DOCTORAL THESIS

A multi-objective optimization approach for design and implementation of sustainable diets

Bashir Bashiri

TALLINNA TEHNIKAÜLIKOOL
TALLINN UNIVERSITY OF TECHNOLOGY
TALLINN 2025

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DOCTORAL THESIS
72/2025

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TAL TECH PRESS

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This dissertation was accepted for the defence of the degree Doctor of Philosophy in Food Science on 23/09/2025.

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Defence of the thesis: 23/10/2025, Tallinn

Declaration:
Hereby I declare that this doctoral thesis, my original investigation and achievement, submitted for the doctoral degree at Tallinn University of Technology has not been submitted for doctoral or equivalent academic degree.

Bashir Bashiri

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ISSN 2585-6898 (publication)
ISBN 978-9916-80-383-7 (publication)
ISSN 2585-6901 (PDF)
ISBN 978-9916-80-384-4 (PDF)
DOI https://doi.org/10.23658/taltech.72/2025

Bashiri, B. (2025). *A multi-objective optimization approach for design and implementation of sustainable diets* [TalTech Press]. https://doi.org/10.23658/taltech.72/2025

TALLINNA TEHNIKAÜLIKOOL
DOKTORITÖÖ
72/2025

Jätkusuutlike dieetide kavandamine ja rakendamine mitme-eesmärgilise optimeerimise abil

BASHIR BASHIRI

KIRJASTUS

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List of Publications

The list of the author's publications, based on which the thesis has been prepared:

I **Bashiri, B.**, Kaleda, A., Gavrilova, O., & Vilu, R. (2024). A Culturally Acceptable Shift in Diet to Reduce Land Footprint: An Optimization Study for Estonia. *Environmental Modeling & Assessment*, 1-15. https://doi.org/10.1007/s10666-024-09996-4

II **Bashiri, B.**, Kaleda, A., & Vilu, R. (2025). Integrating multi-criteria decision-making with multi-objective optimization for sustainable diet design. *Journal of Cleaner Production*, 500, 145233. https://doi.org/10.1016/j.jclepro.2025.145233

III **Bashiri, B.**, Kaleda, A., & Vilu, R. (2025). Sustainable diets, from design to implementation by multi-objective optimization-based methods and policy instruments. Frontiers in Sustainable Food Systems, 9, 1629739. https://doi.org/10.3389/fsufs.2025.1629739

Author’s Contribution to the Publications

Contributions to the papers in this thesis are:

I The author designed the study, collected the required data, performed land footprint calculation, developed the optimization model, analysed the results, and wrote the manuscript.

II The author was involved in study design, collected the required data, developed the optimization model, analysed the results, and wrote the manuscript.

III The author designed the study, conducted the literature review, and wrote the manuscript.

Preface

The global food system is a major contributor to environmental damage, greatly impacting greenhouse gas emissions, freshwater use, land use, acidification, and eutrophication. If current consumption and production habits continue, these environmental issues are likely to worsen over the next few decades. As a result, minimizing the environmental impact of our diets has become an urgent goal in achieving global sustainability.

At the same time, dietary choices play a critical role in public health. Many of today's health challenges are linked to poor dietary habits, including low intake of fruits, vegetables, nuts, and whole grains, and high consumption of red and processed meats. This double burden (environmental and health-related) underscores the need for dietary transitions that are not only environmentally sustainable but also nutritionally adequate.

While transitioning to more sustainable diets holds significant potential to address both environmental and health concerns, it is not without challenges. Diets that significantly reduce animal-based foods may result in nutritional deficiencies if not carefully designed. Moreover, proposed dietary changes often conflict with existing cultural norms, traditions, and individual preferences, which may hinder their acceptance by the general population. These observations reveal that the problem of sustainable diet design is inherently multidimensional. This calls for a more integrated and holistic approach to dietary planning and implementation.

Optimization methods have long been used to improve dietary design, with single-objective optimization offering valuable insights into isolated aspects such as environmental impacts, cultural acceptability, cost, or nutrient adequacy. However, when the complexity of the problem is fully acknowledged, it becomes clear that more advanced tools are needed. Multi-objective optimization (MOO) provides a powerful framework for navigating trade-offs, allowing multiple, often conflicting goals to be addressed simultaneously.

In this thesis, we apply MOO to the challenge of designing sustainable, healthy, and culturally acceptable diets. We introduce a novel approach that incorporates multiple environmental indicators into a single indicator, addressing a common limitation in previous studies that tend to focus on only one or two environmental footprints. Furthermore, we explore the implementation of the designed diet and investigate how policy instruments can facilitate adoption and overcome behavioural resistance.

Abbreviations

PB	Planetary Boundary
GHG	Greenhouse Gas
OR	Operations Research
MOO	Multi-Objective Optimization
BOO	Bi-objective optimization
MCDM	Multi-Criteria Decision-Making
LF	Land Footprint
LF_{int}	Internal Land Footprint
LF_{ext}	External Land Footprint
CLF	Consumption Land Footprint
CLF_{total}	Total Consumption Land Footprint
LCA	Life Cycle Assessment
NRD	Nationally Recommended Diet
SDG	Sustainable Development Goal
FBS	Food Balance Sheet

1 Background

1.1 Food system in the context of planetary boundaries

We live on a planet with defined operating boundaries, known as planetary boundaries (PBs) (Steffen et al., 2015). These planetary boundaries are defined to a large extent by physical processes of the Earth system. We can ensure safety for both people and the planet only by staying within planetary boundaries (Rockström et al., 2009). Human activities in the Anthropocene era[1] are placing unprecedented pressure on resources and have resulted in exceeding these boundaries. Scientists have identified nine planetary boundaries, and evidence collected suggests that human society has already exceeded six of these planetary boundaries (Richardson et al., 2023).

The current food system supplying food for human consumption is among the main contributors to the transgression of the planetary boundaries (Liao et al., 2023). GHG emissions, freshwater scarcity, eutrophication, land degradation, and biodiversity loss are among the environmental problems intensified by the food system (Poore & Nemecek, 2018). In 2015, food system emissions amounted to 18 gigatons CO_2 equivalent per year globally (1 gigaton = 10^9 tons), representing 34% of the total GHG emissions of human society. The largest contribution comes from agriculture and land use activities (71%), with the remaining being from supply chain activities (Crippa et al., 2021).

Supply-side and demand-side interventions could mitigate the environmental impacts of the food system (Rosenzweig et al., 2020). Supply-side interventions refer to closing yield gaps, agricultural expansion, and intensification (Scherer & Verburg, 2017). While demand-side interventions refer to changes in the consumption pattern (such as a diet change) (Garvey et al., 2021). Mitigating the environmental impacts of the food system requires fundamental changes in both the supply-side and demand-side.

Supply-side efforts are either associated with an increase in resource inputs (e.g., fertilizer, water, land) or are not sufficient to meet the global food demand by 2050 if current dietary patterns and the present rate of population growth continue. Moreover, currently, less affluent regions will expect a necessary growth in the consumption of diverse food products, including animal protein, to tackle food insecurity and malnutrition. Hence, demand-side interventions are also necessary. A shift toward healthy and sustainable eating patterns worldwide as a key demand-side measure is, therefore, imperative for feeding the global population within PBs.

1.2 Diet change could make the food system more sustainable

Diet change has important benefits in addressing food system impacts by changing both the quantity and structure of demand for imported and produced goods, practically in all countries of the world. Poore & Nemecek (2018) believe that today and probably in the future, dietary change can deliver environmental benefits on a scale not achievable exclusively by producers since it acts on all food supply chains irrespective of national origin.

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[1] The Anthropocene Epoch is a proposed geological epoch. It reflects the major impact of human activity on Earth's climate, ecosystems, and geology. It marks a shift from the Holocene, recognizing humans as the dominant force shaping the environment. These effects are global, long-lasting, and may be preserved in the geological record for millions of years (Lewis & Maslin, 2015).

Chen et al. (2022) argue that although a diet change has not been directly mentioned in the 17 Sustainable Development Goals (SDGs)[2] of the United Nations, the achievement of these goals is highly dependent on the dietary habits of people across the world. A global transition toward sustainable diets that are nutritionally adequate and environmentally sparing will be key to achieving several SDGs simultaneously.

1.3 Diet change could promote human health

Although there is a significant potential for dietary changes to mitigate environmental impacts, studies have shown that shifting towards sustainable diets that are rich in plant-based foods and low in animal-based products can improve public health (Aleksandrowicz et al., 2016; Garvey et al., 2021). The dietary change can reduce hidden costs stemming from health problems and could potentially reduce the mortality rate and risks (Lucas et al., 2023). The research-based evidence confirms the role of diets in determining mortality rates through their contribution to non-communicable diseases[3] (Afshin et al., 2019). The current diets of most people around the world are either lacking essential micronutrients or have a high environmental footprint, or both (Springmann et al., 2020). Although transitioning to healthier and eco-friendly diets can substantially decrease the environmental impacts of food consumption, it can lead to a lack of certain micronutrients, including vitamin B12, selenium, and calcium, and deteriorate health conditions (Beal et al., 2023). Hence, when making changes to diets, it is vital to adopt a holistic approach that considers both health and sustainability objectives to prevent any undesired trade-offs.

1.4 Optimization algorithms for sustainable and healthy diet design

Optimization is a mathematical approach used to identify the best solution to a problem by either minimizing or maximizing an objective function, subject to a set of constraints (Arora, 2015; McKelvey & Neves, 2021). It originates from the field of operations research (OR), which was initially developed to improve efficiency in industrial and logistic systems (Petropoulos et al., 2024). Over time, optimization techniques have evolved to address more complex, multidimensional challenges, including those related to sustainability (Sadollah et al., 2020) and public health.

In its simplest form, when the objective function and constraints are linear, the problem is referred to as linear optimization or linear programming (van Dooren, 2018). This class of problems can often be solved geometrically. For instance, consider an illustrative example where the objective is to maximize a linear function:

[2] The Sustainable Development Goals (SDGs) are a set of 17 global goals adopted by the United Nations on September 25, 2015, as part of the 2030 Agenda for Sustainable Development. They include 169 targets and 232 unique indicators aimed at addressing global challenges such as poverty, inequality, climate change, and environmental degradation (Carlsen & Bruggemann, 2022).

[3] Noncommunicable diseases (NCDs), also known as chronic diseases, are medical conditions that are typically of long duration and result from a combination of genetic, physiological, environmental, and behavioural factors. The main types include cardiovascular diseases, cancers, chronic respiratory diseases, and diabetes (Noncommunicable Diseases, WHO).

$$maximize\ Z = 5x + 4y, \qquad (1)$$

subject to the following constraints:

$$x + 2y \leq 8, \quad (2)$$
$$3x + y \leq 9, \quad (3)$$
$$x \geq 0, y \geq 0 \quad (4)$$

This problem can be visualized graphically (see **Figure 1**), where each inequality represents a boundary line, and the feasible region is the area where all constraints are simultaneously satisfied. The feasible region represents all feasible solutions that satisfy the given constraints. The optimal solution is found where the objective function reaches its maximum within this region, and in this case, at the point (2,3).

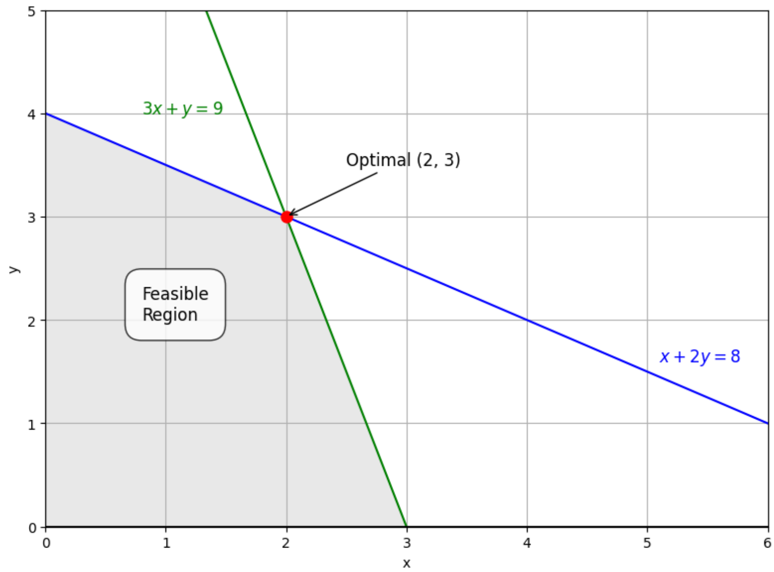

Figure 1: Graphical solution of the linear programming problem explained by equations 1,2,3, and 4 showing the feasible region and optimal solution.

However, not all optimization problems are linear. In many real-world cases, the objective function or constraints may be nonlinear, making graphical solutions impractical (Sharma & Kumar, 2022). These problems require computational tools and specialized solvers for their solution.

1.4.1 Multi-objective optimization (MOO)

Multi-objective optimization (MOO) is a mathematical approach used to identify optimal solutions that simultaneously maximize or minimize more than one objective (Deb, 2011; Gunantara, 2018). This type of optimization is particularly useful in real-world applications where trade-offs between conflicting goals are necessary (Aghaei Pour et al., 2024; Deb, 2011; Rangaiah et al., 2020; Sharma & Kumar, 2022), for example, balancing cultural acceptability with environmental sustainability in diet design (see **Publication III**).

Instead of solving multiple optimization problems separately, MOO enables integrated decision-making by considering all objectives within a single framework. It provides decision-makers with a set of solutions, rather than a single optimum, supporting informed choices based on preferences or priorities.

In MOO, the objective function is represented as a vector of functions, with each component corresponding to a different goal:

$$min/\max \qquad f_1(x), f_2(x), \dots., f_n(x), \qquad (5)$$

subject to constraints on the decision variables x. Here, x represents the vector of decision variables, and n is the number of objective functions.

1.4.2 Weighted sum method

One of the most widely used and straightforward techniques for solving MOO problems is the weighted sum method. In this approach, multiple objective functions are combined into a single composite objective function by assigning a weight to each objective:

$$F(x) = w_1 f_1(x) + w_2 f_2(x) + \dots + w_n f_n(x), \qquad (6)$$

where:

- $w_1, w_2, \dots, w_n$ are weights factors assigned to each objective function,
- $\sum_1^n w_i = 1$

These weights reflect the relative importance or priority of each objective. A higher weight indicates a higher priority. By varying the weight combinations, different trade-offs can be explored, and multiple optimal solutions can be generated. Repeating this process with different sets of weights helps map the trade-off figure (Pareto front) and provides a range of viable solutions from which decision-makers can choose based on specific goals or constraints.

1.4.3 Pareto front: Option for the presentation and decision-making

In MOO, the best solution is usually found when improving one objective cannot be done without worsening the other. This condition is known as Pareto optimality. The collection of these best possible solutions is called the Pareto optimal set.

A solution that is not outperformed by any other in all objectives is known as a non-dominated solution or a Pareto efficient solution (Deb, 2011; Gunantara, 2018; Null et al., 2021; Sharma & Kumar, 2022). When optimizing two objectives, these non-dominated solutions can be visualized using a Pareto front, which appears as a curve or boundary on a two-dimensional graph, showing the trade-offs between the two competing objectives (**Figure 2**).

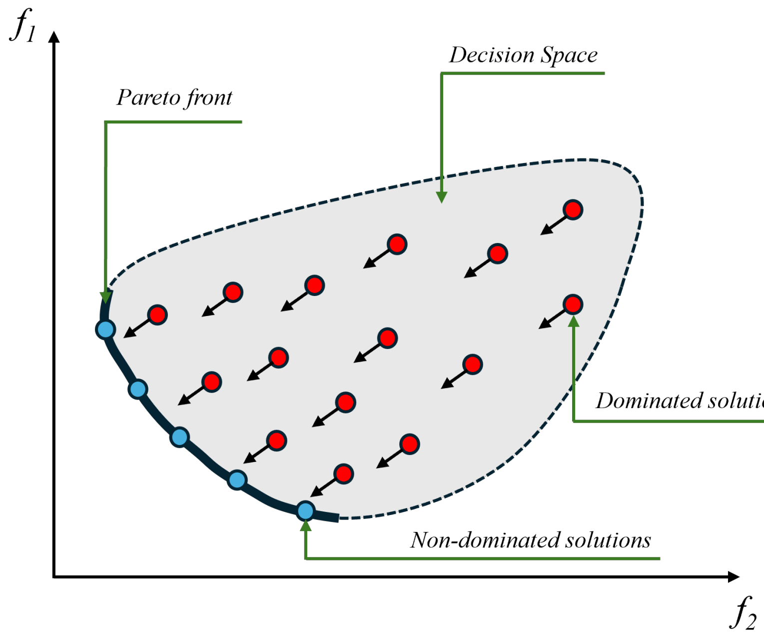

Figure 2: Illustration of Pareto optimality in MOO.

The shaded region in **Figure 2** represents the decision space, defined by the objective functions. The red points inside this space represent dominated solutions, which can be improved in at least one objective without worsening others. As optimization progresses, these dominated solutions are replaced by better alternatives until no further improvement is possible. The resulting non-dominated solutions lie on the boundary of the decision space and form the Pareto front.

1.5 Complexities associated with MOO models

Optimization problems with many objectives introduce some difficulties.

- The proportion of equally good solutions according to the Pareto front increases rapidly with the number of objectives, hence making the final selection complicated. This difficulty is called the deterioration of searchability (Ruppert et al., 2022).
- Another challenge in MOO is the presence of outliers or dominance-resistant solutions. These are solutions with a poor value in at least one objective but with near-optimal values in the others (Jaimes & Coello, 2015; Wang et al., 2023).
- The number of points required to represent a Pareto front accurately in MOO increases exponentially with the number of objectives. So, in a problem with many objectives, the generation of the Pareto front needs high resource consumption and might be time-consuming. This difficulty is known as the curse of dimensionality (Jaimes & Coello, 2015; Ma et al., 2020).
- It is not possible to visualize a Pareto front with more than three objectives (dimensions); therefore, this hinders the decision-making process (Alvarado-Ramírez et al., 2022).

1.6 MCDM could help ease MOO-associated complexities

Multi-Criteria Decision Making (MCDM) is a well-established area within OR that focuses on supporting complex decision-making (Barretta et al., 2023). It provides a structured way to evaluate and compare multiple alternatives based on several criteria, helping decision-makers identify the most suitable option according to their preferences (Mardani et al., 2015).

In many real-life situations, decision-making can be extremely challenging. This is often due to the presence of multiple conflicting criteria. For example, an option might be cost-effective but have lower performance, while another might offer better results but be more expensive (Hadian & Madani, 2015). Additionally, decision-makers frequently face information overload, making it hard to process all the available data (Barretta et al., 2023). Uncertainty about future outcomes and personal biases can also make the process more difficult and less objective (Hodgett & Siraj, 2019a).

Furthermore, without a clear and systematic way to compare alternatives, it becomes hard to understand the trade-offs involved or justify a final decision. These challenges often exceed the limits of intuitive or purely experience-based decision-making.

This is where MCDM becomes especially valuable. It simplifies complex problems by breaking them down into smaller components, such as defining the available options, identifying relevant criteria, assigning importance (weights) to each criterion, and evaluating how well each option meets the criteria. This structured process makes decision-making more transparent, rational, and consistent.

Given the challenges associated with high-dimensional MOO problems, MCDM methods can serve as effective tools for aggregating multiple objectives into a single score. This approach helps reduce the number of objectives, thereby simplifying both the optimization and decision-making processes (Ferdous et al., 2024; Wheeler et al., 2018).

1.7 Literature review of the application of MOO for sustainable diet design

Given the significant pressure that global agriculture places on planetary boundaries and the associated challenges, a critical question arises: how can we ensure future food security without compromising the resilience of the Earth system? Gerten et al. (2020) demonstrate that nearly half of current global food production depends on practices that transgress these environmental limits. If PBs were strictly adhered to, the existing food system could provide a nutritionally adequate diet (2,355 kcal per capita per day) for only 3.4 billion people. However, their findings also suggest that through changes in both production and consumption patterns, the food system could be transformed to sustainably support up to 10.2 billion people within the analysed planetary boundaries. Key requirements for this transformation include the spatial redistribution of cropland, improved management of water and nutrients, a reduction in food waste, and dietary change. This thesis places particular emphasis on dietary change as a pivotal strategy for aligning the global food system with PBs. Jalava et al. (2016) investigated the combined effects of dietary change and food loss reduction on global water use and water scarcity. Their findings indicate that implementing both strategies together could reduce global water consumption significantly, resulting in a 28% decrease in the water scarcity index[4].

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[4] Water scarcity index quantifies the availability of water resources relative to human needs, often expressed as the amount of renewable freshwater available per person per year(Understanding Water Scarcity: Definitions and Measurements | Global Water Forum).

Notably, dietary change alone has the potential to reduce both blue and green water[5] consumption by approximately 18%. An important conclusion of their study is that, at the global scale, the effects of dietary change and food loss reduction are synergistic, with food loss reductions being more effective when implemented alongside dietary changes. This suggests that the maximum impact on water sustainability can be achieved when any intervention is accompanied by a shift in dietary patterns.

Research consistently shows that reducing meat consumption is the most effective option for lowering the environmental impact of diets across all age-gender groups, with meat from ruminants having the largest environmental impact per unit for most indicators (Chen et al., 2019; Clark et al., 2020; Kramer et al., 2017; Springmann et al., 2018; Tilman & Clark, 2014). It has been shown that changing diet towards the consumption of less animal products offers the potential to save water resources up to the amount currently required to feed 1.8 billion additional people globally (Jalava et al., 2014).

Although shifting to plant-based diets, for example, can lead to globally significant GHG benefits and reductions in other environmental footprints like nitrogen and phosphorus application and cropland use (Chen et al., 2019; Clark et al., 2020; Springmann et al., 2018; Tilman & Clark, 2014), Kim et al. (2020) concluded that reducing the overall consumption of animal-based foods is generally more climate-friendly than eliminating meat. This is because eliminating meat often necessitates a significant increase in the consumption of plant-based products to meet nutritional needs, which can lead to higher overall environmental footprints due to the quantity and types of plant-based foods required. From a societal perspective, complete meat elimination also raises concerns regarding public acceptability, as such drastic dietary shifts may not be widely embraced. Therefore, it is essential to identify balanced dietary solutions that are both environmentally sustainable and culturally acceptable.

Nationally recommended diets (NRDs) are a prominent tool that is designed to support cultural acceptability in food consumption. Studies show that the adoption of NRDs can result in combined benefits, including a 36% reduction in environmental footprint, 33% savings in food expenditure, and 2.67% lower adverse health outcomes compared to current diets. Although some facts suggest NRDs could become even more sustainable. For example, Behrens et al. (2017) argue that '*Little or no attention is placed on the environmental impacts within NRDs'*. However, in recent years, there has been an increasing focus on the environmental impacts of food consumption in NRDs (Trolle et al., 2024). Therefore, there is still more room for NRD for the inclusion of sustainability while remaining culturally acceptable.

Dietary optimization has been recognized as a valuable tool to find sustainable and culturally acceptable dietary solutions. Recent studies using dietary optimization techniques have shown that limiting meat consumption can reduce climate impacts by up to sevenfold and increase healthy life (life without any health complaints) by as much as 700 minutes per week (Gebara et al., 2025). Mazac et al. (2022) demonstrated that replacing animal-based foods in current diets with novel food alternatives (plant-based alternatives, cultured meat, insect-based meat) can reduce all measured environmental impacts by over 80%, while still meeting nutritional requirements and realistic

[5] Blue water is the water that flows on the surface (such as rivers and streams) or underground, and can be stored in aquifers, lakes, or reservoirs. Green water is the part of rainfall that soaks into the soil as moisture or stays briefly on the soil or plants, before eventually returning to the atmosphere through evaporation and transpiration (Falkenmark & Rockström, 2006).

consumption constraints. This is a highly significant finding, as food technologists are increasingly developing novel food alternatives (such as microbial- or plant-based products) to replace conventional animal products. However, it is essential to ensure that these alternatives are not only similar in texture and taste but also nutritionally adequate.

However, using single-objective optimization methods can lead to extreme outcomes, such as the complete exclusion of red meat. For example, Chaudhary & Krishna (2019) demonstrated that an optimized diet for Estonia resulted in zero red meat consumption, an outcome that may be unrealistic in practice.

Some studies have employed MOO to develop sustainable and nutritionally balanced diets, often aiming to minimize environmental impact, cost, and nutritional inadequacy while maintaining cultural acceptability (Donati et al., 2016; Mirzaie-Nodoushan et al., 2020; Muñoz-Martínez et al., 2023). A scoping review on the studies using MOO for sustainable diet design is provided in **Publication III** (Bashiri et al., 2025b).

The following key conclusions can be drawn from this literature review:

- Dietary change is a crucial lever for aligning the global food system with planetary boundaries.
- While transforming food production practices and reducing food loss are important, the most substantial and synergistic environmental and health benefits emerge when these strategies are combined with shifts in consumption patterns.
- However, care must be taken to avoid overly prescriptive or culturally unrealistic recommendations, such as the complete elimination of red meat.
- Optimization is a widely accepted tool for diet design; however, given the multidimensional nature of diets, MOO provides a more comprehensive and effective approach for identifying balanced and practical solutions. The multidimensional nature of dietary changes would be difficult to grasp without MOO, which effectively balances the often-competing objectives.

1.8 What is a culturally acceptable diet?

The concept of cultural acceptability is included in the FAO's definition of sustainable diets (Burlingame & Dernini, 2012):

> Sustainable Diets are those diets with low environmental impacts that contribute to food and nutrition security and healthy life for present and future generations. Sustainable diets are protective and respectful of biodiversity and ecosystems, culturally acceptable, accessible, economically fair and affordable, nutritionally adequate, safe and healthy, while optimizing natural and human resources.

The terms cultural acceptability and cultural appropriateness are generally used interchangeably in the literature. Less frequently, the terms social acceptability and social appropriateness are also used.

House et al., (2023) have identified six key themes that represent different ways in which the cultural acceptability of food consumption is conceptualised. These themes are summarised in **Table 1**, each with a brief explanation.

Table 1. Summary of six conceptual themes of cultural acceptability in food consumption, as identified by House et al. (2023)

Themes	Explanation
Conforming to existing dietary customs	The customary food practices of a particular group of people are considered inherently culturally acceptable.
Substitutability	Food that provides a satisfactory substitute for a conventional equivalent
Reception and Integration	Usually, it is defined by answering a binary (Yes/No) question, such as, Would you eat this, or wouldn't you?
Alignment with cultural preferences	Foods that are preferred as a result of an individual's socio-cultural background.
Context of eating	This theme focuses on two main themes: what is eaten and how it is eaten. This theme says that cultural acceptability is not an inherent property of food, but rather it is shaped by meal structure and eating situation.
Context of food acquisition and preparation	This theme shows that cultural acceptability depends not just on the food itself, but also on how people get and prepare it. When people cannot choose their food, rely on food aid, or use methods seen as socially unacceptable, the food is often experienced as culturally inappropriate.

Among these six themes, the idea of conforming to existing dietary customs is the most widely applied in dietary optimisation studies. In this context, cultural acceptability is operationalised as minimising deviation from current diets. These current diets are typically represented using national dietary data, which provide the baseline input for optimisation models.

For instance, if the current per capita consumption of a food item 1 is denoted by x_1 and the consumption of the same food item in the optimised diet is x_1^* the relative linear deviation can be calculated as:

$$\frac{x_1^* - x_1}{x_1} \qquad (7)$$

For a diet consisting of n food items, the total deviation can be expressed as:

$$\frac{x_1^* - x_1}{x_1} + \frac{x_2^* - x_2}{x_2} + \cdots + \frac{x_n^* - x_n}{x_n}, \quad (8)$$

which can be written in compact form as:

$$\sum_{1}^{n} \frac{x_i^* - x_i}{x_i}, \quad (9)$$

In the linear deviation form, while it provides a clear indication of the direction of change, positive and negative deviations can offset each other, potentially underestimating the overall deviation. To address this, the squared deviation is often used, as it prevents cancellation and places greater emphasis on larger changes.

$$\sum_{1}^{n} (\frac{x_i^* - x_i}{x_i})^2 \quad (10)$$

The squared relative deviation tends to favour larger changes in food groups that are already widely consumed, while disproportionately penalizing changes in food groups with low baseline consumption.

1.9 Research gaps

There is a gap in developing optimization methods that achieve sustainability while maintaining culturally acceptable diets and aligning them with existing dietary patterns. Although MOO offers a potential solution, limited research has explored its application in sustainable diet design. There is a need for methods that effectively balance multiple objectives without causing drastic changes to the diet. Addressing this gap would allow for the creation of more practical and acceptable sustainable diets (**Publication I**).

Another gap in current research is the limited focus on environmental indicators. Most studies examine only one or two factors, despite sustainability involving multiple, often conflicting, environmental goals. There is a gap in combining multiple environmental indicators into the diet design process to provide a more complete assessment of sustainability. While including multiple sustainability indicators is important, it can also make the optimization process more complex. There is a lack of methods that balance several objectives without overly complicating the problem (**Publication II**).

After designing a healthy and environmentally friendly diet, a key gap lies in understanding how to support its practical adoption. Social and cultural barriers often hinder individual dietary change, yet these factors remain insufficiently explored. Additionally, the role of policies in facilitating large-scale dietary transitions is under-researched. Addressing these gaps is essential to promote effective and equitable implementation strategies (**Publication III**).

2 The aims and the structure of this dissertation

The primary aim of this dissertation is to advance the integration of sustainability into diet design while ensuring nutritional adequacy and cultural acceptability and facilitate the successful implementation of the diet. To achieve this, the research:

- Uses MOO as a method to design a culturally acceptable and environmentally sustainable diet.
- Investigates the inclusion of multiple environmental indicators in sustainable diet design through the integration of MCDM and MOO.
- Explores the barriers in the adoption of a sustainable diet and investigate policy tools to address them.

To address the aims, this thesis is structured into a) design and b) implementation phases according to Figure 3. The design phase is approached using MOO models, while the implementation phase focuses on identifying social barriers and proposing effective policy instruments for the implementation.

During the design phase, two optimization models were created. The first model, described in **Publication I**, aimed to develop a culturally acceptable diet with the smallest land footprint. In this model, land use was the only environmental indicator considered. The second model, discussed in **Publication II**, expanded the scope by including five environmental indicators, providing a more comprehensive framework for designing sustainable diets.

The implementation phase, presented in **Publication III**, involved a systematic literature review to identify internal and external social barriers that hinder the adoption of sustainable diets, and a set of policy tools was proposed to overcome them. This part of the thesis bridges the gap between theoretical diet optimization and real-world implementation, emphasizing the need for multi-level, evidence-based strategies to facilitate the dietary transition.

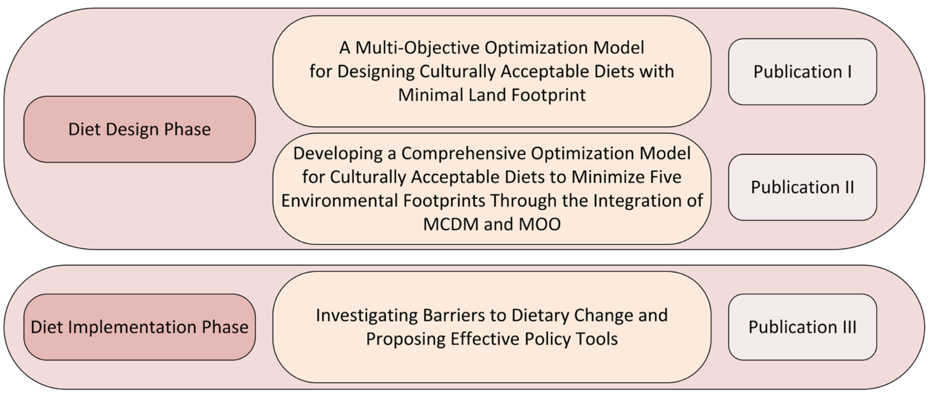

Figure 3. The structure of the thesis

3 Materials and methods

3.1 Reference diet of Estonians

Daily per capita food consumption data (g cap^{-1} d^{-1}) for 2018 and 2021, sourced from the FAOSTAT Food Balance Sheet (FBS) (FAOSTAT)(FAOSTAT), served as a reference diet for the Estonian population. The nationally recommended diet (NRD) was provided by the National Institute of Health Development (NIHD) (in Estonian: Tervise Arengu Instituut)(Pitsi et al., 2015). The characteristics of the reference diet associated with **Publications I** and **II** are provided in Appendices 1 and 2.

3.2 Grouping of food items

The FBS dataset from FAOSTAT includes 74 different food items, but we excluded 26 items with zero or negligible intake for this study. The remaining 48 food items were then grouped into 14 categories, including cereals, tubers, pulses, nuts, vegetables, vegetable oils, fruits, sugar, red meat[6], poultry, eggs, milk, fish, and alcoholic beverages. The list of food groups and items is provided in Appendix 1, SI Table 1.

3.3 Culturally acceptable diet to reduce land footprint (Publication I)

In this part, the aim is to design a diet that has a lower land footprint compared to the reference diet but also is acceptable for Estonian people and is nutritionally adequate using the MOO approach. This problem has two objectives to be minimized and constrained by nutritional constraints, as shown in **Figure 4**.

