences by averaging it with the average of her neighbours, with weights represented by her influenceability;
6. She changes her *attitude* towards food waste by averaging it with the average of her neighbours, with weights represented by her influenceability;

7. To measure injunctive social norms (what others think), the average attitude towards food waste of each agent's neighbours is calculated;
8. To measure descriptive social norms (what we think others do), the median food waste of each agent's neighbours (net of an error, due to the lack of visibility) is calculated;
9. If there were no neighbours within the threshold of point 2, thus no change has taken place, the agent's opinions on all motivations get back to past values following a "relaxation mechanism".

Figure 20.3. Semi-structured Bayesian Network used to estimate agents' food waste levels in the integrated consumer model. Adapted from Grainger et al. (2018c), p. 15.



Once these intra-steps have been completed for all agents, the new values of the competing goals and motivations for every agent are sent to the consumer BN. The BN returns the probability that her food waste falls within each of five classes. Then, for each agent, a specific value of food waste is extracted from her individual probability distribution. Afterwards, a new time step of the ABM starts, in which this food waste level is used as a parameter.

The consumer BN was machine-learnt to identify the inherent structure of the data. Then, the arcs were reversed to obtain a structure compatible with the Food Waste Model (Van Geffen et al. 2017). This semi-structured BN, shown in Figure 2, represents a compromise between a fully structured model and a fully machine-learnt one in order to reduce computational complexity. While the values of motivations and competing goals are set for each agent at each step, the other features (opportunities, abilities, psychographics and socio-demographics) are used to estimate the BN, but no hypothesis on their value is made during the single time steps.

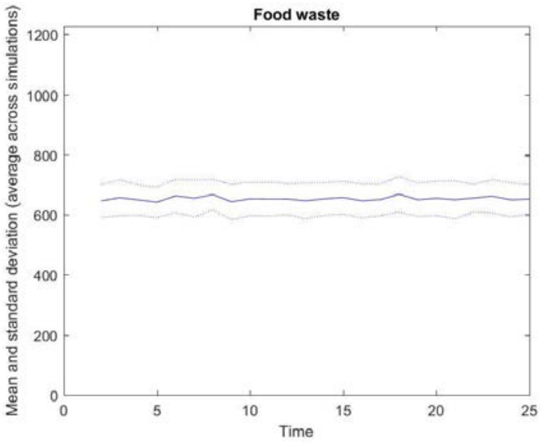
Applications and preliminary results

To assess the potential impact on food waste of interventions insisting on a specific element of the waste-generating mechanism, changes can be applied to the baseline populations. The variables to consider could be chosen based on their impact on the food waste node in the BN. The changes can be implemented one by one (single policy), or jointly (policy mix); then, by means of extensive simulations, the evolution of food waste can be plotted and compared to the baseline. Potential interventions on different typologies of variables include:

1. For opportunities, an incentive to purchase more efficient or more spacious freezers or fridges;
2. For abilities, the provision of training (e.g. by retailers) on the reuse of leftovers;
3. For competing goals or motivations, informational campaigns focused on the negative effects of food waste for the society (e.g. environmental damage, waste of resources, inequality, etc.).

The changes proposed can be implemented either at the onset of every simulation, or at a certain time step, including an evolution dynamic (e.g. through exchange of opinions, or through a rule for the diffusion of innovations). For example, consumers' *awareness* of food waste consequences may increase either because they are hit directly by the informational campaign, or because they discuss with peers. Since the BN model is not fully factorial (some combinations of values of the variables were not present in the dataset used to estimate it), increasing the number of conditioning variables may increase the number of zeros (the consumers for whom the food waste distribution cannot be estimated) and thus the arbitrariness of the outcomes. Therefore, only a limited set of features can be subject to an intervention in a single simulation.

Figure 20.4. Mean and standard deviation of food waste (grams) across simulated populations at each time step. Adapted from Grainger et al. (2018c), p. 25.



Preliminary simulations show that model is in equilibrium, with time-specific averages of motivations, competing goals and food waste (see Figure 3) oscillating around a central value derived from the data. This is as expected in the short-term, when the composition of the populations does not change, and in absence of either policies to reduce food waste or relevant shocks (e.g., food safety scandals, etc.). The effect of motivation changes on food waste is, instead, limited and, in some cases, counterintuitive. This is probably due to social desirability bias affecting the consumers, which prevents the detection of real motivations and distorts the data of the questionnaires used for calibration. The fact that the model is essentially in equilibrium allows the attention to be focus on the marginal effect of policy interventions, both cross-sectionally and dynamically.

