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UNCERTAINTIES IN LCA

Rebound effects in food-system life cycle assessments: insights from practitioners

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Abstract

Purpose Demand-side interventions, including food waste prevention, are widely promoted as means to reduce the environmental impacts of food systems. Life Cycle Assessment is central to quantifying these benefits, yet assessments often rely on substitution assumptions, while other behavioural and economic responses remain weakly addressed. This study examines how Life Cycle Assessment practitioners understand, consider, and address rebound effects in food-system assessments, using food-waste prevention as a salient example.

Methods An online survey was conducted among Life Cycle Assessment practitioners working with food-system and food-waste-related assessments ($n = 79$). The survey combined quantitative questions on familiarity, perceived importance, and current practice with open-ended questions capturing motivations, barriers, and reasoning. Quantitative responses were analysed descriptively, and qualitative responses were analysed thematically to identify recurring patterns and explanatory themes.

Results and discussion Rebound effects were rated as moderately important but were rarely included in quantitative modelling. Practitioners did not exclude rebound effects because they were considered irrelevant, but because conditions for credible inclusion were often lacking, including data limitations, high uncertainty, limited procedural guidance, and insufficient interdisciplinary capacity. In contrast, substitution assumptions implemented via system expansion are routinely applied despite comparable uncertainty. This suggests an asymmetric treatment of substitution assumptions and rebound effects in applied food-system Life Cycle Assessment practice, where uncertainty functions as a selective gatekeeper rather than a consistent criterion for inclusion or exclusion.

Conclusions The findings indicate a structural misalignment between the recognised relevance of rebound effects and their practical treatment in food-system Life Cycle Assessments. Addressing this misalignment requires clearer methodological guidance on how rebound mechanisms relate to commonly applied substitution assumptions and how uncertainty can be handled more consistently when Life Cycle Assessment is used to inform food-system policies, mitigation targets, and intervention prioritisation.

Keywords Environmental assessment · Food waste prevention · Sustainable consumption · Expert survey · Behavioural effects · Demand-side interventions · Uncertainty

1 Introduction

Agrifood systems account for a substantial share of global greenhouse-gas emissions, amounting roughly to one-third of the total emissions (Crippa et al. 2021). At the same time, more than one-third of food produced for human consumption is lost or wasted worldwide, representing a major inefficiency in resource use and highlighting the potential benefits of avoiding unnecessary food production (FAO, 2014; UNEP, 2021). In response, policy frameworks, particularly within the European Union (EU), have intensified efforts to reduce food waste through legally mandated

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monitoring, reduction targets and prevention measures (European Commission 2020, 2023). Within this policy landscape, Life Cycle Assessment (LCA) plays a central role: it is the recommended method for assessing environmental impacts in the EU and provides the methodological foundation for the Product Environmental Footprint framework (European Commission 2021).

LCA studies have frequently shown that food-waste prevention and reduction can avoid substantial environmental burdens embedded in upstream production, processing and transport, and can reduce downstream emissions from waste management (Albizzati et al. 2021; Beretta and Hellweg 2019; Eriksson et al. 2025; Salemdeeb et al. 2017). These estimated benefits typically rely on the assumption that avoided food waste leads to avoided production of an equivalent quantity of food, an assumption commonly operationalised through system expansion in food-waste LCA studies (Corrado et al. 2017; Laurent et al. 2014; Caldeira et al. 2019). This approach provides a practical means of representing the environmental savings from waste prevention interventions, having become a common practise, even when the empirical basis for such production adjustments remains limited due to rigidities in food supply chains and the complexities of agricultural and retail planning (Caldeira et al. 2019; Ranundeniya et al. 2025). While food-waste prevention provides a particularly clear example of demand-side intervention within food systems, similar substitution assumptions and modelling conventions are commonly applied across food-system LCAs, including studies of dietary change, and product substitution (Mazac et al. 2023; Payró et al. 2024; Taherzadeh and Kanemoto 2022).

In parallel, a growing body of research highlights that other behavioural and economic responses may also arise when food waste is avoided and that these responses can carry considerable environmental implications. For example, households may re-spend money saved from reducing waste or altering diets on other goods or services or adjust consumption patterns in ways that influence environmental outcomes (Chitnis et al. 2013; Grabs 2015; Lekve Bjelle et al. 2018; Sundin et al. 2022). At broader system levels, changes in demand can affect prices, trade flows or production volumes (Hegwood et al. 2023; Thiesen et al. 2008). These behavioural and market-mediated adjustments, collectively referred to as rebound effects, are well documented in energy and resource-efficiency research but remain comparatively underexplored in food-system assessments, including but not limited to food-waste prevention (Druckman et al. 2011; Greening et al. 2000; Sorrell and Dimitropoulos 2008). Growing evidence, nevertheless, suggests that rebound effects associated with food-waste prevention may substantially offset expected environmental benefits. Reported magnitudes vary widely: income-driven rebounds from surplus-food redistribution were shown to offset 31–90% of potential climate benefits (Sundin et al. 2022, 2023, 2025); macroeconomic adjustments (i.e. how markets and the wider economy adjust in response to an intervention) were estimated to reduce net greenhouse-gas savings by around 38% (Albizzati et al. 2022); price-driven consumption rebounds were suggested to offset 53–71% of expected benefits (Hegwood et al. 2023); and combined substitution and income effects in peer-to-peer food sharing were estimated to offset up to 94% of environmental gains (Meshulam et al. 2021). Despite this body of evidence, rebound effects are rarely considered in applied LCA, creating a gap between empirical insights and current practice.

Methodological guidance on whether and how rebound effects should be addressed in LCA remains limited. Attributional LCA, which dominates food-system assessments, typically applies system boundaries and modelling conventions that do not explicitly represent behavioural or systemic feedback (Ranundeniya et al. 2025). This can increase the likelihood that mitigation benefits are overestimated when rebound effects are omitted from assessments (Sala et al. 2023). Consequential LCA can, in principle, represent broader system changes but is less commonly used in food-waste studies and requires more demanding data, modelling and interpretative choices (Corrado et al. 2017). Some scholars further caution that incorporating rebound mechanisms without robust behavioural or economic data may introduce new uncertainties (Sorrell and Dimitropoulos 2008). As a result, methodological debate remains fragmented, and it is unclear how practitioners interpret these expectations in their applied work.

Despite increasing attention to rebound effects in sustainability and policy discussions, little is known about how LCA practitioners understand them, whether they consider them in food-related LCAs, or what prevents their inclusion. Practitioner-focused surveys in adjacent areas have shown that practical constraints often extend beyond what is acknowledged in methodological literature, including limited data availability, time pressures, software limitations and uncertainty about appropriate system boundaries (Backes and Traverso 2021; Olanrewaju et al. 2024). However, it remains unknown if and how such or any other challenges manifest specifically for rebound effects in food-system LCAs. This gap is particularly relevant given growing expectations in recent EU research and funding calls on food-system sustainability that rebound effects should not only be acknowledged but, where feasible, explicitly addressed in assessments of food-system interventions.

Building on this background, the aim of the present study was to investigate how LCA practitioners working across food-system assessments, including food-waste prevention as a concrete example, understand rebound effects and how

they approach them in applied work. The specific objectives of the study were to examine: (i) practitioners' familiarity with rebound effects, (ii) whether and how they consider or model such effects, (iii) the motivations behind inclusion or exclusion, and (iv) the barriers and needs practitioners identify. By providing empirical insight into how rebound effects are interpreted and operationalised in practice, the study clarifies the gap between policy ambitions and how rebound effects are currently handled in applied LCA practice and identifies areas where further methodological development or guidance may be required.

2 Methods

2.1 Study design and overall approach

This mixed-methods study used a cross-sectional online survey to examine how LCA practitioners approach rebound effects in food-system and food-waste-related assessments and to understand why they include or omit them. The study was descriptive and exploratory, reflecting the limited prior empirical work on practitioners' handling of rebound effects and the aim of mapping current practice and barriers rather than testing pre-defined hypotheses. Survey-based approaches are well established in life cycle research as a means of eliciting practitioner perspectives on methodological challenges, implementation barriers, and interpretation practices (Backes and Traverso 2021).

The survey combined quantitative items (closed questions on respondent characteristics, familiarity, current practice, perceived importance and significance of rebound effects, methods used, data challenges, and collaboration) with qualitative items that captured respondents' reasoning, motivations, barriers and broader reflections (Supplementary Material). Combining closed and open-ended questions allowed both descriptive analysis of general patterns and deeper insight into how practitioners reason about uncertainty, relevance, and feasibility, consistent with established survey design principles (Dillman et al. 2014). The study targeted practitioners conducting LCAs in food-related domains, broadly defined to include food waste, food products, diets, or interventions that influence food-related consumption or production. This broad scope reflects that behavioural and economic rebound mechanisms relevant to food waste prevention also arise across the wider food system.

2.2 Survey development and piloting

The survey (Supplementary Material) was developed as a complement to a semi-structured literature review conducted within the WASTEWISE project (Deliverable D2.2), which examined how environmental rebound effects had been conceptualised and assessed in previous studies. Because no existing survey instruments addressed rebound effects in food-system LCAs, the questionnaire was developed specifically for this study, informed by relevant methodological and empirical literature and refined iteratively based on the researcher team's expertise, following established principles for survey design in sustainability and life cycle research (Backes and Traverso 2021).