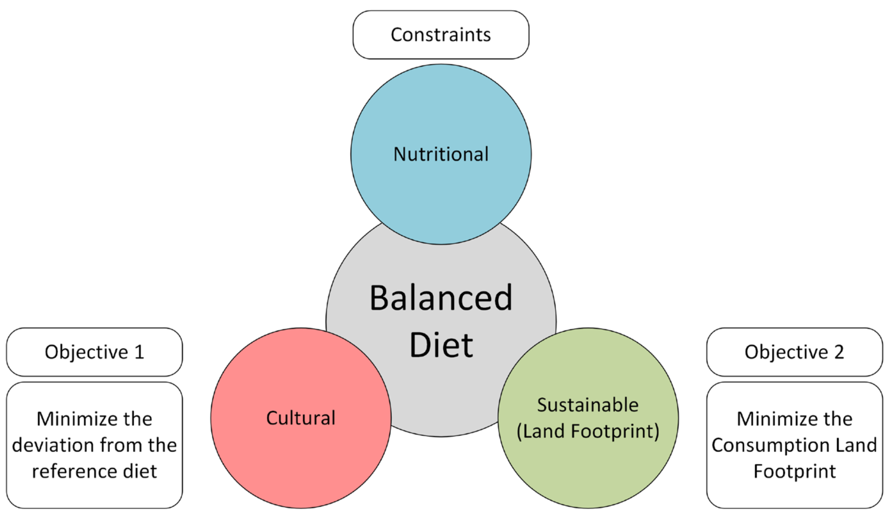

Figure 4. Illustration of the MOO problem for designing a culturally acceptable diet to reduce land footprint.

[6] Red meat group includes bovine meat, goat & mutton, and pig meat. According to FAOSTAT, the Estonian average daily intake of red meat in 2018 was 126 g cap^{-1} d^{-1}.

3.3.1 Land footprint estimation

To conduct this analysis, we require the land footprint (LF) of food groups. The LF represents the amount of land needed to produce 1 kg of agricultural product. In **Publication I**, the land footprint of food consumed in Estonia is calculated by distinguishing between land used for domestically produced food (internal land footprint, LF_{int}) and land used for imported food (external land footprint, LF_{ext}). While the methodology is discussed in detail in **Publication I**, a brief explanation is also provided here and illustrated in **Figure 5**.

The LF calculation follows a bottom-up approach, enabling the assessment of individual food products in relation to national consumption patterns. For crop-based products such as cereals, fruits, and vegetables, LF is calculated as the inverse of production yield. LF_{int} is based on production yields in Estonia, while LF_{ext} relies on global average yields (de Ruiter et al., 2017; Osei-Owusu et al., 2019).

For animal products, LF includes both cropland and grassland components. Instead of calculating total land use directly, the study allocates existing grassland and feed cropland resources to different animal products. LF_{int} is estimated using feed conversion ratios (FCRs) and the share of grass in livestock diets. Total grassland and feed cropland areas in Estonia are distributed among livestock based on these factors. The analysis covers pig meat, poultry, beef, mutton, milk, and eggs; fish is excluded.

To account for imported animal products and feed, LF_{ext} includes the cropland required for imported feed and the land used for raising livestock abroad. A detailed trade matrix from FAOSTAT identifies the origins of Estonia's imports, including major suppliers such as Denmark, Finland, Germany, and Poland. The same allocation method used for domestic production is applied to estimate LF_{ext}. List of countries contributing to the import of animal products in Estonia is provided in Appendix 1, SI Table 2.

LF values for each food group are calculated as a weighted average of LF_{int} and LF_{ext}, based on the share of domestic versus imported sources and based on the relative abundance of food items in each food group. For example, according to FAOSTAT, red meat consumption in Estonia comprises 80% pork, 19% beef, and 1% mutton; the total LF of red meat is computed by weighting the LFs of each type accordingly (FAOSTAT).

Finally, the total consumption land footprint (CLF_{total}) is calculated by multiplying the amount of each consumed food item by its respective LF. This provides a comprehensive estimate of the land resources linked to Estonia's dietary patterns and supports the development of the objective function for the analysis.

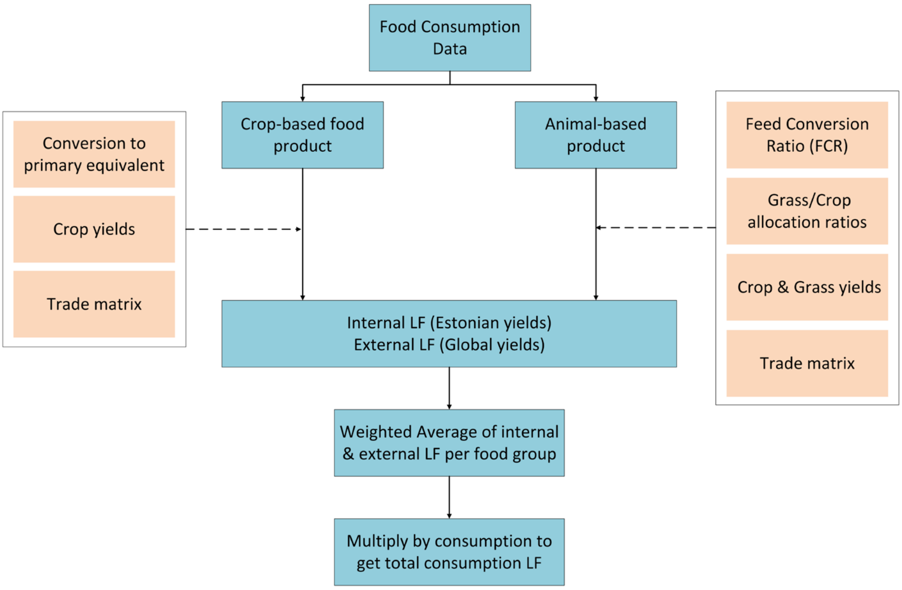

Figure 5. Flowchart of the Land Footprint (LF) calculations.

3.3.2 Formulation of the optimization problem to minimize land footprint

In this case, to obtain an optimized diet, the goal is to minimize the CLF_{total} while minimizing the deviation from the reference diet. Since this is an MOO problem, we used a multi-objective nonlinear programming method. The objective function was constructed as follows:

$$min[\, x^*] = w_1 \sum_{1}^{n} (\frac{x_i^* - x_i}{x_i})^2 + w_2 \sum_{1}^{n} (x_i^* \times LF_i), \quad (11)$$

where x_i and x_i^* represent the current and optimized consumption of the food group i respectively and LF_i is the land footprint of the food group i. The first part of the equation (11) is the sum of the squared deviations between the current and optimized consumption of each food group (Arnoult et al., 2010). The second term is used to calculate the CLF_{total} of the optimized diet. The first and second parts of equation (11) are multiplied by weight factors $w_1, w_2 > 0$, $w_1 + w_2 = 1$ which enables us to build a Pareto optimal front by varying the weights.

3.4 Culturally acceptable diet to reduce five environmental footprints (Publication II)

Here, we expanded the scope of sustainability by considering five environmental footprints. Here we have two options to do that. We can use the classical MOO, or we can combine the classical MOO with MCDM. As shown in **Figure 6**, first, a classical MOO is developed to simultaneously minimize all five footprints, though this method is computationally more complex. To simplify the problem, the five environmental indicators are aggregated into a single composite index, transforming the problem into a bi-objective optimization (BOO) that balances environmental impact with cultural acceptability.

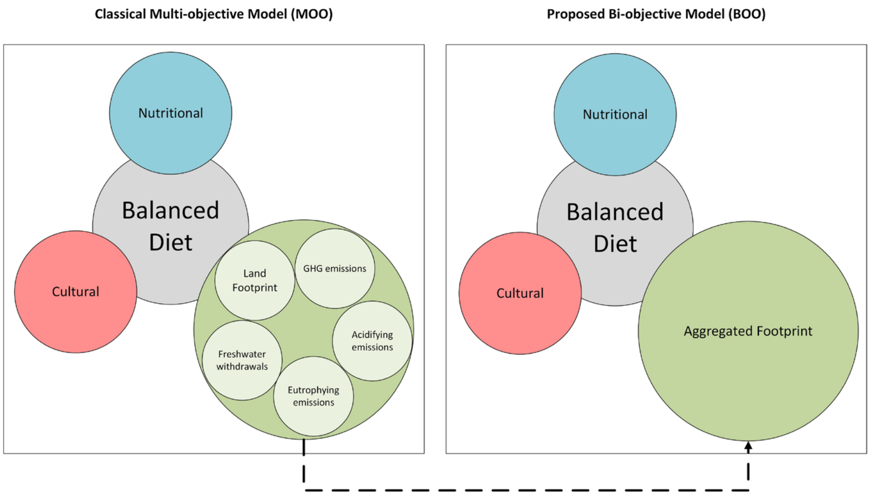

Figure 6. Illustration of an optimization problem for designing a culturally acceptable diet aimed at reducing five environmental footprints.

3.4.1 Footprint preparation and statistical analysis prior to optimization

We utilized a comprehensive dataset generated by Poore & Nemecek (2018), which encompasses life cycle assessment (LCA) data for 43 food items and covers five environmental footprints: land use (m^2 FU^{-1}), GHG emissions (kg CO_2 eq FU^{-1}), acidifying emissions (g SO_2eq FU^{-1}), freshwater withdrawals (L FU^{-1}), and eutrophying emissions (g PO_4^{3-}eq FU^{-1}). The FU is 1 kg of product. The list of environmental footprints, and associated uncertainties, is provided in Appendix 2. The uncertainties in this dataset are reported by statistical characteristics: mean, median, and 5th, 10th, 90th, and 95th percentile values. However, according to Poore & Nemecek (2018), the distribution of footprints is multi-modal. We determined that the log-normal distribution provided a reasonable approximation for this study and thus fitted the log-normal function to the published percentile values to model the distributions of the footprints for individual food items. Water footprint was modelled using the triangular distribution. Both fit distributions were truncated at the 5th and 95th percentiles to set minimum and maximum bounds. The footprint of a group consisting of multiple food items was calculated by resampling the fitted distributions, with the number of samples weighted by the share of the food item in the group. The minimum, maximum, and mode of these resampled distributions were then used in further calculations.

3.4.2 Formulation of the optimization problem to minimize five footprints

For the classical MOO model, where all footprints were implemented individually, the following objective function was developed:

$$min[\,x^*] = w_1 \sum_1^n (\frac{x_i^* - x_i}{x_i})^2 + w_2 \sum_1^n (x_i^* \times LF_i) + w_3 \sum_1^n (x_i^* \times GHG_i)$$
$$+ w_4 \sum_1^n (x_i^* \times Acid_i) + w_5 \sum_1^n (x_i^* \times Eutr_i) + w_6 \sum_1^n (x_i^* \times WF_i)\,, \quad (12)$$

where LF_i, GHG_i, $Acid_i$, $Eutr_i$ and WF_i are land use, GHG emission, acidifying emission, eutrophying emission, and freshwater withdrawals of food group *i*, respectively, and x_i and x_i^* are the current and optimized consumption.

The first term in equation 8 is the cultural acceptability term. All terms are correlated by weight factors $w_1, w_2, w_3, w_4, w_5, w_6 > 0$, $w_1 + w_2 + w_3 + w_4 + w_5 + w_6 = 1$.

3.4.3 Integrating MOO with MCDM

We propose a method to reduce the complexity in equation 12 while keeping the comprehensiveness of the optimization model. The proposed method is based on using MCDM. We want to summarize five environmental footprints into one single score. So that equation 12 would be shorter. The proposed method is based on using MCDM. We used the SURE MCDM method (Hodgett & Siraj, 2019a) as shown in **Figure 7**. This is a good method for MCDM under uncertainty. The mathematical background of the SURE method is explained in Appendix 2.

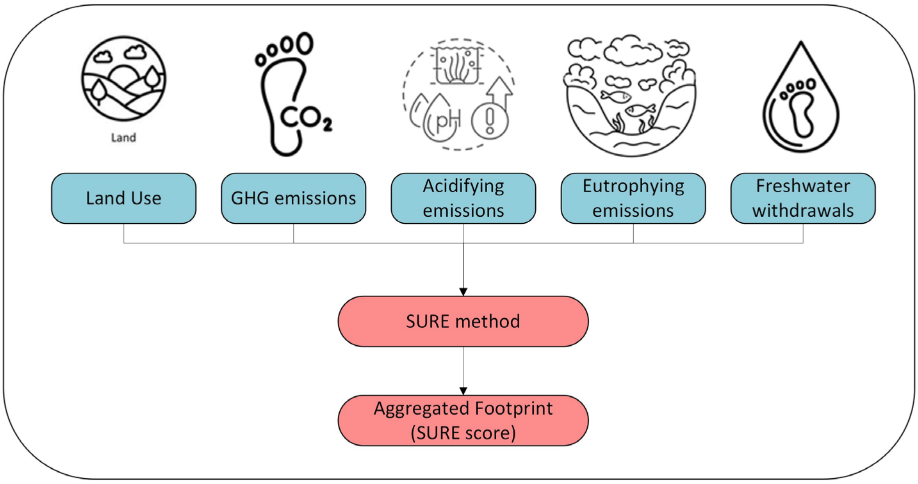

Figure 7. Aggregating five environmental footprints into one aggregated footprint by using the SURE MCDM method.

In this study, the lower and upper limits of the environmental impact distribution were set as the minimum and maximum values, while the most common value in the data was used as the expected impact in the SURE method.

Using the aggregated footprint (SURE score), equation 12 could be shortened, and the model could be converted to a bi-objective optimization model (BOO):

$$min[\, x^*] = w_1 \sum_{1}^{n} (\frac{x_i^* - x_i}{x_i})^2 + w_2 \sum_{1}^{n} (x_i^* \times SURE\_score_i) \,, \quad (13)$$

where x_i and x_i^* represent the current and optimized consumption of the food group i, respectively.

3.5 Nutritional constraints

To ensure that the optimized diet aligns with nutritional recommendations, the objective functions were constrained using values calculated by Springmann et al. (2018) and reported by Chaudhary & Krishna (2019). Carbohydrate intake was restricted to provide 50% to 60% of total dietary energy, following Estonian dietary guidelines, which are based on Nordic recommendations (Pitsi et al., 2015). The Estonian guidelines specify energy requirements ranging from 1,400 to 3,600 kcal, with 2,400 kcal selected as a representative average within this range. To maintain cultural acceptability, the consumption of alcoholic beverages was held constant (Chaudhary & Krishna, 2019). In total, 20 constraints were applied to the objective function, with detailed values presented in **Table 2**. It is important to note that these nutritional constraints reflect recommended intake levels. As outlined by Springmann et al. (2018) these values are based on WHO guidelines and represent an average across all adult age and gender groups.

We utilized the average values of energy content and 18 essential nutrients per food group (e.g., grams of protein per 1 gram of red meat) from the study by Gephart et al. (2016), which are based on the United States Department of Agriculture National Nutrient Database (USDA) (USDA National Nutrient Database for Standard Reference).

Table 2. Nutritional constraints applied in diet optimization. Adapted from Bashiri et al. (2024) with permission from Springer Nature.

Constraint	**Value**
Energy	≥ 2400 kcal cap^{-1} day^{-1}
Proteins	≥ 52 g cap^{-1} day^{-1}
Carbohydrates (% total energy)	50–60
Fiber, total dietary	≥ 29 g cap^{-1} day^{-1}
Calcium	≥ 520 mg cap^{-1} day^{-1}
Iron	≥ 17 mg cap^{-1} day^{-1}
Magnesium, Mg	≥ 250 mg cap^{-1} day^{-1}
Phosphorus, P	≥ 752 mg cap^{-1} day^{-1}
Potassium, K	≥ 3247 mg cap^{-1} day^{-1}
Zinc, Zn	≥ 6.1 mg cap^{-1} day^{-1}
Vitamin C	≥ 42 mg cap^{-1} day^{-1}
Thiamin	≥ 1.1 mg cap^{-1} day^{-1}
Riboflavin	≥ 1.1 mg cap^{-1} day^{-1}
Niacin	≥ 14 mg cap^{-1} day^{-1}
Vitamin B6	≥ 1.2 mg cap^{-1} day^{-1}
Folate, DFE[a]	≥ 364 µg cap^{-1} day^{-1}
Vitamin B-12	≥ 2.2 µg cap^{-1} day^{-1}
Vitamin E (alpha-tocopherol)	≥ 10 mg cap^{-1} day^{-1}
Vitamin K (Phylloquinone)	≥ 80 µg cap^{-1} day^{-1}
Alcoholic beverages	Current level (constant)

[a] Dietary Folate Equivalent

4 Results and discussion

A summary of the findings of the **publications I, II, and III** is presented in this section. More detailed discussions are available in the papers

4.1 Footprint analysis of the Estonian reference diet

To contextualize the environmental impact of dietary consumption in Estonia, it is essential to establish a baseline understanding of the current consumption-related environmental footprints. This baseline serves as a reference point against which potential improvements can be assessed. The environmental footprint of the average Estonian diet has been analysed in **Publications I** and **II**. In **Publication I**, we calculated the consumption land footprint (or Land use) using footprint values derived in **Publication I**.

Publication II expanded this analysis by evaluating five types of consumption footprints based on the values reported by Poore & Nemecek (2018). These results were further compared with similar studies conducted in Nordic countries, including Sweden, Denmark, Finland, Iceland, and Norway, as well as other countries such as Portugal and the United States, and are provided in **Table 3**. Despite variations in the definitions of certain footprint categories, a direct comparison is feasible. Furthermore, the results are evaluated against two PBs, providing a broader context for sustainability assessment.

There are some variations in the land use calculations between **Publications I** and **II**. In **Publication I**, we assessed the land footprint of food consumption in Estonia using a land allocation approach that considered both imported and locally produced food products, based on the consumption and trade matrix of a single year (2018). In contrast, **Publication II** relied on a database derived from a global LCA analysis taking into account the cradle-to-grave system boundary. Given the several factors that introduce uncertainties into LCA results, we also performed statistical analyses on this database to make it more suitable for our model. Specifically, we generated distributions and employed the mode of these distributions (the most probable values) for footprint analysis. Carvalho et al. (2023) investigated the effects of using different LCA databases on the food consumption footprints in Portugal and observed notable variations. In addition to methodological differences in database preparation, the varying structures of the datasets required the use of different approaches to link the environmental footprints of foods with the food consumption data.

Overall, the comparative analysis demonstrated a high degree of consistency across different estimations, though some variation was observed due to methodological differences and data uncertainties. Estonia's per capita GHG emissions fall within the range observed in Nordic countries, being higher than those of Denmark but lower than those of Iceland, Finland, and Norway. Notably, the findings indicate that the Estonian diet exceeds the PB for land use by approximately 40% and for GHG emissions by 200%, underscoring its significant environmental impact. These results align with the conclusions drawn by Hallström et al. (2022) in which they assessed the environmental impacts of diets across six impact categories, comparing them to planetary boundaries and concluding that dietary impacts exceeded these boundaries in all categories. A detailed discussion is provided in **Publication II**.

Table 3. Environmental impacts of the Estonian diet based on FAOSTAT data on food consumption. The values are compared to values reported in the literature.

	GHG emissions (kg CO_2 eq cap^{-1} d^{-1}) *	Land use (m^{2}cap^{-1} d^{-1})	Acidifying emissions (g SO_2 eq cap^{-1} d^{-1})	Eutrophying emissions (g PO_4^{3-}eq cap^{-1} d^{-1})	Freshwater withdrawals (L cap^{-1} d^{-1})
Estonian reference diet (**Publication II)**	5.32	6.49	45.82	27.11	1352.17
Estonian reference diet (**Publication I)**	---	7.97	---	---	---
Estonian NRD **(Publication I**)	---	7.68	---	---	---
Finland (Saarinen et al., 2023)	6.02	---	---	---	---
Iceland (Guðmannsdóttir et al., 2024)	5.58	---	---	---	---
Norway (Abadie et al., 2016)	6.75	---	---	---	---
Denmark (Trolle et al., 2022)	4.4	---	---	---	---
Sweden (Hallström et al., 2021)	6.01	7.31	---	---	---
Portugal (Carvalho et al., 2023)	6.17 (4.46–8.41)	13.45 (9.22–19.41)	39.7 (30.0–51.4)	34.0 (24.9–45.2)	855 (674–1056)
Average Americans (Afrouzi et al., 2023)	6.71	---	---	---	---
Planetary boundaries (Hallström et al., 2022)	1.77 (1.67-1.92)	4.62 (3.91-5.33)	---	---	---

*Kilogram carbon dioxide equivalent per capita per day

4.1.1 Contribution analysis of food groups in the footprints

The contribution of food groups to the CLF_{total} of the reference diet (average Estonian diet) and NRD has been assessed in **Publication I**. As shown in **Figure 8**, for the reference diet, milk products contributed the largest share (37%) to CLF_{total} followed by red meat (24%). Altogether, for the reference diet, animal-based products (excluding fish) accounted for 67% of the CLF_{total}, indicating their dominant role in land use. For the NRD, although milk would still be the highest contributor to the CLF_{total}, cereals would be the second most important food group before red meat. These results highlight the substantial impact of livestock-derived foods on land resources in Estonia.

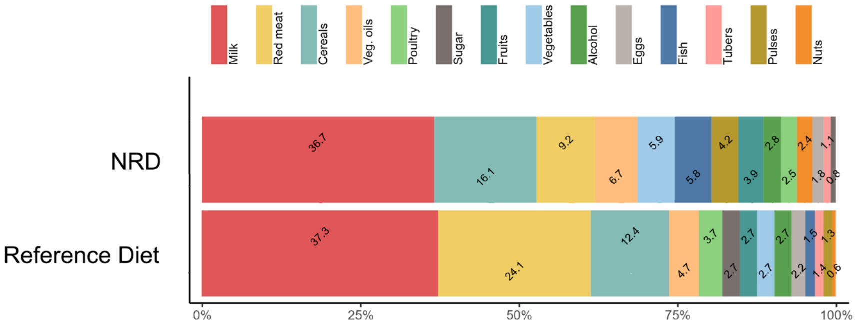

Figure 8. Contribution of food groups to the consumption land footprint (CLF_{total}) of the reference diet and Estonian nationally recommended diet (NRD) based on the results of Publication I. Reproduced from Bashiri et al. (2024), with permission from Springer Nature.

Building on this, **Publication II** expanded the scope by evaluating five environmental footprints of the reference diet (land use, GHG emissions, eutrophication, acidification, and freshwater withdrawals). As illustrated in **Figure 9**, red meat and dairy products consistently ranked among the top contributors across all categories. Dairy had the highest impact on freshwater use, while fish contributed significantly to eutrophication (23.3%) but minimally to other indicators. The share of animal products ranged from 61.8% in land use to 78.8% in eutrophication. Some plant-based foods showed trade-offs: for example, nuts had a high contribution in freshwater use (20.6%) but negative GHG emissions (-3.6%), and vegetable oils had a higher land use footprint relative to other categories. Cereals were more prominent in land use, while tubers, pulses, vegetables, and fruits had low impacts across all footprints. Alcohol showed relatively high contributions to land use, GHG emissions, and acidification. These differences across indicators emphasize the importance of multi-criteria assessment when evaluating dietary environmental impacts.

Figure 9 is generated using the mode of distribution of final footprints of food groups obtained by resampling from subitem distributions. The statistical characteristics of footprints distributions are provided in Appendix 2. The absolute values of the footprint of the reference diet are provided in Appendix 2.

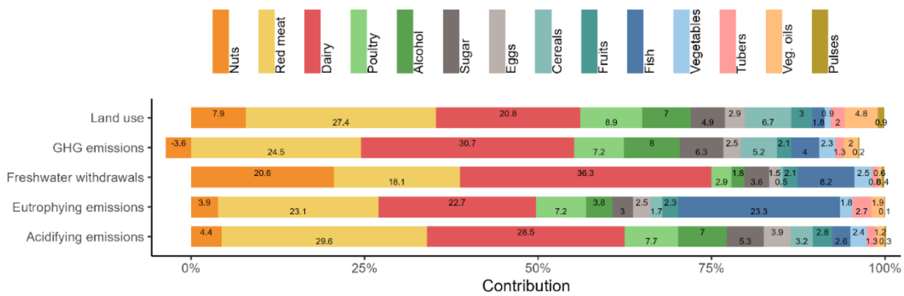

Figure 9. Contribution of food groups to footprints of the reference diet based on the results of Publication II. From Bashiri et al. (2025) with permission from Elsevier.

4.2 Culturally acceptable diet to reduce land footprint

Figure 10 illustrates a Pareto front representing the trade-off between dietary deviation from the reference diet and the CLF_{total}. Each point on the Pareto front curve represents an optimal solution, meaning that all the constraints in the optimization problem are satisfied. The Pareto front was generated by varying the objective weights in equation 11. The Pareto front ranges from the reference point 2910.42 (m^2 cap^{-1} yr^{-1}) to 1154.44 (m^2 cap^{-1} yr^{-1}) for CLF_{total}. This framework provides a valuable tool for constructing future dietary scenarios based on varying levels of ambition. For example, moderate interventions may target a 15% reduction in CLF_{total} (= 2464.51 m^2 cap^{-1} yr^{-1}) with minimal deviations, while more transformative scenarios could aim for 50% reductions in CLF_{total} (= 1461.05 m^2 cap^{-1} yr^{-1}) requiring broader systematic changes in the consumption and diet structure. This figure also provides the most ambitious scenario, a 56% reduction in CLF_{total} (= 1279.61 m^2 cap^{-1} yr^{-1}). As such, the Pareto front supports the development of incremental, policy-relevant dietary strategies by linking environmental benefits with the degree of dietary change required.

Over time, additional adjustments can be introduced, progressively moving toward the more ambitious scenarios. This stepwise approach facilitates behavioural adaptation, reduces resistance to change, and allows for the gradual alignment of food systems, policies, and infrastructure.

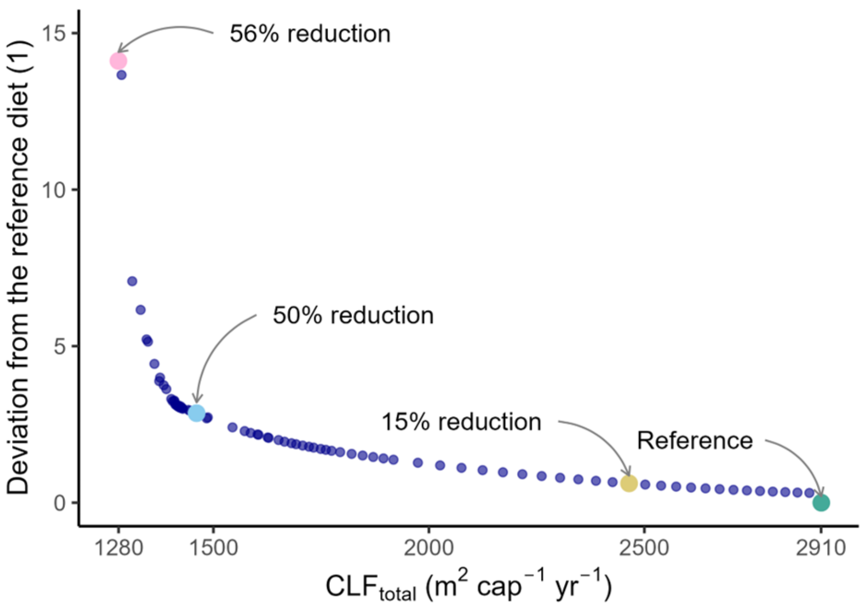

Figure 10. The Pareto front of the MOO problem to design a culturally acceptable diet to reduce land footprint (Publication I) based on Equation 11. Each point represents an optimal diet. The vertical axis is unitless. From Bashiri et al. (2024), with permission from Springer Nature.

4.3 Culturally acceptable diet to reduce five environmental footprints (Publication II)

4.3.1 Ranking the food groups

While it is relatively straightforward to compare food items based on a single environmental indicator such as land use or GHG emissions, making comparisons across multiple footprints simultaneously is more complex. Using an aggregated footprint score that integrates multiple environmental impacts into a single metric allows for comprehensive comparison (ranking) across food groups. The ranking is a judgment about which food groups are more sustainable than the others, considering five footprints. **Figure 11** presents the ranking of food groups based on their aggregated environmental footprint, expressed as SURE scores.

However, this aggregation is associated with considerable uncertainty due to differences in the quality and consistency of underlying data. To reflect this, each food group's aggregated footprint is represented as a probability distribution rather than a single value. These distributions capture the uncertainty around the estimated environmental impact. Despite this uncertainty, the mode (i.e., the peak) of each distribution provides a useful central estimate that can be used to rank food groups. As shown in **Figure 11**, food groups such as red meat and dairy exhibit the highest mode of SURE score, indicating their relatively high aggregated environmental impact, while tubers and vegetables rank lowest. Each food group's SURE score is represented as a probability distribution, capturing the uncertainty arising from variability in underlying data quality. The mode of each distribution (its peak) serves as a central estimate for comparing food groups. Food groups with higher modes (e.g., red meat and dairy) indicate greater environmental impact, whereas those with lower modes (e.g., tubers and vegetables) are comparatively more sustainable. Based on the result in **Publication II**.

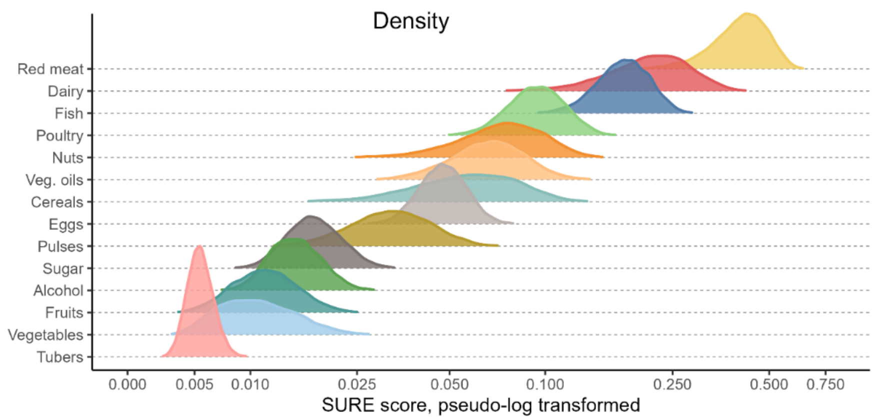

Figure 11. Distribution of aggregated environmental footprint scores (SURE scores) across food groups, reflecting relative sustainability. From Bashiri et al. (2025) with permission from Elsevier.

Integrating MCDM with MOO enables us to have a simpler optimization model in which five environmental footprints are replaced by one aggregated footprint (SURE score) as shown in equation 13. Therefore, the Pareto front curve could be generated, in which the trade-off between SURE score and deviation from the reference diet could be visualised. The decision-making using the Pareto front curve is subjective. For further analysis, one optimal solution was selected from the Pareto front. This point corresponds to a 25% reduction in the SURE score of the diet. This specific optimal solution has a corresponding sum of the deviations. We then run the MOO model (classical model, equation 12) to get the same sum of the deviations. This process established a criterion for selecting comparable points from the BOO and MOO, ensuring that the two selected diets satisfy all nutritional constraints and exhibit equal acceptability.

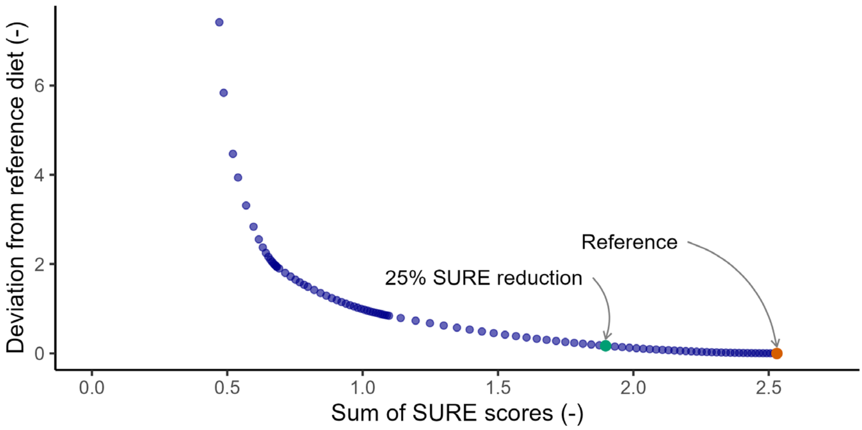

Figure 12. The Pareto front of the BOO problem to design a culturally acceptable diet to reduce five footprints (Publication II) based on Equation 13. Each point represents an optimal diet. The vertical axis is unitless. From Bashiri et al. (2025) with permission from Elsevier.

4.4 How has the consumption of food groups changed? (Publication I&II)

Figure 13 illustrates the reference diet in red, while the lines represent all optimal diet solutions based on the results of **Publication I**. The colour of each line corresponds to its total consumption land footprint (CLF_{total}), and food groups are ordered based on their standard deviation across solutions.

The analysis reveals that all optimal diets consistently recommend reducing the consumption of milk, red meat, and sugars, while suggesting an increase in the intake of tubers, vegetable oils, cereals, and fish. In contrast, the recommended intake of fruits and vegetables varies: some optimal solutions propose an increase, while others suggest a decrease, depending on the ambition level in reducing CLF_{total}.

In the most ambitious optimal solution, a decrease in poultry and egg consumption is also observed. However, in other solutions, an increase in poultry and eggs is recommended, highlighting the variability based on optimization priorities. (Please see **Publication I**, Figure 7)

Among all food groups, milk shows the highest deviation from the reference diet, indicating it is the most flexible lever in optimization, whereas nuts exhibit the least deviation, second only to alcohol, which was held constant throughout the analysis. This pattern likely stems from the differences in nutrient density and land footprint per kilogram among food groups. Moreover, the observed trends are influenced by the structure of the objective function (Equation 11), which uses a squared relative deviation. This formulation tends to favour larger adjustments in food groups with higher baseline consumption, while constraining changes in those consumed in smaller quantities. Appendix 2 includes the intake of Food groups in different dietary scenarios (g cap^{-1} d^{-1}).