Mass (Energy) balance estimation

There are several examples of mass balances used to quantify food waste. The traditional mass balance approach infers food loss, waste or surplus by comparing inputs (e.g., food entering a store) and outputs (e.g., products sold to customers) alongside changes in levels of stock. In some sectors, changes to the weight of food during processing (e.g., evaporation of water during cooking) have to be considered too. This method can be applied to individual or multiple stages of the food supply chain, and have been used to estimate food waste at a national level. More broad details of this method can be found in the annex on quantification methods of the *FLW Standard (*World Resources Institute, 2016).

An unique example of mass balance is a study by Hall et al. (2009). This presents a mass balance across a range of supply chain stages, estimating food loss as the difference between food consumption and food supply in the United States. Unlike most traditional mass balances, the food loss and waste estimate presented in this paper was based on energy content, rather than on weight. Food consumption was estimated from the weight distribution of the US population, using a mathematical model of metabolism, which relates measures of food intake and physical activity to body weight. Food supply is the US food supply data from the FAO food balance sheets, more details on the method are provided below. The Hall methodology further inspired others to extend and/or modify the method.

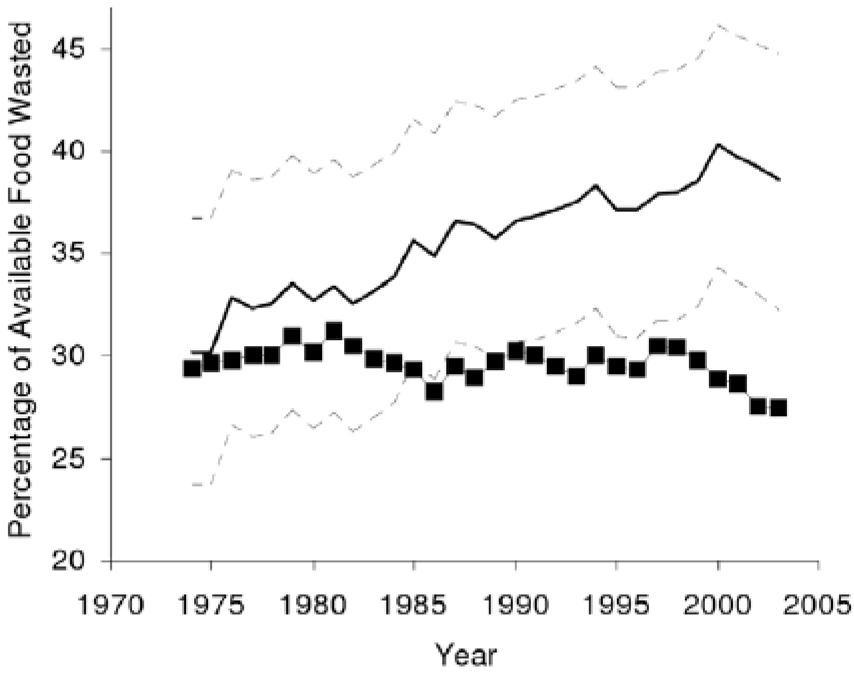
Quantifying Food Waste as balance between availability, metabolism, and calories consumed (Hall et al 2009)

Hall et al.(2009) propose that food consumption can be imputed using the mathematical model of metabolism. Consumed food provides energy to perform physical activities and support basal metabolism.[1] Surplus energy from overconsumption is stored in the body and increases body weight. And the difference between food availability and imputed food consumption is food waste. Using this method they show that waste as share of food supply has been increasing, and estimates for US using Hall et al approach are much higher than those reported by FAO, 2011. The benefit of the approach is that while fixed waste factors approach behind FAO implicitly assumes that consumer food waste is explained solely by food supply available to consumers, Hall et al approach accounts for both the supply (food availability) and demand (consumption) side factors.[2] On the downside, the estimates of waste are highly aggregated (in calories per capita) without any information on waste associated with the underlying individual food commodities. Figure 20.5 shows their main results. While using FAO's approach yields a more or less stable percentage of available food being wasted by consumers (line connecting solid squares), the energy balance approach shows that this percentage has been steadily rising over the decades (solid line).