In line with established survey design principles, particular attention was paid to question clarity, logical sequencing, and the balance between structured and open-ended items to support both quantitative analysis and qualitative interpretation (Dillman et al. 2014). An initial draft was reviewed by two food waste researchers to assess clarity, coverage and alignment with the study aim. The survey was then pilot tested with two LCA experts outside the research team (one specialising in food waste and one in broader food systems). Minor wording and functional adjustments were made based on their feedback before the survey was launched. The final questionnaire contained 24 questions, spanning multiple-choice, Likert scale, and open-ended items (Supplementary Material).

2.3 Recruitment strategy and sampling

The survey commenced in mid-April 2025 using the Netigate (2025) online survey platform and remained open for 53 days. A convenience and snowball sampling strategy was used, reflecting the absence of a central registry of food system LCA practitioners. As no comprehensive sampling frame or registry of food-system LCA practitioners exists, the representativeness of the sample could not be formally assessed. The questionnaire was disseminated through the LCA Discussion List, the Swedish Life Cycle Centre, and the WASTEWISE project's communication channels (LinkedIn, Instagram, Facebook and X). In addition, members of the WASTEWISE project consortium (based in Finland, Italy, Romania, Spain, Sweden, and Switzerland) shared the survey through professional LinkedIn networks and LCA-focused groups. This approach aimed to reach practitioners internationally across academia, consultancy, industry, government and NGOs. Participation was voluntary, and no incentives were offered.

2.4 Data analysis

Quantitative data were analysed descriptively. Frequencies, percentages, and summary statistics (means and standard deviations where relevant) were used to summarise respondent characteristics, familiarity with rebound effects, current

practice, perceived importance, methodological approaches and reported data challenges. No inferential analyses were performed, as the objective was to describe current practice rather than compare subgroups or test hypotheses.

Qualitative responses (Q11.2, Q18.2, Q22, Q23 and Q24) were analysed thematically following the six-phase approach by Braun and Clarke (2006). Coding was conducted inductively, with meaning units identified and coded response by response. Codes were iteratively reviewed and grouped into themes that captured how practitioners justify their quantitative ratings and choices, including their reasoning about relevance, scope, feasibility, uncertainty and methodological fit. The analysis focused on both explicit statements and reasoning provided by respondents, with particular attention to how qualitative responses explained, contextualised or problematised the quantitative findings. Findings from the quantitative and qualitative analyses were brought together during interpretation to contextualise survey patterns and deepen understanding of practitioners' reasoning.

2.5 Ethical considerations

The study involved no personal or sensitive data collection, and no formal ethical board review was therefore required. Participation was voluntary, and informed consent was obtained before completing the survey. Respondents were informed about the purpose of the study, the anonymity of responses, data handling procedures and their right to withdraw before submission. No IP addresses were collected.

3 Results

3.1 Respondent characteristics

A total of 79 practitioners answered the survey. The number of respondents (n) varies between analyses because some questions were displayed conditionally based on previous responses and because not all participants completed the entire questionnaire. The relevant sample size is reported throughout the Results.

Most respondents worked in academia ($n=52$; 66%), followed by industry ($n=11$; 14%), consultancy ($n=9$; 11%), and government ($n=4$; 5%) (Fig. 1A). This distribution indicates that the survey responses predominantly reflect research-oriented perspectives rather than those of commercial consultancy. Because the survey was disseminated primarily through academic and professional networks using convenience and snowball sampling, this distribution should not be interpreted as representative of the wider LCA practitioner community.

Respondents represented a broad range of experience levels: 29 respondents (37%) had 0–2 years of experience conducting LCAs, 21 (27%) had 3–5 years, 11 (14%) had 6–10 years, and 17 (22%) had more than 10 years (Fig. 1B). Overall, the respondent sample was somewhat skewed toward those with fewer years of experience, which is relevant when interpreting results related to methodological familiarity and established modelling routines.

Experience with food-related LCAs varied. Thirty-eight respondents (48%) had conducted LCAs related to food systems, 31 (39%) had worked with food waste–related LCAs, and 26 (33%) had not previously conducted food-related assessments. Attributional LCA was the most used method, 52 (66%). In addition, 27 respondents (34%) reported using process-based LCA, 12 (15%) consequential LCA, and 10 (13%) hybrid approaches (Fig. 1C). The dominance of attributional practice among respondents is important to note, as many of the views reported later in the survey, particularly concerns about scope and methodological fit, should be interpreted in this context.

Most respondents were based in Europe (85%), with smaller shares in Asia (8%), North America (4%), Africa (3%) and South America (1%). This distribution likely reflects the European composition of the research consortium and its professional networks through which the survey was disseminated. The regions where respondents primarily conducted LCAs showed a similar pattern. Academic backgrounds were diverse but dominated by engineering 22 (56%) and environmental or sustainability science 22 (56%) (Fig. 1D). Smaller groups had training in agronomy, food systems or nutrition 10 (26%), economics or policy studies 3 (8%), and social sciences 2 (5%). The limited representation of economics and behavioural sciences may be relevant given their importance for understanding rebound mechanisms.

3.2 Familiarity, current practice and perceived importance

3.2.1 Familiarity with rebound effects

Familiarity with rebound effects varied widely among respondents, with the average familiarity score being 2.72 (SD = 1.59) ($n=79$). Twenty-six respondents (33%) fell into the "Not familiar" group, while the remaining respondents were distributed across moderate and higher familiarity levels: 9 respondents (11%) selected "2", 12 (15%) selected "3", 20 (25%) selected "4", and 12 (15%) selected "Very familiar" (Fig. 2A). This variation indicates that respondents differed considerably in how familiar they were with rebound effects, although a larger share reported being "not familiar" than "very familiar".

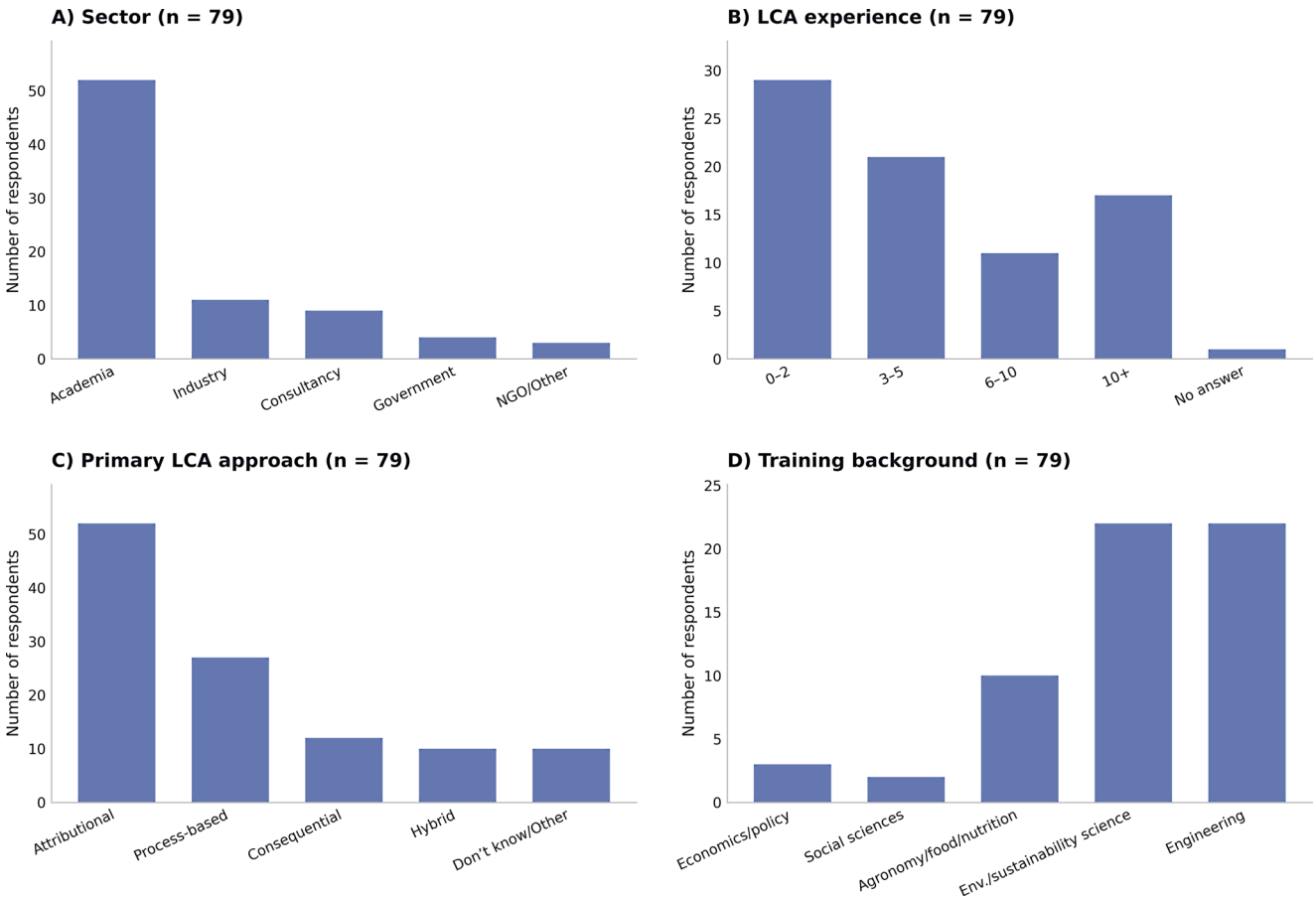


Fig. 1 Distribution of respondents by (**A**) primary sector of employment, (**B**) years of experience conducting LCA studies, (**C**) primary LCA approach used, and (**D**) academic training background. Values represent counts of respondents; multiple selections were possible for the primary LCA approach and training background