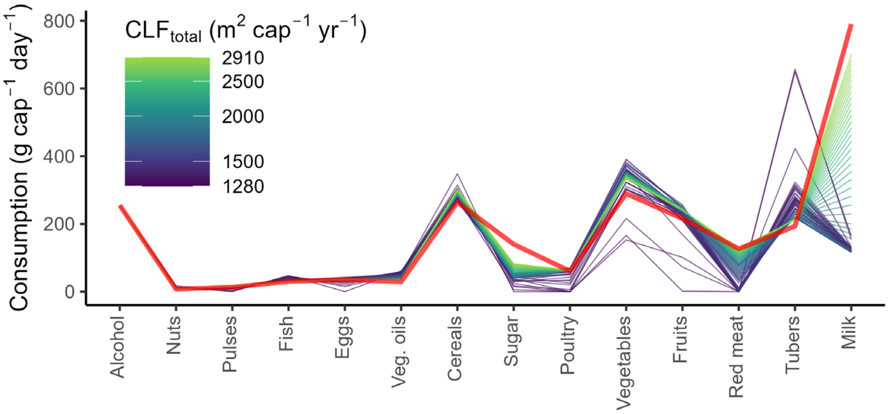

Figure 13. Changes in food group consumption across Pareto-optimal diets compared to the reference diet (results from Publication I). From Bashiri et al. (2024) with permission from Springer Nature.

In **Publication II**, both optimization approaches produced diets that deviate only slightly from the reference diet, avoiding drastic shifts in food group consumption as shown in panel (a) of **Figure 14**. This indicates that the optimized diets are practically feasible, more culturally acceptable, and thus more likely to be adopted by the population. According to panel (b) of **Figure 14**, the results show a general decrease in the consumption of most food groups across both optimized diets, suggesting an overall overconsumption of food in Estonia.

Among the food groups, dairy products exhibit the most significant reductions (263.8 g cap^{-1} day^{-1} in the BOO model and 199.6 g cap^{-1} day^{-1} in the MOO model), reflecting their high environmental impact, as demonstrated by their elevated SURE score in **Figure 11**. Red meat also shows notable reductions (BOO: 16.2 g cap^{-1} day^{-1}; MOO: 33.1 g cap^{-1} day^{-1}), consistent with its large environmental footprint.

Poultry consumption decreases slightly in the BOO model and by around 4 g cap^{-1} day^{-1} in the MOO model, indicating its comparatively lower environmental burden. Reductions are also observed for sugar, cereals, tubers, fruits, and vegetables in both optimized diets.

These findings of **Publication II** contrast with the results of **Publication I**, which focused solely on minimizing land footprint and recommended increased consumption of most plant-based food groups. This shift underscores the trade-offs among different environmental impacts and highlights the importance of balancing multiple environmental objectives when designing sustainable diets.

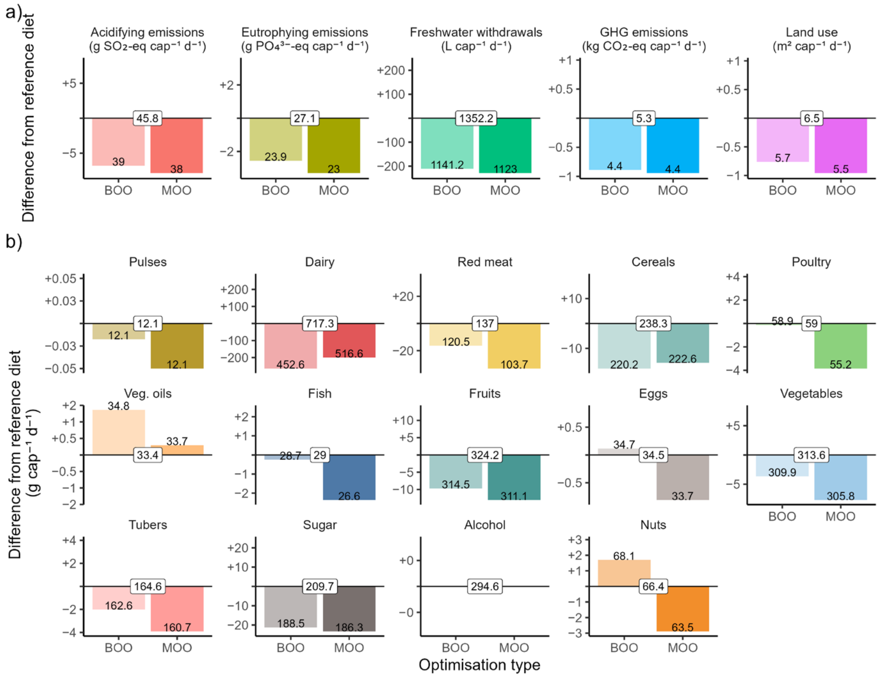

Figure 14. Changes in environmental footprints and food group consumption following dietary optimization (results from Publication II). From Bashiri et al. (2025) with permission from Elsevier.

4.5 Impacts of diet change on trade structure (Publication I)

Changes in the consumption of food groups can have significant implications for production and import patterns, which may pose challenges. However, our optimized diet approach offers a practical solution by suggesting a more moderate adjustment in food intake. This balanced approach allows the economy to gradually adapt to the recommended dietary changes without disrupting existing production and import systems.

Prior research by Põldaru et al. (2018) explored the capacity of Estonia to attain self-sufficiency in agricultural production but did not focus on diets. They recommended expanding the production and export of red meat and dairy products, suggesting that Estonia's agricultural sector has the necessary resources to achieve self-sufficiency in crucial food items. Our analysis suggests that decreasing consumption could potentially assist in reaching self-sufficiency in food production. Detailed discussion is provided in **Publication I**.

4.6 Implementation of sustainable diets (Publication III)

The successful implementation of sustainable diets depends not only on the sound design but also on its adoption by individuals. Adopting new diets frequently faces resistance. Muñoz-Martínez et al. (2024) identified two categories of barriers to adopting sustainable diets called internal and external. Addressing these barriers requires targeted policy interventions.

Internal barriers include limited food literacy (Ares et al., 2024), low perceived behavioural control, emotional attachments to food, and convenience-driven habits (Muñoz-Martínez et al., 2024). Misconceptions about plant-based diets (Perez-Cueto et al., 2022), lack of cooking skills (Wu et al., 2024), and financial insecurity (Nam & Suk, 2024) can all hinder dietary change. Policy tools such as culinary education, financial incentives (Ammann et al., 2023; Huangfu et al., 2024), food labelling (Fresacher & Johnson, 2023; Shangguan et al., 2019) and redesigned supermarket layouts can help overcome these barriers. For example, school-based plant-based cooking programs, subsidies for healthy foods, and default plant-based options in public procurement can improve access and acceptance.

External barriers relate to broader societal influences, including social norms, media misinformation, taste expectations, and limited food access (Higgs et al., 2019; Stok et al., 2016). Cultural associations between meat and masculinity (Camilleri et al., 2024; Vrijsen et al., 2025), misleading marketing and poor availability of affordable, sustainable foods all present challenges. Solutions include media literacy campaigns, improved food labelling, support for local sustainable agriculture, and stronger governance frameworks. Public institutions can also play a critical role by setting sustainability standards for food procurement (Metcalfe et al., 2022).

To systematically design effective interventions, behaviour change frameworks such as the COM-B model and the Behaviour Change Wheel (Michie et al., 2011) can be integrated with MOO. These tools help identify how to enhance individuals' capabilities, opportunities, and motivations to adopt sustainable diets. Translating behavioural factors into quantitative indicators using tools like the Analytic Hierarchy Process (AHP) enables the incorporation of behavioural and environmental goals into optimized policy solutions.

Ultimately, promoting sustainable diets requires a comprehensive, multi-level approach that combines education, economic incentives, regulation, and evidence-based dietary recommendations. When embedded within supportive food environments and aligned with public policy, such approaches can facilitate the shift toward healthier and more sustainable eating patterns across diverse population groups.

4.7 Implication for National Dietary Recommendations (NRDs) (Publication III)

NRDs are key tools for promoting healthy eating habits, but to be more effective, they must also incorporate sustainability and flexibility, particularly to accommodate different socio-economic groups. MOO offers a promising approach to achieve this.

Although NRDs are generally more sustainable than current average diets, there is still room for improvement. Existing guidelines are often too broad and not easily actionable (Behrens et al., 2017; Trolle et al., 2024). To enhance their relevance, NRDs should be tailored to account for individual preferences, health conditions, age groups, and other demographic factors. As van Dooren (2018) has noted, dietary guidelines often assume that following recommendations guarantees nutrient adequacy, which is not always the case (Maillot et al., 2010).

Using MOO-based approaches allows for the design of personalized and feasible dietary patterns that respect both nutritional needs and sustainability goals. Clustering techniques, as demonstrated by Eustachio Colombo et al. (2023) and Nordman et al.

(2024), can further help target specific population segments by identifying distinct dietary patterns and needs.

For MOO to be effective in shaping NRDs, the baseline data should reflect actual consumption habits, ensuring practical and acceptable outcomes. Additionally, model constraints should be aligned with recent dietary standards such as the Nordic Nutrition Recommendations (NNR2023) (Blomhoff et al., 2023), which integrates sustainability with nutritional adequacy. Incorporating expert input, regional eating habits, and culturally relevant factors can further improve the acceptability and policy alignment of MOO-optimized diets.

NRDs also have the potential to influence food choices not only at the individual level but across society. When supported by public awareness campaigns and grounded in transparent scientific evidence (Advisory Report, 2025) they can shape both consumer behaviour and broader food policies. Moreover, NRDs can inform government food services and assistance programs, offering a foundation for healthier and more sustainable procurement standards.

Although NRDs are often categorized as “soft” policy instruments, they can indirectly drive change, such as encouraging food industry reformulation when widely adopted (Mozaffarian et al., 2018). However, their current impact on population-level dietary shifts is limited by infrequent updates and weak integration into concrete policy measures (Wood et al., 2023).

To improve their effectiveness, NRDs should be updated more regularly and serve as part of a coherent system of recommendations that supports individual health while respecting planetary boundaries (Rossi et al., 2023).

4.8 Special remarks from Publication III

- Literature review shows conflicting outcomes when minimizing different environmental footprints. Deciding which footprint to prioritize is critical, as focusing on one or multiple footprints can yield different results. A single diet cannot effectively address all individuals’ needs, so capturing diversity in the population is essential. Machine Learning methods, such as clustering, can detect hidden patterns in food consumption that socio-economic groupings alone cannot reveal.
- Internal and external barriers must be identified and addressed through targeted policy tools. Although many barriers exist at the individual level, they also extend to interpersonal and broader social contexts.
- The DONE framework provides a comprehensive structure for analysing determinants of dietary behaviour across biological, psychological, social, and environmental domains. The Behaviour Change Wheel (BCW) is a practical tool for identifying what must change for a specific behaviour to occur, based on the COM-B model (Capability, Opportunity, Motivation → Behaviour). For example, improving dietary behaviour may require enhancing cooking skills, increasing access to healthy foods, and strengthening motivation through social support or incentives.
- Combining multiple policy tools is necessary to achieve maximum impact.
- NRDs guide healthy eating but should become more sustainable and adaptable for diverse socio-economic groups. This goal can be supported by MOO. Current NRDs provide broad recommendations but should be more specific and

actionable, enabling individuals to select sustainable foods suited to their unique needs and preferences. Dietary guidelines can influence food choices at both individual and societal levels and should be promoted through mass communication campaigns supported by rigorous, transparent reviews of scientific evidence.

- MOO can be combined with frameworks like the BCW to assess trade-offs and identify optimal intervention mixes. This requires translating qualitative behavioural determinants into quantitative metrics, which can be achieved through methods such as the Analytic Hierarchy Process (AHP).

4.9 Limitations of the publications I,II,III, and further opportunities for using MOO for the development of sustainable food systems

This study presents an application of MOO in sustainable diet design. However, several limitations should be acknowledged, and opportunities for future development are outlined below:

The food consumption data used in this study are sourced from the FAOSTAT database, which primarily reports values in terms of primary product equivalents. As a result, the level of detail in food categorization does not fully reflect actual dietary patterns. This simplification can limit the cultural specificity of the optimized diet.

The model in **Publication I** assumes constant feed conversion ratios (FCR) across all livestock types and regions. FCRs vary significantly depending on the production system, animal species, and feed composition. Additionally, the model assumes a uniform grass content in livestock feed across countries. These assumptions introduce uncertainty into land footprint (LF) estimates. Incorporating country-specific FCRs or differentiating between production systems would enhance the model's accuracy. It should also be noted that fish is excluded from the LF analysis. This omission is justifiable, as previous studies (Modelling the Land Footprint of EU Consumption - Publications Office of the EU) have shown that fish contribute minimally to the EU's overall LF.

The model does not tailor dietary recommendations to specific population groups (e.g., age, gender, health status), which could limit its applicability in contexts where such distinctions are crucial. Future research should consider population-specific requirements to enhance the relevance of dietary recommendations as suggested by **Publication III**.

The nutritional content data used in this study, derived from the USDA database as reported by Gephart et al. (2016), may not accurately reflect nutritional content in Estonia or other target regions. Using region-specific nutrient databases would improve the precision of nutrient adequacy assessments.

The economic aspect of diets is not included as an objective function in the current optimization models. However, **Publication III** highlights the importance of economic feasibility for real-world diet adoption. Integrating cost as an objective function would provide a more comprehensive approach to sustainable diet design.

There is a critical need for a comprehensive optimization framework that links the demand side (consumer diet choices) and the supply side (agricultural production systems) of the food system. Such an environmental-economic optimization model would enable simultaneous consideration of dietary needs, environmental impacts, and agricultural constraints. In this context, the author and supervisors have developed a preliminary overview that could serve as a foundation for future research aimed at constructing a whole-system optimization model. The components of the proposed model are explained in **Table 4**.

Table 4. The structure of the Proposed MOO model, which aims to balance the supply and demand sides of the food system

Modules	Component (Role)	Equation	Description
Demand-side module	Diet change component (objective function)	$\sum_{1}^{n}(\frac{x_i^* - x_i}{x_i})^2$	Minimize total squared relative deviation from the current diet, ensuring changes remain culturally acceptable.
	Nutritional Component (Constraints)	$N_{min} \leq \sum_{1}^{n} x_i^* \times a_i \leq N_{max}$	Optimized diets must satisfy recommended intakes of energy and essential nutrients. a_i is the amount of corresponding nutrition per unit weight of food product i. N_{min} and N_{max} are the lower bound and upper bound of the nutrition as per dietary recommendations.
Supply-side module	Revenue Term (objective function)	$\sum_{1}^{n}(Production\ revenue + Import\ revenu + export\ revenue)$	Maximize net economic revenue from domestic production, imports, and exports.
	Cropland Use (constraint)	$\sum Cropland\ use \leq available\ cropland$	Cropland demand from domestic production must stay within land availability.
	Grassland Use (constraint)	$\sum Grassland\ use \leq available\ grassland$	Grassland use must also stay within the national limit.
	Supply-Demand Balance (constraint)	production + imports – exports = Demand	Total supply must equal dietary demand.
	Self-Sufficiency Range (constraint)	$Lower\ band \leq self-sufficiency\ ratio \leq\ upper\ bound$	Ensures flexibility in production while preserving some level of domestic self-sufficiency.
	Non-Negativity (constraint)	Trade parameters cannot be negative	No negative values for production, import, or export quantities.

5 Conclusion

In this work, investigates two multi-objective optimization (MOO) cases for designing culturally acceptable and sustainable diets based on Estonia's nationally recommended diet (NRD), while also addressing challenges related to their efficient implementation.

In the first MOO case study showed that implementing a moderate and socially acceptable dietary shift based on Estonia's NRD would significantly reduce land footprint (LF) of food production. Our results confirmed that while following the standard NRD of Estonia would reduce the LF of the diet, optimizing the NRD using MOO identifies opportunities for future substantial reduction.

The second MOO case study addressed sustainable diet optimization by incorporating multiple environmental indicators into diet optimization frameworks. Integration of multi-criteria decision-making (MCDM) and MOO methods, which simplifies the inclusion of five environmental footprints into optimization process was carried out. We showed that the combined MCDM-MOO approach effectively addresses trade-offs among footprints, enabling the design of diets that reduce five environmental impacts while maintaining nutritional adequacy and cultural acceptability. The proposed method makes the model more interpretable and simplifies decision-making.

Both MOO case studies showed that adopting more culturally acceptable and environmentally friendly diet requires a significant reduction in meat and dairy products consumption.

The results of both MOO case studies showed that an incremental approach towards diet change should be taken. This helps ensure that, instead of big changes that are not successful, small steps should be taken with a future perspective of bigger achievements. This makes the diet change a more efficient and feasible process.

After designing a culturally acceptable and sustainable diet, it is still needed to take advantage of developing policy tools to further support a successful transition (implementation). Implementation of a sustainable diet demands the integration of behavioural insights, consumer engagement, and supportive policy instruments to identify and overcome internal and external barriers to diet adoption. It is important to understand how these factors operate not only at the individual level but also across interpersonal and broader social contexts. Behaviour change models can offer valuable insights to support this understanding.

NRDs have a pivotal role in steering dietary behaviour but must evolve to reflect sustainability considerations. They also need to be translated into concrete policies and regulations and should be updated regularly to remain relevant and effective. To develop and make optimized diets work in real life, we need a well-coordinated approach that brings together different elements. This includes using scientific methods to design diets, giving people personalized advice, creating supportive policies, and involving the public. When these parts work together, it becomes easier for governments and other organizations to help people shift toward diets that are not only healthy and sustainable but also realistic and fair for everyone.

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Acknowledgements

"Laudation to the God of majesty and glory! Obedience to him is a cause of approach and gratitude in increase of benefits. Every inhalation of the breath prolongs life and every expiration of it gladdens our nature; wherefore every breath confers two benefits and for every benefit gratitude is due. Whose hand and tongue is capable to fulfill the obligations of thanks to him?"

(The ROSE GARDEN of Sa'di, composed in 1258 CE, translated from Persian to English by Edward Rehatsek, Omphaloskepsis, Ames, Iowa)

This work has been conducted in TFTAK AS (Tallinn, Estonia). This work was written at writing retreats organized by The University of Tartu Institute of Genomics and the Estonian Doctoral School for Natural and Agricultural Sciences (2021-2027.4.04.24-0003), co-funded by the European Union.

I would like to express my sincere gratitude to my supervisors, Prof. Emer. Raivo Vilu and Dr. Olga Gavrilova, for their trust in me and for giving me the opportunity to carry out this research. I was introduced to Prof. Vilu by Dr. Gavrilova, and for that, I am especially thankful to Olga for establishing this valuable connection and for supporting me at the beginning of my PhD journey.

I am deeply thankful to Prof. Vilu for our daily conversations, knowledge exchange, intensive meetings and discussions, and for sharing his passion for multi-objective optimization. Raivo, your extensive experience and broad knowledge across various fields have profoundly helped me see the world through a wider lens.

I would also like to extend my heartfelt thanks to Dr. Aleksei Kaleda. His humble support, thoughtful consultations, and remarkable programming and statistical skills were crucial in making this work possible. Aleksei, I will never forget your support.

I am deeply grateful to Dr. Cecilia Sarmiento and Ms. Maarja Märss for their continuous support throughout my four years of study. I also wish to thank the teachers and lecturers whose guidance greatly contributed to my learning.

During this thesis, I had the privilege of sharing the office with the TFTAK's Genomics Research Group. I am grateful to the head of the group, Dr. Jekaterina Kazantseva, and her team members for their kindness and for including me in their events and joyful moments.

Finally, I am deeply thankful to my wife, Mehrnaz. This achievement would not have been possible without your constant love, encouragement, and support. I also thank my parents and family, who have supported me throughout this journey, both directly and indirectly. I am grateful to all my friends who helped make my transition and life in Estonia much easier.

To my homeland, Iran, and to all the scholars who once walked its soil…

Abstract

A multi-objective optimization approach for design and implementation of sustainable diets

The degradation of natural resources remains a critical global challenge, with the food system contributing significantly to environmental pressures. The food system is responsible for up to 30% of anthropogenic greenhouse gas (GHG) emissions, 32% of global terrestrial acidification, 78% of eutrophication, and consumes nearly 70% of freshwater resources while occupying more than one-third of all potentially cultivable land. Simultaneously, dietary patterns play a major role in the global burden of non-communicable diseases due to excessive consumption of red and processed meats and insufficient intake of plant-based foods. Thus, shifting towards sustainable diets offers a dual opportunity: reducing environmental impacts and improving population health.

However, such shifts are constrained by the cultural acceptability of dietary changes. Cultural acceptability, understood as minimizing deviation from existing dietary habits, can often conflict with environmental objectives. Many food products that are low in one environmental footprint may score poorly on others, making it difficult to design universally sustainable diets. This study addresses these trade-offs by employing a comprehensive, data-driven approach to balance sustainability and acceptability in dietary transitions.

We applied a multi-objective optimization (MOO) framework to design culturally acceptable and environmentally sustainable diets in Estonia. In the first phase, we used land footprint as the environmental metric and minimized both the land use and deviation from the reference Estonian diet. In the second phase, we broadened the scope by incorporating five environmental indicators: GHG emissions, land use, water use, acidification, and eutrophication. Using a multi-criteria decision-making (MCDM) method, we aggregated these into a single environmental score, simplifying the optimization process without neglecting the multidimensional nature of sustainability. Furthermore, the thesis identifies barriers to sustainable diet adoption and outlines policy solutions to facilitate dietary transitions.

Our findings indicate that a more sustainable diet necessitates a marked reduction in meat and dairy consumption, a transition that may face resistance due to personal and cultural preferences. However, the MOO approach allows for a gradual and balanced transition, offering multiple feasible solutions that involve moderate dietary shifts. Notably, we observed that diets optimized solely for one environmental indicator (e.g., land use) recommended increasing certain plant-based food groups, while the multi-indicator model suggested reducing them, revealing significant trade-offs among environmental goals.

These results underscore the importance of adopting integrative, multi-objective approaches to dietary planning. By accommodating environmental, nutritional, and cultural dimensions, the MOO framework supports policy development for sustainable food systems. Our model offers a scalable tool for informing dietary guidelines and public health strategies, particularly in high-dimensional systems where objectives may conflict.

Lühikokkuvõte
Jätkusuutlike toitumisviiside kavandamine ja rakendamine mitme-eesmärgilise optimeerimise abil

Loodusvarade seisundi halvenemine on endiselt kriitiline ülemaailmne probleem, kusjuures toidusüsteem annab olulise panuse keskkonnakoormusesse. Toidusüsteem vastutab kuni 30% inimtekkeliste kasvuhoonegaaside (KHG) heitkoguste, 32% globaalse maismaa hapestumise, 78% eutrofeerumise eest ning tarbib ligi 70% mageveevarudest, hõivates samal ajal enam kui kolmandiku kogu potentsiaalselt haritavast maast. Samal ajal mängivad toitumisharjumused olulist rolli mittenakkuslike haiguste globaalses koormuses, mis on tingitud punase ja töödeldud liha ning piimatoodete liigsest ning taimse toidu ebapiisavast tarbimisest. Seega pakub üleminek jätkusuutlikule toitumisele kahekordset võimalust: vähendada keskkonnamõju ja parandada rahvastiku tervist.

Kirjeldatud muutusi piirab aga toitumismuutuste kultuurilise vastuvõetavuse barjäär. Kultuuriline vastuvõetavus, mida mõistetakse traditsioonilistest, valdavatest toitumisharjumustest kõrvalekaldumise minimeerimise probleemina, võib sageli olla vastuolus keskkonnaeesmärkidega. Paljud toiduained, millel on teatud kontekstis väike keskkonnajalajälg, võivad teiste hindamistingimuste kasutamise puhul olla suure negatiivse keskkonnamõjuga, mistõttu on keeruline kujundada universaalselt jätkusuutlikke toitumisharjumusi. Käesolev uuring käsitleb vajalikke kompromisse, kasutades terviklikku ja andmepõhist lähenemisviisi, et tasakaalustada toitumisüleminekute jätkusuutlikkust ja vastuvõetavust.

Eesti kultuuriliselt vastuvõetavate ja keskkonnasäästlike toitumisharjumuste kujundamiseks rakendasime mitme eesmärgiga optimeerimise (MOO – Multiobjective Optimization) raamistikku. Esimeses etapis kasutasime keskkonnamõõdikuna maa jalajälge ja minimeerisime nii maakasutust kui ka kõrvalekallet Eesti võrdlustoitumisviisist. Teises etapis laiendasime optimeerimise ulatust, lisades viis keskkonnaindikaatorit: kasvuhoonegaaside heitkogused, maakasutuse, veekasutuse, veekogude ja muldade hapestumise ja eutrofeerumise. Mitme kriteeriumipõhise otsustusmeetodi (MCDM) abil koondasime need üheks keskkonnaskooriks, lihtsustades optimeerimisprotsessi, jättes seejuures tähelepanuta jätkusuutlikkuse mitmemõõtmelist olemust. Väitekirjas on analüüsitud jätkusuutliku toitumise omaksvõtmise erinevaid barjääre ja esitatud toitumisüleminekute hõlbustamiseks sobivad poliitilised meetmed.

Meie tulemused näitavad, et jätkusuutlikum toitumine eeldab liha- ja piimatoodete tarbimise märkimisväärset vähendamist, mis võib isiklike ja kultuuriliste eelistuste tõttu olla oluliseks mõistlike üleminekuprotsesside realiseerimise takistuseks. MOO lähenemisviis võimaldab planeerida ja ellu viia järkjärgulisi ja tasakaalustatud üleminekuprotsesse, pakkudes mitmeid aktsepteeritavaid lahendusi, mis hõlmavad mõõdukaid toitumismuutusi. Tähelepanuväärseks tuleb pidada asjaolu, et ainult ühe keskkonnanäitaja (näiteks maakasutus) jaoks optimeeritud toitumisharjumused soovitasid teatud taimsete toidugruppide suurendamist, samas kui mitme indikaatoriga mudel soovitas neid vähendada, mis näitas vajadust leida keskkonnaeesmärkide vahel olulisi kompromisse.

Saadud tulemused rõhutavad integreerivate ja mitme eesmärgiga lähenemisviiside olulisust optimaalsete toitumisharjumuste planeerimisel. Keskkonna-, toitumis- ja kultuurimõõtmete arvessevõtmisega toetab MOO raamistik säästvate toidusüsteemide poliitika väljatöötamist. Meie mudel pakub skaleeritavat tööriista toitumisjuhiste ja rahvatervise strateegiate kujundamiseks, eriti mitmemõõtmelistes süsteemides, kus eesmärgid võivad olla ka omavahel vastuolus ning vajalik on leida praktiliselt mõistlikud kompromissid.

Appendix 1

Publication I

Bashiri, B., Kaleda, A., Gavrilova, O., & Vilu, R. (2024). A Culturally Acceptable Shift in Diet to Reduce Land Footprint: an Optimization Study for Estonia. Environmental Modeling & Assessment, 1-15. https://doi.org/10.1007/s10666-024-09996-4

Environmental Modeling & Assessment (2025) 30:125–139
https://doi.org/10.1007/s10666-024-09996-4

RESEARCH

A Culturally Acceptable Shift in Diet to Reduce Land Footprint: an Optimization Study for Estonia

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Received: 25 September 2023 / Accepted: 6 September 2024 / Published online: 12 September 2024

Abstract
We investigated how the land footprint of food consumption in Estonia could be decreased through socially acceptable moderate dietary changes while ensuring adequate nutrition. Estonian food consumption was categorized into 14 groups. Five diets were evaluated, including a reference diet, a nationally recommended diet (NRD) by the National Institute of Health Development, and three optimized diets that minimized the consumption land footprint and deviation from the reference diet. The study found that adopting an optimized diet resulted in a decrease in the consumption of milk and red meat, and an increase in the consumption of cereals, tubers, vegetable oils, and nuts, ultimately leading to an up to 56% reduction in the diet-related land footprint. Internal and external land footprints were also estimated using the share of import in the supply. This research offers a highly adaptable modeling framework that could be useful in similar research endeavors.

Keywords Consumption land footprint · Diet change · Multi-objective nonlinear programming · Estonia

1 Introduction

The availability of agricultural land worldwide is limited, and demand for it is expected to increase due to a rise in the global population and a shift in food consumption patterns towards environmentally intensive products like meat and dairy [1]. According to Foley et al. [2], approximately 40% of the ice-free land surface is used for food production. This extensive use of land not only compromises carbon sinks but also disrupts the natural habitats of species and threatens the integrity of ecosystems, as noted by Kastner et al [3]. If the current trend persists, it is anticipated that the environmental impacts related to food production will continue to rise over the next three decades [4]. It is crucial to comprehend the land requirements of food consumption to establish sustainable food systems that adequately fulfill the nutritional requirements of the population.

However, there is a significant potential for dietary changes to mitigate these environmental impacts and improve human health. Studies have shown that shifting towards sustainable diets that are rich in plant-based foods and low in animal-based products can reduce the environmental footprint of food production and improve public health outcomes [5, 6]. The dietary change can reduce hidden costs stemming from health problems [7] and could potentially reduce the mortality rate and risks. The research-based evidence confirms the role of diet in mortality rate through contribution to noncommunicable diseases [8]. The health benefits of dietary change may derive from a reduction in red and processed meat consumption and increases in fruit and vegetable consumption [8]. Poore and Nemecek [9] found that dietary changes offer greater environmental benefits than what producers can achieve currently or in the future through intensification of production. Therefore, shifting to a sustainable diet has been proposed as a key strategy to achieve the Sustainable Development Goals (SDGs) and ensure the well-being of both people and the planet [10].

The patterns of food consumption have significant implications for both human nutrition/health, as well as environmental issues. Nationally recommended diets (NRDs) serve as a crucial policy instrument for providing nutritional guidance [11, 12]. Originally, NRDs emphasized nutrient intake to promote adequate consumption, which inadvertently encouraged the consumption of animal-based products [13], and, thus, neglected to address the environmental

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implications [14]. However, in recent years, there has been an increasing focus on the environmental impacts of food consumption in NRDs. Although transitioning to eco-friendly diets can substantially decrease the environmental impacts of food consumption, it can lead to a lack of certain micronutrients, including vitamin B12, selenium, and calcium [15]. Hence, when making changes to diets, it is vital to adopt a holistic approach that considers both health and sustainability objectives to prevent any undesired trade-offs.

The literature contains numerous studies aimed at creating sustainable diets that take into account both nutritional and environmental factors [16–22]. However, it is important to acknowledge the likelihood that recommended diets, despite being healthy and eco-friendly, may not be culturally or personally acceptable if they deviate significantly from the current dietary practices. Thus, creating sustainable diets that satisfy the requirements of being environmentally sustainable, nutritionally sufficient, and culturally acceptable in a particular region or country continues to be a significant challenge.

Using optimization algorithms presents a viable solution to the challenge of creating region-specific sustainable diets that fulfill various objectives [23–25]. By employing the optimization approach, a sustainable diet (single objective) can be attained by meeting specific criteria, such as minimizing deviations from the current intake levels, while also adhering to various nutritional, cultural, and environmental constraints. Linear [26–28] and nonlinear [4] optimization algorithms with a single objective have been extensively employed in studies related to diet optimization.

Cultural acceptability (minimizing the deviation from the current diet) and ensuring sustainability are two objectives that are interdependent, as achieving one may compromise the other. Therefore, a comprehensive approach that considers both objectives simultaneously is needed to find a feasible solution. Multi-objective optimization serves as a valuable tool for balancing conflicting objectives. Donati et al. [29] were among the pioneers who utilized multi-objective programming to simultaneously investigate the environmental and economic aspects of the diet. Similarly, Abejón et al. [30] employed multi-objective optimization to link three simultaneous objectives: maximizing nutritional contribution, minimizing greenhouse gas emissions, and minimizing costs. Additionally, Mirzaie-Nodoushan et al. [31] applied multi-objective optimization to achieve a culturally acceptable diet while minimizing the water footprint. In a recently published study, Muñoz-Martínez et al. aimed to create a sustainable and healthy diet for Spain [32]. This involved multi-objective optimization to minimize costs and environmental impact, including greenhouse gas emission, land use, and blue-water use, while minimizing deviations from current diets. The study also compared the optimized diet to Spanish dietary guidelines and explored the advantages of reducing animal products in favor of plant-based alternatives [32]. These studies showcase the versatility and effectiveness of multi-objective optimization in addressing diverse challenges related to diet and sustainability.

In this study, we aimed to analyze the impact of dietary change in Estonia on reducing land footprint and its effects on agricultural production and imports. Estonia faces a pressing need for such an investigation due to alarming trends in dietary habits. For instance, in the year 2018, protein consumption in Estonia was found to be 121 g cap^{-1} day^{-1} [33] which is two times higher than the WHO recommended levels (52 g cap^{-1} day^{-1}) [4, 18, 34]. This excessive consumption raises serious health concerns. A recently published study shows that higher consumption of protein sources such as ultra-processed animal-based products increases the risk of cancer and cardiovascular disease [35]. Overconsumption of protein sources also exacerbates environmental problems associated with livestock farming, such as greenhouse gas emissions and land use. To address these critical issues, we estimated the Estonia-specific land footprint of various food groups and employed a nonlinear multi-objective optimization algorithm to develop culturally acceptable diets that not only meet the WHO's recommended nutrient levels but also help mitigate the adverse impacts of unsustainable dietary practices on the environment.