Figure 20.5: Comparison of results for US consumer food waste using FAO approach and Energy balance Approach. Adapted from Hall et al. (2009)

[1] As measured by physical activity level depending on lifestyle: vigorously active, moderately active, sedentary; and basal metabolic rate dependent on body weight.

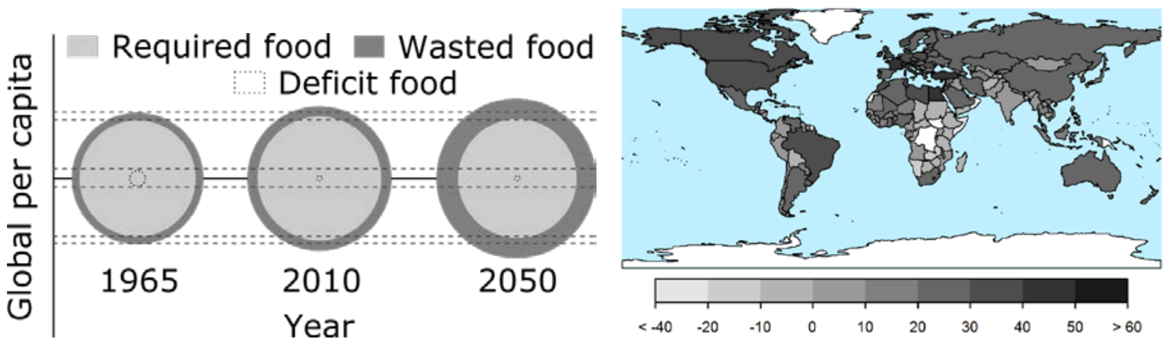
[2] There is work looking at demand side drivers, for example Britton et al. (2014) attempt to look at demand side drivers but analysis is limited to UK or other specific countries.



Some extensions of Hall et al (2009) include Hic et al (2016) and Verma et al (2016). Both adapt the Hall method to cross-section data, and show how this approach can also be used to identify food deficit (negative food waste estimates) and food surplus countries (positive food waste estimates).

Hic et al. apply the Hall et al method to a larger set of countries to obtain waste estimates and quantify greenhouse gas emissions associated with food waste to have increased by 300% in the last 50 years. Their estimates of per capita per day waste stands at 516Kcal (for year 2010) in comparison to FAO's 214Kcal (Kummu et al. 2012, based on FAO, 2011) for years 2005-07. Figure 20.6 shows the selected findings from Hic et al (2016). Globally, food production has outpaced food requirements and waste has been steadily increasing (left panel). At a finer level, however we see a lot of variation across countries (right panel). While some countries are facing food deficit others produce and waste more than what they require. In the figure below, countries in shades of red belong to this latter group while in those in green represent members of the former group.

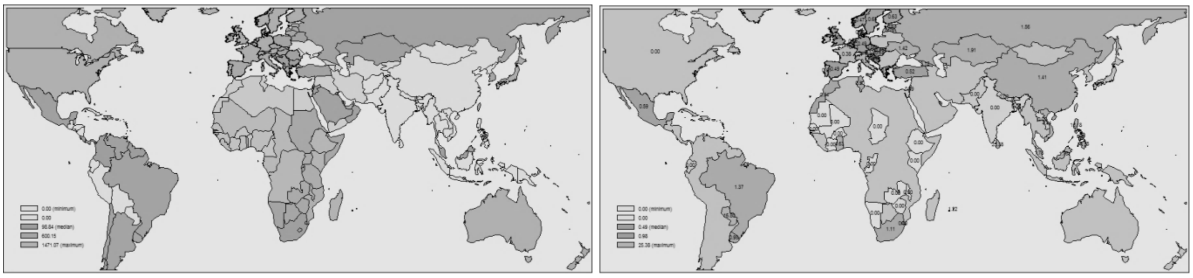
Figure 20.6: Global and country food waste estimates adapted from Hic et al. (2016)



Verma et al start by using Hall et al method to obtain consumer waste data for a set of countries and use the statistical relationship (based on the fact that consumers with higher incomes waste more food) to make out of sample predictions. Their estimates show food waste estimates of 526Kcal