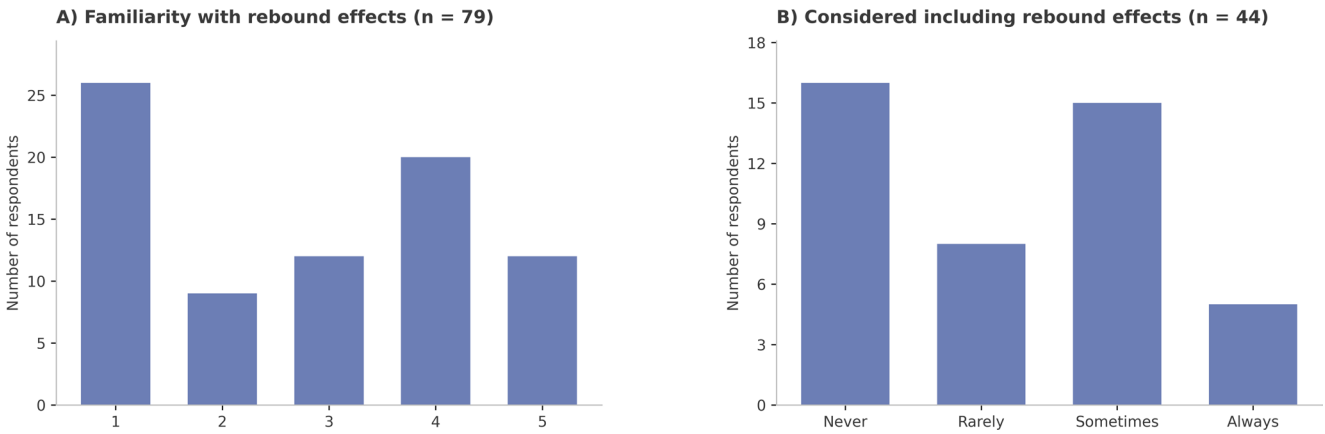


Fig. 2 Panel A shows respondents' familiarity with rebound effects on a five-point scale (1 = Not familiar, 5 = Very familiar; $n = 79$). Panel B shows how often respondents had considered including rebound effects in an LCA study ($n = 44$). Values represent counts of respondents

3.2.2 Consideration of rebound effects in practice

Whether respondents had considered including rebound effects in their LCA studies varied. Among the 44 respondents who answered this question, 16 (36%) reported that they had never considered including rebound effects, 8 (18%) reported rarely, 15 (34%) reported sometimes, and 5 (11%) reported always (Fig. 2B). As the question asked specifically about considering the inclusion of rebound effects, the responses reflect how often practitioners had

actively reflected on whether rebound effects should be integrated into an LCA, rather than whether they had actually modelled them. The results, therefore, indicate that while a small share of practitioners had always at least considered rebound effects during study design or scoping, a substantial share had neither considered nor included them.

3.2.3 Perceived importance of rebound effects

Respondents generally considered rebound effects to be of moderate importance in LCA studies. For food-system LCAs, the mean rating was 3.39 (SD = 1.21) on a five-point scale (1 = Not important, 5 = Very important; $n = 44$). Ratings for food-waste LCAs followed a similar pattern, with a slightly lower mean of 3.25 (SD = 1.26). These results indicate that respondents, on average, perceived rebound effects as potentially relevant, even though, as shown above, relatively few had routinely considered including them in their own work.

3.3 Reasons for not including rebound effects

Among respondents who reported ($n = 41$) that they did not include rebound effects in their LCA studies, several reasons were frequently reported (multiple-choice question). The most common barriers were a lack of standardised methods ($n = 25$; 61%) and a lack of reliable data ($n = 21$; 51%) (Fig. 3). A considerable share also pointed to methodological or practical challenges, including perceiving rebound effects as outside the scope of LCA ($n = 15$; 37%), not being sure how to include them ($n = 12$; 29%), which points to uncertainty not only about data but also about operational procedures, and finding the work too complex or time-consuming ($n = 10$; 24%). Some respondents noted that rebound effects were not relevant to their particular case studies ($n = 11$; 27%) or that clients or stakeholders did not request their inclusion ($n = 7$; 17%). A smaller group indicated a lack of awareness of the concept ($n = 5$; 12%), and a few selected "other" ($n = 3$; 7%), referring to uncertainty about methodological fit or attributional LCA boundaries.

These results suggest that barriers to including rebound effects stem from both methodological and practical constraints, with uncertainty about appropriate approaches and limited data availability being the most prominent factors.

3.4 Collaboration and capability gap

Collaboration with disciplines relevant to modelling rebound effects was limited. Among the 39 respondents who answered this question, six (15%) reported collaborating regularly with economists or behavioural scientists, 11 (28%) collaborated occasionally, and a majority, 21 (54%), indicated that they would like to collaborate but currently do not. Only one respondent indicated no collaboration and no perceived need for it. When considered alongside the limited representation of economics and social science

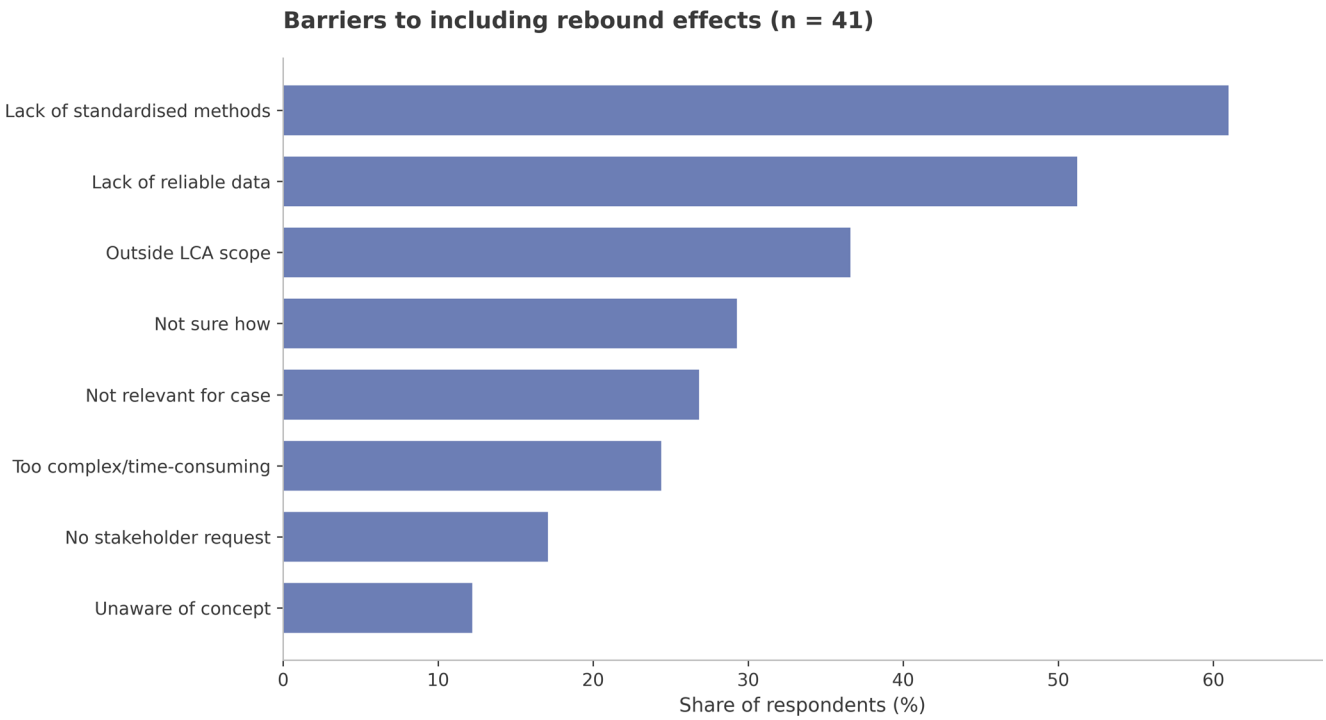


Fig. 3 Barriers to including rebound effects in LCA studies. Values represent percentages of respondents selecting each barrier ($n = 41$); multiple selections were possible

backgrounds noted in Sect. 3.1, these findings suggest a structural capability gap: practitioners perceive rebound effects as relevant and express interest in drawing on behavioural and economic insights, yet often lack access to the expertise and data needed to do so.

3.5 Data challenges and needs

Respondents highlighted several data-related challenges that hinder the inclusion of rebound effects in LCA. Among the 39 respondents who answered this question, the most frequently selected issues were the lack of behavioural data ($n=23$; 59%) and the lack of primary data ($n=22$; 56%), followed by uncertainty in system-wide impacts ($n=18$; 46%) and limited availability of suitable market or economic data ($n=15$; 38%). A further 15 respondents (38%) pointed to the absence of consensus on appropriate methods, and 15 (23%) noted the lack of tool or software integration. Fewer respondents identified time constraints or the complexity of interpreting rebound effects as key challenges ($n=5$; 13%).

Respondents also expressed interest in using suitable behavioural or economic datasets for rebound modelling if such datasets were available. Among the 39 respondents who answered this question, the average likelihood of using such data was 3.87 (SD = 1.07) on a five-point scale (1 = Not at all likely, 5 = Very likely). This suggests that the lack of existing datasets is a significant barrier, rather than a lack of demand or willingness to use them.