2 Methods

2.1 Data Collection

Figure 1 demonstrates a simplified flowchart of the calculation methodology. To assess the supply and demand of agricultural products in Estonia, we utilized the food balance sheet (FBS) for 2018 [33] of the Food and Agricultural Organization of the United Nations Statistics (FAOSTAT) [33]. This comprehensive data set accounts for various factors such as production, imports, exports, food, losses, animal feed, non-food use, and per capita consumption. The per capita food consumption (g $capita^{-1}$ day^{-1}) data for 2018 served as a reference diet for the Estonian population. The FAOSTAT [33] also provides information on crop yields for specific countries and different crops each year. The FAOSTAT [33] is considered one of the most comprehensive data sets available for examining food supply patterns at both the national and global levels, as noted in various studies [1, 16, 36–38].

2.2 Food Items

The FBS dataset covers 74 different food items, but for this study, we excluded 26 items that had zero or negligible intake. The remaining 48 food items were then categorized

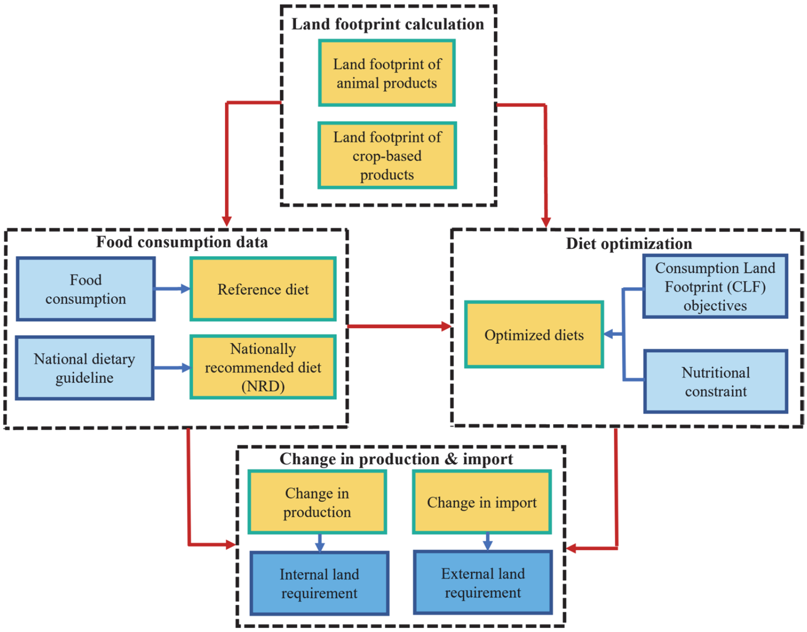

Fig. 1 Chart of the calculation flow. Light blue blocks—input data, orange blocks—intermediate results, dark blue blocks—final results, blue arrows—the flow of inputs, red arrows—the flow of intermediate results

into 14 different food groups, including cereals, tubers, pulses, nuts, vegetables, vegetable oils, fruits, sugar, red meat, poultry meat, eggs, milk, fish, and alcoholic beverages. The plant-based food items in this study range from primary crops (raw agricultural products) to processed products (such as vegetable oil and sugar). The processed products (e.g., sunflower seed oil) should be converted to the primary crop equivalents (e.g., sunflower seed) for further analysis. To convert the processed products to primary crop equivalents, we utilized conversion factors from [36], which are based on the relative caloric value of the processed product compared to the primary product. For example, the caloric value of sunflower seed is 308 kcal per 100 g, whereas sunflower seed oil has a caloric value of 884 kcal per 100 g. Based on this ratio, it takes approximately 2.87 units of sunflower seed to produce 1 unit of sunflower seed oil. A list of the food items and their respective groups can be found in Supplementary Table 1. No co-products were included in the list of food items ensuring that there is no double counting of land footprint in the calculations.

2.3 Land Footprint Calculation

Figure 2 shows a general overview of the land footprint (LF) calculation methodology. The LF of food products is calculated using the bottom-top approach. This method enables us to calculate the LF for each food product separately and link it to the consumption. The consumption land footprint (CLF_{total}) was chosen as an environmental indicator in this study due to its ability to explore demand-side interventions aimed at reducing land footprint. It also encompasses the nutritional productivity of the land and captures the land associated with the production of food. By examining the land footprint from a consumption perspective, it accounts for both the internal and external land associated with food consumption. Within this methodology, we have allocated the existing grassland and feed cropland to animal products, as opposed to calculating the land requirement directly. This method helps prevent overestimation or underestimation of land resources. The consumption footprints for different environmental indicators have been used previously as a useful tool to investigate the sustainability of consumption [39–41].

The LF is a measure of the amount of land needed to produce 1 kg of agricultural products, considering both domestic production and imports. As the production yields of domestically produced and imported agricultural products differ, the land footprints also differ. When referring to the land required to produce one unit of food item within Estonia, we use the term "internal LF" (LF_{int}). Conversely, the land required to produce one unit of imported food item is referred to as "external LF" (LF_{ext}). For crop-based products such as cereals, fruits, and vegetables, the LF is the inverse of the production yield. To calculate the (LF_{int}), we used the production yield data for Estonia

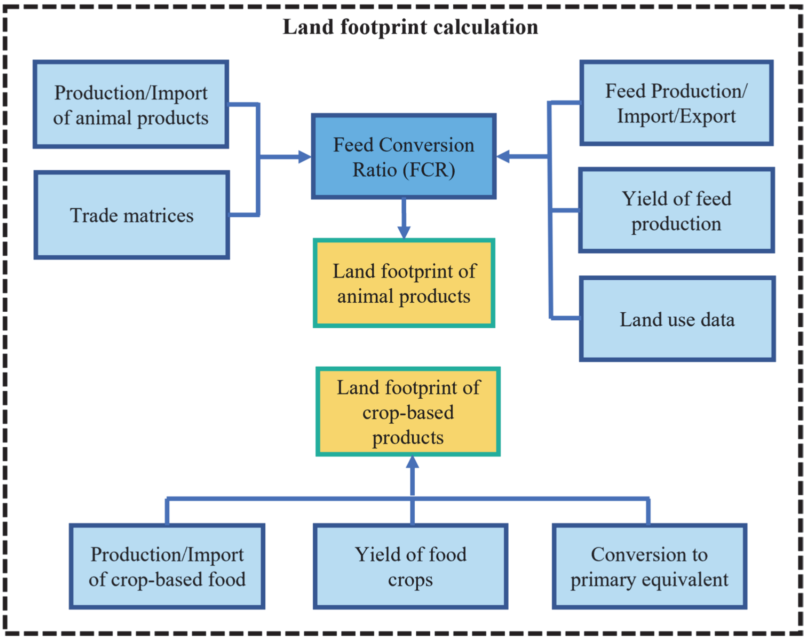

Fig. 2 Flowchart of the land footprint (LF) calculation

provided by FAOSTAT [33], while the average global production yields were used to estimate the (LF_{ext}).

The LF of animal products consists of both internal and external components. The internal component includes the domestic cropland and grassland required to produce animal products in Estonia, while the external component includes the cropland required to produce imported feed and the land required to produce imported animal products. To estimate the LF_{int} of animal products, we used the method developed by de Ruiter et al. [1], which takes into account the relative feed conversion ratios (FCRs) of different animal

Table 1 Feed conversion ratios (FCR) and grass content in feed for animal products considered in this study [1]

Animal product	FCR	% grass in feed
Pig meat	3.6	0
Poultry meat	2	0
Milk	1.1	75
Beef	18.5	75
Eggs	2.2	0
Mutton	31.7	90

Note that the LF_{int} and LF_{ext} are averaged based on the relative consumption of food items within each food group. For instance, the red meat group consists of bovine meat, pig meat, and mutton and goat meat items. According to FAOSTAT [31], pig meat accounts for 80% of red meat consumption in Estonia, followed by bovine meat (19%) and mutton and goat meat (1%).

products and the relative grass content in the feed. Grass is a crucial source of feed for animals and its inclusion in the analysis significantly influences LF calculation. Using this method, we allocated the total feed cropland and grassland in the country to animal products based on their relative FCRs and the percentage of grass content in the feed. The animal products considered in this analysis were pig meat, poultry meat, beef, mutton, milk, and eggs. The FCRs and grass content in the feed are listed in Table 1. We assumed that there was no difference in crop feed composition. Note that fish was excluded from this analysis. To calculate the required grass and feed crop for each animal product, the following formulas were used:

$$Greq_i = P_i \times FCR_i \times Gc_i, \tag{1}$$

$$Creq_i = P_i \times FCR_i \times (1 - Gc_i), \tag{2}$$

where $Greq_i$ and $Creq_i$ are grass and feed crop demand for animal product i respectively, P_i is produced amount of animal product i, FCR_i is the feed conversion ratio for animal product i, and Gc_i is the fraction of grass content in the feed. Secondly, we have assigned the total grassland area and total feed cropland area in the country to the animal products according to the following equations:

$$Garea_i = \frac{Greq_i}{\sum_i Greq} \times Garea_t, \tag{3}$$

$$Carea_i = \frac{Creq_i}{\sum_i Creq} \times Carea_t, \tag{4}$$

in which $Garea_i$ and $Carea_i$ are grassland and feed cropland areas assigned to animal product i. $Garea_t$ and $Carea_t$ are total grassland and total feed cropland area in the country. The total feed cropland area ($Carea_t$) is determined by dividing the feed quantity of crops reported by FAOSTAT by the yield of the corresponding crop. This approach helps us to ensure that there is no double counting in the LF estimation. LF_{int} of animal product i equals the following:

$$LF_{int_i} = \frac{Garea_i + Carea_i}{Production_i}, \tag{5}$$

where the $Production_i$ is the total amount of food item i that is produced internally. We allocated land associated with the import of feed crops to each animal product to estimate LF_{ext}, as explained earlier. In addition, we accounted for the land required to produce imported animal products in their country of origin by using a detailed trade matrix from FAOSTAT [33]. We identified the top countries that contribute more than 1.5% [1, 42] to the import of animal products in Estonia, including Denmark, Finland, Germany, Latvia, Lithuania, the Netherlands, Poland, the UK, Belgium, Ireland, and Spain. We used the same approach as described above to estimate their land footprints as well. The list of these countries is included in Supplementary Table 2.

To determine the LFs of agricultural products, we calculate a weighted average of LF_{int} and LF_{ext}. To achieve this, we distribute the proportion of each food item between imports and domestic production, using Eq. 6 from Kim et al. [16]. We then use the ratio obtained from Eq. 6 to calculate the weighted average of LF. Equation 6 is expressed as follows:

$$\%imported = \frac{Imports}{Domesticproduction + stockchanges + imports - exports}, \tag{6}$$

Finally, the total consumption land footprint ($\mathrm{CLF_{total}}$) can be estimated as the agricultural products consumed in each group multiplied by the corresponding LF using the following formula:

$$CLF_{total} = \sum_i^n (Con_i \times LF_i), \tag{7}$$

where Con_i is the consumption of i_{th} food item (kg day^{-1}) and LF_i is the LF of i_{th} food item (m^2 kg^{-1}).

2.4 Diets

In addition to the reference diet, we analyzed the following dietary scenarios to evaluate the impact on LF of food consumption:

- The nationally recommended diet (NRD) [14], which promotes a higher intake of cereals, fruits, vegetables, milk, dairy products, poultry, and fish, while limiting sweets and drinks. The recommended intake amounts are provided by the National Institute of Health Development (NIHD), and food items are categorized into the same 14 food groups as described in Sect. 2.2.
- Three optimized diets, which provide sufficient energy and 18 nutrients while minimizing the $\mathrm{CLF_{total}}$ by a different amount. The optimization model used to achieve this is explained in Sect. 2.6, and it aims to minimize the deviation from the reference diet to ensure cultural acceptability.

2.5 Optimization of Diet Pattern

To obtain an optimized diet, the goal is to minimize the $\mathrm{CLF_{total}}$ while minimizing the deviation from the reference diet. Since this is a multi-objective optimization problem, we used a multi-objective nonlinear programming method [31]. The objective function was constructed as follows:

$$min\left[x^*\right] = w_1 \sum\nolimits_1^n \left(\frac{x_i^* - x_i}{x_i}\right)^2 + w_2 \sum\nolimits_1^n (x_i^* \times LF_i), \tag{8}$$

where x_i and x_i^* represent the current and optimized consumption of food group i respectively and LF_i is the land footprint of food group i. The first part of Eq. (8) is the sum of the squared deviations between the current and optimized consumption of each food group [43]. The second part calculates the $\mathrm{CLF_{total}}$ of the optimized diet. The first and second parts of Eq. (8) are multiplied by weight factors $w_1, w_2 > 0$, $w_1 + w_2 = 1$ which enables us to build a Pareto optimal front by varying the weights.

The optimization was performed in R version 4.2.2 (the R Foundation for Statistical Computing, Vienna, Austria) using the function "constrOptim.nl" from package "alabama" version 2022.4–1. This function applies the augmented Lagrangian adaptive barrier minimization algorithm for optimizing smooth nonlinear objective functions with constraints. We improved calculation accuracy by switching to 90-bit precision using package "Rmpfr" version 0.9–1.

2.6 Nutritional Content and Constraints

We utilized the average values of energy content and 18 essential nutrients per food group (e.g., gram protein per 1 g of red meat) from the study by Gephart et al. [44], which are based on the United States Department of Agriculture National Nutrient Database (USDA) [45]. The daily per capita calorie and nutrient intake was calculated by multiplying the amount of food consumption in each group (g capita^{-1}

day^{-1}) by the corresponding nutrient content (e.g., g protein per g of red meat).

To ensure that the optimized diet meets nutritional recommendations, the objective function was constrained by the nutritional recommendations calculated by Springmann et al. [34] reported by Chaudhary and Krishna [4]. The carbohydrate is constrained to provide 50 to 60% of total dietary energy according to the Estonian recommendation which is based on the Nordic recommendation [14]. Estonian recommendation provides different energy consumption values yielding 1400–3600 kcal. The choice of 2400 kcal was selected since it is in the middle of this range and serves as an average value. The consumption of alcoholic beverages was held constant to respect the cultural acceptability of the optimized diet [4]. A total of 20 constraints were applied to the objective function. The list of constraints and their values can be found in Table 2. Note that the values of nutritional constraints are the recommended intakes. According to Springmann et al. [34], these values follow WHO guidelines and are averaged across all adult age and sex groups.

Table 2 Constraints applied in multi-objective nonlinear optimization of diet [4]. The range for carbohydrates is taken from Estonian dietary recommendations [16]

Constraint	Value
Energy	≥ 2400 kcal cap^{-1} day^{-1}
Proteins	≥ 52 g cap^{-1} day^{-1}
Carbohydrates (% total energy)	50–60
Fiber, total dietary	≥ 29 g cap^{-1} day^{-1}
Calcium	≥ 520 mg cap^{-1} day^{-1}
Iron	≥ 17 mg cap^{-1} day^{-1}
Magnesium, Mg	≥ 250 mg cap^{-1} day^{-1}
Phosphorus, P	≥ 752 mg cap^{-1} day^{-1}
Potassium, K	≥ 3247 mg cap^{-1} day^{-1}
Zinc, Zn	≥ 6.1 mg cap^{-1} day^{-1}
Vitamin C	≥ 42 mg cap^{-1} day^{-1}
Thiamin	≥ 1.1 mg cap^{-1} day^{-1}
Riboflavin	≥ 1.1 mg cap^{-1} day^{-1}
Niacin	≥ 14 mg cap^{-1} day^{-1}
Vitamin B6	≥ 1.2 mg cap^{-1} day^{-1}
Folate, DFE[a]	≥ 364 µg cap^{-1} day^{-1}
Vitamin B12	≥ 2.2 µg cap^{-1} day^{-1}
Vitamin E (alpha-tocopherol)	≥ 10 mg cap^{-1} day^{-1}
Vitamin K (phylloquinone)	≥ 80 µg cap^{-1} day^{-1}
Alcoholic beverages	Current level (constant)

[a]Dietary folate equivalent

3 Results and Discussion

3.1 LF of Food Groups

Table 3 presents the LF_{int} and LF_{ext} values for food groups in Estonia. Thus, the LF is estimated based on these relative proportions. The weighted average considers the percentage of imports. Our analysis reveals that red meat and vegetable oils have the highest LF among all food groups. The LF_{int} of animal products, except for red meat, is lower than the LF_{ext}. This is attributable to the advanced livestock management systems in Estonia, which result in high yields of dairy production [46]. Furthermore, Nijdam et al. [47] conducted a comparative assessment of the land footprint associated with livestock products using an extensive range of studies. Their analysis indicated a wide range of values for red meat products including beef, pork, mutton, and lamb, with estimates varying from 7 to 420 m^2 kg^{-1} depending on the livestock systems employed. Specifically, the estimated range for pork was found to be 8–15 m^2 kg^{-1}. Given that pork accounts for over 80% of the red meat consumption in Estonia, our calculated land footprint for this category is in concurrence with findings in the literature. This suggests that our results are consistent with previous research, which reinforces the validity of our approach.

Tubers and pulses also have a lower LF_{int} compared to the LF_{ext}. The LF_{int} of alcoholic beverages is smaller than the LF_{ext} since only beer is domestically produced, while other alcoholic beverages are imported. The LF of beer is lower than that of its primary ingredient (barley) due to a higher conversion factor (1-kg barley = 6.66-kg beer) [16, 36].

Table 3 Calculated internal and external LFs (land footprint) of food groups in Estonia (m^2 kg^{-1}), and weighted average is calculated using % imported

Food groups	LF_{int}	LF_{ext}	% imported	Weighted average LF
Cereals	3.85	3.49	33	3.73
Tubers	0.56	0.64	23	0.57
Pulses	7.63	10.56	16	8.09
Nuts	6.39	5.56	17	6.24
Vegetables	1.32	0.49	67.7	0.75
Vegetable oils	11.46	13.28	78.9	12.89
Fruits	4.50	0.81	94.4	1.01
Sugar	–	1.56	100	1.56
Red meat	20.51	11.64	59.7	15.21
Poultry	4.09	5.31	66.6	4.89
Eggs	4.50	5.46	47.6	4.95
Milk	3.36	5.62	18	3.76
Fish	–	–	–	4*
Alcohol	0.40	0.94	82	0.84

*This value is taken from Nijdam et al. [48]. Fish is not considered among the animal products in our approach, so no LF is allocated to fish production. The range of 2–6 m^2 kg^{-1} is reported, and we used the average value

3.2 CLF_{total} and CLF_{int} of the Reference Diet

The CLF_{total} of the reference diet amounts to 2910.42 m^2 cap^{-1} yr^{-1}, with $CLF_{int}=1633.22$ m^2 cap^{-1} yr^{-1} and $CLF_{ext}=1277.19$ m^2 cap^{-1} yr^{-1}. The contribution of each food group to CLF_{total} and CLF_{int} is presented in Fig. 3. Milk, red meat, and cereals are the most significant contributors to CLF_{total} and CLF_{int}. Milk products account for 37% of the CLF_{total} and 54% of the CLF_{int}. Red meat is the second major contributor to CLF_{total} and CLF_{int}, with a share of 24% and 17%, respectively. The results indicate that animal products (without fish) have a considerable impact on the CLF of food in Estonia, accounting for 67% of the CLF_{total} and 76% of the CLF_{int}.

Table 4 displays the CLF_{total} of the reference diet, distinguishing between cropland and grassland footprints. The values calculated in this study are compared to those from other studies, which provide average values for 27 European countries. The cropland and grassland footprints in this study are lower than values reported in other research, possibly due to the different food consumption habits, differences in reference year, and calculation methodology. This discrepancy may also be attributed to differences in scope, as the current study estimates the land footprint of food consumption, while the studies used for comparison consider the overall land footprint.

3.3 CLF_{total} and CLF_{int} of NRD

Adopting the NRD of Estonia would result in a decrease in both CLF_{total} and CLF_{int} to 2806.75 and 1594.41 m^2 cap^{-1} yr^{-1}, respectively. As shown in Fig. 4, similarly to the reference diet, milk remains the top contributor to both CLF_{total} and CLF_{int} in the NRD. The second-largest contributor to CLF in the NRD is cereals, due to an increase in their consumption (20%) compared to the reference diet. A detailed list of food group intake for dietary scenarios can be found in Supplementary Table 3. The red meat group is the third contributor to both CLF_{total} and CLF_{int}. The proportion of animal products (without fish) in the CLF_{total} of NRD is 50%, which is approximately 17% points lower than that of the reference diet.

The primary objective of the NRD in Estonia is to improve overall health by preventing nutrient deficiencies and promoting physical activity. The NRD guidelines advocate for the simultaneous promotion of nutritional adequacy and physical activity among the public, with the goal of ensuring sufficient intake of essential nutrients. This is achieved through recommendations that include increased consumption of specific food groups and reduced intake of others [14] as described in Sect. 3.4 leading to a decrease in CLF. In addition, the NRD also acknowledges that changing diet could have potential environmental benefits.

3.4 CLF_{total} of Optimized Diet

When optimizing conflicting objectives, the results can be visualized as a hyperbolic Pareto front, where decreasing one objective comes at the cost of another [31, 50, 51]. The optimization model, along with its associated

Fig. 3 Contribution of food groups to CLF_{total} (total consumption land footprint) and CLF_{int} (internal consumption land footprint) for reference diet

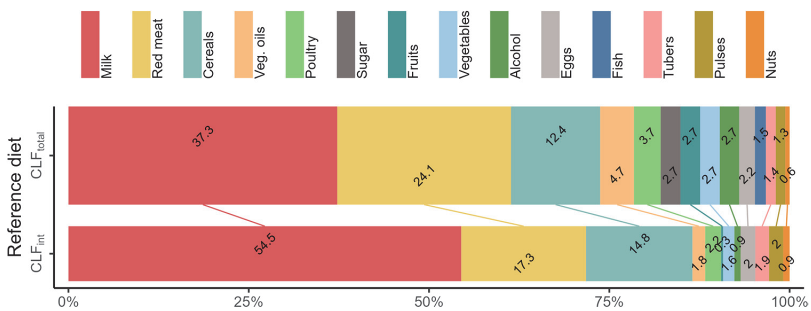

Table 4 Total food consumption land footprint (CLF_{total}) distinguished between cropland and grassland footprint. The values are in ha cap^{-1} yr^{-1} to be compared to values reported in the literature

Food groups	Current study	Laurentiis et al. (2022)* [42]	Kastner et al. (2014)** [49]	Bruckner et al. (2019)*** [50]	O'Brien et al. (2015)**** [51]
CLF_{total} (cropland)	0.19894	0.30	0.25	0.28	0.29
CLF_{total} (grassland)	0.09209	0.11	-	-	-

*Reference year 2018, average for 27 European countries. **Reference year 2009, average for 27 European countries. ***Reference year 2013, average for 27 European countries. ****Reference year 2011, average for 27 European countries

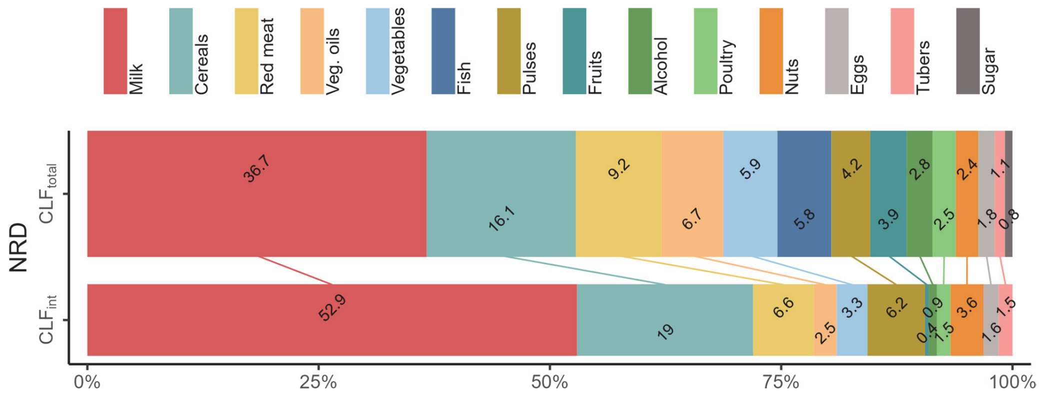

Fig. 4 Contribution of food groups to CLF_{total} (total consumption land footprint) and CLF_{int} (internal consumption land footprint) for NRD (nationally recommended diet)

constraints, yielded a Pareto front range of 1154.44 to 2910.42 (m^2 cap^{-1} $year^{-1}$) for CLF_{total}, displayed in Fig. 5. This Pareto front was generated by varying the objective weights in Eq. (8). Figure 5 illustrates that larger reductions in CLF_{total} lead to greater deviations from the reference diet. Three highlighted optimal solutions achieved a 15% reduction in CLF_{total} (= 2464.51 m^2 cap^{-1} yr^{-1}) with weights $w_1 = 0.73$ and $w_2 = 0.27$, a 50% reduction in CLF_{total} (= 1461.05 m^2 cap^{-1} yr^{-1}) with weights $w_1 = 0.37$ and $w_2 = 0.63$, and the most ambitious one a 56% reduction in CLF_{total} (= 1279.61 m^2 cap^{-1} yr^{-1}) with weights $w_1 = 0.02$ and $w_2 = 0.98$ were selected for a more detailed analysis. The 15% reduction point was selected based on its proximity to the reference diet (green point in Fig. 5), as it exhibited a smaller deviation from the reference diet. In contrast, the 50% reduction point was chosen just before a region where the deviation from the reference diet demonstrated a significant change. The 56% reduction was chosen because it is the most ambitious diet change scenario. In Fig. 6, the reference diet is shown in red, the lines represent all optimal diets, the color corresponds to their CLF_{total}, and food groups are sorted by their standard deviation. As per the findings of Fig. 6, all optimal solutions generated by the analysis suggest a reduction in the consumption of milk, red meat, and sugars. Conversely, an increase in the intake of tubers, vegetable oils, cereals, and fish is recommended by all optimal solutions. However, for the fruit and vegetable groups, the results are varied, with some optimal solutions suggesting an increase in intake and others suggesting a decrease, depending on the degree of ambition in reducing CLF_{total}. However, in the most optimal solution, it is suggested to decrease the consumption of poultry and eggs. Nevertheless, there are some cases where increasing the consumption of poultry

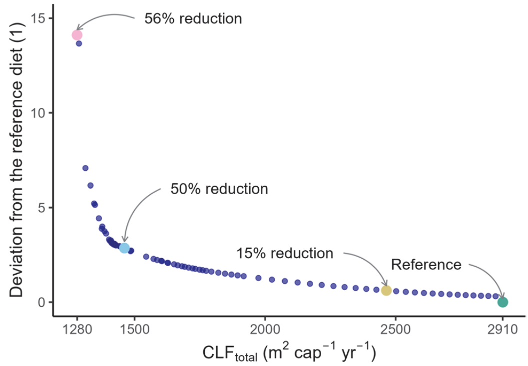

Fig. 5 CLF_{total} (total consumption land footprint) optimization Pareto front, and this graph shows all optimal diets. The vertical axis is unitless

and eggs is recommended. Milk shows the greatest tendency to deviate from the reference diet in the cases of different optimized diets, while nuts have the smallest tendency after the alcohol consumption which was kept constant during optimization. This observation may be due to inherent differences in nutrient composition between these food groups and their LF per kilogram. In addition, these patterns are influenced by the choice of the objective function (Eq. 8), specifically the squared relative deviation, which favors larger changes in food groups that are already consumed at higher amounts while penalizing food groups with limited consumption values.

Figure 7 compares the intake quantities of the reference diet, NRD, and the three selected optimal diets. The optimal diets with 15% and 50% CLF_{total} reductions show an

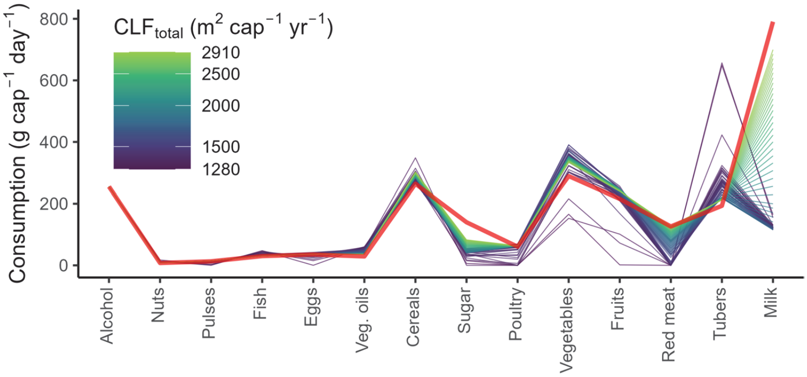

Fig. 6 Change in the consumption of food groups (g cap^{-1} day^{-1}) of each optimal diet in comparison to the reference diet (red line). Food groups are sorted according to their standard deviation

increase in consumption of cereals, tubers, pulses, vegetables, poultry, and fruits, while there is a reduction in the intake of red meat and milk. The most ambitious optimized diet (56% reduction in CLF_{total}) proposes an increase in the consumption of tubers, cereals, nuts, and vegetable oils. The consumption of red meat and poultry is zero in the most ambitious optimal solution. It proposes to reduce the consumption of sugar, vegetables, and eggs. These variations in consumption are primarily attributable to the constraints that are imposed in the optimization problem. Different optimal solutions may result in different amounts of nutrition, but the minimum values are always met due to the constraints. Figure 7 also presents differences in NRD intake values. The NRD in Estonia proposes significant adjustments to food consumption in comparison to the reference diet. The NRD advocates for a substantial increase in the consumption of fish (3.7-fold), pulses (threefold), nuts (3.9-fold), vegetables (twofold), vegetable oils (1.38-fold), and fruits (1.3-fold). Conversely, the NRD advises a notable reduction in the consumption of sugar (3.5-fold), red meat (2.7-fold), poultry (1.5-fold), eggs (1.28-fold), tubers (1.28-fold), and a moderate reduction in the consumption of milk (1.05-fold). These recommendations aim to promote a healthier and more balanced diet, aligning with the goals of the NRD to improve overall health and prevent nutrient deficiencies. Supplementary Table 3 presents the intake values for various food groups in different dietary scenarios.

Our multi-objective optimization approach presents multiple solutions, which offer flexibility in decision-making. Examination of Fig. 7 reinforces that it is essential

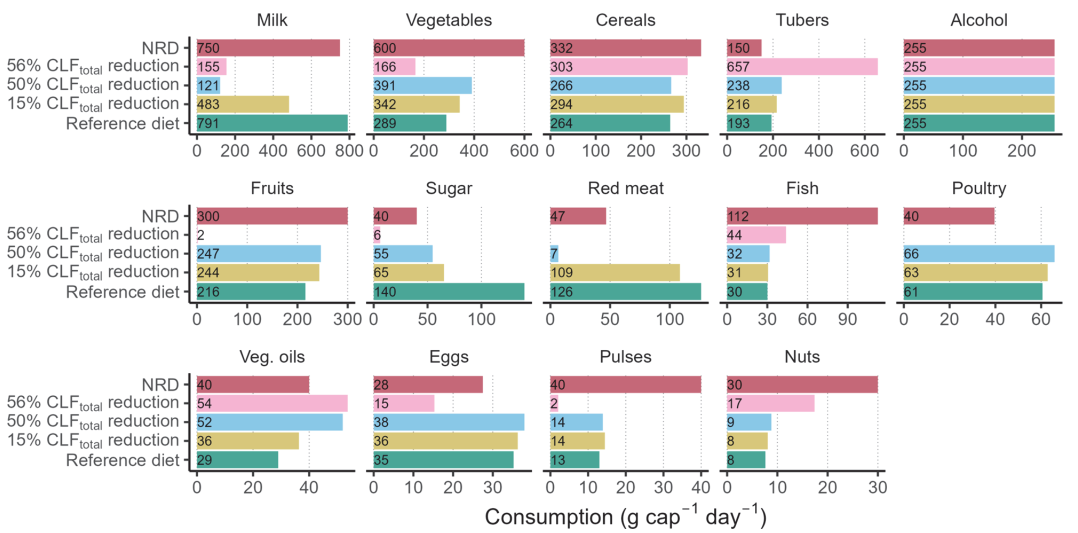

Fig. 7 Comparing the consumption of reference diet (2018), NRD, and three illustrative optimal diets

to consider cultural acceptability when making dietary changes, as demonstrated by the significant drop in red meat consumption towards zero at the 50% and 56% reduction points of CLF_{total}. The diet with a 15% reduction in CLF_{total} may be more feasible to achieve since it has a smaller deviation; thus, we will continue our analysis with it. It is also possible to take an incremental approach in this respect and propose more stringent reduction levels gradually through time. This could facilitate reaching a larger reduction in LF while minimizing the deviation from cultural acceptability, as the reference diet would also change with time.

