



An integrated pollution-generating technology and temperature alignment rating model for eco-efficiency estimation

Andreas Dellnitz^a, Madjid Tavana^{b,c,1,*}, Salome Dellnitz^d, Andreas Kleine^e, Lukas Dalhoff^a

^a Leibniz-FH University of Applied Sciences, Hannover, Germany

^b Business Systems and Analytics Department, Distinguished Chair of Business Analytics, La Salle University, Philadelphia, USA

^c Business Information Systems Department, Faculty of Business Administration and Economics, University of Paderborn, Paderborn, Germany

^d EDEKABANK AG, 22297 Hamburg, Germany

^e FernUniversität in Hagen, Hagen, Germany

ARTICLE INFO

Keywords:

Data envelopment analysis

Eco-efficiency

Pollution-generating technologies

Temperature alignment rating

Retail food industry

ABSTRACT

Measuring environmental efficiency, or eco-efficiency, has become increasingly critical as regulatory frameworks tighten in developed countries, requiring companies to mitigate climate change actively. Data Envelopment Analysis (DEA) is a widely used, non-parametric method for assessing eco-efficiency in comparable decision-making units (DMUs). Traditionally, DEA has relied on single-technology models, which are effective for macro-level analyses but present challenges in micro-level studies involving pollutants due to incompatibility with the material balance principle. This study applies an established DEA approach based on pollution-generating technologies to evaluate the eco-efficiency of 25 food retailers, incorporating both operational and environmental performance. For the first time in a DEA-based application, we link eco-efficiency scores with temperature alignment scores. This emerging sustainability metric assesses a company's compatibility with the Paris Agreement's 1.5 °C target. Our findings reveal that focusing solely on emission reduction based on DEA recommendations does not necessarily ensure alignment with global climate goals, underscoring the importance of an integrated assessment approach. Moreover, pure benchmarking based on empirical observations is insufficient; assessing sustainability improvements requires concrete measures, such as upgrading refrigeration systems or implementing energy-efficient technologies. This study provides practical insights for corporate decision-makers and policymakers, supporting more comprehensive, sustainability-driven management actions in the retail sector.

1. Introduction

1.1. Motivation and structure of the work

The global food supply chain comprises multiple stages, ranging from raw material production (e.g., cereals, sugar beets, potatoes, oilseeds, milk, meat, eggs, vegetables, and fruits) to food processing, distribution, and final consumption. These processes contribute significantly to greenhouse gas (GHG) emissions, making the food sector a critical focus for climate mitigation efforts. Food systems are estimated to account for 23 % to 42 % of total global emissions, with this range reflecting the 95 % confidence interval of emission estimates [46]. Variability in global emission contributions also arises from uncertainties in emission data, including those related to land use change, agricultural inputs, processing, transportation, and retail operations. Despite these uncertain-

ties, it is widely recognized that farm production and land use change contribute the largest share of food system emissions, while processing, transportation, and retail further add to the overall environmental performance [46]. As pressure to decarbonize food systems increases, improving the eco-efficiency of all actors in the food supply chain, particularly within the retail sector, is crucial for achieving sustainability and climate targets.

Although the food retail sector plays a crucial role in shaping both upstream production and downstream consumption patterns, its environmental efficiency remains largely underexplored. Prior research has predominantly focused on supply-side mitigation strategies, such as reducing agricultural emissions, optimizing fertilizer use, and minimizing food waste [3]. However, limited attention has been given to assessing the eco-efficiency of food retailers themselves, particularly through quantitative, non-parametric methods. Given that retailers serve as key

Peer review under the responsibility of Editorial Board of Sustainable Operations and Computers.

* Corresponding author at: Business Systems and Analytics Department, Distinguished Chair of Business Analytics, La Salle University, Philadelphia, PA 19141, United States.

E-mail address: tavana@lasalle.edu (M. Tavana).

¹ Web: <http://tavana.us/>.

<https://doi.org/10.1016/j.susoc.2025.09.002>

Received 20 June 2024; Received in revised form 28 July 2025; Accepted 30 September 2025

Available online 1 October 2025

2666-4127/© 2025 The Authors. Published by Elsevier B.V. on behalf of KeAi Communications Co., Ltd. This is an open access article under the CC BY-NC-ND license (<http://creativecommons.org/licenses/by-nc-nd/4.0/>)

intermediaries, influencing both agricultural supply chains and consumer behavior, understanding their eco-efficiency is essential for developing holistic sustainability strategies.