3.6 Motivations for including rebound effects

Among the respondents who answered the question on motivations for including rebound effects ($n=44$), half (50%) selected "I have never included rebound effects in my LCA studies". The remaining respondents, those who had included rebound effects at least once, reported several motivations for doing so. The most frequently selected motivations were to make assessments more accurate or comprehensive ($n=13$; 30%) and to capture real-world system behaviour more accurately ($n=11$; 25%). A similar share ($n=12$; 27%) noted an interest in exploring potential unintended consequences of interventions. Smaller proportions selected advancing the field ($n=5$; 11%), responding to policy or stakeholder demand ($n=4$; 9%), or personal academic interest ($n=6$; 14%). No respondents cited recent methodological advancements as a motivation. These results, therefore, reflect motivations among practitioners with at least some experience integrating rebound effects into their LCA work.

3.7 Types of rebound effects considered

Respondents who had considered rebound effects in their LCA work ($n=19$) reported a range of mechanisms (multiple-choice question). Income-driven rebounds (additional consumption enabled by money saved) were selected most frequently ($n=11$; 58%), followed by price-driven rebounds (changes in consumption due to price shifts) ($n=8$; 42%) and technological rebounds (increased total use following efficiency improvements) ($n=7$; 37%). Substitution effects (shifts toward other products or services) ($n=5$; 26%), time-related rebounds (changes in activity patterns due to altered time use) ($n=5$; 26%), and behavioural or moral licensing effects (less sustainable behaviours that "offset" prior pro-environmental actions) ($n=4$; 21%) were also reported. Transformational or systemic rebounds (longer-term structural or behavioural shifts) were selected by 5 (26%) respondents. Only a small share chose "I don't know" ($n=2$; 11%) or "Other" ($n=3$; 16%), suggesting that most respondents were able to classify the mechanisms they had considered.

3.8 Approaches used to estimate rebound effects

Respondents who had attempted to estimate rebound effects ($n=21$) reported using a wide range of estimation approaches, including different data sources, modelling logics, proxy measures (multiple-choice question). The most commonly selected options were the use of primary data ($n=7$; 37%), literature-based values ($n=6$; 32%), and input–output analysis ($n=6$; 32%). Smaller shares reported using expert judgement ($n=5$; 26%), econometric modelling ($n=4$; 21%), market modelling ($n=4$; 21%), scenario analysis ($n=4$; 21%), proxy indicators ($n=3$; 16%) or behavioural modelling ($n=2$; 11%). Overall, the responses suggest that practitioners apply a range of approaches, likely reflecting differences in study scope, data availability, and the specific rebound mechanisms under investigation.

3.9 Methods and tools

Respondents reported using a wide range of methods to account for rebound effects in LCA ($n=18$). No single approach dominated in this multiple-choice question. Some reported using attributional LCA ($n=2$; 11%) or attributional LCA with system expansion ($n=3$; 17%), while others used consequential LCA ($n=4$; 22%), hybrid LCA ($n=3$; 17%), or environmentally extended input–output modelling ($n=2$; 11%). A smaller number reported using system dynamics modelling ($n=1$; 6%), agent-based modelling ($n=2$; 11%), or econometric modelling ($n=2$; 11%). The largest share ($n=7$; 39%) indicated that they do not use any specific method for assessing rebound effects. This variety suggests

that practitioners draw on methods aligned with their disciplinary background and study context, rather than relying on a single established approach.

By contrast, software use was dominated by a few tools (multiple-choice question; $n=18$). SimaPro and Excel were the most commonly used ($n=10$; 56% each), followed by openLCA ($n=5$; 28%) and Brightway2 ($n=2$; 11%). Only two respondents had ever encountered built-in functionality for modelling rebound effects, and none had used such functionality. This indicates that current LCA software provides little explicit support for incorporating rebound effects.

3.10 Qualitative insights from open responses

The open-ended responses provided explanatory insight into how practitioners reasoned about their quantitative ratings and choices regarding rebound effects. Rather than introducing entirely new concerns, responses largely clarified *why* rebound effects were considered moderately important yet rarely included in practice. Five interrelated themes were identified.

3.10.1 Theme 1: Multi-dimensional data inadequacy as a dominant bottleneck

Respondents described data-related barriers in varied and nuanced ways, extending beyond a simple absence of a certain type of data. In addition, the open-ended responses highlighted limitations in data reliability, consistency, timeliness, accessibility, and relevance, as well as uncertainty about how available data could be meaningfully operationalised within LCA models. Several respondents emphasised the lack of appropriate economic or behavioural parameters, for example, noting:

> The detail of demographic data on purchase and consumption is really needed to enable us to do this.

Others highlighted challenges related to data quality and representativeness, stressing the need for it:

> Reliable and representative data at the consumer level, and an easy way to integrate it in LCA models.

Concerns were also raised about the consistency and currency of available datasets, including the use of outdated or highly aggregated economic data that were perceived as ill-suited for analysing rebound effects in specific food-system contexts. In addition, some responses indicated that data challenges were not limited to access, but also to *use*, with uncertainty about how behavioural or economic data should be translated into LCA-relevant modelling choices:

> It's not just the data challenge; it's also about knowing how to use this data and combine it within the LCA framework.

Taken together, these responses indicate that practitioners face a layered data problem: even when data exist, they may be inaccessible, outdated, inconsistent, poorly aligned with typical LCA system boundaries, or difficult to operationalise. This helps to explain the frequent exclusion of rebound effects in practice, despite their perceived relevance.

3.10.2 Theme 2: High uncertainty and limited predictability of rebound effects

Many respondents described rebound effects as difficult to assess due to high levels of uncertainty related to behavioural, economic, and systemic dynamics. Several emphasised that rebound mechanisms are hard to predict, particularly when they involve changes in consumer behaviour or monetary re-spending, and that this uncertainty complicates quantification efforts.

Some respondents reflected on the inherent limits of predicting food-related behaviour, noting that rebound effects linked to food consumption may differ from other sectors, while financial rebounds remain especially uncertain:

> I believe regarding the amount of food consumed, rebound effects are more limited compared to other sectors because the amount of food people can eat does not change that drastically from day to day. Regarding money that becomes available, it is hard to predict.

Others highlighted uncertainty related to how savings might translate into different consumption choices, which may not necessarily lead to higher environmental impacts:

> It could also be that people just go for more expensive food products, which don't necessarily have higher impacts, e.g., organic products.

Uncertainty was also linked to limited knowledge of underlying mechanisms and difficulties in mapping impacts:

> I am unaware of the specific mechanisms for rebound effects in food waste, more familiar on a food system level. There are high uncertainties, but nonetheless, it can be significant.

Some respondents emphasised behavioural unpredictability and the proliferation of possible scenarios, which can lead to ambiguous results despite substantial analytical effort:

> I feel like we can never precisely assess consumers' behaviour, so one challenge is that we often come up with several possible scenarios that all might tell a different story. So, at the end of the day, it might be a lot of additional work without a clear message.

These responses indicate that uncertainty is not limited to data gaps but also reflects fundamental challenges in predicting behavioural and economic responses, contributing to hesitation about quantitatively incorporating rebound effects in LCA.

3.10.3 Theme 3: Context- and goal-dependence of rebound relevance in LCA

Many respondents emphasised that the relevance of rebound effects depends strongly on the goal, scope, and context of the LCA study. Rather than viewing rebound effects as universally applicable, practitioners framed their importance as conditional on the type of intervention assessed, the analytical scope, and the decision context.

Several responses highlighted cost differences between alternatives as a key contextual factor, noting that rebound effects become particularly relevant when interventions affect consumer expenditure:

> If comparing options that do not have the same costs, they are very important. If costs are the same for all alternatives, then it is not so important.

Others linked rebound relevance explicitly to study scope, describing that including rebound effects would entail a shift from product-focused assessments toward broader consumption or system perspectives. Several respondents contrasted attributional and consequential approaches, suggesting that rebound effects are more relevant in consequential, prospective, or system-level analyses than in conventional product LCAs:

> I think in prospective LCAs, e.g., regarding the protein transition, rebound effects could be important and should be considered. For conventional, attributional LCAs, they seem out of scope.

> It definitely has more relevance for consequential and large-scale LCAs than for single product LCAs.

Respondents also described contextual variation across intervention types and system settings, including dietary shifts, food-waste prevention, and household consumption:

> In the context of dietary shift, for instance, we could imagine that if people eat healthier, they might have better health (so a positive rebound effect in this case). In the context of avoiding food waste, I think it is even more relevant, as avoiding food waste is often synonymous with saving money.

> Households are a hotspot due to the rebound effect.

Several responses emphasised that rebound effects are difficult to generalise across geographical, political, or industrial contexts, reinforcing their context-specific nature:

> Rebound effects can be very dependent on the context (geographical, political, industrial), so I believe it is tricky to produce a generic database.

Finally, some respondents framed rebound relevance in relation to broader system-level or sustainability goals, indicating that rebound effects matter particularly when assessments aim to address wider economic or environmental limits:

> It is important, but as always in LCA, it depends on the goal of the study. It is important if we want to assess the broader effects on the economic system.

> This evaluation would be very important in a wider scope to give relief to the strained planetary boundaries.

Taken together, these responses indicate that practitioners do not reject rebound effects as irrelevant, but instead situate their relevance within specific analytical purposes, methodological choices, and system contexts, particularly when LCAs aim to inform policy, consumption-level decisions, or system-wide sustainability outcomes.