Figure 8 depicts the absolute CLF_{total} values for each food group in various dietary scenarios, as well as the corresponding relative changes in food group contributions to the diet under investigation. The data indicates that the reference diet exhibits the highest CLF_{total}, which is largely attributed to the higher intake of milk and red meat. According to Table 3, red meat has the highest LF value; thus, even a slight reduction in red meat consumption can have a significant impact on CLF_{total}. Furthermore, our study shows that a reduction in milk and red meat consumption by 39% and 13%, respectively, can lead to a decrease of 446 m^2 cap^{-1} yr^{-1} in CLF_{total}. Some researchers even propose a 50% reduction in consumption of these products as a reasonable target [18]. Chaudhary and Krishna [4] conducted a global-scale study that designed diets that are both nutritionally adequate and environmentally sustainable while minimizing deviation from current average diets. Their research suggests that in Estonia, reducing milk consumption by 96%, and red and

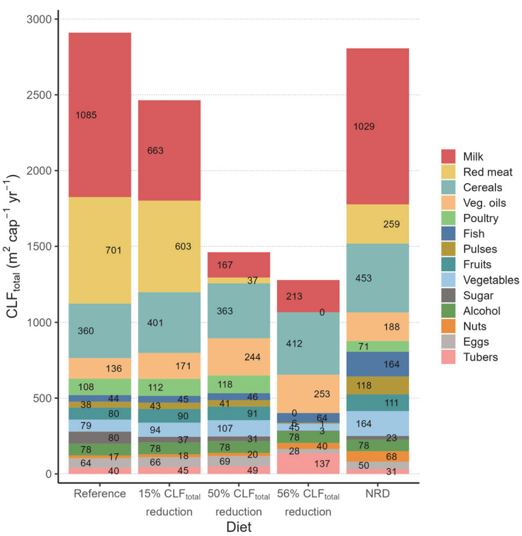

Fig. 8 Absolute CLF (consumption land footprint) of food groups by dietary scenarios. NRD, nationally recommended diet

poultry meat consumption by 45% and 47%, respectively, and increasing the intake of plant-based products such as fruits, nuts, and cereals, can limit the environmental impacts of the diet within planetary boundaries. However, the feasibility of achieving such significant changes in consumption remains in question. The recent EAT-Lancet Commission [52] on healthy diets from sustainable food systems has put forth a proposal for a nutritious diet that aligns with daily nutritional guidelines while respecting environmental planetary boundaries. This diet suggests limiting the consumption of red meat to 14 g per day, milk to 250 g per day, and chicken to 29 g per day. To achieve this goal, intermediate objectives and milestones are necessary to ensure a gradual and feasible transition toward these dietary recommendations [52]. This emphasizes the conflicting objectives of cultural acceptability and sustainability when it comes to diet, which should be considered simultaneously.

3.5 Change in CLF_{int} and CLF_{ext}

Our approach for assessing the influence of dietary changes on production and import in the country relies on a simple assumption. According to this assumption, the production and import of food groups will vary in response to changes in consumption. Specifically, if there is an x% change in the consumption of a particular food group, there will be a corresponding x% change in the production and import of that food group. Note that the export is assumed to remain constant. The methodology described was employed in the studies conducted by Hess et al. [53] and Mirzaie-Nodoushan et al. [31]

Table 5 displays the changes in the production and import of food items, the CLF_{int}, CLF_{ext}, and CLF_{total}, based on the previously stated assumptions. The reference diet exhibits the greatest CLF_{int} and CLF_{ext}, which can be attributed to the elevated consumption of food categories such as red meat, poultry, egg, and milk. In comparison to the reference diet, the CLF_{total} of the NRD diet is 3% lower, while the chosen optimized diet has a 15% reduction in CLF_{total}. Note that certain food groups, such as red meat, poultry, and sugar, require a substantial change in consumption as recommended by the NRD. Implementing such changes can have significant implications for production and import patterns, which may pose challenges. However, our optimized diet approach offers a practical solution by suggesting a more moderate adjustment in food intake. This balanced approach allows the economy to gradually adapt to the recommended dietary changes without disrupting existing production and import systems. By providing a feasible transition, our optimized diet facilitates a smoother and more sustainable adoption of healthier eating habits.

Table 5 Production and import quantities of food products under the reference diet, NRD, and the optimized diet with a 15% reduction in CLF_{total} (values in 1000 ton)

	Reference diet			NRD diet		Optimized diet with a 15% reduction in CLF_{total}	
	Production	Import	Export	Production	Import	Production	Import
Cereals	923	165	589	1161.41	207.62	1027.85	183.72
Tubers	88	21	4	68.23	16.28	98.47	23.49
Pulses	88	5	63	270.77	15.38	94.76	5.38
Nuts	114	18	27	449.03	70.90	114	18
Vegetables	56	101	11	116.17	209.52	66.26	119.51
Veg. oils	57	30	51	78.73	41.44	70.75	37.23
Fruits	9	103	4	12.51	143.22	10.16	116.34
Sugar	4	98	20	1.14	28.01	1.85	45.50
Red meat	56	46	31	20.70	17.00	48.44	39.79
Poultry	19	30	12	12.42	19.61	19.62	30.98
Eggs	13	10	3	10.15	7.81	13.37	10.28
Milk	798	97	366	757.07	92.02	487.33	59.23
Fish	83.66	50.02	111.74	311.48	186.23	86.44	51.68
Alcohol	147	82	122	147.00	82.00	147.00	82.00
CLF_{int} (kha yr^{-1})	215.44	–	–	210.23	–	171.21	–
CLF_{ext} (kha yr^{-1})	168.47	–	–	159.92	–	153.88	–
CLF_{total} (kha yr^{-1})	383.92	–	–	370.25	–	325.10	–

NRD nationally recommended diet, *CLF* consumption land footprint

Prior research by Põldaru et al. [54] explored the capacity of Estonia to attain self-sufficiency in agricultural production but did not focus on diets. They recommended expanding the production and export of red meat and dairy products, suggesting that Estonia's agricultural sector has the necessary resources to achieve self-sufficiency in crucial food items. Our analysis suggests that decreasing consumption could potentially assist in reaching self-sufficiency in food production.

3.6 Limitations and Suggestions

The use of the global average production yield for all food products imported to Estonia can lead to an overestimation or underestimation of the land footprint. This is because the actual yield of specific food products may vary depending on the country or region of production. Furthermore, our land footprint methodology does not allocate any land to fish food products.

The assumption of constant feed conversion ratios (FCRs) can also lead to inaccuracies in land footprint calculations, as FCRs vary depending on the livestock production system and the type of feed used. It is also assumed that the grass content in the feed is the same for all countries. This assumption may also lead to inaccuracies as the diet of livestock varies across countries. It would be more accurate to use country-specific FCRs or to account for variations in FCRs within different livestock production systems. Fish is excluded from the LF analysis in this study. This omission is justifiable since the contribution of fish products to the land footprint of the EU was negligible as shown in other studies [40].

In this analysis, all food items are aggregated into 14 food groups. This reduction in the number of food groups could potentially limit the flexibility of the model to find more feasible solutions. Land footprints and nutritional values of the food items within the food groups may also vary, and this variation may be lost at the high level of aggregation. On the other hand, this reduction in decision variables simplifies result communication for easier integration into dietary guidelines as also discussed by Nordman et al. [55]. Note that the food consumption data in this study are sourced from the FAOSTAT database, where values are mainly reported in primary product equivalents. This means that the food items are not as detailed as in the diet. For example, processed meat products are reported in their red meat equivalent. Thus, further aggregation of food items may not cause further uncertainty in the calculations of land footprint.

Applying the nutritional content from USDA as reported by Gephart et al. [44] for diet optimization in Estonia might be a limitation. However, as mentioned above, the list of food items provided in the FAOSTAT database is standard and similar for every country. Therefore, although the nutritional content may differ slightly from country to country, it may not have a considerable impact on the final results of this study.

We have assumed that changes in consumption patterns will lead to variations in the production and import of different food groups equally. This assumption may not always hold in practice, as there may be other factors that influence production and import beyond just changes in consumption. For example, changes in global market conditions or domestic policies could impact the production and import of certain food groups independent of changes in consumption. Additionally, supply chain disruptions or shortages could also affect production and import regardless of consumption patterns. For future studies, the multi-objective optimization approach could be utilized to model the change in the supply side (production, import, export) considering economic and environmental indicators simultaneously. Also in the future, diet optimization should be carried out with food items more specific to Estonian food consumption, and their nutritional content should be taken from local databases to enhance the accuracy and reliability of the results.

3.7 General Discussion

The land footprint of a diet plays a pivotal role in addressing environmental concerns. Its significance is related to inevitable opportunity costs or benefits when one option is chosen over another [56]. In the context of a diet, the land used for growing crops and raising livestock could otherwise be restored to forests or wild grasslands. The act of storing carbon in vegetation and soils results in negative emissions. Given the urgent need to reduce atmospheric CO_2 levels, minimizing the land required to meet food needs at a national level emerges as a viable strategy. Also, it is important to note that with an increasing global population and changing consumption patterns, an increase in the global cropland translates into deforestation, with further negative consequences on climate change. This is the reason for limiting the global cropland use in the planetary boundaries framework.

Our research shows that adopting a more environmentally friendly diet requires a significant reduction in meat and dairy consumption. Some people may resist this change due to their social, personal, and cultural values. Generally, consumers are hesitant to alter their food preferences for the sake of better health or a healthier environment [4, 57]. In Estonia, where meat and milk production are well-established [54], there is significant economic and political opposition to transitioning towards plant-based proteins. To address these challenges, policymakers must create interventions and incentives that encourage consumers to adopt more sustainable diets. To mitigate resistance to change, dietary modifications should be modest, consider regional eating habits, and aim for the greatest possible sustainability impact. Policymakers must also consider factors like prices, product availability, accessibility, consumer awareness, shopping habits, and personal benefits [58, 59]. Studies show that even though a decrease in red meat consumption may hurt the economy, both demand-side and supply-side interventions would support economic growth [60]. Interventions that make meat alternatives more accessible, change the presentation of meat- and plant-based alternatives at the point of purchase, and reduce portion sizes of meat servings have shown the most potential for reducing meat consumption [61]. In addition, it has been advocated that public procurement (purchasing of goods and services using public funds) is a successful strategy for achieving environmental objectives in the food sector [62].

A multitude of synergistic approaches could enhance the feasibility and speed of the transition towards sustainability. One crucial strategy involves addressing food waste within the supply chain [63]. Measures to reduce waste can optimize resources and minimize the environmental impact of food production. Simultaneous improvement of agricultural practices will also promote environmental sustainability [2], ensuring that our food systems can meet the demands of a growing population while minimizing their ecological footprint. Another avenue to explore is harnessing the potential of dietary alternatives [64] like cultured meat, plant-based meat analogs, and edible insects [65]. Furthermore, the reformulation of existing food items and the creation of novel alternatives can cater to changing consumer preferences while promoting a healthier planet. Integration of these diverse strategies could create a driving force for positive change in the food systems.

4 Conclusion

Our study focused on the reduction of the land footprint of the Estonian diet while maintaining its nutritional benefits and cultural familiarity. We calculated the land footprint of 14 different food groups using data from production and imports. Next, we assessed the total consumption land footprint of the reference diet and compared it to a nationally recommended diet (NRD) recommended by the National Institute of Health Development, as well as a diet that aimed to minimize total consumption land footprint (optimized diet).

The assessment of the NRD in Estonia revealed a slight decrease in the CLF_{total} when adhering to the NRD. Using a multi-objective optimization algorithm with nutritional constraints, we generated a set of optimal diets, all with reduced CLF_{total}. From this set, we selected a diet that exhibited an acceptably small deviation from the reference diet. Notably, the adoption of this selected diet in Estonia resulted in a significant 15% reduction in land use, highlighting its potential environmental benefits.

The distinctive feature of this study lies in its potential for broader applicability in analogous research endeavors. The results of our study strongly suggest that making a moderate and socially acceptable change in dietary habits has the potential to significantly reduce land footprints (LFs). This not only underscores the practical implications of our study but also highlights the prospect of its relevance and utility in the context of future research endeavors.

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s10666-024-09996-4.

Acknowledgements The authors express their sincere gratitude for the valuable insights contributed by the researchers involved in the Tervisekonto project no. 2014-2020.4.02.21-0338. The authors appreciate the constructive comments and input from two anonymous reviewers on an earlier version of this manuscript.

Author Contribution Conceptualization: B.B., R.V., O.G.; Methodology: B.B., A.K.; Formal analysis: B.B., A.K., R.V.; Writing- original draft preparation: B.B.; Writing- review and editing: A.K., R.V.; Funding acquisition: R.V.; Resources: O.G., B.B.; Supervision: O.G., R.V.

Funding This study was conducted as a part of the Tervisekonto project no. 2014–2020.4.02.21–0338.

Data Availability All data utilized for the assessment have been appropriately cited and are accessible online. The list of food items and their respective food groups analyzed, the list of countries contributing to the import of animal products in Estonia, and the food group intake data for dietary scenarios are provided within the supplementary information file.

Declarations

Conflict of Interest The authors declare no competing interests.

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SI Table 1. Food items and corresponding food groups included in the analysis

Food groups	**Food items**
Cereals	Wheat and products
	Rice and products
	Barley and products
	Maize and products
	Rye and products
	Oats
	Cereals, Other
Tubers	Potatoes and products
	Sweet potatoes
Pulses	Beans
	Peas
	Pulses, Other, and products
Nuts	Nuts and products
	Soybeans
	Groundnuts
	Olives (including preserved)
Vegetables	Tomatoes and products
	Onions
	Vegetables, Other
Fruits	Oranges, Mandarines
	Lemons, Limes, and products
	Grapefruit and products
	Citrus, Other
	Bananas
	Plantains
	Apples and products
	Pineapples and products
	Dates
	Grapes and products (excl. wine)
	Fruits, Other
Veg. oils	Soyabean Oil
	Sunflower seed Oil
	Rape and Mustard Oil
	Olive Oil
	Maize Germ Oil

	Oilcrops Oil, Other
Alcohol	Wine
	Beer
	Beverages, Alcoholic
Sugar	Sugar (Raw Equivalent)
	Sweeteners, Other
Red meat	Bovine meat
	Mutton & goat meat
	Pig meat
Poultry	Poultry meat
Eggs	Eggs
Milk	Milk
Fish	Fish

SI Table 2. List of countries contributing to the import of animal products in Estonia (highlight means it has been considered in the analysis according to the inclusion criteria)

Countries	Animal product	Share in import
Austria	Meat of pig boneless, fresh or chilled	0%
Belgium	Meat of pig boneless, fresh or chilled	3%
Denmark	Meat of pig boneless, fresh or chilled	21%
Finland	Meat of pig boneless, fresh or chilled	7%
France	Meat of pig boneless, fresh or chilled	1%
Germany	Meat of pig boneless, fresh or chilled	23%
Hungary	Meat of pig boneless, fresh or chilled	1%
Ireland	Meat of pig boneless, fresh or chilled	6%
Latvia	Meat of pig boneless, fresh or chilled	3%
Lithuania	Meat of pig boneless, fresh or chilled	4%
Netherlands	Meat of pig boneless, fresh or chilled	3%
New Zealand	Meat of pig boneless, fresh or chilled	0%
Poland	Meat of pig boneless, fresh or chilled	18%
Portugal	Meat of pig boneless, fresh or chilled	1%
Spain	Meat of pig boneless, fresh or chilled	9%
Sweden	Meat of pig boneless, fresh or chilled	0%
United Kingdom of Great Britain and Northern Ireland	Meat of pig boneless, fresh or chilled	0%
Denmark	Bovine meat, salted, dried or smoked	3%
Finland	Bovine meat, salted, dried or smoked	73%
Germany	Bovine meat, salted, dried or smoked	18%
Italy	Bovine meat, salted, dried or smoked	1%
Latvia	Bovine meat, salted, dried or smoked	0%
Poland	Bovine meat, salted, dried or smoked	4%
Spain	Bovine meat, salted, dried or smoked	1%
Denmark	Hen eggs in shell, fresh	1%
Finland	Hen eggs in shell, fresh	6%
Latvia	Hen eggs in shell, fresh	50%
Lithuania	Hen eggs in shell, fresh	17%
Poland	Hen eggs in shell, fresh	26%
Denmark	Raw milk of cattle	0%
Finland	Raw milk of cattle	0%
Germany	Raw milk of cattle	0%
Greece	Raw milk of cattle	0%
Italy	Raw milk of cattle	0%
Latvia	Raw milk of cattle	96%
Lithuania	Raw milk of cattle	1%
Netherlands	Raw milk of cattle	0%

Poland	Raw milk of cattle	2%
Sweden	Raw milk of cattle	0%
Belgium	Meat of sheep, fresh or chilled	11%
Denmark	Meat of sheep, fresh or chilled	2%
Finland	Meat of sheep, fresh or chilled	1%
France	Meat of sheep, fresh or chilled	0%
Germany	Meat of sheep, fresh or chilled	3%
Latvia	Meat of sheep, fresh or chilled	2%
Lithuania	Meat of sheep, fresh or chilled	4%
Netherlands	Meat of sheep, fresh or chilled	14%
New Zealand	Meat of sheep, fresh or chilled	36%
Poland	Meat of sheep, fresh or chilled	2%
Spain	Meat of sheep, fresh or chilled	25%

SI Table 3. Food group intake for dietary scenarios (g cap^{-1} d^{-1})

	Dietary Scenarios				
Food groups	Reference diet	NRD	15% CLFtotal reduction	50% CLFtotal reduction	56% CLFtotal reduction
Cereals	264	332.5	294.3	266.5	302.8
Tubers	193	150	216.4	237.9	656.9
Pulses	14	40	14.4	13.9	2.1
Nuts	8	30	8.1	8.8	17.4
Vegetables	289	600	342.3	390.7	166.1
Veg. oils	29	40	36.4	52.0	53.7
Fruits	216	300	243.5	246.6	1.5
Sugar	140	40	65.3	54.7	6.0
Red meat	126	46.69	108.5	6.6	0.0
Poultry	61	39.6	62.9	65.9	0.0
Eggs	35	27.5	36.3	38.0	15.3
Milk	791	750	483.0	121.4	154.9
Fish	30	112.5	30.6	31.7	44.0
Alcohol	255	255	255.1	255.1	255.1

Appendix 2

Publication II

Bashiri, B., Kaleda, A., & Vilu, R. (2025). Integrating multi-criteria decision-making with multi-objective optimization for sustainable diet design. *Journal of Cleaner Production*, 500, 145233. https://doi.org/10.1016/j.jclepro.2025.145233

Journal of Cleaner Production 500 (2025) 145233

Contents lists available at ScienceDirect

Journal of Cleaner Production

journal homepage: www.elsevier.com/locate/jclepro

Integrating multi-criteria decision-making with multi-objective optimization for sustainable diet design

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A R T I C L E I N F O

Handling Editor: Yutao Wang

Keywords:
MCDM
Multi-objective optimization
Food consumption
Diet change
Environmental impacts

A B S T R A C T

We present an approach to optimize diet sustainability by combining multi-criteria decision-making (MCDM) with multi-objective optimization (MOO). A sustainable diet must balance cultural acceptability, nutritional adequacy, and environmental sustainability. However, a single food group may perform well in one indicator but poorly in others, necessitating the inclusion of multiple indicators to achieve a truly sustainable diet. This, in turn, increases the complexity of the optimization process and the interpretation of its results. To address this challenge, we applied the SURE method as an MCDM tool before MOO to reduce the number of objectives. The SURE score can integrate multiple environmental indicators, capturing their conflicting characteristics and simplifying the optimization problem. The proposed method was applied to optimize the Estonian diet. Estonian food consumption was categorized into 14 groups, and footprint data with uncertainty ranges were collected for analysis. A bi-objective optimization problem was formulated to simultaneously minimize five aggregated environmental footprints and deviations from the reference diet while satisfying nutritional constraints. For comparison, a classical multi-objective optimization approach was also implemented. The results demonstrated that both approaches successfully reduced all environmental impacts. However, the bi-objective optimization offered a more straightforward decision-making process, allowing for the visual representation of results and easier adjustments to objective weights based on decision-maker preferences. This method facilitates the design of sustainable diets by streamlining complex trade-offs and providing a clear framework for informed decision-making.

1. Introduction

The degradation of natural resources poses a pressing global challenge, and the food supply chain contributes up to 30 % of anthropogenic greenhouse gas (GHG) emissions (Crippa et al., 2021), is responsible for approximately 32 % of global terrestrial acidification and 78 % of eutrophication (Poore and Nemecek, 2018), consumes about 70 % of freshwater resources, and occupies over one-third of all potentially cultivable land (Foley et al., 2011). At the same time, dietary risk factors are significant contributors to the burden of non-communicable diseases (Nordman et al., 2023), primarily due to inadequate intake of fruits, vegetables, nuts, seeds, and dietary fiber, alongside excessive consumption of red and processed meats (Afshin et al., 2019). Therefore, there is substantial potential for dietary changes to mitigate environmental impacts and improve human health (Poore and Nemecek, 2018; Bashiri et al., 2024a; Garvey et al., 2021; Pais et al., 2020).

The environmental sustainability of a diet can be quantified using various environmental footprints (Matuštík and Kočí, 2021). However, the multiple types of footprints often lead to conflicting environmental goals (Vanham et al., 2019). For example, a food product that minimizes carbon emissions may instead require greater amounts of water or land. Poore and Nemecek point out that the relationships between footprints are generally weakly positive and sometimes even negative (Poore and Nemecek, 2018). Research shows that reducing land by half use can increase GHG emissions per kilogram of grain by 2.5 times and acidification by 3.7 times because reducing land use leads to more intensified agriculture and increased applications of fertilizers. These trade-offs pose significant challenges for decision-makers and policymakers to implement comprehensive strategies for sustainable food production and consumption (Han et al., 2024). An integrative and systematic analysis of the interdependencies among environmental footprints is

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https://doi.org/10.1016/j.jclepro.2025.145233
Received 24 December 2024; Received in revised form 25 February 2025; Accepted 6 March 2025
Available online 10 March 2025
0959-6526/

essential to mitigate potential trade-offs, minimize unintended environmental impacts, and guide the formulation of evidence-based, sustainable policy choices.

In mathematics, optimization refers to the process of finding the best solution from a set of feasible alternatives (Arora, 2015; McKelvey and Neves, 2021). Using optimization algorithms presents a viable solution to the challenge of creating sustainable diets that fulfill various objectives (van Dooren and Aiking, 2016; van Dooren, 2018; Colombo et al., 2019). By employing the optimization approach, a sustainable diet can be attained by meeting specific criteria, such as minimizing deviations from current intake levels, while adhering to nutritional, cultural, and environmental constraints. Studies have employed linear (Lauk et al., 2020; Colombo et al., 2021; Eini-Zinab et al., 2021) and nonlinear (Chaudhary and Krishna, 2019) optimization algorithms with a single objective to optimize diets. Single objective optimization yields a single solution often with extreme changes to diet (Bashiri et al., 2024a), which may be difficult to adopt. Conversely, such calculations have low complexity and are easy to perform.

Multi-objective optimization (MOO) is an approach to finding a balance between several conflicting objectives (Gunantara, 2018). By incorporating some parameters from constraints into the objective function, MOO relaxes these constraints, generating numerous possible solutions. When applied to diet, MOO may suggest a gradual and moderate shift in consumption patterns (Bashiri et al., 2024a).

Donati et al. (2016) were among the pioneers who used MOO to investigate the environmental and economic aspects of diets simultaneously. They found that a healthier and eco-friendly diet is not necessarily more expensive. Abejón et al. (2020) employed MOO to maximize nutritional contribution and minimize greenhouse gas emissions while minimizing costs. Their results demonstrated that dietary patterns with enhanced nutritional profiles and lower environmental impacts can be achieved without incurring additional costs. This can be accomplished by increasing the consumption of vegetables, fruits, and legumes while reducing the intake of meat and fish. Mirzaie-Nodoushan et al. (2020) applied MOO to achieve a culturally acceptable diet while minimizing the water footprint. In a recent study, Muñoz-Martínez et al. (2023) aimed to create a sustainable and healthy diet for Spain by using MOO to minimize costs and environmental impact, including greenhouse gas emission, land use, and freshwater withdrawals, while minimizing deviations from current diets. The study compared the optimized diet to Spanish dietary guidelines and explored the advantages of reducing animal products in favor of plant-based alternatives. The results showed that the optimized diet could be healthier, and reduce GHG emissions, land footprint, and water consumption. The authors also concluded that shifting to fortified plant-based milk alternatives may add additional environmental benefits. Studies have since been conducted to propose customized provincial sustainable diets across China (Fu et al., 2024; Wang et al., 2024a), and other studies suggest that diet optimization can improve global nutrition while reducing greenhouse gas emissions and land use (Liu et al., 2024). Benvenuti and De Santis (Benvenuti and De Santis, 2020) developed a MOO algorithm aiming to move beyond traditional linear programming to a methodology that could address acceptability alongside health, cultural, environmental, and economic dimensions in the design of meal plans. Benvenuti et al. (2019) applied MOO to design cycle menus for nursing homes. They concluded that it is feasible to achieve a menu with a significantly reduced environmental impact at a marginally increased cost. These studies showcase the versatility and effectiveness of MOO in addressing diverse challenges related to diet and sustainability.

Most of these studies have evaluated problems with only two or three objectives, despite the fact that many real-world problems involve more. Optimization problems with many objectives introduce some difficulties. One of the difficulties is the deterioration of searchability (Ruppert et al., 2022) as the proportion of equally good solutions according to Pareto dominance increases rapidly with the number of objectives, making the final selection complicated. Another challenge in MOO is the presence of dominance-resistant solutions or outliers (Wang et al., 2023), which are solutions with a poor value in at least one objective but with near-optimal values in the others (Jaimes and Coello, 2015). The number of points required to represent a Pareto front accurately in MOO increases exponentially with the number of objectives, a problem known as the curse of dimensionality (Jaimes and Coello, 2015; Ma et al., 2020). This makes it impossible to clearly visualize a Pareto front with more than three objectives (dimensions), hindering the decision-making process (Alvarado-Ramírez et al., 2022).

Reducing the number of objectives can be a viable strategy to overcome difficulties when dealing with too many objectives. One approach is to identify non-conflicting objectives and eliminate them. However, this method is not applicable when all objectives are conflicting. In such cases, using multi criteria decision making (MCDM) methods prior to MOO can help to reduce the number of objectives. When applied to diet optimization, MCDM methods can help to reduce the number of environmental footprints included in the objective function by assigning an aggregate footprint score to each food group. For example, Wheeler et al. (2018) used MCDM prior to MOO to reduce the number of objectives in a biomass supply chain study. They found that this methodology simplifies MOO problems by providing a framework that allows stakeholders to agree on a final solution through the reliable judgment of the relative importance of conflicting objectives. Russel et al. (Russell and Allman, 2023) also presented an algorithm to reduce the dimensionality of linear MOO problems using a weighting approach for objectives prior to generating Pareto optimal points. This algorithm can simplify an intractable and uninterpretable high-dimensional many--objective problem into manageable two- or three-objective problems. Ferdous et al. provided a comprehensive review of the integration of MCDM and MOO (Ferdous et al., 2024). Overall, studies suggest that the integration of MCDM and MOO is a viable strategy to simplify MOO and subsequent decision making.

A research gap exists in incorporating multiple sustainability indicators into dietary optimization, as current studies have been limited to a maximum of three indicators. Despite growing evidence that various environmental indicators often show opposing trends, no research has yet explored the integration of a broader range of footprints. To address this gap, we propose a method that combines MCDM and MOO to simplify the inclusion of a wider set of sustainability indicators in diet optimization. We demonstrate the application of the proposed methodology using the Estonian diet as a case study. In our previous study, we conducted diet optimization for Estonia using land footprint as the sole environmental indicator (Bashiri et al., 2024a). In the current study, we extend this approach by incorporating five environmental indicators into the model using the proposed method, demonstrating how the results can differ when multiple indicators are considered instead of a single one. Additionally, we provide a ranking of food groups based on these five environmental footprints. The proposed method also enables us to effectively address the uncertainties associated with footprint data, enhancing the robustness of the analysis.

2. Methodology

2.1. Data collection of food consumption

We collected food consumption data from the food balance sheet (FBS) of the Food and Agricultural Organization of the United Nations Statistics (FAOSTAT) (Bashiri et al., 2024a; Food and Agricultural Organization of the United Nations, 2022; Bashiri et al., 2023; Kim et al., 2020). The daily per capita food consumption (g cap^{-1} d^{-1}) data for 2021 served as a reference diet for the Estonian population. Data from 2021 was selected as it closely represents the average food consumption of the Estonian population from 2018 to 2021. Only minor fluctuations were observed across these years. From the FBS dataset, which covers 74 different food items, we excluded 26 items that had zero or negligible intake in Estonia. This left us with 48 food items, which we then categorized into 14 food groups: cereals, tubers, pulses, nuts, vegetables, vegetable oils, fruits, sugar, red meat, poultry meat, eggs, dairy, fish, and alcoholic beverages.

2.2. *Data collection of environmental footprints*

We utilized a comprehensive dataset generated by Poore and Nemecek (2018), which encompasses life cycle assessment (LCA) data for 43 food items and covers five environmental footprints: land use (m^2 FU^{-1}), GHG emissions (kg CO_2eq FU^{-1}), acidifying emissions (g SO_2eq FU^{-1}), freshwater withdrawals (L FU^{-1}), and eutrophying emissions (g PO_4^{3-}eq FU^{-1}). The FU is 1 kg of product. The list of food products, environmental footprints, and associated uncertainties is provided in Supplementary. The uncertainties in this dataset are reported by statistical characteristics: mean, median, and 5th, 10th, 90th, and 95th percentile values. However, according to Poore and Nemecek (2018), the distribution of footprints is multi-modal. We determined that the log-normal distribution provided a reasonable approximation for the purpose of this study and thus fitted the log-normal function to the published percentile values to model the distributions of the footprints for individual food items. Water footprint was modeled using the triangular distribution. Both fit distributions were truncated at the 5th and 95th percentiles to set minimum and maximum bounds. The footprint of a group consisting of multiple food items was calculated by resampling the fitted distributions, with the number of samples weighted by the share of the food item in the group. The minimum, maximum, and mode of these resampled distributions were then used in further calculations.

2.3. *Choice of MCDM method*

We used an MCDM method termed Simulated Uncertainty Range Evaluations (SURE) (Hodgett and Siraj, 2019). This method is designed to aid decision makers in situations characterized by high uncertainty. The method utilizes simulations based on triangular distributions to create a visual representation of decision alternatives and their overlapping uncertainties. Case studies demonstrate that SURE can outperform other existing methods for decision-making involving multiple criteria and uncertainty. SURE can integrate multiple environmental indicators into a single score for each food product, taking into account uncertainty inherent in the assessment process. The mathematical background of the SURE method is thoroughly explained by Hodgett and Siraj (2019).

2.4. *Optimizations of diet pattern*

The term “optimized diet” refers to a diet that minimizes deviation from the reference diet (maximizes the cultural acceptability) and minimizes environmental impacts in five footprints while satisfying nutritional constraints. To investigate the feasibility of combining MCDM with MOO, two objective functions were formulated.

- Bi-objective optimization (BOO) that applied SURE prior to the optimization to calculate the aggregate SURE score of five footprints for each food group:

$$min[x^*] = w_1 \sum_1^n \left(\frac{x_i^* - x_i}{x_i}\right)^2 + w_2 \sum_1^n \left(x_i^* \times SURE\_score_i\right), \tag{1}$$

where x_i and x_i^* represent the current and optimized consumption of food group i, respectively.

- Multi-objective optimization (MOO) where all footprints were implemented individually:

$$min[x^*] = w_1 \sum_1^n \left(\frac{x_i^* - x_i}{x_i}\right)^2 + w_2 \sum_1^n \left(x_i^* \times LF_i\right) + w_3 \sum_1^n \left(x_i^* \times GHG_i\right) + w_4 \sum_1^n \left(x_i^* \times Acid_i\right) + w_5 \sum_1^n \left(x_i^* \times Eutr_i\right) + w_6 \sum_1^n \left(x_i^* \times WF_i\right), \tag{2}$$

where LF_i, GHG_i, $Acid_i$, $Eutr_i$ and WF_i are land use, GHG emission, acidifying emission, eutrophying emission, and freshwater withdrawals of food group i, respectively, and where x_i and x_i^* are the current and optimized consumption.

The first part of both equations is the cultural acceptability term (Arnoult et al., 2010). Both equations utilize weight factors $w_1, w_2, w_3, w_4, w_5, w_6 > 0$, $w_1 + w_2 + w_3 + w_4 + w_5 + w_6 = 1$ that are varied to build a Pareto optimal front. Both objective functions are constrained by 19 nutritional constraints as explained in our previous article (Bashiri et al., 2024a).

2.5. *Calculation workflow*

The workflow is depicted in Fig. 1. It commences with the selection of food items and their consumption values from FAOSTAT, followed by the grouping of food items into 14 food groups. The next step involves collecting environmental footprint data for various food items with their uncertainty ranges. To account for this uncertainty, the footprint data are fitted to log-normal distributions, which enable a probabilistic representation of the data. From these distributions, critical parameters such as mode, minimum, and maximum values are extracted for further use. Once the food items are grouped, their environmental footprints are aggregated using the SURE method, which combines multiple environmental indicators into a single score. Subsequently, the optimization process is performed using BOO and MOO. BOO is first run using the weighted sum method to identify all non-dominated solutions, from which the desired level of cultural acceptability is selected. MOO is then run with fixed cultural acceptability as an equality constraint to ensure consistency and enable fair comparison across solutions. In this case, besides the nutritional constraints, the following constraint is applied to the MOO objective function:

$$\sum_1^n \left(\frac{x_i^* - x_i}{x_i}\right)^2 = constant, \tag{3}$$

Following optimization, footprint analysis is conducted to evaluate the environmental impacts of the proposed diets in comparison to the reference diet. This step assesses the extent to which the optimized diets achieve sustainability targets. Finally, a sensitivity analysis is performed to examine the robustness of the results.