Furthermore, conventional efficiency benchmarking approaches predominantly emphasize emission reductions, yet mitigating emissions alone does not necessarily ensure alignment with global climate objectives. To address these gaps, this study links eco-efficiency scores with temperature alignment scores. This emerging sustainability metric evaluates whether a company's climate performance aligns with the Paris Agreement's 1.5 °C target. Adopted in 2015, the Paris Agreement is a legally binding international treaty under the United Nations Framework Convention on Climate Change (UNFCCC), aimed at mitigating climate change by significantly reducing greenhouse gas emissions and achieving global net-zero emissions by 2050. The 1.5 °C threshold is particularly critical, as scientific research [12,13,50] highlights that exceeding this limit could result in severe climate-related consequences, including extreme weather events, rising sea levels, and biodiversity loss.

This study bridges the existing research gap by applying a DEA-based approach to pollution-generating technology in food retail, ensuring that efficiency improvements contribute to broader climate action goals. To further explore these issues, this study seeks to answer the following research questions:

1. How can the environmental efficiency of food retailers be quantitatively assessed, incorporating both direct (Scope 1) and indirect (Scope 2) emissions?
2. What are the primary determinants of eco-efficiency in food retail, and how do they vary across different retail formats?
3. How does eco-efficiency in food retail relate to sustainability performance metrics, such as temperature alignment scores, which assess alignment with the Paris Agreement's 1.5 °C target?

To answer these questions, we determine the eco-efficiency of supermarkets or grocery stores, focusing on direct and indirect CO₂ emissions (so-called Scope 1 and Scope 2 emissions) arising from the operation of the buildings; for a recent study on embodied greenhouse gas emissions in buildings, see Rankin et al. [49] and the references therein. Our findings offer practical implications for corporate decision-makers and policymakers, supporting more targeted sustainability management actions in the retail sector.

The remainder of this paper is organized as follows: To frame this issue better, we provide an overview of related work in [Section 1.2](#). [Section 2.1](#) presents preliminaries on classical DEA; [Section 2.2](#) discusses the established approach of pollution-generating technologies and its adaptation to the specific context of food retail efficiency assessment. [Section 3](#) addresses eco-efficiency in food retailing and presents our findings on eco-efficiency. [Section 4.1](#) relates the results from [Section 3](#)—pinpointing corresponding managerial implications—to the ever more important subject of temperature alignment. [Section 4.2](#) discusses the managerial implications in light of the available measures, while [Section 4.3](#) outlines the limitations of this study. Finally, [Section 5](#) concludes this work.

1.2. Related work

There is a large body of research connecting eco-efficiency analysis with Data Envelopment Analysis (DEA). A search conducted in the Web of Science Core Collection database using the keywords 'eco-efficiency analysis' and 'Data Envelopment Analysis' in the topic field yielded 860 results. The search covered publications from 2004 to 2025, highlighting applications across various sectors, including agriculture [47,53], energy supply [31,33], and supply chain management [41,55]. However, a notable research gap exists—none of the 860 identified scientific papers establishes a direct connection between eco-efficiency analysis and temperature alignment. As a result, no studies attempt to connect eco-efficiency findings with global warming indicators, an issue of

particular importance in sustainability assessments of the retail sector. Furthermore, as outlined in the introduction, research focusing on eco-efficiency in food retailing remains limited. A literature search using the terms 'environmental efficiency' OR 'eco-efficiency' AND 'food retailing' in Web of Science yields only 79 results from 2010 to the beginning of 2025, with a secondary Science Direct search revealing no additional sources.

The majority of studies on food retail focus on food waste reduction using various methods, including experiments, simulations, life cycle assessments, and surveys [16,35,45]. Another key research stream examines the environmental footprint of different supply chain strategies and business models, such as comparing pooling systems, optimizing energy supply strategies, and transportation route optimization [28,32,43,48,58].

A handful of studies attempt to assess the environmental performance of food retailing, but they rely on alternative methodologies such as life cycle assessments and utility analysis-based benchmarking, rather than DEA [15,25,26,29]. Notably, Ferreira et al. [26] employed descriptive statistics to establish carbon emission benchmarks for the largest 250 retailers, revealing that best-in-class retail buildings emit less than 115 kg CO₂ per square meter annually for food retail and below 70 kg for non-food retail. These benchmarks serve as a useful reference for evaluating the eco-efficiency of food retail, as further discussed in [Section 4.1](#).