3.10.4 Theme 4: Procedural, knowledge, and capacity constraints in operationalising rebound effects

Many respondents emphasised that challenges related to rebound effects extend beyond data availability or relevance and relate to limited procedural guidance, lack of standardised methods, and insufficient expertise to operationalise rebound effects within LCA frameworks. Several responses pointed explicitly to the absence of standards or agreed-upon methodological approaches. Others highlighted uncertainty about *how* rebound-related data should be used and integrated into LCA models, even when data might be available:

> Most LCA experts probably do not know which data to use and how to use it within the LCA framework. More guidance on this would probably help!

Several respondents referred to limited familiarity with the rebound concept itself, particularly among early-career practitioners, indicating a knowledge and training gap:

> I'm not well aware, as I have started studying LCA only recently.

Capacity constraints were also described in terms of disciplinary boundaries and expertise, with respondents noting that rebound effects require a multidisciplinary approach, including economic and behavioural knowledge that many LCA practitioners do not possess:

> Representing correctly rebound effects, as they depend on many factors – behavioural, economic, etc. – in which, as an LCA expert, I don't have expertise.

Several responses explicitly called for clearer methodological alignment and practical examples to support implementation:

> Method alignment: clearly stating in which cases which method should be applied, how and which data sources to use and how to use the results.

Finally, some respondents linked the need for guidance to the strong context-dependence of rebound effects, arguing that this further increases the need for structured frameworks and tools:

> Rebound effects can be very dependent on the context (geographical, political, industrial), so I believe it is tricky to produce a generic database. It is then important to produce a framework, methodology and tools to take it into account.

These responses indicate that rebound effects are not only constrained by data and uncertainty, but also by limited methodological guidance, uneven familiarity with the concept, and a lack of interdisciplinary capacity within current LCA practice.

3.10.5 Theme 5: Rebound effects as relevant for interpretation, trade-offs, and decision support

Several respondents emphasised that rebound effects matter not only as a modelling challenge, but because they influence how LCA results should be interpreted and used. Rebound effects were described as important for avoiding overestimation of environmental benefits, identifying trade-offs and burden-shifting, and improving the relevance of LCAs for decision-making.

Some respondents explicitly framed rebound effects as necessary to obtain more accurate estimates of environmental mitigation, warning that omitting them may lead to overly optimistic conclusions:

> Important to capture potential trade-offs in calculations for environmental savings to have more accurate estimates on environmental mitigation due to attempted improvements within the food systems. So that we do not overestimate their impacts.

Others stressed that ignoring rebound effects can reduce the effectiveness of food-system interventions or shift impacts elsewhere:

> Solutions to food systems problems which do not account for potential rebounds are rendered less effective.

> They should be evaluated in both cases to avoid burden-shifts.

Several responses highlighted the role of rebound effects in capturing trade-offs, cascading impacts, and interactions across categories or system components:

> Assessing the rebound effects in FW by category may affect the other categories either directly or indirectly; therefore, this assessment may help in balancing some trade-offs.

Respondents also linked rebound effects to broader economic and behavioural dynamics, particularly those related to savings and re-spending:

> I believe that in both cases [broader food system and food waste studies] they are very important as consumers will use money for something else.

> I think rebound effect should always be explored as much as possible, but even more so in the case where there is a clear effect on economic savings, as this might often result in spending in alternative impactful categories (e.g. end consumers saving money on food and spending it on travelling by plane and holidays).

Some respondents situated rebound effects within wider system transitions and sustainability goals, noting their

relevance for socio-economic impacts, policy support, and absolute sustainability perspectives:

> It has a large socio-economic impact, majorly understudied in literature.

> If there were a demand for policy decision support in putting prices on and paying for non-marketed services.

This reflects the view that rebound effects become particularly relevant when LCAs are used to support policy decisions that involve valuing environmental or social externalities.

Finally, a few responses pointed to the potential for both negative and positive rebound effects:

> I think it could be interesting to look into the positive rebound effect, life health impacts, or think of ways to make sure the message is that it's better to reduce food waste than the alternative.

These responses indicate that practitioners view rebound effects as important for interpreting LCA results, understanding trade-offs and unintended consequences, and ensuring that food-system interventions and policies are not evaluated in isolation from their wider economic, behavioural, and environmental effects.

However, some respondents also noted that rebound effects were sometimes addressed through discussion or interpretive framing rather than through quantitative inclusion in LCA models, consistent with the quantitative finding that a notable share of respondents reported not using a specific method to assess rebound effects. For example:

> Rebound effects should be part of interpretation and discussion.

Overall, the qualitative findings help explain the quantitative pattern observed in Sect. 3.2–3.6, where rebound effects were rated as moderately important but were rarely considered or included in practice.

4 Discussion

This study surveyed LCA practitioners working on food-system LCAs, including food-waste prevention as a key example, to examine how rebound effects are understood, considered, and addressed in applied LCA practice, and to identify the motivations, barriers, and needs shaping their inclusion. The results indicated that rebound effects are not absent from practice because practitioners dismiss them, but because the conditions for their credible inclusion are often lacking. While rebound effects were rated as moderately important, practitioners treated their inclusion as conditional on study goals and scope and were constrained by multi-dimensional data inadequacy, high uncertainty, limited predictability, and a lack of procedural guidance and interdisciplinary capacity. At the same time, respondents emphasised that rebound effects matter for result interpretation, identifying trade-offs, and avoiding overestimation of the environmental benefits of mitigation measures.

Building on these findings, a central and somewhat paradoxical pattern emerging from the survey is that rebound effects are not excluded from applied food-system LCAs because practitioners consider them irrelevant, but because they are perceived as too uncertain to be quantified credibly. This stands in contrast to other assumptions that are routinely modelled despite comparable or even greater uncertainty. For example, food-waste LCAs rely on substitution assumptions that are typically implemented via system expansion or avoided burden approaches that credit waste prevention with avoided upstream production (Caldeira et al. 2019). Yet, the coupling between reduced consumption and reduced production is weak and indirect in real food systems. Even where reduced demand can be plausibly assumed, avoided production represents a further and substantially stronger assumption, as food-system supply does not respond proportionally or immediately to marginal changes in demand (Rutten 2013; World Bank 2012). Food supply chains are characterised by perishability, contractual arrangements, buffering through storage and trade, and policy interventions, all of which dampen or delay production responses to marginal demand changes (Chauhan et al. 2021; De Boni et al. 2022). Small variations in consumer demand are often amplified and distorted upstream due to inventory buffering and forecasting lags, a phenomenon known as the bullwhip effect (Lee et al. 1997), rather than triggering immediate production adjustments. Perishable food supply chains also face short shelf lives and demand uncertainty, complicating stock management and limiting responsiveness (Weber et al. 2023; Zhang and Mohammad 2024). As a result, short- to medium-term reductions in food purchases may be absorbed through alternative outlets, exports, price adjustments, or increased availability elsewhere rather than translating into reduced primary production (Liu et al. 2025; Rutten 2013; World Bank 2012). Nevertheless, avoided production is frequently modelled as if reduced demand automatically translates into avoided production, as reviews of waste and waste-prevention LCAs show that environmental benefits are driven by such avoided production effects, while methodological choices related to substitution (e.g., marginal versus average data, displaced technologies,

substitution rates) are among the dominant sources of result variability and uncertainty (Laurent et al. 2014).

At the same time, uncertainty is a long-recognised characteristic of LCA (Huijbregts 1998). Sources of uncertainty arise from uncertainty of the underlying data, data gaps, model structure, scenario assumptions, and system boundary choices, and increase as assessments extend across space, time, and indirect causal chains (Huijbregts et al. 2001). Rather than being treated as grounds for exclusion, such uncertainty is typically managed through uncertainty analysis, scenario analysis, sensitivity testing, and transparent reporting, with the understanding that LCA provides decision support rather than precise prediction (De Bruijn et al., 2002; Finnveden et al. 2009; Igos et al. 2019). The survey results are consistent with this broader understanding: practitioners did not reject rebound effects in principle, but emphasised uncertainty as a challenge that must be weighed against relevance, feasibility, and interpretability. This position is consistent with foundational LCA literature, which explicitly recognises demand–supply responses, economic feedback, and rebound effects as conceptually relevant consequences of efficiency and prevention measures, while also acknowledging that uncertainty increases as system boundaries are expanded across time and causal chains (Finnveden et al. 2009).

A further key insight emerging from these findings is that the limited inclusion of rebound effects cannot be explained solely by uncertainty but reflects deeper boundary tensions within LCA practice. As most respondents primarily work with attributional LCA, this highlights a structural tension: attributional LCA is designed to describe shares of environmental burdens associated with a product or activity, rather than to trace behavioural or economic consequences of change (Brander and Wylie 2011; Schaubroeck et al. 2021). Nevertheless, in food waste-prevention LCAs, as discussed above, substitution effects are routinely modelled through system expansion or avoided burden approaches, implicitly assuming that reduced consumption leads to avoided upstream production. In addition to being subject to substantial uncertainty, such assumptions are consequential in nature, and yet, they have become normalised within applied attributional practice, creating a modelling practice in which consequential assumptions are embedded without being explicitly acknowledged as such (Brander and Wylie 2011; Schaubroeck et al. 2021; Weidema et al. 2018). Moreover, they are often treated as *technical modelling choices* rather than as behavioural or economic hypotheses (Laurent et al. 2014; Caldeira et al. 2019). Where rebound effects differ is that they make behavioural and economic causality explicit, thereby exposing the limits of attributional system boundaries more directly. The survey responses suggest that practitioners are aware of this asymmetry and navigate it pragmatically: substitution effects are included because they fit within established conventions, tools, and practitioners' educational backgrounds, whereas rebound effects are excluded because their inclusion would require crossing methodological, disciplinary, and boundary assumptions that attributional LCA is not well equipped to handle, particularly in the absence of established interdisciplinary collaboration. This structural constraint is further reinforced by the highly standardised nature of LCA practice. Practitioners typically work within established frameworks such as ISO 14,040/44, ILCD, or PEF guidelines, which provide structured guidance on system modelling and uncertainty analysis but offer little explicit direction on how rebound effects should be identified or integrated.