The calculations were performed in R version 4.3.0 (The R Foundation for Statistical Computing, Vienna, Austria) (R). Log-normal distributions were fitted using package “rriskDistributions” version 2.1.2 (R Package, 2022), sampling from distributions was done using package “mc2d” version 0.2.1 (Pouillot and Delignette-Muller, 2010), SURE calculation was done using package “MCDA” version 0.1.0 (Bigaret et al., 2017), optimization was performed using package “alabama” version 2023.1.0, which applies the augmented Lagrangian adaptive barrier minimization algorithm for optimizing smooth nonlinear

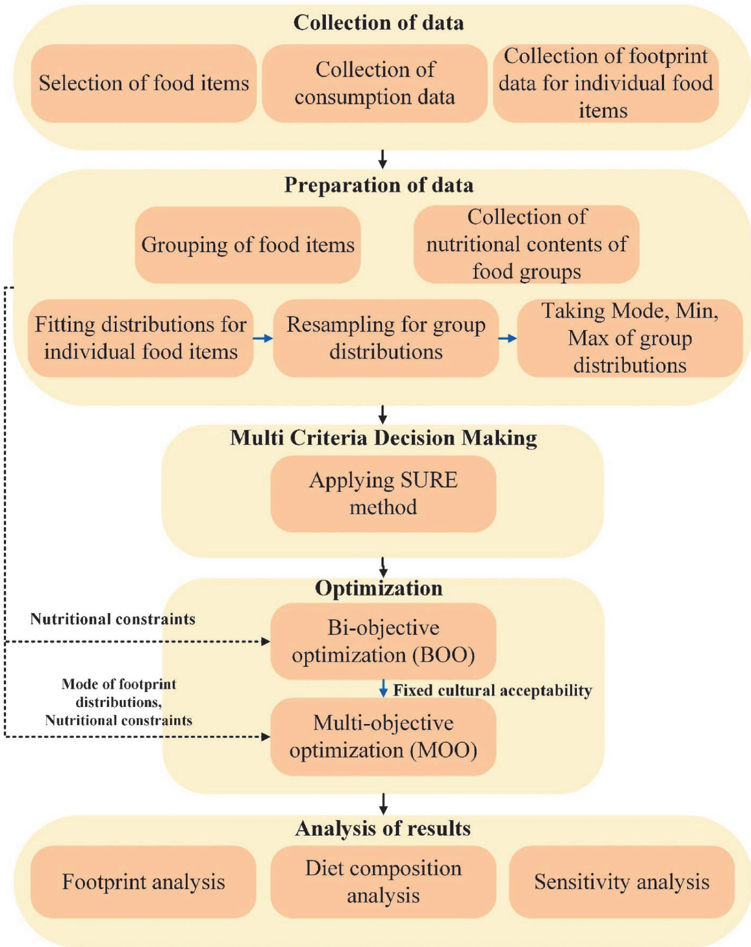

Fig. 1. The workflow of the calculations.

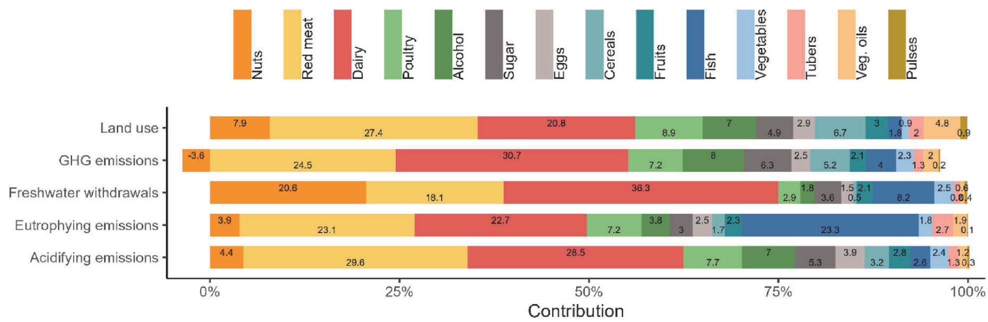

Fig. 2. Contribution of food groups to footprints of the reference diet.

objective functions with constraints. Augmented Lagrangian algorithm is well-suited for handling large-scale, nonlinear optimization problems. Augmented Lagrangian method is advantageous due to its matrix-free implementation, global and local convergence guarantees under relatively weak assumptions, and effectiveness in solving structured problems (Curtis et al., 2016).

3. Results and discussion

3.1. Environmental footprint of the reference diet

Fig. 2 illustrates the contributions of various food groups to each environmental footprint, calculated using the mode values of their resampled distributions. Red meat and dairy are significant contributors across all footprints, with dairy having the largest share in freshwater withdrawals. Fish have substantial contribution to eutrophication emissions (23.3 %) but lower contributions to the other footprints. Generally, the share of animal products varies from 61.8 % in land use to 78.8 % in eutrophication. Previous research estimated the share of animal products in land use of diet at 67 % (Bashiri et al., 2024a). Nuts exhibit high freshwater withdrawals but contribute negatively to GHG emissions (−3.6 %). Vegetable oils show higher land use footprints compared to the other four footprints, while cereals contribute more prominently to land use footprints than other categories. Tubers, pulses, vegetables, and fruits have consistently low contributions across all footprints. Alcohol shows a higher contribution to land use, GHG emissions, and acidification, but a lower impact on the other footprints. The variations in the contributions of a food group across different footprints highlight that a food group may perform better environmentally in one footprint while performing worse in another. This shows the importance of accounting for various impacts of diet.

Table 1 presents the environmental footprints of the reference diet calculated in this study and compares them to previous research. Carvalho et al. (2023) estimated diet footprints for the Portuguese population, their values generally aligning with those calculated in the current study. Bashiri et al. (2024a) assessed the land footprint of food consumption in Estonia, employing a land allocation approach that accounted for both imported and locally produced food products. Afrouzi et al. (2023) analyzed the average GHG emissions of American diets. Hallström et al. (2022) assessed the environmental impacts of diets across six impact categories, comparing them to planetary boundaries and concluding that dietary impacts exceeded these boundaries in all categories. While differences exist in the units and definitions of certain footprints between the study by Hallström et al. and the current research, a direct comparison is feasible for land use and GHG emissions. Our findings indicate that the Estonian diet exceeds the planetary boundary for land use by 40 % and for GHG emissions by 200 %. This underscores the significant environmental burden of dietary patterns in Estonia, consistent with the conclusion by Hallström et al. Generally, the comparative study shows a good overall agreement between different estimations. However, different methodologies of the footprint assessment and inherent uncertainties in data cause some variations, as noted by Carvalho et al. (2023). Additionally, the variations observed in our study could be attributed to uncertainties in the footprint data used. We employed the mode of distributions (the most probable values) for footprint analysis, but we acknowledge that the footprints themselves are distributions rather than single-point estimates.

Table 2
The SURE score (unitless) of food groups was calculated using five environmental impacts.

Food group	SURE score (mode of distribution)
Red meat	0.420281
Dairy	0.210553
Fish	0.169973
Poultry	0.090328
Nuts	0.069278
Veg. oils	0.063099
Cereals	0.051830
Eggs	0.045474
Pulses	0.029614
Sugar	0.017182
Alcohol	0.014318
Fruits	0.010745
Vegetables	0.008785
Tubers	0.005294

3.2. Ranking the food groups using the SURE score

Table 2 presents the SURE scores for various food groups, calculated based on five decision criteria (footprints) with equal weight assigned to each. SURE scores with unequal weights are also analyzed and discussed in Section 3-4. A lower SURE score indicates better environmental performance. The statistical characteristics and uncertainties associated with the SURE score are detailed in the supplementary material. Fig. 3 depicts the distribution of SURE scores, obtained after 10,000 iterations. We performed 10,000 iterations in the SURE method because the SURE scores and their associated uncertainties stabilized at this threshold, with no significant changes observed in their values beyond 10,000 iterations. Fig. 3 reveals that plant-based food groups generally have lower environmental impacts than animal-based food groups. Specifically, tubers, vegetables, and fruits are the most sustainable among plant-based food groups, while nuts are the most impactful. Red meat, dairy, and fish are the most impactful animal-based groups, whereas poultry is the most sustainable within this category. Additionally, Fig. 3 highlights uncertainty in the SURE scores for cereals. Overall, animal-based food groups are notably less sustainable than plant-based groups.

3.3. Environmental footprint of optimized diets

When optimizing conflicting objectives, the results can be represented as a hyperbolic Pareto front, illustrating the trade-off where improving one objective leads to a compromise in another. The Pareto front is generated by varying the weight coefficients of the objectives. However, when the number of objectives exceeds three, direct visualization of the Pareto front is challenging, posing a limitation in MOO. Decision-making can be subjective, thus visualization aids in communicating trade-offs more clearly. Specifically, for five-objective optimization, visualization is possible only by fixing two objectives and examining the relationships among the remaining three. In this study, BOO produced a Pareto front, as shown in Fig. 4. The Pareto front

Table 1
Environmental impacts of Estonian diet based on FAOSTAT data on food consumption for the year 2021. The values are compared to values reported in literature.

	Land use (m^2/cap/d)	GHG emissions (kg CO_2eq/cap/d)	Acidifying emissions (g SO_2eq/cap/d)	Eutrophying emissions (g PO_4^{3-}eq/cap/d)	Freshwater withdrawals (L/cap/d)
Current study	6.49	5.32	45.82	27.11	1352.17
Carvalho et al. (Carvalho et al., 2023)	13.45 (9.22–19.41)	6.17 (4.46–8.41)	39.7 (30.0–51.4)	34.0 (24.9–45.2)	855 (674–1056)
Bashiri et al. (Bashiri et al., 2024a)	7.97	–	–	–	–
Afrouzi et al. (Afrouzi et al., 2023) (Average Americans)	–	6.71	–	–	–
Hallström et al. (Hallström et al., 2022)	7.31	6.01	–	–	–
Planetary boundaries (Hallström et al., 2022)	4.62 (3.91–5.33)	1.77 (1.67–1.92)			

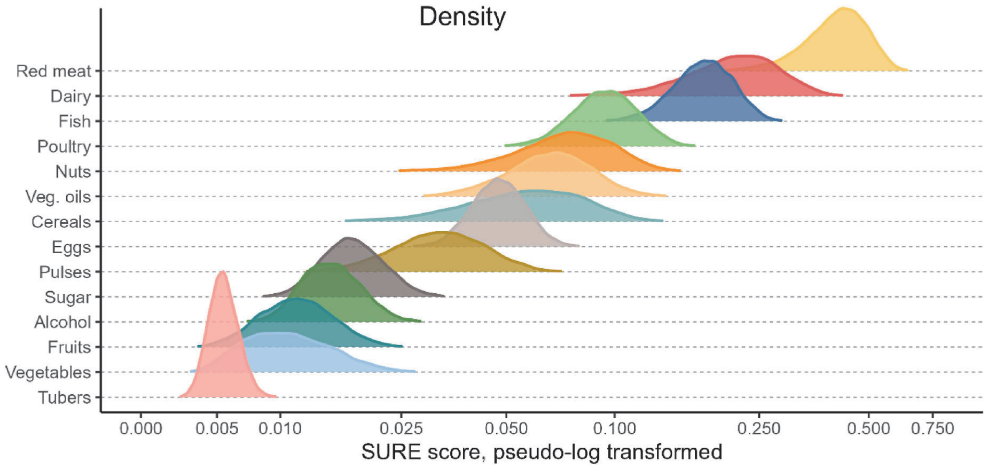

Fig. 3. Distributions of SURE scores of various food groups achieved after 10,000 iterations. All five footprints have equal weights.

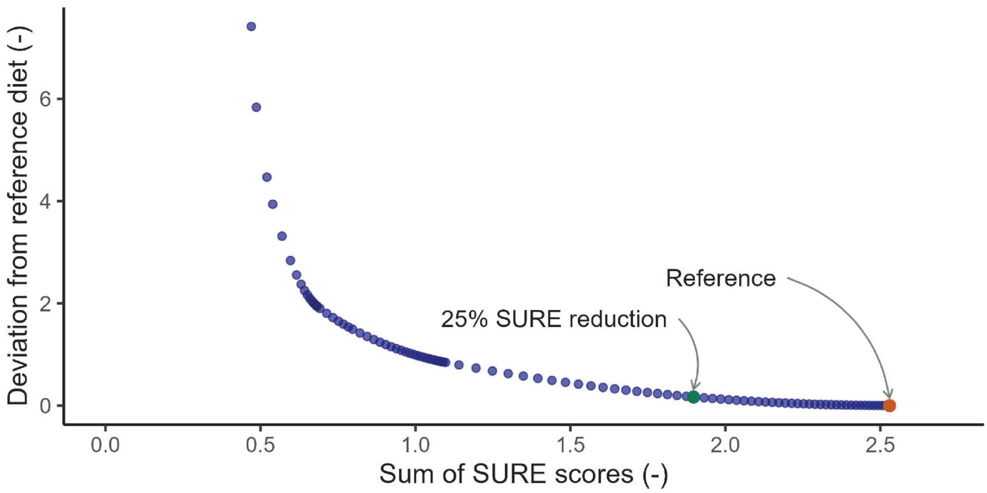

Fig. 4. The Pareto front of bi-objective optimization. This graph shows all the optimal solutions. Both axes are unitless.

includes all non-dominated solutions, each point on the curve represents optimized outcomes that satisfy all constraints. The Pareto front reveals that achieving a more sustainable diet, characterized by a reduced SURE score, comes at the expense of increased deviation from the reference diet. This implies that enhancing dietary sustainability reduces cultural acceptability. This trade-off highlights the inherent tension between balancing sustainability and cultural alignment.

For further analysis, one optimal solution was selected from the BOO Pareto front. This point, indicated by the green dot in Fig. 4, corresponds to a 25 % reduction in the SURE score of the diet. This selection was based on subjective judgment informed by previous analyses and its proximity to the reference diet, which shows a smaller deviation from the baseline. The sum of deviations for this point was used as the target deviation in the MOO. The MOO was then run to achieve the same sum of deviations. This process established a criterion for selecting comparable points from the BOO and MOO, ensuring that the two selected diets satisfy all nutritional constraints and exhibit equal acceptability. Fig. 5a presents the five footprint values for the BOO- and MOO-optimized diets alongside the reference diet. The results demonstrate that both optimization algorithms successfully reduced all environmental footprints while meeting all nutritional requirements. However, the MOO-optimized diet achieved slightly lower footprints than the BOO-optimized diet. While MOO has greater flexibility in optimization, allowing for more precise minimization of individual footprints, BOO offers distinct advantages, particularly in decision-making. BOO simplifies the process by focusing on only two objectives, enabling decision-makers to adjust weights and set decision criteria more intuitively. In contrast, MOO involves managing multiple objectives and their associated weights, which can complicate the decision-making process and introduce additional complexity. The results demonstrate that both algorithms are valuable for addressing diet optimization problems. However, BOO stands out for its streamlined approach, offering decision-makers greater control and ease of use when balancing competing priorities.

Fig. 5b illustrates the changes in the consumption of various food groups (g cap^{-1} day^{-1}) of the optimized diets (BOO and MOO) in

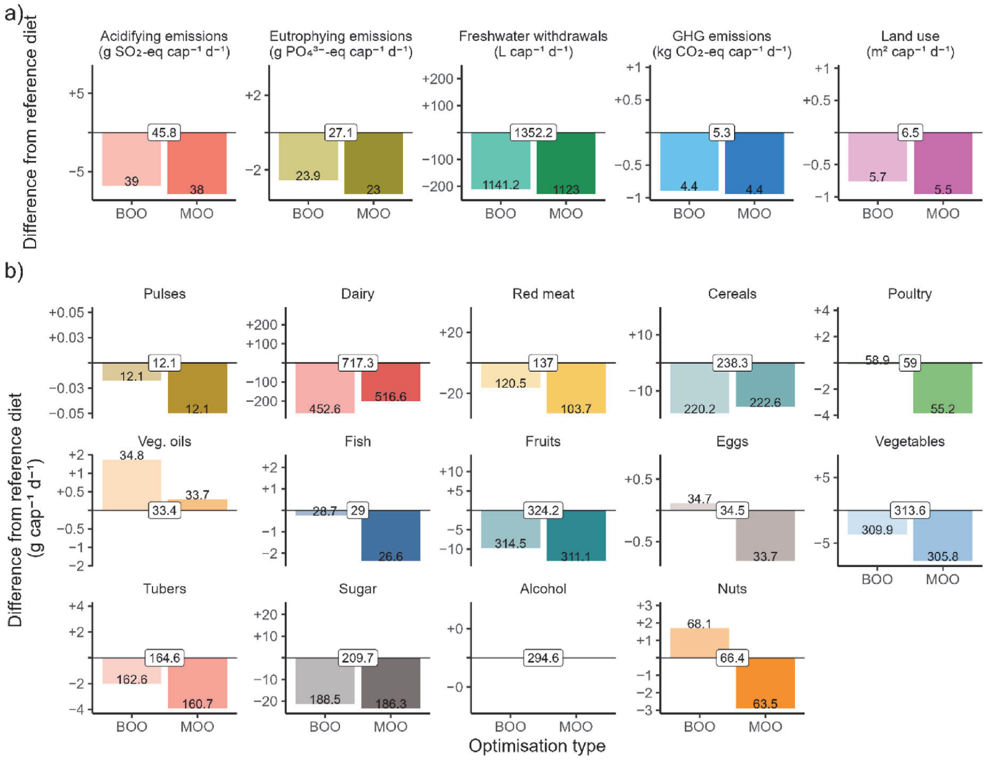

Fig. 5. Panel a) shows the change in diet footprints after bi-objective optimization (BOO) and many-objective optimization (MOO). Panel b) shows the change in the consumption of food groups after optimization. In both panels, values are compared to the reference diet shown as a horizontal line in the center.

comparison to the reference diet. Both optimization approaches generated diets with relatively small deviations from the reference diet, avoiding drastic shifts in food group consumption. This suggests that optimized diets are practically feasible and more likely to align with existing dietary habits, thereby enhancing cultural acceptability and facilitating adoption. Most food groups show a decrease in consumption in both optimized diets indicating general overconsumption of food in Estonia. Dairy products exhibit the most significant reduction (BOO: 263.8 g cap^{-1} d^{-1}; MOO: 199.6 g cap^{-1} d^{-1}), reflecting their high environmental impact as indicated by their elevated SURE score in Fig. 3. Red meat also shows a notable reduction (BOO: 16.2 g cap^{-1} d^{-1}; MOO: 33.1 g cap^{-1} d^{-1}), consistent with its substantial contribution to environmental footprints. Poultry consumption decreases minimally in BOO and by approximately 4 g cap^{-1} d^{-1} in MOO, highlighting its relatively moderate environmental footprint. Additionally, sugar, cereals, tubers, fruits, and vegetables are also reduced in the optimized diets. MOO suggests a decrease in the consumption of eggs and nuts, whereas BOO proposes an increase. In Table 2, both eggs and nuts are in the middle of the SURE score ranking table, indicating that they are neither highly sustainable nor highly unsustainable relative to other food groups. This difference in optimization outcomes reflects the differences in the relative impacts of food groups. The correlation analysis between the SURE score and individual footprints shows that they are not highly correlated ($r = 0.39$–0.80), as the SURE score is an aggregated factor that attempts to capture the characteristics of all footprints. The low correlation arises from significant conflicts among attributes, with some indicators having completely opposite directions.

3.4. Sensitivity analysis

A sensitivity analysis was conducted to examine the impact of varying the weights assigned to decision parameters on the optimization results during the MCDM application. As described in the methods section, all environmental footprints were initially given equal weights, ensuring that no single footprint was prioritized over the others. However, it is crucial to explore how the SURE score responds when one footprint is deemed more important than the others and how this shift influences the optimization outcomes. The analysis showed that minor adjustments to the weights had a negligible effect on the SURE score. Consequently, substantial changes to the weights were tested. Specifically, the weight of each footprint was increased sixfold compared to the others, one at a time, while keeping the weights of the remaining footprints equal.

Five new SURE scores were generated based on adjusted weights for each environmental footprint and were then incorporated into the BOO framework. The optimization process was repeated using the new SURE scores to assess how changes in the prioritization of individual footprints influenced the optimization results, as shown in Table 3. When land use, acidifying emissions, or eutrophying emissions were prioritized, the optimized diets achieved larger reductions in environmental impacts compared to the equal-weight scenario. Conversely, prioritizing GHG emissions or freshwater withdrawals resulted in lower overall reductions in footprint values compared to the equal-weight case. This difference stems from the fact that BOO targeted a 25 % decrease in the SURE score sum of the diet, but because weight emphasis changed individual SURE scores of the food groups and their relative contributions, this resulted in smaller or larger deviations from the current diet after

Table 3
BOO diet footprints calculated using SURE scores with different weights.

SURE weight emphasis	Land use (m^2/cap/d)	GHG emissions (kg CO_2eq/cap/d)	Acidifying emissions (g SO_2eq/cap/d)	Eutrophying emissions (g PO_4^{3-}eq/cap/d)	Freshwater withdrawals (L/cap/d)
Equal weights	5.73	4.43	39.0	23.9	1141
Land use	5.55	4.33	37.9	23.4	1139
GHG emissions	5.83	4.52	39.8	24.3	1160
Acidifying emissions	5.57	4.31	37.9	23.4	1122
Eutrophying emissions	5.60	4.32	38.1	23.4	1121
Freshwater withdrawals	5.91	4.61	40.5	24.6	1174

optimization at the chosen point. This also confirms the presence of trade-offs between these categories, where reducing GHG emissions or water use may come at the expense of higher land requirements or increased acidifying and eutrophying emissions. The interdependencies of environmental footprints complicate the optimization process, underscoring the need for a careful balance of trade-offs.

3.5. General discussion

A systematic approach is essential for addressing sustainability challenges, and MOO can help in balancing competing goals. However, a notable limitation of MOO in decision-making arises when problems involve four or more objectives. As Russell and Allman (2023) highlighted, visualizing trade-offs between multiple objectives becomes increasingly difficult and generating a complete set of solution points becomes computationally prohibitive. Sustainability goals are often uncorrelated and can conflict with one another and the context of a sustainable diet is a good example: a food group may have a lower carbon footprint than another but require greater land use. Consequently, analyzing consumption changes based exclusively on carbon footprint may yield different conclusions compared to an approach that considers both carbon footprint and land use. Our previous study on diet optimization (Bashiri et al., 2024a), which focused solely on land footprint as the environmental indicator, recommended increasing the consumption of most plant-based food groups. In contrast, the current study, which considers multiple environmental footprints, suggests decreasing the consumption of the same food groups. This difference highlights the inherent trade-offs between different environmental impacts and emphasizes the need to balance multiple environmental objectives when optimizing diets for sustainability.

MCDM has been widely used after applying MOO to find the most suitable optimal solution from the Pareto front (Wang et al., 2024b), but few researchers used it before MOO to reduce the number of objectives. Among those who applied MCDM before MOO, Russel and Allman (Russell and Allman, 2023) proposed a methodology to effectively reduce the number of objectives in MOO by grouping correlated objectives using graph-based community detection, forming two or three objective groups for streamlined optimization. This approach is particularly advantageous for high-dimensional systems. Grouping objectives and identifying contrasting relationships added complexity to the model, nevertheless, the methodology was successfully applied to several real-world scenarios. Our method, in contrast, simplifies the optimization process by aggregating multiple objectives into a single score under high uncertainties, thereby supporting practical decision-making with more interpretable solutions.

Wheeler et al. (2018) combined MCDM and MOO to incorporate preferences of decision-makers into the optimization process. Unlike methodologies that reduce the number of objectives through aggregation or grouping, Wheeler et al. (2018) retained all objectives and applied various MCDM techniques to select the most suitable solution from the Pareto front. Their approach focused on identifying a single optimal solution that aligned with expert opinions, effectively simplifying decision-making without reducing the dimensionality of the problem. They applied this framework to biomass supply chain design, demonstrating its ability to streamline complex decision-making processes. However, while their approach simplifies preference integration, it leaves open the question of how to effectively handle optimization problems with more than three objectives.

While the SURE MCDM approach is well-established, the choice of a specific MCDM method can influence the optimization results due to their differing optimality search strategies. Hadian and Madani (2015) proposed to combine multiple MCDM methods (system of systems approach) to address the bias in the definition of optimality inherent in each method. Although MCDM methods such as the Analytic Hierarchy Process (AHP) are very popular in ranking different alternatives (Ktori et al., 2025; Chiu et al., 2024), they mostly need decision-maker engagement for pairwise comparison. This process makes uncertainty inclusion difficult in decision-making, while the SURE method takes it into account.

The aggregation of multiple environmental footprints into a single score can result in some loss of detailed information by obscuring potential trade-offs between individual environmental indicators. Nonetheless, the findings of this study suggest that aggregation has a minimal impact on the diet optimization process, as the primary environmental insights remain consistent. Other studies also used several environmental and economic indicators to propose an aggregated footprint for energy alternatives (Hadian and Madani, 2015). They ultimately ranked the energy alternatives based on the aggregated footprint; however, they used the Monte Carlo method to address the uncertainties in the footprints, employing uniform sampling from uncertainty ranges. We also ranked food groups and addressed uncertainties using sampling from triangular distributions of uncertainty ranges embedded in the SURE method.

Reducing complexity becomes crucial for supporting effective decision-making especially when addressing more complex problems with additional criteria, including social, environmental, and economic factors. This is because facilitating a transition can be more important than the magnitude of the transition. In social problems such as diet change, people often resist, which is why, as previously concluded (Bashiri et al., 2024a), taking small steps towards change is necessary in the early phase of a transition. Acceptability is indeed a complex issue, as highlighted by Van Dooren and Aiking (van Dooren and Aiking, 2016). To address this complexity, other researchers (Benvenuti and De Santis, 2020; Martos-Barrachina et al., 2022) have moved from diet planning to meal planning which is done using recipes following cultural habits. Our method can be effectively integrated with meal planning models, allowing for the simultaneous consideration of multiple environmental indicators while maintaining a practical and manageable approach.

In this study, MCDM under uncertainty generated a distribution of SURE scores, from which the most probable value (mode) was used for BOO. Uncertainty is inherent to LCA results and often arises from factors such as data quality, geographical variations, and differences in technologies and their efficiencies (Bashiri et al., 2024b, 2025). Given that the distribution of SURE scores stabilized after 10,000 iterations, with no significant changes in its statistical characteristics, the mode remained consistent. Consequently, the uncertainty in SURE scores was not expected to influence the optimization results.

We used the weighted sum method to solve BOO due to its simplicity and computational efficiency. By systematically adjusting the weights, this method facilitates smooth exploration of trade-offs between objectives, making it particularly effective for visualizing the Pareto front with minimal computational effort. Among the solutions, the desired level of cultural acceptability was selected. The MOO was then run with cultural acceptability fixed as an equality constraint to ensure consistency and enable fair comparison across solutions. This approach is called the ε-constrained method when one or more objectives are treated as equality or inequality constraints, providing a structured mechanism to target specific regions of the Pareto front (Rangaiah et al., 2020). The method offers precision and flexibility in handling diverse problem requirements and is particularly suitable when the decision-maker has a clear understanding of the objective functions and can reliably select appropriate ε values.

Although efficient algorithms for finding non-dominated solutions are well-established (Deb et al., 2002; Custódio et al., 2011; Liuzzi et al., 2016) and can complement the approach used in this study for balancing multiple impacts, our method provides a ranking of food groups under high uncertainties, offering additional support for decision-making.

3.6. Limitations and suggestions

A key limitation is the assumption made about the distribution of footprint data, specifically the use of log-normal and triangular distributions to approximate uncertainties in the data. However, water footprint data did not align well with the log-normal distribution, necessitating the use of the triangular distribution instead. The available water footprint data had insufficient resolution to fit lognormal distributions, as some percentile values were the same. This substitution may influence the accuracy and reliability of the results. To improve model precision, future research should explore the use of empirical distributions derived directly from the data to better represent its characteristics.

The food items were categorized into 14 food groups. This simplification reduces the number of decision variables, making the optimization process more manageable and improving the communication of results. However, it may limit the flexibility of the model to identify more feasible solutions, as can be seen in other studies (Abejón et al., 2020; Mirzaie-Nodoushan et al., 2020; Muñoz-Martínez et al., 2023; Fu et al., 2024; Wang et al., 2024a; Liu et al., 2024).

Aggregating and resampling the footprints of individual food items to create group-level distributions introduces additional uncertainties. This approach, while simplifying the analysis, obscures nutritional and environmental differences among individual food items within a group, potentially impacting overall findings.

Integrating environmental footprints into a composite score simplifies sustainability assessment, but it is crucial to consider socio-economic and cultural factors like food affordability and accessibility. These dimensions are often difficult to quantify, thereby adding complexity to decision-making. Participatory methods (stakeholder engagements) (Pahker et al., 2024) can help prioritize criteria and develop specific strategies to involve socially and economically viable food systems.

Another limitation is the dependence on FAOSTAT, which primarily reports consumption in terms of raw product equivalents. This approach simplifies reporting but may not accurately reflect the implications of the consumption of individual food items. Future work should consider integrating data from other databases that provide more detailed information on processed food consumption or adapting conversion factors to bridge this gap.

4. Conclusion

Our research addressed the gap in sustainable dietary optimization by incorporating multiple environmental indicators into diet optimization frameworks. We developed an approach to integrate multi-criteria decision-making and multi-objective optimization methods, which simplifies the inclusion of many environmental indicators. We showed that the combined MCDM-MOO approach effectively addresses trade-offs among indicators, enabling the design of diets that reduce environmental impacts while maintaining nutritional adequacy and cultural acceptability. The proposed method makes the model more interpretable, simplifying decision-making.

Our case study on the Estonian diet revealed opportunities for improving the sustainability of the diet by optimizing the proportions of various food groups, while maintaining cultural and nutritional relevance. The robust and adaptable nature of our approach makes it suitable for broader applications in other regions and dietary contexts, ultimately paving the way for more comprehensive and actionable dietary guidelines.

This study demonstrates that the proposed framework can be extended to address complex decision-making problems by integrating social, economic, and environmental factors. The novel ranking system for food groups offers valuable insights into sustainability and highlights food groups that are truly sustainable.

CRediT authorship contribution statement

Bashir Bashiri: Writing – original draft, Validation, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Aleksei Kaleda:** Writing – review & editing, Visualization, Validation, Supervision, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Raivo Vilu:** Writing – review & editing, Supervision, Project administration, Funding acquisition.

Ethical approval

Not applicable.

Availability of data and materials

All data have been appropriately cited and are accessible online. The list of food items, their respective food groups, the food group intake data for dietary scenarios, the environmental footprints of food groups and their nutritional contents are provided within the Supplementary Information file.

Funding statement

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgment

The authors would like to appreciate the constructive comments and input from three anonymous reviewers on an earlier version of this manuscript.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jclepro.2025.145233.

Data availability

All data used for the preparation of the manuscript are appropriately cited and provided in supplementary materials.