(2005) and 727Kcal (2011).[3] They also provide a monetary threshold beyond which food waste in a country becomes a real problem. They further show how that standard consumption elasticities are usually overestimated on account of food waste and how to correct for those in an applied simulation model. The main limitations for is they implicitly assume that food availability and body weights in all underdeveloped countries follows the path as already observed in the developed world. Figure 20.7 show a graphical representation of their estimates of food waste (Kcal/capita/day) for individual countries (left panel). The more red the shade the higher the food waste per capita. This colour pattern however reverses for the panel on the right, which represents responsiveness of consumer food waste to increases in a measure consumer affluence, highlighting how waste increases as countries grow richer.

Figure 20.7: Predicted Food Waste (Kcal/day/cap) and waste responsiveness to affluence (2011), (Verma et al. 2016)



Conclusions

Discrete event simulation

The single piece of published research in this area has illustrated that application of DES to household food waste is promising. The method allows known dynamics around food waste to be incorporated, has brought to life many characteristics of waste prevention and allows estimation of their importance. The modelling has also been able to estimate the effect of changes that it would be hard to test in a real-world setting. For instance, it would be difficult to measure a change in milk waste from changing any single factor e.g. increasing the shelf life of milk, for both methodological and practical reasons.

The results demonstrate that activities with a positive impact on waste prevention (e.g. adjusting purchases according to stock levels) don't always eradicate waste: they usually reduce the quantity wasted or the likelihood of waste being produced, but don't guard against any chance of waste being produced.

Moreover, this model can act as a tool for explaining how waste generation can be conceptualised. It can engage people on the subject and therefore can be used in many contexts to facilitate conversations – most notably, it illustrates that the generation of waste in the home requires an understanding of both the flow of material through the home and social factors relating to the use of that material.

The Milk Model showed promise in helping answer practical questions by those seeking to prevent food from being wasted. For this reason, work is underway (at the time of writing) by Sheffield

[3] These are the numbers based on revisions to their 2016 work and can be obtained from the authors.

University and WRAP to extend the model: to include a wide range of products and to incorporate additional household dynamics important to food waste – see Kandemir et al (2019). Alongside this other milk simulation models are being developed – for instance see Stankiewicz et al (2019). It is hoped these new models will provide an important tool to help understand this particularly knotty problem and provide guidance on the most effective methods for reduce household food waste.

Machine Learning and Bayesian Networks

Though complex in appearance both Bayesian Networks and machine learning algorithms are simply new tools that can support decision making and data analysis. However, there are limitations to both modelling approaches. It should be stressed that Bayesian Networks and machine learning algorithms have allowed the identification of dependencies among variables, but not their direction and their mechanisms (i.e. causality). Understanding why age and country-level differences occur may be of paramount importance for designing better food waste policy interventions, and needs further research via multiple methods. Nevertheless, the probabilistic understanding of the drivers of food waste that have been showcased in Grainger, M. J. et al. (2018a, 2018b, 2018d) allows future action and research.

Agent-based modelling

ABMs are well suited for studying a phenomenon like the generation of food waste, which results from the aggregation of individual decisions and whose drivers are complex and interrelated. In the framework of the EU Horizon 2020 REFRESH ("Resource Efficient Food and dRink for the Entire Supply cHain") two ABM were developed to study respectively the interaction between innovation adoption and food waste generation in the retail sector, and the process of food waste generation at consumer level. A relevant innovation of the consumer ABM consisted in its integration with Bayesian Networks analysis techniques (Grainger et al. 2018d).

Mass (Energy) balance estimation

Adoption of Sustainable Development Goals (SDGs) as part of the 2030 Agenda for Sustainable Development necessitates finding a way to measure the present situation and progress. SDG 12 seeks to "ensure sustainable consumption and production patterns", including a specific target on food loss and waste (FLW). In order to measure progress towards achieving SDG 12 two indices have been proposed: a Food Waste Index and a Food Loss Index. The Food Loss Index has already been created by FAO, however the Food Waste Index is still under development. With some modifications, this method could generate globally comparable Food Waste Index using limited available data in a transparent manner. Mass balance estimation could also be used to enhance macro modelling concerning food waste and consumption specifically due to its implications for the standard income elasticity of consumption.

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