In the absence of such guidance, including rebound effects may be perceived as moving beyond standard-compliant practice, helping to explain why respondents repeatedly emphasised the lack of a standardised approach despite LCA itself being a highly standardised method. In practice, this steers methodological choices toward approaches that are already embedded within LCA conventions, while more integrative alternatives remain peripheral. Hybrid approaches that link LCA with food system or optimisation models have been used in some cases to explore system-level scenarios, such as dietary shifts or food-waste avoidance, and are better suited to represent complex supply–demand relationships than simplified consequential approaches; however, such approaches remain relatively rare and resource-intensive in applied LCA practice (von Ow et al. 2020). This disciplinary imbalance also echoes broader patterns in LCA practice, where social and behavioural dimensions have historically been less developed and less systematically integrated than environmental aspects, a tendency reflected in the comparatively slower and fragmented uptake of Social Life Cycle Assessment in agri-food LCAs (Tragnone et al. 2022). In this context, system expansion is already a tolerated methodological compromise in attributional food-waste LCAs where rebound effects reveal, rather than introduce, the boundary tensions that this compromise entails (Brander and Wylie 2011; Weidema et al. 2018). Rebound effects thus act as a stress test for attributional LCA boundaries, exposing tensions that substitution modelling has largely been allowed to bypass rather than resolve.

Income-driven rebound effects arising from re-spending of monetary savings represent a comparatively direct and conceptually well-defined consequence of, for example, food waste prevention or dietary change, particularly at the household level. When food waste is reduced, or dietary habits shift from, for example, meat-based to plant-based foods, households may spend less on food purchases, generating disposable income that may be reallocated to other goods

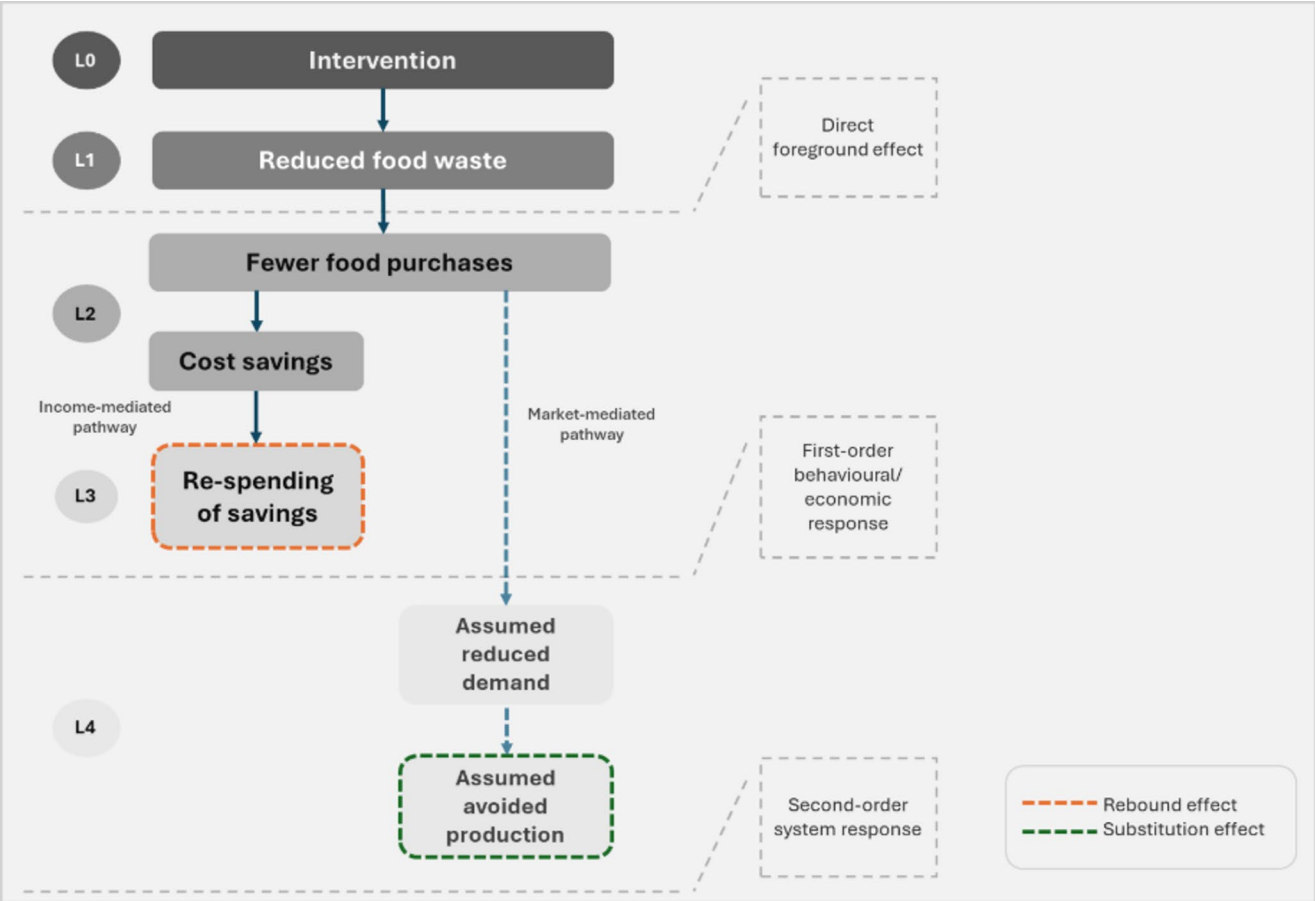


Fig. 4 Conceptual decomposition of assumptions embedded in food-waste LCA modelling scenarios, illustrating where rebound effects and substitution effects sit along the causal chain. The figure shows one example of successive responses following a food-waste prevention intervention (**L0**), including reduced food waste (**L1**), fewer food purchases and associated cost savings (**L2**), income-driven re-spending of monetary savings on other goods and services or retained as savings (**L3**), and assumed demand- and supply-side responses in the form of reduced demand and avoided production (**L4**). Income-driven rebound effects arise from direct behavioural responses and occur earlier in the causal chain, whereas substitution effects depend on more distant and uncertain market-mediated adjustments between reduced demand and avoided production, typically represented through system expansion or avoided-burden approaches. The figure does not represent a scenario-modelling workflow or prescribe a particular system boundary

and services with their own environmental footprints (Grabs 2015; Lekve Bjelle et al. 2018) or retained as savings. Unlike substitution-driven production responses, which depend on complex and often opaque market dynamics, re-spending behaviour is grounded in established economic principles and can, in principle, be approximated using observed consumption patterns or average expenditure profiles (Chitnis et al. 2013). The relevance of such rebound effects has long been recognised in LCA methodology, where increased economic activity following efficiency gains is understood to partially offset initial environmental benefits, even though quantification remains uncertain (Finnveden et al. 2009). To put it more clearly, income-driven rebound effects operate through direct re-spending of monetary savings on existing goods and services, whereas substitution effects represent assumed supply-side responses to reduced demand. Although both mechanisms involve uncertainty in how demand changes propagate through the system, the former is behaviourally proximate while the latter depends on market-mediated adjustments between reduced demand and avoided production that are more distant and uncertain in real food systems (Rutten 2013; World Bank 2012) (Fig. 4). In the present study, several respondents explicitly identified household-level rebound effects as conceptually relevant, yet still highlighted substantial barriers to their inclusion, including limited data availability, methodological guidance, and concerns about added complexity. Open responses also highlighted a layered data problem: even when potentially relevant behavioural or expenditure data exist, they are often too aggregated, outdated, inaccessible, or difficult to operationalise within common LCA data structures. This pattern suggests that income-driven rebound effects are not excluded because they are conceptually remote, but because they sit uncomfortably with prevailing modelling boundaries

and conventions in attributional LCA. Paradoxically, effects that are behaviourally proximate and grounded in observable re-spending patterns remain marginal in practice, while substitution effects, which are dependent on more distant and opaque supply-side assumptions, are routinely implemented in food-waste LCAs (Fig. 4).