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SI Table 1. Characteristics of the reference diet in Estonia (2021) based on FAOSTAT

Food group	Food item	Consumption, kg/cap/yr	Consumption, g/cap/d	Share of consumption in food group	Name in Footprints table
Cereals	Wheat and products	51.26	140.45	0.59	Wheat & Rye (Bread)
	Rice and products	6.37	17.46	0.07	Rice
	Barley and products	9.82	26.92	0.11	Barley (Beer)
	Maize and products	11.62	31.85	0.13	Maize (Meal)
	Oats	7.89	21.63	0.09	Oatmeal
Tubers	Potatoes and products	60.08	164.60	1.00	Potatoes
Pulses	Peas	4.40	12.04	0.99	Peas
	Pulses, Other, and products	0.04	0.10	0.01	Other Pulses
Nuts	Nuts and products	21.50	58.89	0.89	Nuts
	Groundnuts	2.73	7.47	0.11	Groundnuts
Vegetables	Tomatoes and products	21.39	58.60	0.19	Tomatoes
	Onions	6.94	19.01	0.06	Onions & Leeks
	Vegetables, Other	86.12	235.95	0.75	Other Vegetables
Fruits	Citrus, Other	55.53	152.13	0.47	Citrus Fruit
	Bananas	15.42	42.24	0.13	Bananas
	Apples and products	16.96	46.45	0.14	Apples
	Grapes and products (excl. wine)	5.05	13.82	0.04	Berries & Grapes
	Fruits, Other	25.40	69.58	0.21	Other Fruit
Veg. oils	Soyabean Oil	2.00	5.47	0.16	Soybean Oil
	Sunflower seed Oil	4.19	11.47	0.34	Sunflower Oil
	Rape and Mustard Oil	4.11	11.25	0.34	Rapeseed Oil
	Olive Oil	1.91	5.22	0.16	Olive Oil
Alcohol	Wine	107.54	294.63	1.00	Wine
Sugar	Sugar (Raw Equivalent)	76.54	209.70	1.00	Beet Sugar
Red meat	Bovine meat	9.79	26.82	0.20	Bovine Meat (dairy herd)
	Mutton & goat meat	0.37	1.01	0.01	Lamb & Mutton
	Pig meat	39.83	109.12	0.80	Pig Meat
Poultry	Poultry meat	21.55	59.04	1.00	Poultry Meat
Eggs	Eggs	12.61	34.55	1.00	Eggs

Dairy	Cheese	65.46	179.34	0.20	Cheese
	Milk	261.83	717.35	0.80	Milk
Fish	Fish	10.57	28.96	1.00	Fish (farmed)

SI Table 2. Land Use factors used in Publication II. Sourced from Poore & Nemecek (2018)

		Land Use (m^2/FU)					
Food group	**Food item**	5th pctl	10th pctl	Mean	Median	90th pctl	95th pctl
Cereals	Wheat & Rye (Bread)	1.0	1.1	3.9	2.7	7.9	10.0
	Maize (Meal)	1.0	1.1	2.9	1.8	5.7	9.0
	Barley (Beer)	0.2	0.3	1.1	0.9	2.4	2.9
	Oatmeal	2.6	2.9	7.6	7.7	12.9	14.0
	Rice	1.0	1.1	2.8	2.2	6.2	7.2
Tubers	Potatoes	0.4	0.4	0.9	0.8	1.4	1.7
Sugar	Beet Sugar	1.1	1.2	1.8	1.5	3.1	3.3
Pulses	Other Pulses	4.1	9.9	15.6	12.2	41.3	41.9
	Peas	2.3	2.8	7.5	6.7	14.2	20.5
Nuts	Nuts	4.2	4.5	13.0	8.7	26.6	26.6
	Groundnuts	4.2	4.7	9.1	7.9	15.4	15.4
Veg. oils	Soybean Oil	4.8	5.3	10.5	9.6	14.6	17.5
	Sunflower Oil	7.5	8.4	17.7	16.3	27.0	29.7
	Rapeseed Oil	5.0	5.2	10.6	9.4	19.0	21.0
	Olive Oil	7.9	7.9	26.3	17.3	36.3	36.3
Vegetables	Tomatoes	0.1	0.1	0.8	0.2	0.9	5.6
	Onions & Leeks	0.1	0.1	0.4	0.3	0.6	0.6
	Other Vegetables	0.2	0.2	0.4	0.2	0.8	1.1
Fruits	Citrus Fruit	0.3	0.4	0.9	0.7	1.8	1.8
	Bananas	0.2	0.3	1.9	1.4	3.0	9.4
	Apples	0.3	0.3	0.6	0.5	1.0	1.0
	Berries & Grapes	0.2	0.3	2.4	2.6	6.9	6.9
	Other Fruit	0.2	0.2	0.9	0.9	1.4	1.9
Alcohol	Wine	0.9	0.9	1.8	1.6	2.8	3.5
Red meat	Bovine Meat (dairy herd)	12.3	14.4	43.2	25.9	64.1	106.4
	Lamb & Mutton	47.9	60.1	369.8	127.4	442.3	724.7
	Pig Meat	7.4	7.8	17.4	13.4	31.1	34.1
Poultry	Poultry Meat	6.5	6.7	12.2	11.0	16.0	20.4
Dairy	Cheese	7.9	9.6	87.8	20.2	239.2	323.5
	Milk	0.8	1.1	9.0	2.1	9.3	32.2
Eggs	Eggs	4.3	4.4	6.3	5.7	8.8	8.8
Fish	Fish (farmed)	0.3	0.8	8.4	5.6	10.5	26.3

SI Table 3. GHG emissions used in Publication II. Sourced from Poore & Nemecek (2018)

		GHG Emissions (kg CO_2eq/FU, IPCC 2013 incl. CC feedbacks)					
Food group	**Food item**	5th pctl	10th pctl	Mean	Median	90th pctl	95th pctl
Cereals	Wheat & Rye (Bread)	0.7	0.8	1.6	1.3	2.3	3.1
	Maize (Meal)	0.7	0.7	1.7	1.2	2.3	3.5
	Barley (Beer)	0.6	0.7	1.2	1.2	1.6	1.8
	Oatmeal	0.8	0.9	2.5	2.6	4.1	4.3
	Rice	1.2	1.5	4.5	3.7	8.8	10.3
Tubers	Potatoes	0.1	0.2	0.5	0.5	0.6	0.7
Sugar	Beet Sugar	1.0	1.2	1.8	1.8	2.4	2.6
Pulses	Other Pulses	0.9	1.0	1.8	1.4	3.8	4.0
	Peas	0.5	0.6	1.0	0.8	1.7	1.9
Nuts	Nuts	-4.0	-3.7	0.4	-1.3	3.8	10.8
	Groundnuts	1.4	1.6	3.2	3.3	5.8	6.2
Veg. oils	Soybean Oil	2.2	2.4	6.3	3.9	13.4	18.8
	Sunflower Oil	2.2	2.5	3.6	3.5	4.6	4.9
	Rapeseed Oil	2.2	2.5	3.8	3.5	4.6	7.2
	Olive Oil	2.1	2.9	5.4	5.1	7.6	10.8
Vegetables	Tomatoes	0.4	0.4	2.1	0.7	6.0	12.6
	Onions & Leeks	0.3	0.3	0.5	0.4	0.8	0.8
	Other Vegetables	0.2	0.2	0.5	0.4	1.0	1.1
Fruits	Citrus Fruit	0.0	0.1	0.4	0.3	0.6	0.7
	Bananas	0.6	0.6	0.9	0.8	1.2	1.3
	Apples	0.3	0.3	0.4	0.4	0.6	0.6
	Berries & Grapes	0.6	0.8	1.5	1.4	2.7	2.9
	Other Fruit	0.3	0.4	1.1	0.7	2.9	3.0
Alcohol	Wine	0.7	0.9	1.8	1.6	2.7	4.7
Red meat	Bovine Meat (dairy herd)	14.9	17.9	33.3	34.1	50.9	56.7
	Lamb & Mutton	23.7	24.5	39.7	40.6	54.4	60.2
	Pig Meat	6.9	7.4	12.3	10.6	22.3	23.8
Poultry	Poultry Meat	4.0	4.2	9.9	7.5	20.1	20.8
Dairy	Cheese	10.2	10.9	23.9	18.6	39.3	58.8
	Milk	1.5	1.7	3.2	2.7	4.8	7.0
Eggs	Eggs	2.9	2.9	4.7	4.2	8.4	8.5
Fish	Fish (farmed)	5.4	5.7	13.6	7.9	26.5	32.6

SI Table 4. Acidifying emissions used in Publication II. Sourced from Poore & Nemecek (2018)

		Acidifying Emissions (g SO2eq/FU, CML2 Baseline)					
Food group	Food item	5th pctl	10th pctl	Mean	Median	90th pctl	95th pctl
Cereals	Wheat & Rye (Bread)	5.9	6.7	13.4	13.3	20.2	25.0
	Maize (Meal)	5.6	5.9	11.7	10.2	20.9	22.8
	Barley (Beer)	5.2	5.4	6.6	6.1	7.5	8.2
	Oatmeal	6.2	7.5	10.7	9.6	14.8	17.4
	Rice	8.8	9.8	27.2	18.6	62.8	75.0
Tubers	Potatoes	2.3	2.6	3.9	3.6	5.3	6.9
Sugar	Beet Sugar	4.4	4.4	12.6	12.4	18.3	20.6
Pulses	Other Pulses	5.7	10.9	22.1	19.0	33.8	36.7
	Peas	3.2	3.6	8.5	10.3	10.9	11.1
Nuts	Nuts	19.1	20.6	45.2	35.0	67.0	95.9
	Groundnuts	10.1	10.4	22.6	16.4	55.7	56.8
Veg. oils	Soybean Oil	11.2	11.6	15.7	15.0	20.4	23.0
	Sunflower Oil	10.4	10.8	28.0	19.3	61.2	67.2
	Rapeseed Oil	14.7	15.1	28.5	23.2	49.5	61.1
	Olive Oil	18.8	27.5	37.6	33.9	57.9	62.0
Vegetables	Tomatoes	2.9	3.2	17.2	5.2	68.0	83.4
	Onions & Leeks	2.7	2.8	3.6	3.3	4.9	5.0
	Other Vegetables	2.6	2.9	6.4	3.7	6.6	9.7
Fruits	Citrus Fruit	2.2	2.6	4.0	3.8	6.0	6.2
	Bananas	4.1	4.5	6.4	6.1	8.6	10.0
	Apples	1.8	2.1	3.5	4.0	4.5	4.6
	Berries & Grapes	4.1	4.8	12.3	6.9	38.7	39.4
	Other Fruit	3.2	3.6	5.8	5.4	8.1	9.0
Alcohol	Wine	8.8	9.0	12.8	10.9	23.9	32.0
Red meat	Bovine Meat (dairy herd)	165.2	219.0	343.6	289.1	497.2	1099.2
	Lamb & Mutton	79.2	81.8	139.0	135.2	149.8	273.6
	Pig Meat	63.2	69.0	142.7	114.8	434.1	469.0
Poultry	Poultry Meat	39.9	43.1	102.4	64.7	192.8	197.1
Dairy	Cheese	45.6	57.6	165.5	173.0	267.2	304.8
	Milk	6.6	8.0	20.0	20.6	31.8	35.2
Eggs	Eggs	20.3	21.4	53.7	54.2	78.1	78.3
Fish	Fish (farmed)	34.7	34.8	65.9	40.2	108.8	193.2

SI Table 5. Eutrophying emissions used in Publication II. Sourced from Poore & Nemecek (2018)

		Eutrophying Emissions (g PO43-eq/FU, CML2 Baseline)					
Food group	Food item	5th pctl	10th pctl	Mean	Median	90th pctl	95th pctl
Cereals	Wheat & Rye (Bread)	1.0	2.3	7.2	5.4	13.4	18.2
	Maize (Meal)	1.2	1.3	4.0	2.4	8.1	12.6
	Barley (Beer)	1.1	1.2	2.3	1.8	3.8	4.8
	Oatmeal	5.8	6.7	11.2	10.1	16.3	24.3
	Rice	2.9	3.4	35.1	9.3	135.8	156.0
Tubers	Potatoes	0.6	0.6	3.5	4.4	6.1	6.2
Sugar	Beet Sugar	2.1	2.1	5.4	4.3	14.1	16.9
Pulses	Other Pulses	1.6	1.6	17.1	13.8	46.6	50.2
	Peas	0.7	0.8	7.5	1.7	33.6	33.7
Nuts	Nuts	6.6	8.0	19.2	14.5	40.0	47.2
	Groundnuts	5.7	5.8	14.1	17.1	19.7	21.0
Veg. oils	Soybean Oil	2.6	2.6	11.7	14.4	20.2	20.9
	Sunflower Oil	10.1	11.7	50.7	18.9	175.7	175.7
	Rapeseed Oil	6.4	7.2	19.2	16.4	35.5	55.7
	Olive Oil	5.8	17.1	37.3	39.1	56.3	61.2
Vegetables	Tomatoes	0.6	0.8	7.5	1.9	32.1	39.5
	Onions & Leeks	1.0	1.5	3.2	1.6	7.5	7.5
	Other Vegetables	0.9	1.1	2.3	1.8	2.5	4.9
Fruits	Citrus Fruit	0.3	0.3	2.2	1.7	6.5	6.5
	Bananas	1.5	1.7	3.3	2.1	5.8	6.4
	Apples	0.4	0.5	1.5	2.0	2.0	2.1
	Berries & Grapes	0.6	0.7	6.1	1.0	17.4	17.4
	Other Fruit	0.8	1.0	2.4	2.1	4.2	5.2
Alcohol	Wine	0.5	2.2	4.6	3.8	10.3	12.4
Red meat	Bovine Meat (dairy herd)	79.8	81.4	365.3	140.9	1515.7	2509.4
	Lamb & Mutton	22.0	24.6	97.1	101.9	128.7	133.4
	Pig Meat	29.5	31.6	76.4	53.5	219.7	237.6
Poultry	Poultry Meat	22.7	25.0	48.7	34.5	101.5	101.5
Dairy	Cheese	26.3	29.5	98.4	99.5	167.9	192.3
	Milk	2.9	3.0	10.7	10.7	18.6	21.2
Eggs	Eggs	12.0	14.3	21.8	21.3	31.6	33.6
Fish	Fish (farmed)	58.3	70.8	235.1	243.6	365.7	420.9

SI Table 6. Freshwater withdrawals used in Publication II. Sourced from Poore & Nemecek (2018)

		Freshwater Withdrawals (L/FU)					
Food group	Food item	5th pctl	10th pctl	Mean	Median	90th pctl	95th pctl
Cereals	Wheat & Rye (Bread)	2	2	648	419	1081	3369
	Maize (Meal)	0	0	216	44	531	598
	Barley (Beer)	6	7	17	7	11	48
	Oatmeal	0	0	482	670	804	850
	Rice	0	0	2248	1575	3936	10574
Tubers	Potatoes	0	1	59	3	133	236
Sugar	Beet Sugar	10	12	218	12	506	1656
Pulses	Other Pulses	0	0	436	0	1250	2201
	Peas	0	0	397	0	3100	3584
Nuts	Nuts	0	0	4134	1823	9107	11384
	Groundnuts	54	694	1852	900	6525	6525
Veg. oils	Soybean Oil	2	2	415	2	2245	2487
	Sunflower Oil	3	3	1008	10	3841	4037
	Rapeseed Oil	1	1	238	1	764	778
	Olive Oil	9	9	2142	318	6908	6908
Vegetables	Tomatoes	33	48	370	77	1334	1994
	Onions & Leeks	1	1	14	2	72	76
	Other Vegetables	56	56	103	81	168	360
Fruits	Citrus Fruit	0	0	83	37	185	245
	Bananas	0	0	115	1	320	376
	Apples	0	1	180	115	585	585
	Berries & Grapes	134	134	420	404	1027	1027
	Other Fruit	0	0	154	4	701	798
Alcohol	Wine	2	2	79	5	328	349
Red meat	Bovine Meat (dairy herd)	188	192	2714	2614	5799	8744
	Lamb & Mutton	88	98	1803	461	7133	7826
	Pig Meat	83	88	1796	1810	3315	3556
Poultry	Poultry Meat	19	19	660	370	1662	1694
Dairy	Cheese	158	178	5605	1559	23449	25756
	Milk	19	19	628	197	2593	2664
Eggs	Eggs	139	140	578	633	965	1033
Fish	Fish (farmed)	604	1117	3691	1581	10473	12190

SI Table 7. Distribution characteristics of final footprints of food groups obtained by resampling from subitem distributions, share of consumption of individual food items has been taken into account.

Footprint	Food group	Min	**Mode**	Median	Mean	Max
Acidifying Emissions	Alcohol	8.78	10.82	10.97	11.10	18.95
Acidifying Emissions	Cereals	5.22	6.21	11.74	12.70	70.58
Acidifying Emissions	Dairy	6.58	18.19	22.26	51.19	304.76
Acidifying Emissions	Eggs	20.27	51.21	52.76	53.21	78.29
Acidifying Emissions	Fish	34.71	40.35	40.63	41.01	61.05
Acidifying Emissions	Fruits	2.19	3.92	4.37	4.70	19.45
Acidifying Emissions	Nuts	10.08	30.64	34.56	37.28	95.88
Acidifying Emissions	Poultry	39.88	59.73	66.05	69.43	194.96
Acidifying Emissions	Pulses	5.72	10.26	10.26	10.31	36.65
Acidifying Emissions	Red meat	63.23	98.94	132.21	162.35	929.87
Acidifying Emissions	Sugar	4.38	11.50	11.98	12.22	20.55
Acidifying Emissions	Tubers	2.33	3.57	3.70	3.80	6.89
Acidifying Emissions	Veg. oils	10.44	16.27	21.99	23.69	65.41
Acidifying Emissions	Vegetables	2.64	3.56	3.82	4.08	16.44
Eutrophying Emissions	Alcohol	0.48	3.46	3.76	3.86	12.32
Eutrophying Emissions	Cereals	1.02	1.88	4.98	6.05	75.04
Eutrophying Emissions	Dairy	2.90	8.60	11.91	28.79	192.20
Eutrophying Emissions	Eggs	11.97	19.95	21.05	21.49	33.58
Eutrophying Emissions	Fish	63.43	218.56	239.38	246.10	420.91
Eutrophying Emissions	Fruits	0.31	1.96	1.96	2.01	6.47
Eutrophying Emissions	Nuts	6.64	15.85	15.58	16.35	47.14
Eutrophying Emissions	Poultry	22.69	33.24	35.02	36.19	100.35
Eutrophying Emissions	Pulses	0.74	1.60	1.75	1.94	49.90
Eutrophying Emissions	Red meat	29.47	45.71	61.83	78.99	612.64
Eutrophying Emissions	Sugar	2.10	3.83	4.50	4.73	15.85
Eutrophying Emissions	Tubers	0.85	4.39	4.33	4.31	6.17
Eutrophying Emissions	Veg. oils	3.59	15.10	18.80	21.96	74.63
Eutrophying Emissions	Vegetables	0.62	1.59	1.79	1.88	6.79
Freshwater Withdrawals	Alcohol	2.21	82.92	132.04	143.11	348.74
Freshwater Withdrawals	Cereals	2.65	30.16	794.06	1183.07	10385.58
Freshwater Withdrawals	Dairy	20.68	684.69	1241.93	2981.26	25637.63
Freshwater Withdrawals	Eggs	141.00	579.28	583.02	583.89	1031.20
Freshwater Withdrawals	Fish	626.13	3848.54	5168.06	5498.52	12174.68
Freshwater Withdrawals	Fruits	0.24	88.58	151.29	199.67	1018.56
Freshwater Withdrawals	Nuts	48.13	4203.34	4658.41	4916.83	11372.60

Freshwater Withdrawals	Poultry	20.50	674.36	764.26	791.52	1687.37
Freshwater Withdrawals	Pulses	2.71	467.48	1186.14	1322.55	3579.15
Freshwater Withdrawals	Red meat	90.68	1783.92	1969.80	2226.76	8708.04
Freshwater Withdrawals	Sugar	10.95	229.27	568.76	627.43	1651.47
Freshwater Withdrawals	Tubers	0.26	62.34	91.37	98.39	235.36
Freshwater Withdrawals	Veg. oils	4.77	259.63	910.73	1325.60	6901.08
Freshwater Withdrawals	Vegetables	1.58	106.74	177.50	280.81	1987.46
GHG Emissions	Alcohol	0.74	1.56	1.66	1.71	4.66
GHG Emissions	Cereals	0.59	1.25	1.35	1.63	10.25
GHG Emissions	Dairy	1.51	2.46	2.99	6.46	58.51
GHG Emissions	Eggs	2.85	4.15	4.29	4.40	8.46
GHG Emissions	Fish	5.41	7.93	8.06	8.26	18.62
GHG Emissions	Fruits	0.01	0.38	0.47	0.56	2.91
GHG Emissions	Nuts	-4.02	-3.12	-0.84	0.01	10.79
GHG Emissions	Poultry	3.95	7.01	7.78	8.21	20.81
GHG Emissions	Pulses	0.51	0.82	0.82	0.83	2.64
GHG Emissions	Red meat	6.91	10.24	11.65	15.76	59.58
GHG Emissions	Sugar	1.01	1.74	1.77	1.78	2.64
GHG Emissions	Tubers	0.09	0.46	0.46	0.45	0.70
GHG Emissions	Veg. oils	2.13	3.42	3.72	3.94	10.99
GHG Emissions	Vegetables	0.21	0.42	0.46	0.48	1.43
Land Use	Alcohol	0.86	1.55	1.73	1.79	3.48
Land Use	Cereals	0.21	1.82	2.48	3.00	13.97
Land Use	Dairy	0.80	1.88	2.41	6.49	186.03
Land Use	Eggs	4.25	5.48	5.83	5.93	8.81
Land Use	Fish	0.30	3.97	5.64	6.43	26.18
Land Use	Fruits	0.21	0.61	0.75	0.95	6.85
Land Use	Nuts	4.15	7.69	8.97	9.59	26.58
Land Use	Poultry	6.46	9.80	11.24	11.64	20.40
Land Use	Pulses	2.28	4.80	7.20	7.86	20.47
Land Use	Red meat	7.39	12.97	15.53	19.10	723.47
Land Use	Sugar	1.11	1.51	1.54	1.55	2.76
Land Use	Tubers	0.37	0.78	0.86	0.88	1.66
Land Use	Veg. oils	4.77	9.39	12.53	13.81	36.31
Land Use	Vegetables	0.07	0.19	0.19	0.20	0.62

SI Table 8. Footprints of the reference diet calculated using mode of resampled food group distributions.

Food group	Land use (m2/cap/d)	GHG emissions (kg CO2-eq/cap/d)	Acidifying emissions (g SO2-eq/cap/d)	Eutrophying emissions (g PO43-eq/cap/d)	Freshwater withdrawals (L/cap/d)
Cereals	0.435	0.298	1.480	0.448	7.187
Tubers	0.128	0.075	0.588	0.722	10.261
Pulses	0.058	0.010	0.124	0.019	5.674
Nuts	0.510	-0.207	2.033	1.052	278.917
Vegetables	0.060	0.132	1.115	0.498	33.471
Veg. oils	0.314	0.114	0.543	0.504	8.671
Fruits	0.198	0.122	1.271	0.634	28.719
Sugar	0.317	0.364	2.411	0.803	48.078
Red meat	1.776	1.403	13.551	6.261	244.324
Poultry	0.578	0.414	3.527	1.962	39.815
Eggs	0.189	0.143	1.769	0.689	20.013
Dairy	1.351	1.763	13.048	6.167	491.162
Fish	0.115	0.230	1.168	6.329	111.449
Alcohol	0.457	0.460	3.189	1.021	24.430
Sum	6.487	5.320	45.818	27.111	1352.171

Supplementary information

Mathematical background of the SURE method(Hodgett & Siraj, 2019b)
In this method, the performance of each food product (alternative A_i) across environmental indicators (C_j) is represented using three values: the minimum value (a_{ij}^{min}) representing the best-case scenario, the most likely value (a_{ij}) representing the expected outcome, and the maximum value (a_{ij}^{max}) representing the worst-case scenario. These values define a triangular probability distribution, where the minimum and maximum values form the bounds, and the most likely value is the mode. To capture the uncertainty in the environmental impact data, random values are generated from this triangular distribution to simulate decision tables. Since environmental indicators are cost indicators (where lower values are better), normalization is applied to ensure comparability across different scales. For each simulation, the normalized value (a_{ij}^*) is computed using the following equation:

$$a_{ij}^* = \frac{a_j^{max} - a_{ij}}{a_j^{max} - a_j^{min}} \ , \qquad (1)$$

where a_j^{max} and a_j^{min} are the highest and smallest decision variable with respect to the j_{th} criterion. This normalization scales the values so that higher normalized scores represent better performance (lower environmental impacts). To aggregate the environmental performance across all indicators, a weighted sum method is applied for each simulated decision table. The SURE score for alternative A_i in simulation is calculated as:

$$SURE\ Score_i = \sum_{j=1}^{n} w_j \cdot a_{ij}^* \ , \quad (2)$$

where w_j represents the relative weight of each indicator as determined by the decision-maker. After conducting a certain number of iterations, statistical analysis is then performed. Finally, the results are visualized using kernel density plots, which display the distribution of SURE scores for each food product. Alternatives with distributions positioned further to the left are preferred due to their lower environmental impacts. The width of each distribution reflects the uncertainty, with narrower distributions indicating more consistent performance.
In the current study, after finding the joint distributions of footprints for each group, the lower bound and upper bound of the distribution have been set as minimum value (a_{ij}^{min}) and maximum value (a_{ij}^{max}) and the mode of the distribution was set as the most likely value (a_{ij}) in the SURE method.

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Appendix 3

Publication III

Bashiri, B., Kaleda, A., & Vilu, R. (2025). Sustainable diets, from design to implementation by multi-objective optimization-based methods and policy instruments. Frontiers in Sustainable Food Systems, 9, 1629739. https://doi.org/10.3389/fsufs.2025.1629739

frontiers | Frontiers in Sustainable Food Systems

TYPE Review
PUBLISHED 30 June 2025
DOI 10.3389/fsufs.2025.1629739

Check for updates

OPEN ACCESS

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RECEIVED 16 May 2025
ACCEPTED 13 June 2025
PUBLISHED 30 June 2025

CITATION
Bashiri B, Kaleda A and Vilu R (2025) Sustainable diets, from design to implementation by multi-objective optimization-based methods and policy instruments.
Front. Sustain. Food Syst. 9:1629739.
doi: 10.3389/fsufs.2025.1629739

Sustainable diets, from design to implementation by multi-objective optimization-based methods and policy instruments

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The growing concerns over climate change, food security, and public health necessitate a transition toward sustainable diets. However, designing diets that are simultaneously healthy, environmentally friendly, culturally acceptable, and affordable presents significant challenges. This review explores the potential of multi-objective optimization (MOO) as a tool for sustainable diet design and a central element of implementation of optimized diets. MOO allows researchers to balance conflicting objectives, such as minimizing environmental impact while maintaining cultural acceptability and economic feasibility in design and implementation of healthy diets. The review highlights the limitations of traditional single-objective optimization and emphasizes the need for population-specific dietary recommendations using MOO. Furthermore, the paper identifies barriers to sustainable diet adoption and outlines policy solutions to facilitate dietary transitions. Finally, it underscores the need for the development and implementation of flexible national dietary guidelines to incorporate optimization methods for enhanced sustainability. By integrating mathematical modeling, behavioral insights, and policy interventions, this review outlines a holistic approach to development sustainable food systems capable for meeting efficiently global challenges.

KEYWORDS

diet, sustainability, multi-objective optimization, policy, regulations

1 The need for sustainable diet design

The global food systems contribute approximately 30% of anthropogenic greenhouse gas (GHG) emissions (Crippa et al., 2021), 32% of global terrestrial acidification, and 78% of eutrophication (Poore and Nemecek, 2018), consumes about 70% of freshwater resources, and occupies over one-third of all potentially cultivable land (Foley et al., 2011). Simultaneously, diet-related health issues, including obesity, malnutrition, and non-communicable diseases, are becoming globally more prevalent (WHO European Office for the Prevention and Control of Noncommunicable Diseases, 2021; Al-Jawaldeh and Abbass, 2022; Ma et al., 2025; Pineda et al., 2024). Dietary patterns, particularly in high- and middle-income countries, contribute significantly to both chronic diseases and environmental degradation (Hundscheid et al., 2022; Clark et al., 2020). These challenges highlight the urgent need to transition toward more sustainable dietary patterns promoting human health and environmental well-being.

Research indicates that shifting to diets rich in plant-based foods and lower in animal-based products can significantly reduce the environmental footprint of food production while improving public health (Espinosa-Marrón et al., 2022). Such dietary changes lower greenhouse gas emissions and mitigate the hidden costs associated with diet-related health conditions (Lucas et al., 2023). The Intergovernmental Panel on Climate Change (IPCC) has identified dietary change as a demand-side option with a large potential to mitigate emissions. Estimated annual GHG emissions reductions by 2050 associated with dietary shifts to low-meat, vegetarian, or vegan diets are in the range of 0.7–7.3, 4.3–6.4, and 7.8–8 $GtCO_2e$, respectively (Creutzig et al., 2021; Shukla et al., 2019), and thus can help achieve the targets of the Paris Agreement (Clark et al., 2020). Additionally, research carried out suggests that dietary modifications offer greater environmental benefits than improvements in agricultural production efficiency, emphasizing the critical role of consumption choices in reducing environmental impact (Poore and Nemecek, 2018; Garvey et al., 2021). Therefore, dietary shifts can play a crucial role in achieving the Sustainable Development Goals (SDGs), particularly those related to Zero Hunger, Good Health and Well-Being, and Responsible Consumption and Production (Chen et al., 2022).

Diet should be healthy and sustainable. The World Health Organization (WHO) together with the Food and Agricultural Organization of the United Nations (FAO) define sustainable healthy diets as '*dietary patterns that promote all dimensions of individuals' health and wellbeing; have low environmental pressure and impact; are accessible, affordable, safe and equitable; and are culturally acceptable*' (WHO, 2025). Food production depends on the continued functioning of biophysical systems that regulate and maintain a stable Earth system. Within this context, diets are closely linked to both human health and environmental sustainability, and a shared framework enables the identification of diets that are simultaneously healthy and environmentally friendly (Willett et al., 2019). Although dietary shifts toward sustainable diets can reduce health risks and environmental impacts, reducing animal-based food consumption can lead to deficiencies in essential micronutrients (e.g., vitamin B12, selenium, calcium) if diets are not well planned (Beal et al., 2023).

Even the most scientifically sound and sustainable dietary recommendations may be met with resistance if they require significant departures from traditional eating patterns and habits (Van Dooren, 2024; Zhu et al., 2024). The cultural acceptability or 'consumer inconvenience' (as Nordman and coauthors refer to it (Nordman et al., 2024)) of the unusual, modified diet plays an important role in ensuring success of the diet optimization. To account for cultural acceptability, diet optimization models often limit the distance between the modeled diet and the observed diet (Heerschop et al., 2024; van Dooren, 2018). Cultural acceptability must be balanced with other complex responses, including sustainability, health, and affordability, ensuring that none of these criteria are neglected (Nordman et al., 2024; van Dooren, 2018). Designing diets that are in agreement with these complex and often conflicting criteria is not a simple task, as it requires careful consideration of balancing multiple factors simultaneously.

Despite growing recognition of the need for the development and implementation of sustainable diets, several important gaps persist. In the diet design phase, while many studies emphasize the environmental and health benefits of dietary shifts, there remains a lack of comprehensive frameworks that integrate multiple criteria into diet design. Existing research tends to focus predominantly on either health or environmental outcomes, without adequately addressing how to balance these dimensions in a practical and socially acceptable manner simultaneously (Fu et al., 2024). The authors of this review advocate for utilizing multi-objective optimization (MOO) to enable a holistic and carefully balanced approach to diet design (Bashiri et al., 2025; Bashiri et al., 2024) in the complex situation described.

In the adoption phase, cultural preferences and behavioral resistance are increasingly acknowledged as barriers to dietary change (Muñoz-Martínez et al., 2024). While a range of policy tools has been proposed to support the shift toward more sustainable diets (Ammann et al., 2023), there appears to be relatively limited exploration of approaches that link specific barriers with corresponding policy interventions. This gap is suggested by analyses showing that the implementation of food environment policies remains generally weak (Pineda et al., 2024).

In this article, we discuss diets from their design to their adoption. Section 2 provides an overview of the MOO method and its application in the context of sustainable diet design. Section 3 focuses on the social dimensions of dietary transition, examining the processes of social adoption and the barriers that hinder the shift toward new dietary patterns. It also discusses policy instruments that can help overcome these barriers. The authors argue that this work contributes to promoting a just and sustainable dietary transition for society.

2 Design of sustainable diets

2.1 Multi-objective optimization for the design of a sustainable diet

Mathematical optimization tools have been used in many studies to develop sustainable diets. Linear and non-linear single-objective optimization techniques have been used widely in diet-related studies to minimize the cost, minimize environmental footprints, or minimize the deviation from the reference diet. For more information, the reader is referred to a literature review about mathematical optimization for diet design (van Dooren, 2018; Gazan et al., 2018). Single-objective approaches often fail to capture the complex trade-offs required in sustainable diet planning. However, given the multidimensional nature of sustainability, MOO appears to be a suitable approach in these situations. This method allows us to carry out comprehensive analysis, enabling researchers to account for trade-offs between different dietary dimensions and develop balanced, sustainable dietary solutions. Table 1 summarizes an example of diet MOO problem solving, showing the mathematical formulation of the objective function and nutritional constraints.

The relationship between objectives in the MOO method can be represented by a hyperbolic Pareto front, which is calculated by varying weight coefficients. In a two-objective optimization, the trade-off between two objectives is visualized as a two-dimensional curve (Figure 1A), while for three objectives, presentation of the trade-off forms a surface (Figure 1B). These visualizations assist decision-makers in understanding the trade-offs and making informed choices. However, when MOO involves more than three objectives, visualizing the Pareto front becomes impractical, making decision-making excessively more complex (Bashiri et al., 2025). In this situation, multi-criteria decision-making (MCDM) methods could be used to reduce the number of

TABLE 1 Structure of a sample MOO model used for sustainable diet design.

$\min(w_1 f_1 + w_2 f_2 + w_3 f_3 + \ldots)$	Final objective function of the MOO model to be minimized. The function includes three terms as defined separately below, but more can be added. The relative importance of terms is adjusted using weight coefficients w_1, w_2, w_3 yielding the Pareto fronts as shown in Figure 1.
$f_1 = \sum_1^n \left(\frac{x_i^* - x_i}{x_i} \right)^2$	This term minimizes deviation from the current consumption pattern, ensuring that the new diet is culturally acceptable and easier to adopt. x_i^* is optimized consumption of food item *i*. x_i is current consumption of food item *i*, and n are the numbers of food items included in the model.
$f_2 = \sum_1^n x_i^* \times CF_i$	Minimizes the sum of carbon emissions associated with new diet. CF_i is carbon footprint per unit weight of food item
$f_3 = \sum_1^n x_i^* \times price_i$	Minimizes the sum of the prices of all selected food items. It ensures that the new diet remains affordable and economically accessible. $price_i$ is market price per unit weight of food item *i*
$N_{\min} \le \sum_1^n x_i^* \times a_i \le N_{\max}$	The objective function is subjected to several nutritional constraints. The constraints ensure that the optimal diet fulfills the nutritional recommendations. a_i is the amount of corresponding nutrition per unit weight of food product i. $N_{\min}$ and $N_{\max}$ are the lower bound and upper bound of the nutrition as per dietary recommendations.

This example model minimizes simultaneously three objective functions, which are incorporated as multiple terms into one equation: (1) deviation from the current dietary habits to maintain cultural acceptability, (2) total carbon footprint to reduce environmental impact, and (3) total diet cost to ensure affordability. These objectives are optimized under a set of nutritional constraints that ensure dietary adequacy.

objectives, making the decision-making process easier. All the solutions that are located on the Pareto front curve are optimal solutions. Changing the priority of one objective over the other objectives would give different optimal solutions. The selection of an optimal solution from the Pareto front can be based on the decision-makers' preferences or achieved using MCDM methods. In diet MOO problems, the challenge of balancing criteria (such as whether nutrition, health, or environmental impacts should be given greater weight) is particularly relevant. In this context, using the Pareto front allows for the analysis of different scenarios where various weights are assigned to each criterion, facilitating case-specific and transparent decision-making based on the presented trade-offs.

2.2 A scoping review on the multi-objective optimization application for the design of sustainable diets

Some studies have employed MOO to develop sustainable and nutritionally balanced diets, often aiming to minimize environmental impact, cost, and nutritional inadequacy while maintaining cultural acceptability. A pioneering study by Donati et al. (2016). in Italy demonstrated that a sustainable and nutritious diet can be healthier, more affordable, and environmentally friendlier than current consumption patterns. Similarly, Abejón et al. (2020). in Spain, showed that it is possible to reduce environmental impacts while ensuring affordability and nutritional adequacy. Muñoz-Martínez et al. (2023). optimized a sustainable and nutritionally balanced diet for Spain by minimizing costs and environmental impacts (specifically greenhouse gas emissions, land use, and blue-water consumption) while ensuring minimal deviation from existing dietary habits. Their findings suggested that fortified plant-based milk could offer additional environmental benefits. Such targeted strategies illustrate that novel food products could play a crucial role in enhancing the sustainability and acceptability of the designed diet. These studies emphasize the feasibility of achieving sustainability without increasing costs, underscoring the importance of promoting sustainable food choices.

Several researchers have explored the balance between environmental sustainability and dietary acceptability, noting the challenges posed by significant deviations from typical dietary habits. Mirzaie-Nodoushan et al. (2020). designed a model to reduce water footprint through a culturally acceptable dietary change, showing that reasonable reduction of red meat and vegetable oil intake could lower water usage by up to 16%. Yin et al, (2021). optimized diets to minimize carbon, water, and ecological footprints while ensuring cultural acceptability, recommending a 10% reduction in carbon footprint as the optimal balance between environmental, nutritional, and cultural acceptability goals. Fu et al. (2024). further demonstrated that integrating nutrition, environmental goals, and cultural preferences could reduce greenhouse gas emissions by over 60% compared to nutrition-focused diets alone. Nordman et al. (2024). found that reducing greenhouse gas emissions by more than 24–36% led to substantial deviations from conventional diets, impacting acceptability. Bashiri et al. (2024). observed similar trends in Estonia and proposed that incremental dietary changes could achieve environmental goals without compromising adherence to traditional eating patterns (Nordman et al., 2024).

Innovative approaches to optimizing diets through technology have also been investigated. Zhang et al. (2022). introduced a MOO-based food recommendation system in the UK, which integrated user preferences alongside nutritional and environmental factors, resulting in a more balanced recommendations compared to traditional preference-based methods.

Besides the conflicts between sustainability, affordability, and cultural acceptability, conflicts can also be inherent in the case of different environmental indicators. Comparison of footprints of different food products reveals that some are better in terms of one footprint, but worse in terms of another. For example, a food product with a low carbon footprint may require excessive land or water use. Focusing solely on one footprint (e.g., GHG) reduction can lead to unintended environmental consequences, such as increased water use or biodiversity loss (Ran et al., 2024). Poore and Nemecek (2018) pointed out the conflicts between the environmental footprints of food products. While the reduction of GHG emissions is important, it does not fully capture the environmental impact of food production. However, incorporating multiple indicators into dietary optimization increases complexity. Additionally, uncertainties in environmental footprint data (caused by variations in data sources, geographical differences, and farming practices) further complicate decision-making. Without a systematic approach to address these conflicts and uncertainties, dietary recommendations may be misleading or impractical. MOO has a capacity to address such conflicts.

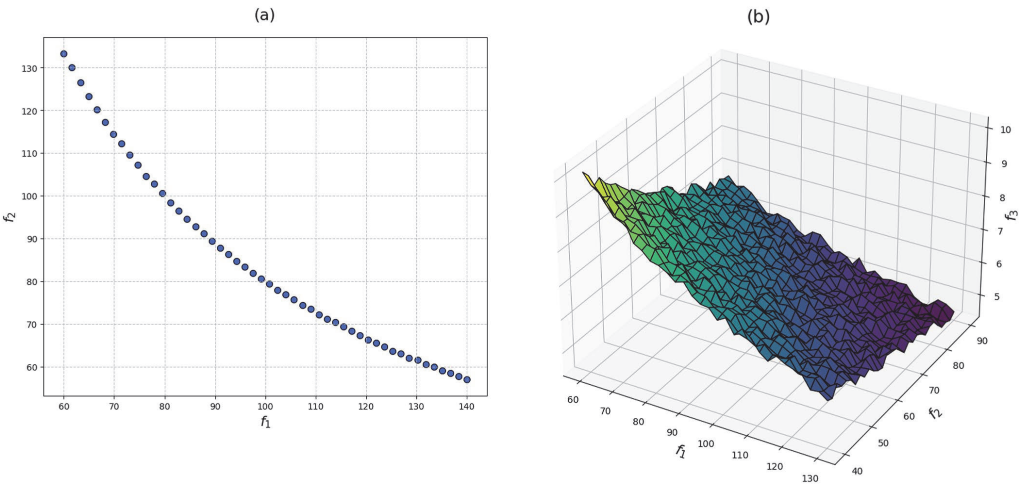

FIGURE 1
Illustration of Pareto front solutions in multi-objective optimization (MOO). **(A)** Two-objective Pareto front showing the trade-off between two competing objective functions f_1 and f_2. Each point on the curve represents a solution where improving one objective would worsen the other. **(B)** Three-objective Pareto front showing the trade-off between three objective functions f_1, f_2, and f_3 forming a surface.

To tackle the conflicts between environmental indicators, the authors of the present review developed a method that integrates MCDM with MOO to optimize diet sustainability (Bashiri et al., 2025). We applied the SURE MCDM (Hodgett and Siraj, 2019) method before performing MOO to aggregate multiple environmental footprints into a single score, simplifying the optimization process while still accounting for trade-offs. The application of this method on the Estonian diet demonstrated that using multiple environmental indicators instead of just one significantly altered the recommended dietary patterns. For instance, a previous study optimizing the Estonian diet based only on land footprint suggested increasing plant-based foods (Bashiri et al., 2024), whereas incorporating multiple footprints suggests decreasing the consumption of the same food groups due to the inherent conflicts between different environmental footprints (Bashiri et al., 2025). This approach is particularly important from a life cycle assessment (LCA) perspective. There are several impact categories that contribute to damage to human health, ecosystems, and resource availability. Therefore, efforts to optimize diets should aim to capture the full spectrum of system-level impacts, rather than focusing on a single indicator. Only by doing so can we begin to assess whether a dietary system is truly sustainable.

Together, these studies provide examples of the complex interplay between environmental sustainability, nutritional adequacy, cost-effectiveness, and cultural acceptability in diet optimization, and illustrate how MOO can support the exploration of trade-offs among competing objectives in a structured and transparent way. For instance, in a global diet optimization study using a single-objective approach, the results often suggest complete elimination of red meat from the optimal diets (Chaudhary and Krishna, 2019). While such diets remain nutritionally adequate and within planetary boundaries, their acceptability is uncertain (Chaudhary and Krishna, 2019). The examples analyzed also indicate that the results of each study are specific to the study region, reflecting the parameters and dimensions incorporated into the model. Cultural acceptability is assessed relative to a reference point, which varies from one region to another. Moreover, even within a single region, multiple dietary patterns exist, requiring individuals to be grouped based on their dietary habits. As a result, both cultural acceptability and sustainability outcomes can differ significantly across groups.

Also, the baseline data used to represent current diets plays a crucial role in shaping optimization outcomes. High-resolution dietary intake data (such as those obtained through food diaries or 24-h recalls) can provide a more accurate representation of actual consumption patterns, as opposed to Food Balance Sheet data, which has been used in previous studies using MOO (Bashiri et al., 2025; Bashiri et al., 2024; Mirzaie-Nodoushan et al., 2020). This is because Food Balance Sheet data overestimates population dietary intakes as it reflects country-level food availability and does not consider household-level food waste or measure actual individual-level consumption. This helps to explain why, in previous work, MOO-optimized dietary patterns can conflict with established sustainable diet principles (e.g., recommending reductions in legume and nut consumption) (Bashiri et al., 2025). Therefore, using more accurate dietary data would enhance the reliability and interpretability of the resulting optimized dietary patterns, thereby improving the potential of the model to inform truly balanced and sustainable dietary recommendations (Table 2).

2.3 Population-specific diet optimization

A key limitation in most dietary studies is the assumption that populations are homogeneous in their adherence to dietary patterns, whereas, in reality, individuals exhibit diverse eating behaviors. Consequently, while proposing a single optimized diet may be theoretically sound from a mathematical modeling perspective, its real-world implementation is likely to face significant challenges. A diet optimized for one demographic group may not be suitable for

TABLE 2 List of publications reviewed in this section.

Author (year)	Number of objectives	MOO solver method	Cultural acceptability included	Economic affordability included	Environmental indicators	Number of nutritional constraints	Scenario analysis
Mirzaie-Nodoushan et al. (2020)	2	Weighted sum method	Yes	No	Water footprint	15	Scenarios for increasing self-sufficiency in food production are investigated.
Bashiri et al. (2024)	2	Weighted sum method	Yes	No	Land footprint	19	Scenarios include reference diet, nationally recommended diet (NRD), and three optimized diets minimizing land footprint and deviation from the reference diet, while ensuring nutritional adequacy.
Nordman et al. (2024)	2	ε-constrained	Yes	No	Carbon footprint	32 (includes 6 limits on the consumption of food items)	Scenarios based on four dietary clusters with stepwise carbon footprint reduction targets
Fu et al. (2024)	2	Pareto method, distance-to-target	Yes	No	Carbon footprint	4	Three scenarios were considered: meeting nutritional needs; minimizing carbon footprint while ensuring nutrition; and balancing nutrition, low emissions, and cultural acceptability.
Abejón et al. (2020)	3	Distance-to-target	Yes	Yes	Carbon footprint	9	Six predefined diets were optimized
Donati et al. (2016)	4	Weighted sum method	No	Yes	Carbon footprint, Water consumption, ecological footprint	9	The lowest-cost diets, lowest-footprint diet, and diets combining both lowest cost and footprint were identified.
Yin et al. (2021)	4	ε-constrained	Yes	No	Carbon footprint, Water consumption, ecological footprint	24	Twelve optimized scenarios targeting stepwise and maximum reductions in water footprint, carbon footprint, and ecological footprint.
Zhang et al. (2022)	4	Pareto method	Yes	No	None	15	Four objectives have been investigated: user preferences, nutritional values, dietary diversity, and user diet patterns.
Muñoz-Martínez et al. (2023)	4	Distance-to-target	Yes	Yes	Carbon footprint, Water consumption, Land use	17	Two optimization scenarios were defined based on margin factors that control allowable deviations from the baseline diet.
Bashiri et al. (2025)	6	Weighted sum method, Pareto method, ε-constrained	Yes	No	Land use, GHG emissions, acidifying emissions, freshwater withdrawals, and eutrophying emissions	19	Scenarios include a bi-objective optimization using an aggregated score and dietary deviation, and a classical multi-objective optimization minimizing five separate environmental footprints alongside dietary deviation, all under nutritional constraints.

The table captures the technical characteristics of the multi-objective optimization (MOO) models in each study. All publications included are peer-reviewed articles indexed in the Web of Science and Scopus.

another due to differences in affordability, accessibility, and dietary norms (Brink et al., 2019; Irz et al., 2024). To develop effective and sustainable dietary strategies, it is essential to take account individual, cultural, and social differences in dietary acceptance and adherence.

Several studies have addressed these issues using traditional segmentation methods, e.g., based on age (Brink et al., 2019), gender (Brink et al., 2019; Irz et al., 2024), geographical location (Wang et al., 2024), education (Irz et al., 2024) and income level (Irz et al., 2024; Lauk et al., 2020; Reynolds et al., 2019). Although traditional population segmentation methods help to understand the difference in the eating patterns of people, they may not fully capture variations in behaviors and diet as observed by Van Dooren et al (van Dooren et al., 2018). because individuals within the same socio-demographic group can have vastly different food choices and motivations. To address the limitations of traditional segmentation methods, researchers have increasingly turned to data-driven methods such as clustering that can better capture the complexity of individual dietary behaviors.

Clustering is an unsupervised machine learning technique used to group unlabeled data based on underlying similarities, without prior knowledge of object relationships. It aims to uncover hidden patterns or natural groupings within datasets, ensuring that items within the same cluster are more like each other than those in different clusters (Oyewole and Thopil, 2023).

Clustering techniques, unlike traditional segmentation methods, segment individuals based on their eating habits. Clustering techniques reveal the hidden patterns in food consumption that cannot be readily recognized by socio-economic grouping. By identifying existing dietary intake patterns within a population, this approach paves the path for a better understanding of how different groups can achieve both nutritional adequacy and environmental sustainability. Clustering techniques could be used before MOO. Some researchers propose that integrating exploratory data-driven analysis with optimization can improve the development of population-specific diets (Nordman et al., 2024; Eustachio Colombo et al., 2023). Therefore, this approach supports the idea of population-specific diet optimization. This methodology has been applied in Sweden (Eustachio Colombo et al., 2023) and Denmark (Nordman et al., 2024). In Sweden, the study applied hierarchical clustering analysis and was able to identify three primary dietary groups. While in Denmark, by using the k-means clustering technique, researchers were able to categorize individuals into four dietary groups. In both studies the recognized dietary clusters were optimized.

In line with the argument presented in the current article, integrating clustering techniques with MOO rather than solely depending on single-objective optimization may offer a useful approach for identifying diets that are potentially more culturally acceptable and contextually appropriate.

3 Factors influencing the transition to a sustainable diet

When a sustainable diet is designed, it must be accepted and followed by people. Although the use of MOO in the design phase is considered to lead to a more balanced optimized solution in terms of sustainability and cultural acceptability, changes and departures from the reference diets are normally expected and observed. It is also normal that changes are met by resistance - adopting new diets often face different barriers in implementation. Muñoz-Martínez et al. (2024). examined a range of such barriers and categorized them into internal and external barriers (Table 3). According to Muñoz-Martínez et al. (2024), internal barriers stem from personal factors such as food literacy, attitudes, habits, and perceived behavioral control, all of which influence an individual's motivation and ability to adopt a sustainable diet. In contrast, external barriers to adopting new (more) sustainable diets arise from social norms, economic constraints, and policy restrictions. To effectively promote sustainable diets, policymakers must implement targeted interventions (systems of policy tools) that address the barriers and create an enabling food environment.

Mozaffarian et al. (2018). have published an extensive review of the policy tools for the adoption of a new diet. The following sections is an analysis of key barriers based on the study by Muñoz-Martínez et al. (2024). along with proposed policy solutions by Mozaffarian et al. (2018) to mitigate them as summarized in Table 3.

3.1 Internal barriers

As listed in Table 3, lack of food literacy is one of the primary internal barriers preventing individuals from adopting (more sustainable) new diets (Ares et al., 2024). Many people have limited knowledge of nutrition, sustainability, and ethical food choices, leading to misconceptions such as the belief that plant-based diets are nutritionally inadequate. In a pan-EU consumer survey majority of the participants agreed to the statement "I would not get energy or strength from these (plant-based) products" (Perez-Cueto et al., 2022). Additionally, insufficient cooking and meal-planning skills make it difficult for individuals to incorporate sustainable foods into their diets (Wu et al., 2024). Addressing this issue requires the integration of plant-based cooking courses into school curricula and community programs, which can enhance food literacy and empower individuals to prepare sustainable meals (Labbé et al., 2023). Governments should also revise national dietary guidelines to emphasize plant-based proteins and environmental sustainability, ensuring these recommendations are reflected in public health initiatives. The MOO method could support the design of more impactful national dietary guidelines. Although more and more countries are incorporating sustainability into their dietary guidelines, the extent to which environmental sustainability is addressed varies. In many cases, discussions are limited to broad explanations of what constitutes a sustainable diet (James-Martin et al., 2022). Implementation of standardized sustainability labels, such as carbon footprint indicators and organic certifications, can improve transparency and enable consumers to make informed choices (Fresacher and Johnson, 2023). A meta-analysis showed that food labeling could reduce energy intake by 6.6% and total fat intake by 10.6%, while increasing vegetable consumption by 13.5% (Shangguan et al., 2019). Also, it has been shown that there is a relationship between food literacy and the financial security of households. Financially secure households have better food literacy and are willing to pay more for healthy and sustainable foods (Nam and Suk, 2024).

Perceived behavioral control is another significant internal barrier. In the context of diet, it shows how much control a person feels they have when choosing healthy and sustainable food, even with financial, time, or accessibility challenges. Many individuals feel constrained by financial limitations, lack of time, and inadequate planning skills when considering sustainable diets. Meal planning tools developed using MOO can serve as tool to advance planning skills, offering individuals

TABLE 3 Internal and external barriers to dietary change and corresponding policy tools to address them.

Barrier type	Barrier	Policy solution
Internal	Lack of food literacy	Culinary education, updated dietary guidelines, and food labeling
	Perceived behavioral control	Financial incentives, supermarket layout changes, public procurement
	Emotions and cognitive dissonance	Awareness campaigns, appealing food descriptions
	Attitudes, beliefs, and convenience-driven habits	Market restrictions, meat reduction policies
	Habits and taste preferences	Gradual introduction, novel product innovation
External	Social norms and household composition	Public procurement rules, community initiatives
	Information and media influence	Stronger food labeling, media literacy programs
	Organoleptic factors	Improved food presentation
	Governance and policy	Advertising regulations, support for sustainable agriculture
	Cost and physical access	Food subsidies, infrastructure investment

the opportunity to design sustainable meals quickly. Helland and Nordbotten in their study (Hagen Helland et al., 2021) showed that individual's decision to change habits is a barrier against diet change. However, even those motivated to make dietary changes often struggle to find affordable and convenient sustainable food options. It has been also shown that as diets are becoming more diverse, a healthy and sustainable diet is becoming more unaffordable (Fanzo et al., 2022). This is because nutrient-rich foods tend to be more expensive because they require more effort and resources to cultivate, store, and transport compared to shelf-stable, low-cost products (Fanzo et al., 2022). To address this challenge, financial incentives (market-based incentives; Ammann et al., 2023) should be introduced to reduce the cost of plant-based proteins, fruits, and vegetables, making them more accessible, particularly to low-income segments of populations. Role of financial incentives on increase of the consumption of plant-based products and fruits have been previously confirmed in the United States Department of Agriculture (USDA) healthy incentives pilot program (Olsho et al., 2016). Results of another study showed that price reductions can lead to increases in purchases of fruit and vegetables (Huangfu et al., 2024). In addition to financial incentives, supermarket layouts should be adjusted to increase the visibility of sustainable foods by placing them at eye level and near checkout counters, thereby encouraging healthier purchases. Vogel et al. showed that healthier supermarket layouts can improve the nutrition profile of store sales and likely improve household purchasing and dietary quality (Vogel et al., 2021). Another effective policy measure is the introduction of default plant-based meal options in public institutions such as schools, hospitals, and workplaces, which can facilitate the transition to a sustainable diet without restricting individual choice. Such policies are referred to as public procurement that has been a successful strategy for achieving health and environmental objectives in the food sector (Smith et al., 2016). For example, the Estonian Ministry of Public Health has decided to place greater emphasis on vegetables and fruits in the school canteens to encourage healthier food consumption among Estonian children (ERR, 2025). Plant-based default menu options have proven effective, offering a simple yet impactful strategy to reduce the consumption of animal products at catered events (Boronowsky et al., 2022).

Emotional attachments to certain foods, particularly meat, create psychological resistance to dietary change. Many individuals value sustainability but continue to engage in unsustainable eating habits. Psychologists refer to such a condition as cognitive dissonance (Rothgerber, 2020). Additionally, distrust in food labels and skepticism toward novel foods further complicates consumer decision-making (Modlinska et al., 2020). Studies indicate that organizational trustworthiness and corporate social responsibility play a significant role in shaping consumers' willingness to purchase cultured meat as a novel food product (Lin-Hi et al., 2022). Public awareness campaigns like "Meatless Monday" (Ammann et al., 2023) can help normalize plant-based diets and positively frame sustainable eating. Research also suggests that renaming plant-based dishes using appealing and familiar language, such as "Slow-Roasted Tomato & Basil Flatbread" instead of "Vegan Flatbread" enhances consumer acceptance and reduces negative biases.

Attitudes, beliefs, and values also play a crucial role in food choices. Furthermore, convenience-driven habits can reinforce unsustainable food choices. Bogard et al. define convenience as a characteristic that minimizes the resources required by consumers (including time, physical effort, mental effort, and skills) across various stages of food-related activities, such as planning, acquisition, preparation, storage, transport, consumption, and cleanup (Bogard et al., 2024). In the context of the food environment, convenience has been described as the "time cost of obtaining, preparing, and consuming a food item." The time required to acquire food is closely associated with features of the food environment that influence physical accessibility. To address these barriers, governments and communities should regulate misleading advertisements that promote unhealthy and unsustainable food products, particularly those targeting children (Graff et al., 2017; Khan et al., 2024). Additionally, policies limiting red meat consumption in public institutions such as schools, hospitals, and government offices can help normalize plant-based diets and reduce overall demand for unsustainable products.

Dietary habits established during childhood often persist in adulthood (Winpenny et al., 2018), making shifting toward more sustainable eating patterns difficult. Furthermore, some consumers find plant-based foods less appealing in terms of taste, texture, and variety. The results of a study indicate that following a healthy dietary pattern is linked to a greater enjoyment of food. In other words, people who maintain a nutritious diet tend to find more pleasure in eating (Dubois et al., 2022). Therefore, plant-based food alternatives should be made more appealing to encourage healthier eating habits and enhance the enjoyment of food. Public institutions can facilitate the transition by gradually introducing blended meat-plant protein (meat hybrids) products (Profeta et al., 2021), which make dietary shifts more acceptable. Investing in research to improve the taste, texture, and sensory appeal of plant-based alternatives is also necessary to enhance consumer acceptance.

3.2 External barriers

Beyond internal barriers, external factors also significantly influence dietary choices (Table 3). Social norms and household composition shape eating habits, with cultural expectations, family dynamics, and peer influence playing a critical role (Higgs et al., 2019; Stok et al., 2016). In many societies, high meat consumption is linked to masculinity and social status (Camilleri et al., 2024; Vrijsen et al., 2025), making plant-based diets less acceptable. To change these norms, governments can require public institutions such as schools and hospitals to source sustainable food products, thereby normalizing plant-based diets and driving systemic change. Community-based initiatives that encourage families to transition toward sustainable eating habits together can also help reshape cultural norms (Metcalfe et al., 2022).

Information and media influence are also key external barriers. Misinformation, conflicting dietary advice, and aggressive marketing by the food industry create confusion and reduce trust in sustainability claims (Nugraha et al., 2024). To combat these challenges, governments must enforce stronger food labeling regulations to ensure that sustainability labels are transparent, science-based, and standardized, preventing greenwashing and enhancing consumer trust (Nugraha et al., 2024). There is evidence that media-based campaigns have successfully influenced dietary behaviors by promoting plant proteins and meat alternatives alongside traditional meat products (Consavage Stanley et al., 2024). Additionally, media literacy programs can educate the public on how to critically assess food-related media messages, helping consumers recognize and resist misleading advertisements (Guyader et al., 2017).

Organoleptic factors, including taste, texture, and appearance, often deter consumers from choosing plant-based alternatives, as they are unfamiliar with their sensory characteristics compared to conventional foods (Alcorta et al., 2021). To improve acceptance, retailers and restaurants should enhance the visual appeal and presentation of plant-based foods, making them more attractive to consumers (Farrar et al., 2024; Ruby et al., 2024).

Governance and policy frameworks also play a fundamental role in shaping food environments. Weak regulations allow misleading marketing practices, promote unsustainable agricultural systems, and create economic barriers to sustainable eating (Even et al., 2024). To address this, governments should implement stricter policies to regulate advertising and marketing, restricting deceptive sustainability claims and curbing the promotion of foods that contribute to poor dietary habits (Taillie et al., 2019). Additionally, financial support for local and sustainable agriculture is essential. Providing incentives for farmers who adopt sustainable practices will ensure a stable and affordable supply of environmentally friendly food options (Desalegn et al., 2024).

Cost and physical access further complicate the transition to sustainable diets (Bogard et al., 2024), as sustainable foods remain expensive and inaccessible, particularly in low-income areas. To make sustainable diets more accessible, subsidies should be provided to reduce the price of plant-based proteins, fruits, and vegetables. Investments in infrastructure, particularly in supply chains and distribution networks, will also ensure that sustainable foods are available in underserved regions.

3.3 Other barriers and implications for behavior change

Although the barriers discussed are primarily at the individual level, it is important to understand that factors extend to interpersonal and broader social levels. The DONE framework offers a comprehensive structure for analyzing the many factors that shape dietary behaviors, including food choices and eating patterns. It considers a wide range of determinants, from biological and psychological to social and environmental (Stok et al., 2017). The Behavior Change Wheel, on the other hand, provides a practical tool for identifying what needs to change for a specific behavior to occur. At its core is the COM-B model, which proposes that behavior (B) arises from the interaction of Capability (C), Opportunity (O), and Motivation (M). For example, improving dietary behavior may involve enhancing an individual's capability (e.g., cooking skills), increasing opportunity (e.g., access to healthy foods), and strengthening motivation (e.g., through social support or incentives). The Behavior Change Wheel connects these behavioral components to appropriate intervention strategies and policy measures, offering a systematic approach from behavioral diagnosis to implementation (Michie et al., 2011) that can be used by researchers and policymakers interested in dietary behavior change.

The barriers discussed in our review align closely with the key factors influencing sustainable (and unsustainable) dietary behaviors proposed by Elliott et al. (2024), demonstrating their possible relevance in influencing sustainable diet consumption. For example, the work by Elliott et al. highlights conscious habitual eating, self-regulation skills, and eating norms as key factors, which aligns with the inclusion of habits and taste preferences, perceived behavioral control, and social norms from Muñoz-Martínez et al. (2024). Similarly, the emphasis on product price and food accessibility in their findings reflects the cost and physical access barrier presented by Muñoz-Martínez et al. (2024). Furthermore, their discussion of the potential importance of food promotion corresponds with the broader examination of information and media influence on dietary behaviors by Muñoz-Martínez et al. (2024). Despite the general concordance between barriers discussed in our review and those proposed as high priority by Elliott et al., dietary behaviors can be influenced by a broader range of factors than those discussed in our review (Stok et al., 2017).

4 Integrating policy tools and the role of national recommendations in diet transition

A comprehensive approach that combines policy tools is necessary for maximum impact (Michie et al., 2011). Isolated interventions, such as labeling or taxation alone, may not lead to long-term behavioral shifts, but when combined with educational initiatives, economic incentives, and regulatory frameworks, they create an enabling environment for sustainable diets (Elliott et al., 2024).

The European Union's Farm-to-Fork Strategy exemplifies this multi-layered approach by integrating food labeling, fiscal policies, and procurement changes into a cohesive framework for sustainability (European Commission, 2025). Free school meal plans, educational initiatives from kindergarten, and taxation on less sustainable food have been emphasized by the Farm-to-Fork guidelines. These measures collectively aim to create a healthier, more sustainable food environment.

MOO can be effectively integrated with behavioral policy design frameworks, such as the Behavior Change Wheel, to assess trade-offs and identify optimal intervention combinations. To implement this approach, qualitative determinants (particularly behavioral factors) must first be translated into quantitative metrics. Methods, such as the Analytic Hierarchy Process (AHP) (Aliasgharzadeh et al., 2022), allow for the systematic weighting of these factors based on expert judgment or stakeholder input. In parallel, monetization techniques, including the assignment of economic values to health outcomes (e.g., avoided cost-of-illness) (Springmann et al., 2021) or environmental impacts, offer an additional means of quantification. Once quantified, these criteria can be incorporated into MOO models to generate policy portfolios that balance competing objectives (such as minimizing implementation costs or environmental impacts while maximizing health benefits or behavioral uptake) within predefined constraints.

Nationally Recommended Diets (NRDs) play a crucial role in guiding healthy eating habits, but they must become more sustainable and flexible to be followed by different socio-economic groups within society which could be achieved using MOO (Springmann et al., 2020). While studies indicate that NRDs are generally more sustainable than the average diet, there is still room for improvement (Bashiri et al., 2024). NRDs currently provide broad recommendations, but they should be more specific and actionable, enabling individuals to identify and choose sustainable foods specifically for the individuals more fully considering their individual peculiarities and preferences. Maillot et al. highlighted a critical limitation in many dietary guidelines: they assume that individuals who follow these recommendations receive all essential nutrients (van Dooren, 2018; Maillot et al., 2010). However, in practice, this is not always the case. Additionally, dietary guidelines should not be designed solely for the general population; they must be more individualized, better targeting different consumer groups, catering to people with specific health conditions and different age groups. As demonstrated by Eustachio Colombo et al. (2023) and Nordman et al. (2024) through clustering analysis, these objectives can be effectively achieved using MOO.

When applying MOO to design sustainable dietary guidelines, it is crucial to use baseline dietary data that reflects actual consumption patterns, as this strongly influences the feasibility of optimized diets. Model constraints should also align with recent national and international dietary updates, such as the Nordic Nutrition Recommendations (NNR2023) (Blomhoff et al., 2023; Lassen et al., 2020), which integrate sustainability with nutritional adequacy. Incorporating expert input, regional dietary norms, and culturally appropriate constraints can improve the relevance, acceptability, and policy coherence of MOO-generated diets.

Dietary guidelines have the potential to influence food choices at both the individual and societal levels. They can be promoted across the population through mass communication campaigns and supported by rigorous, transparent reviews of scientific evidence (Advisory Report, 2025). Additionally, they can directly shape government food service and assistance programs, providing a framework for healthier and more sustainable food policies. While these guidelines are considered a "soft" policy, they can also indirectly encourage industry reformulation efforts to align with healthier standards (Mozaffarian et al., 2018). However, the translation of these guidelines into concrete policies and regulations has been somewhat limited (Wood et al., 2023). NRDs should be updated more frequently and should form a system of recommendations supporting individual choices (Wood et al., 2023), health, and planetary boundaries (Rossi et al., 2023).

5 Conclusion

Sustainable diet transition is crucial for addressing both environmental and public health challenges. MOO can provide a robust framework for balancing nutritional adequacy, affordability, cultural acceptability, and environmental impact. Providing accurate dietary data to the MOO model is essential for generating reliable and meaningful results. However, effective dietary shifts require more than mathematical models. Successful implementation demands the integration of behavioral insights, consumer engagement, and supportive policy instruments to identify and overcome internal and external barriers to diet adoption. It is important to understand how these factors operate not only at the individual level but also across interpersonal and broader social contexts. Behavior change models can offer valuable insights to support this understanding. NRDs have a pivotal role in steering dietary behavior but must evolve to reflect sustainability considerations. They also need to be translated into concrete policies and regulations and should be updated regularly to remain relevant and effective. To make optimized diets work in real life, we need a well-coordinated approach that brings together different elements. This includes using scientific methods to design diets, giving people personalized advice, creating supportive policies, and involving the public. When these parts work together, it becomes easier for governments and other organizations to help people shift toward diets that are not only healthy and sustainable but also realistic and fair for everyone.

Author contributions

BB: Investigation, Software, Data curation, Methodology, Conceptualization, Resources, Writing – original draft, Writing – review & editing, Formal analysis. AK: Supervision, Writing – review & editing, Software, Investigation, Resources, Data curation, Validation, Methodology. RV: Writing – review & editing, Formal analysis, Funding acquisition, Supervision, Project administration, Conceptualization, Methodology, Resources, Investigation.

Funding

The author(s) declare that no financial support was received for the research and/or publication of this article.

Acknowledgments

The authors would like to appreciate the constructive comments and input from the reviewers on an earlier version of this manuscript.

Conflict of interest

BB, AK, and RV were employed by company TFTAK AS.

Generative AI statement

The authors declare that no Gen AI was used in the creation of this manuscript.

Publisher's note

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Curriculum vitae

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Related Publications

- **Bashiri, B.**, Kaleda, A., & Vilu, R. Sustainable diets, from design to implementation by multi-objective optimization-based methods and policy instruments. Frontiers in Sustainable Food Systems, 9, 1629739.
- **Bashiri, B.**, Kaleda, A., & Vilu, R. (2025). Integrating multi-criteria decision-making with multi-objective optimization for sustainable diet design. Journal of Cleaner Production, 500, 145233.
- **Bashiri, B.**, Kaleda, A., Gavrilova, O., & Vilu, R. (2024). A Culturally Acceptable Shift in Diet to Reduce Land Footprint: an Optimization Study for Estonia. Environmental Modeling & Assessment, 1-15.
- **Bashiri, B.**, Cropotova, J., Kvangarsnes, K., Gavrilova, O., & Vilu, R. (2024). Environmental and economic life cycle assessment of enzymatic hydrolysis-based fish protein and oil extraction. Resources, 13(5), 61.
- **Bashiri, B.**, Pinheiro, A. C. D. A. S., Tappi, S., Rocculi, P., Kaleda, A., & Vilu, R. (2025). Life cycle assessment of laboratory-scale chitosan production: Comparison of high-pressure processing-assisted and conventional methods. In Proc. Est. Acad. Sci (Vol. 74, pp. 1-14).
- Rahmani, R., **Bashiri, B.**, Lopes, S. I., Hussain, A., Maurya, H. S., & Vilu, R. (2025). Sustainable Additive Manufacturing: An Overview on Life Cycle Impacts and Cost Efficiency of Laser Powder Bed Fusion. Journal of Manufacturing and Materials Processing, 9(1), 18.
- **Bashiri, B.**, Zehtabvar, M., Gavrilova, O., & Vilu, R. (2023). Change in the carbon footprint of Iranians' food consumption from 1961 to 2019: A decomposition analysis of drivers.

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Seotud publikatsioonid

- **Bashiri, B.**, Kaleda, A., & Vilu, R. Sustainable diets, from design to implementation by multi-objective optimization-based methods and policy instruments. Frontiers in Sustainable Food Systems, 9, 1629739.
- **Bashiri, B.**, Kaleda, & Vilu, R. (2025). Integrating Multi-Criteria Decision-Making with Multi-Objective Optimization for Sustainable Diet Design. Journal of Cleaner Production, 1-15.
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ISSN 2585-6901 (PDF)
ISBN 978-9916-80-384-4 (PDF)