Several limitations of this study should be acknowledged when interpreting the findings. As responses were not analysed by the LCA approach, references to attributional or consequential practice are interpretative rather than based on direct subgroup comparisons. A further limitation concerns the potential influence of cognitive and social biases on responses. Although none of the respondents explicitly stated that rebound effects were excluded because their inclusion might weaken overall mitigation results or undermine the perceived credibility of the assessment, this absence should not be interpreted as evidence that such considerations play no role in practice. The survey was not designed to elicit or probe motivated reasoning, implicit preferences for favourable outcomes, or other forms of desirability bias, and respondents may have been reluctant to articulate such motivations even if they were present. Consequently, the study cannot assess whether concerns about result directionality influence the treatment of rebound effects, and this represents an important limitation of the survey instrument. Further, the survey sample was dominated by respondents working in academia and based in Europe, which likely reflects the survey dissemination strategy but may limit the generalisability of the results to consultancy-led or industry-driven LCA practice, where time constraints, client demands, and modelling conventions may differ. However, the lack of reliable statistics on the overall composition of LCA practitioners makes it difficult to assess the representativeness of the sample relative to the broader practitioner population. Although the survey captures a broad range of experience levels, a substantial share of respondents had relatively limited years of practice, which may influence familiarity with rebound effects and confidence in methodological experimentation. Moreover, the study relies on self-reported perceptions and practices rather than direct analysis of published LCA models or case studies. As such, the results reflect how practitioners reason about rebound effects and uncertainty, rather than how these issues are operationalised in specific modelling exercises. Future research could therefore complement the present findings with a systematic review of published food-system LCA studies to examine the extent to which rebound effects are currently addressed in practice and to compare reported modelling approaches with the barriers and methodological needs identified by practitioners in this study. Finally, the focus on food systems and food waste LCAs means that the findings may not be directly transferable to other sectors, although many of the identified tensions, particularly those related to uncertainty, system boundaries, and system-response assumptions, are likely relevant beyond the food domain. Collectively, these findings both confirm and extend the existing literature on LCA. Consistent with prior methodological work, the results reaffirm that rebound effects are conceptually relevant, context-dependent, and challenging to quantify due to data and uncertainty constraints and lack of standardised methodological guidance (Finnveden et al. 2009; Vivanco and van der Voet 2014). However, the contribution of this study lies in revealing how these challenges are experienced and managed in applied practice. Rather than reflecting conceptual disagreement or lack of awareness, the limited inclusion of rebound effects emerges as a structural misalignment between recognised relevance and practical feasibility, in which uncertainty functions as a selective gatekeeper and modelling limitations are pragmatically displaced into interpretation. This reframing shifts the focus from whether rebound effects belong in LCA to how institutional, procedural, and disciplinary constraints, such as software and database structures, prevailing modelling conventions, and limited expertise, shape which system-response mechanisms are treated as modellable in practice. Future research should build on these findings by examining whether perceptions and practices differ systematically across practitioner groups, such as by employment sector, disciplinary background, years of LCA experience, or methodological approach (e.g. attributional versus consequential LCA). Such analyses could help identify where methodological guidance, training, or interdisciplinary collaboration are most needed. Future studies could also complement survey-based research with interviews or focus groups to explore practitioners' reasoning, experiences, and methodological decision-making in greater depth.

The asymmetric treatment of substitution assumptions and rebound effects has important implications for how food-system LCAs, particularly those assessing food-waste prevention and other consumption-side interventions, are interpreted and used in decision-making. Such studies are frequently applied to support policy targets, prioritise interventions, and communicate mitigation potentials, often with an emphasis on quantified environmental benefits. When substitution effects are embedded quantitatively in results while rebound effects are addressed only qualitatively or deferred to limitations, an epistemic asymmetry is created: quantified impacts tend to be perceived as more robust and decisive than qualitative caveats, even when uncertainty is comparable (Finnveden et al. 2009; Sala et al. 2023). The survey results indicated that practitioners are aware of this risk, repeatedly highlighting concerns about overestimation, trade-offs, and the need for careful interpretation. However, in the absence of standardised methods,

data, or procedural guidance for modelling rebound effects, interpretation becomes the primary mechanism for managing this imbalance. This places a disproportionate burden on narrative framing, transparency, and reader literacy to contextualise results that practitioners themselves recognise as conditional. Therefore, mitigation estimates from food-waste LCAs may appear more definitive to external audiences than practitioners themselves consider them to be, emphasising the need for greater consistency in how uncertainty associated with substitution assumptions and rebound effects is treated and communicated when LCAs are used to inform policy and sustainability strategies.

Taken together, these findings highlight the need for clearer methodological and procedural guidance in LCA practice. These priorities arise directly from the challenges and needs identified by practitioners in both the quantitative and qualitative survey findings, including clarifying (i) when different types of rebound effects should be considered in relation to the study goal and scope, (ii) how assumptions underlying both substitution and rebound mechanisms should be documented and communicated transparently, (iii) how uncertainty associated with substitution assumptions and rebound effects should be handled and communicated consistently, and (iv) which assessment approaches are appropriate for different rebound mechanisms and study objectives. Addressing these aspects could support more transparent and consistent treatment of substitution assumptions and rebound effects and help reduce the asymmetric treatment of these effects in food-system LCAs.

5 Conclusions

The findings of the present study revealed a misalignment that is structural rather than conceptual, rooted in capacity, guidance, and boundary conventions rather than in disagreement about relevance. Practitioners navigate this gap by prioritising modelling choices that are compatible with existing tools, data structures, and conventions, even when these choices rely on highly uncertain assumptions about demand–supply responses and avoided production. Importantly, the survey indicated that practitioners are not unwilling to engage with rebound effects or to collaborate across disciplines to do so; rather, such collaboration remains uncommon, with institutional, procedural, and capacity constraints cited. This structural constraint is further reinforced by the highly standardised nature of LCA practice, where existing frameworks provide little guidance on how rebound effects should be integrated, contributing to their continued exclusion from quantitative modelling. As a result, uncertainty functions as a selective gatekeeper: substitution assumptions that align with established modelling conventions and often strengthen estimated mitigation outcomes are widely accepted and routinely embedded quantitatively in LCA results, while rebound effects, such as income-driven rebounds that have the potential to offset mitigation outcomes, despite being well established in principle, are commonly excluded from modelling and deferred to qualitative discussion or interpretation. In this sense, rebound effects occupy a structurally constrained position in applied LCA practice, being normatively recognised as important, yet systematically excluded from quantitative assessment. The findings highlight the need for future methodological guidance on how substitution assumptions and rebound effects can be handled consistently to avoid asymmetric treatment of uncertainty and to support robust and transparent interpretation of mitigation potentials when food-system LCAs are used for decision-making.

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Data availability The data that support the findings of this study are available from the corresponding author upon reasonable request.

Declarations

Conflict of interest The authors have no competing interests to declare that are relevant to the content of this article.

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References

Albizzati PF, Tonini D, Astrup TF (2021) A Quantitative Sustainability Assessment of Food Waste Management in the European Union. Environ Sci Technol. https://doi.org/10.1021/acs.est.1c03940

Albizzati PF, Rocchi P, Cai M, Tonini D, Astrup TF (2022) Rebound effects of food waste prevention: Environmental impacts. Waste Manag 153:138–146. https://doi.org/10.1016/j.wasman.2022.08.020

Backes JG, Traverso M (2021) Life Cycle Sustainability Assessment—A Survey Based Potential Future Development for Implementation and Interpretation. Sustainability 13:13688. https://doi.org/10.3390/su132413688

Beretta C, Hellweg S (2019) Potential environmental benefits from food waste prevention in the food service sector. Resour Conserv Recycl 147:169–178. https://doi.org/10.1016/j.resconrec.2019.03.023

Brander M, Wylie C (2011) The use of substitution in attributional life cycle assessment. Greenh Gas Meas Manag 1:161–166. https://doi.org/10.1080/20430779.2011.637670

Braun V, Clarke V (2006) Using thematic analysis in psychology. Qual Res Psychol 3:77–101. https://doi.org/10.1191/1478088706qp063oa

Caldeira C, De Laurentiis V, Sala S (2019) Assessment of food waste prevention actions: development of an evaluation framework to assess performance of food waste prevention actions. https://data.europa.eu/doi/10.2760/9773

Chauhan C, Dhir A, Akram MU, Salo J (2021) Food loss and waste in food supply chains. A systematic literature review and framework development approach. J Clean Prod 295:126438. https://doi.org/10.1016/j.jclepro.2021.126438

Chitnis M, Sorrell S, Druckman A, Firth SK, Jackson T (2013) Turning lights into flights: estimating direct and indirect rebound effects for UK households. Energy Policy, Special section: Long Run Transitions to Sustainable Economic Structures in the European Union and Beyond. 55:234–250. https://doi.org/10.1016/j.enpol.2012.12.008

Corrado S, Ardente F, Sala S, Saouter E (2017) Modelling of food loss within life cycle assessment: From current practice towards a systematisation. J Clean Prod Towards eco-efficient Agric food systems: Sel papers addressing global challenges food Syst including those presented Conf LCA Feeding planet energy life (6–8 Oct 2015 Stresa Milan Expo Italy) 140:847–859. https://doi.org/10.1016/j.jclepro.2016.06.050

Crippa M, Solazzo E, Guizzardi D, Monforti-Ferrario F, Tubiello FN, Leip A (2021) Food systems are responsible for a third of global anthropogenic GHG emissions. Nat Food 2:198–209. https://doi.org/10.1038/s43016-021-00225-9

De Boni A, Ottomano Palmisano G, De Angelis M, Minervini F (2022) Challenges for a Sustainable Food Supply Chain: A Review on Food Losses and Waste. Sustainability 14:16764. https://doi.org/10.3390/su142416764

De Bruijn H, Van Duin R, Huijbregts MAJ, Guinee JB, Gorree M, Heijungs R, Huppes G, Kleijn R, De Koning A, Van Oers L, Wegener Sleeswijk A, Suh S, De Haes U, H.A. (eds) 2002. Handbook on Life Cycle Assessment: Operational Guide to the ISO Standards, Eco-Efficiency in Industry and Science. Springer Netherlands, Dordrecht. https://doi.org/10.1007/0-306-48055-7

Dillman DA, Smyth JD, Christian LM (2014) Internet, Phone, Mail, and Mixed-Mode Surveys: The Tailored Design Method, 4th edn. Wiley, Hoboken, NJ

Druckman A, Chitnis M, Sorrell S, Jackson T (2011) Missing carbon reductions? Exploring rebound and backfire effects in UK households. Energy Policy 39:3572–3581. https://doi.org/10.1016/j.enpol.2011.03.058

Eriksson M, Bartek L, Sturén F, Christensen J, Cicatiello C, Giordano C, Malefors C, Pasanen S, Sjölund A, Strid I, Sundin N, Brancoli P (2025) From surplus to sustainability: The role of legislation in reducing climate impact from Swedish bread waste. Curr Res Environ Sustain 10:100301. https://doi.org/10.1016/j.crsust.2025.100301

European Commission (2020) A new Circular Economy Action Plan for a cleaner and more competitive Europe. COM(2020) 98 final. European Commission, Brussels

European Commission (2021) Commission Recommendation (EU) 2021/2279 of 15 December 2021 on the use of the Environmental Footprint methods to measure and communicate the life cycle environmental performance of products and organisations. Official Journal of the European Union. L 471/1

European Commission (2023) Commission Delegated Decision (EU) 2023/1067 of 27 March 2023 supplementing Directive 2008/98/EC as regards reporting on food waste levels. Official Journal of the European Union. L 143/66

FAO (2014) Sustainability pathways: food loss and waste. URL http://www.fao.org/nr/sustainability/food-loss-and-waste. Accessed 21 January 2021

Finnveden G, Hauschild MZ, Ekvall T, Guinée J, Heijungs R, Hellweg S, Koehler A, Pennington D, Suh S (2009) Recent developments in Life Cycle Assessment. J Environ Manage 91:1–21. https://doi.org/10.1016/j.jenvman.2009.06.018

Grabs J (2015) The rebound effects of switching to vegetarianism. A microeconomic analysis of Swedish consumption behavior. Ecol Econ 116:270–279. https://doi.org/10.1016/j.ecolecon.2015.04.030

Greening L, Greene DL, Difiglio C (2000) Energy efficiency and consumption — the rebound effect — a survey. Energy Policy 28:389–401. https://doi.org/10.1016/S0301-4215(00)00021-5

Hegwood M, Burgess MG, Costigliolo EM, Smith P, Bajželj B, Saunders H, Davis SJ (2023) Rebound effects could offset more than half of avoided food loss and waste. Nat Food 4:585–595. https://doi.org/10.1038/s43016-023-00792-z

Huijbregts MAJ (1998) Application of uncertainty and variability in LCA. Int J Life Cycle Assess 3:273–280. https://doi.org/10.1007/BF02979835

Huijbregts MAJ, Norris G, Bretz R, Ciroth A, Maurice B, von Bahr B, Weidema B, de Beaufort ASH (2001) Framework for modelling data uncertainty in life cycle inventories. Int J Life Cycle Assess 6:127–132. https://doi.org/10.1007/BF02978728

Igos E, Benetto E, Meyer R, Baustert P, Othoniel B (2019) How to treat uncertainties in life cycle assessment studies? Int J Life Cycle Assess 24:794–807. https://doi.org/10.1007/s11367-018-1477-1

Laurent A, Bakas I, Clavreul J, Bernstad A, Niero M, Gentil E, Hauschild MZ, Christensen TH (2014) Review of LCA studies of solid waste management systems – Part I: Lessons learned and perspectives. Waste Manag 34:573–588. https://doi.org/10.1016/j.wasman.2013.10.045

Lee HL, Padmanabhan V, Whang S (1997) Information Distortion in a Supply Chain: The Bullwhip Effect. Manag Sci 43:546–558. https://doi.org/10.1287/mnsc.43.4.546

Lekve Bjelle E, Steen-Olsen K, Wood R (2018) Climate change mitigation potential of Norwegian households and the rebound effect. J Clean Prod 172:208–217. https://doi.org/10.1016/j.jclepro.2017.10.089

Liu J, Kang K, Lu L, Dong R, Luo X, Li C, Long P, Yang X, Mao S (2025) Decision analysis considering the resilience level of the food supply chain under the risk of demand disruption. Front Sustain Food Syst 9. https://doi.org/10.3389/fsufs.2025.1563938

Mazac R, Järviö N, Tuomisto HL (2023) Environmental and nutritional Life Cycle Assessment of novel foods in meals as transformative food for the future. Sci Total Environ 876:162796. https://doi.org/10.1016/j.scitotenv.2023.162796

Meshulam T, Font-Vivanco D, Blass V, Makov T (2021) Sharing Economy Rebound- The Case of Peer-2-Peer Sharing of Food Waste. J Ind Ecol. https://doi.org/10.31880/10344/10231

Netigate (2025) Netigate. https://www.netigate.net/sv/ Accessed 3 December 2025

Olanrewaju OI, Enegbuma WI, Donn M (2024) Challenges in life cycle assessment implementation for construction environmental product declaration development: A mixed approach and global perspective. Sustain Prod Consum 49:502–528. https://doi.org/10.1016/j.spc.2024.06.021

Payró C, Taherzadeh O, van Oorschot M, Koch J, Marselis S (2024) Consumer resistance diminishes environmental gains of dietary change. Environ Res Lett 19:054033. https://doi.org/10.1088/1748-9326/ad3c57

Ranundeniya RMNS, Stasinopoulos P, Shiwakoti N, Lockrey S (2025) A critical review of methodological aspects influencing life cycle assessment results of food waste reduction strategies. J Environ Manage 393:127152. https://doi.org/10.1016/j.jenvman.2025.127152

Rutten MM (2013) What economic theory tells us about the impacts of reducing food lossesand/or waste: implications for research, policy and practice. Agric Food Secur 2:13. https://doi.org/10.1186/2048-7010-2-13

Sala S, De LV, Sanye ME (2023) Food consumption and waste: environmental impacts from a supply chain perspective. JRC Publ. Repos. https://publications.jrc.ec.europa.eu/repository/handle/JRC129245. Accessed 28 November 2023

Salemdeeb R, Font Vivanco D, Al-Tabbaa A, zu Ermgassen EKHJ (2017) A holistic approach to the environmental evaluation of food waste prevention. Waste Manag 59:442–450. https://doi.org/10.1016/j.wasman.2016.09.042

Schaubroeck T, Schaubroeck S, Heijungs R, Zamagni A, Brandão M, Benetto E (2021) Attributional & Consequential Life Cycle Assessment: Definitions, Conceptual Characteristics and Modelling Restrictions. Sustainability 13:7386. https://doi.org/10.3390/su13137386

Sorrell S, Dimitropoulos J (2008) The rebound effect: Microeconomic definitions, limitations and extensions. Ecol Econ 65:636–649. https://doi.org/10.1016/j.ecolecon.2007.08.013

Sundin N, Osowski P, Strid C, Eriksson I, M (2022) Surplus food donation: Effectiveness, carbon footprint, and rebound effect. Resour Conserv Recycl 181:106271. https://doi.org/10.1016/j.resconrec.2022.106271

Sundin N, Bartek L, Persson Osowski C, Strid I, Eriksson M (2023) Sustainability assessment of surplus food donation: A transfer system generating environmental, economic, and social values. Sustain Prod Consum 38:41–54. https://doi.org/10.1016/j.spc.2023.03.022

Sundin N, Citro E, Eriksson M (2025) From waste to value? Balancing climate and social outcomes in social supermarkets. J Clean Prod 531:146950. https://doi.org/10.1016/j.jclepro.2025.146950

Taherzadeh O, Kanemoto K (2022) Differentiated responsibilities of US citizens in the country's sustainable dietary transition. Environ Res Lett 17:074037. https://doi.org/10.1088/1748-9326/ac7600

Thiesen J, Christensen TS, Christensen TS, Thomas G, Kristensen, Kristensen TG, Rikke Dorothea Andersen, Andersen R, Andersen RD, Brunoe B, Brunoe B, Trine K, Gregersen, Gregersen TK, Thrane M, Thrane M, Weidema BP, Weidema BP (2008) Rebound effects of price differences. Int J Life Cycle Assess 13:104–114. https://doi.org/10.1065/lca2006.12.297

Tragnone BM, D'Eusanio M, Petti L (2022) The count of what counts in the agri-food Social Life Cycle Assessment. J Clean Prod 354:131624. https://doi.org/10.1016/j.jclepro.2022.131624

UNEP, U.N. (2021) UNEP food waste index report 2021. UNEP - UN Environ. Programme. http://www.unep.org/resources/report/unep-food-waste-index-report-2021

Vivanco DF, van der Voet E (2014) The rebound effect through industrial ecology's eyes: a review of LCA-based studies. Int J Life Cycle Assess 19:1933–1947. https://doi.org/10.1007/s11367-014-0802-6

von Ow A, Waldvogel T, Nemecek T (2020) Environmental optimization of the Swiss population's diet using domestic production resources. J Clean Prod 248:119241. https://doi.org/10.1016/j.jclepro.2019.119241

Weber L, Bartek L, Brancoli P, Sjölund A, Eriksson M (2023) Climate change impact of food distribution: The case of reverse logistics for bread in Sweden. Sustain Prod Consum 36:386–396. https://doi.org/10.1016/j.spc.2023.01.018

Weidema BP, Pizzol M, Schmidt J, Thoma G (2018) Attributional or consequential Life Cycle Assessment: A matter of social responsibility. J Clean Prod 174:305–314. https://doi.org/10.1016/j.jclepro.2017.10.340

World Bank (2012) Global Monitoring Report 2012: Food Prices, Nutrition, and the Millennium Development Goals. International Monetary Fund and World Bank, Washington, DC. https://doi.org/10.1596/978-0-8213-9451-9

Zhang B, Mohammad J (2024) Sustainability of Perishable Food Cold Chain Logistics: A Systematic Literature Review. Sage Open 14:21582440241280455. https://doi.org/10.1177/21582440241280455

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