Recent studies emphasize the importance of incorporating the Material Balance Principle (MBP) into DEA models for more comprehensive assessments of environmental efficiency. Research by Lozano [42], Arabi et al. [7], and Trang et al. [56] has explored DEA applications that incorporate undesirable outputs and MBP constraints, offering valuable insights into efficiency evaluations in pollution-intensive industries. This perspective is crucial, as early eco-efficiency analyses that overlooked the MBP often failed to account for contradictions with fundamental physical laws. The pollution-generating technology approach, which models efficiency by intersecting two production possibility sets to preserve the MBP, has emerged as a robust methodology for incorporating undesirable outputs into DEA models [1,2,18,22,44]. Additionally, new studies have incorporated artificial intelligence techniques to enhance the accuracy of predictions in eco-efficiency assessments [4,59]. The integration of stochastic models into DEA frameworks has also improved the handling of uncertainty in environmental performance evaluation [5], which is particularly relevant given the measurement uncertainty (23 %–42 %) associated with food system emissions [36]. Further, non-radial DEA models have been proposed to better account for input-output trade-offs, which is crucial in sectors where carbon neutrality goals are integral to strategic planning [54].

A significant research gap exists in integrating eco-efficiency assessments with global climate policy objectives that extend beyond merely reducing carbon emissions. While DEA is commonly used to evaluate efficiency within operational, financial, or carbon emission reducing contexts, it has not been systematically linked to temperature alignment scores, which measure how well companies align with the Paris Agreement's 1.5 °C target. This study aims to bridge this gap by applying an established DEA-based approach to pollution-generating technology in food retail, while linking eco-efficiency scores with temperature alignment scores. This novel integration enables a more comprehensive sustainability assessment, ensuring that efficiency improvements align with climate action targets.

2. Preliminaries

DEA enables the efficient measurement of multidimensional activities in comparable profit or non-profit entities, known as decision-making units (DMUs). However, classical DEA, as introduced by Charnes et al. [17], is not well-suited for activities involving pollutants, as these represent a form of joint production [1,18,22,27,44]. To address this limitation, we adopt an established approach from the DEA literature—the “pollution-generating technology” framework, primarily de-

veloped by Murty et al. [44]. Accordingly, Section 2.1 outlines the classical single-technology DEA approach. Section 2.2 presents our adaptation of the pollution-generating technology framework to the supermarket context, leveraging the intersection of two technological perspectives: one representing business efficiency and the other accounting for environmental constraints.

2.1. The classical case of single technologies

In activity analysis, Koopmans [38], Shephard [52], and Deprins et al. [23] focus on production possibility sets or technologies as described by:

$$\mathcal{T} = \{(\mathbf{x}, \mathbf{y}) \mid \mathbf{y} \text{ can be realized by } \mathbf{x}\}, \quad (1)$$

in which $\mathbf{x}^T = (x_1, \dots, x_m, \dots, x_M) \in \mathbb{R}_+^M$ is the vector of inputs allowing the realization of the outputs $\mathbf{y}^T = (y_1, \dots, y_s, \dots, y_S) \in \mathbb{R}_+^S$. Accordingly, Eq. (1) establishes the set of possible activities $(\mathbf{x}, \mathbf{y}) \in \mathbb{R}_+^{M+S}$ in a general form without specifying the exact design of $\mathcal{T}$.

Since Charnes et al. [17] and Banker et al. [9], DEA has been a meaningful non-parametric instrument for measuring efficiency among a group ($j = 1, \dots, J$) of profit or non-profit entities, so-called DMUs, generating $\mathcal{T}$ by:

$$\mathcal{T}(\tau) = \left\{ (\mathbf{x}, \mathbf{y}) \in (\mathbb{R}_+^{M+S}) \mid \mathbf{x} \geq \sum_{j=1}^J \lambda_j \mathbf{x}_j; \mathbf{y} \leq \sum_{j=1}^J \lambda_j \mathbf{y}_j; (\lambda_1, \dots, \lambda_J) \in \Lambda(\tau) \right\}, \quad (2)$$

where $\Lambda(\tau)$ constrains the intensity variables $(\lambda_1, \dots, \lambda_J)$ with which activities may contribute to constructing comparable activities on the right-hand side of the inequalities. The specification of $\Lambda(\tau)$ can be convex or non-convex; the two most prominent convex are given in the following matrix:

	$\Lambda(\tau)$
CCR	$\{(\lambda_1, \dots, \lambda_J) \mid \lambda_j \geq 0 \forall j\}$
BCC	$\{(\lambda_1, \dots, \lambda_J) \mid \lambda_j \geq 0 \forall j; \sum_{j=1}^J \lambda_j = 1\}$

The acronyms CCR and BCC trace back to their inventors, Charnes, Cooper, and Rhodes (CCR) and Banker, Charnes, and Cooper (BCC). For more details on the corresponding axioms and implications, see, e.g., Banker et al. [9], Tulkens [57], Kuosmanen [39], Abad and Briec [1], and Dellnitz and Rödder [21]. Efficiency analysis in the presence of the above technologies may take different forms depending on the controllable parts of the activities and the corresponding efficiency measures; i.e., such analysis can be based on input and output orientation using radial, slack-based, or hyperbolic measures; see Charnes et al. [17], Banker et al. [9], Scheel and Scholtes [51], and Hasananasab et al. [34] again.

Due to the nature of the food retail sector, where outputs depend on external factors such as the number of consumers that can be reached and the income levels of customers, they cannot be directly controlled. As a result, we adopt an input-oriented approach with a classical radial efficiency measure. Specifically, we focus on input orientation rather than slack-based or hyperbolic measures, which attempt to optimize both inputs and outputs simultaneously, for two key reasons:

1. At the operational level of a grocery store, controllable factors primarily include personnel levels and energy intensity related to heating, cooling, and lighting. These inputs can be adjusted to improve efficiency.
2. In contrast, outputs such as sales volume and customer numbers are subject to external market conditions and cannot be directly influenced in the short term. Therefore, they should not be incorporated into the objective function. Instead, these variables serve to define the appropriate set of observations for benchmarking, which we achieve by applying relevant constraints.

We employ a radial efficiency measure because we prefer a conservative estimate that aligns with the logic of a radial approach due to its

reliance on the Tchebychev norm. This ensures that efficiency evaluations remain prudent by proportionally scaling inputs while maintaining feasibility within the production possibility set. Formally, for each activity $(\mathbf{x}_k, \mathbf{y}_k) \in \mathbb{R}_+^{M+S}$, with $k \in \mathcal{J} = \{1, \dots, J\}$, to be evaluated, we need to solve the following optimization problems or envelopment forms:

$$\begin{aligned} \min \quad & h_k \\ \text{s.t.} \quad & \\ & h_k \mathbf{x}_k - \sum_{j=1}^J \lambda_{kj} \mathbf{x}_j \geq 0 \\ & \sum_{j=1}^J \lambda_{kj} \mathbf{y}_j \geq \mathbf{y}_k \\ & (\lambda_{k1}, \dots, \lambda_{kJ}) \in \Lambda(\tau) \text{ and } h_k \text{ free} \end{aligned} \quad (3)$$

Dealing with undesirable or bad outputs (e.g., pollutants or emissions) in efficiency analysis now requires a reformulation of $\mathcal{T}(\tau)$. For more details on axioms regarding different modeling techniques, technology misspecifications, and corresponding properties, see, e.g., Førsund [27], Kuosmanen and Matin [40], Kleine et al. [37], Dellnitz [19], Dellnitz et al. [20], and Abad and Briec [1]. Following the idea of Baumol and Oates [11], one could treat the bad output like the input:

$$\mathcal{T}^b(\tau) = \left\{ (\mathbf{x}, \mathbf{y}) \in (\mathbb{R}_+^{M+S}) \mid \mathbf{x} \geq \sum_{j=1}^J \lambda_j \mathbf{x}_j; \mathbf{y}^g \leq \sum_{j=1}^J \lambda_j \mathbf{y}_j^g; \mathbf{y}^b \geq \sum_{j=1}^J \lambda_j \mathbf{y}_j^b; (\lambda_1, \dots, \lambda_J) \in \Lambda(\tau) \right\}, \quad (4)$$

where $\mathbf{x} \in \mathbb{R}_+^M$ is the vector of inputs as above, but the vector of outputs $\mathbf{y} \in \mathbb{R}_+^S$ is now a composition of two vectors $\mathbf{y} = (\mathbf{y}^g, \mathbf{y}^b)$, namely the good outputs $\mathbf{y}^g \in \mathbb{R}_+^{S^g}$ and the bad outputs $\mathbf{y}^b \in \mathbb{R}_+^{S^b}$ (e.g., pollutants or emissions). This, in turn, leads to the following input-oriented optimization problems:

$$\begin{aligned} \min \quad & h_k \\ \text{s.t.} \quad & \\ & h_k \mathbf{x}_k - \sum_{j=1}^J \lambda_{kj} \mathbf{x}_j \geq 0 \\ & \sum_{j=1}^J \lambda_{kj} \mathbf{y}_j^g \geq \mathbf{y}_k^g \\ & \sum_{j=1}^J \lambda_{kj} \mathbf{y}_j^b \leq \mathbf{y}_k^b \\ & (\lambda_{k1}, \dots, \lambda_{kJ}) \in \Lambda(\tau) \text{ and } h_k \text{ free} \end{aligned} \quad (5)$$

This approach is a simple way to deal with bad outputs in macro analyses [22,27] and, according to Førsund [27], can be considered a “...reduced form of a larger system.” When modeling micro-level activities, however, this approach is flawed because it contradicts the first law of thermodynamics: Obviously, one cannot substitute material inputs and residuals discharged to the environment—but Eq. (5) and its dual, if it exists, allow such trade-offs; see Murty et al. [44] again. The following section shows a modern approach that addresses this shortcoming.

2.2. The emerging case of pollution-generating technologies

Recently, pollution-generating technologies have been developed to measure eco-efficiency and avoid unnatural trade-offs between material inputs and/or outputs and pollutants. These technologies are modeled as the intersection of an intended production technology $\mathcal{T}^1$ and nature’s residual generation set $\mathcal{T}^2$; cf. Murty et al. [44], Dakpo et al. [18], and Abad and Briec [1]. Consequently, we have:

$$\mathcal{T}^1(\tau) \cap \mathcal{T}^2(\tau) \quad (6)$$

with $\mathbf{x}^1 \in \mathbb{R}_+^{M^1}$ and $\mathbf{x}^2 \in \mathbb{R}_+^{M^2}$, $\mathbf{x} = (\mathbf{x}^1, \mathbf{x}^2) \in \mathbb{R}_+^M$, and

$$\mathcal{T}^1(\tau) = \left\{ (\mathbf{x}, \mathbf{y}^g) \in (\mathbb{R}_+^{M+S^g}) \mid \mathbf{x} \geq \sum_{j=1}^J \lambda_j \mathbf{x}_j; \mathbf{y}^g \leq \sum_{j=1}^J \lambda_j \mathbf{y}_j^g; (\lambda_1, \dots, \lambda_J) \in \Lambda(\tau) \right\} \quad (7)$$

and

$$\mathcal{T}^2(\tau) = \left\{ (x^2, y^b) \in (\mathbb{R}_+^{M^2+S^b}) \mid x^2 \leq \sum_{j=1}^J \lambda'_{kj} x^2_j, y^b \geq \sum_{j=1}^J \lambda'_{kj} y^b_j, (\lambda'_{k1}, \dots, \lambda'_{kJ}) \in \Lambda(\tau) \right\} \quad (8)$$

Obviously, $\mathcal{T}^1(\tau)$ establishes the relationship between all inputs $x = (x^1, x^2)$ and the intended outputs y^g . $\mathcal{T}^2(\tau)$ on the other hand, represents the relationship between the inputs x^2 and the undesirable outputs or pollutants y^b ; hence, x^2 are the inputs responsible for the emissions. In the residual-generation technology $\mathcal{T}^2(\tau)$, the intensity variables $\lambda'_{kj} \forall j$ differ from those of $\mathcal{T}^1(\tau)$. With this formulation, we can embed various individual extrapolation properties (e.g., CCR or BCC, etc.) in $\mathcal{T}^1(\tau)$ and $\mathcal{T}^2(\tau)$. This nomenclature leads to the input-oriented optimization problem (9). Here, we adhere to the same reasoning as outlined in Section 2.1; neither the good nor the bad outputs can be directly controlled at the operational level. Instead, carbon emission reduction is a consequence of input reduction, reinforcing the rationale for an input-oriented approach.

$$\begin{aligned} \min \quad & h_k \\ \text{s.t.} \quad & \sum_{j=1}^J \lambda_{kj} x^1_j \leq x^1_k \\ & h_k x^2_k - \sum_{j=1}^J \lambda_{kj} x^2_j \geq 0 \\ & \sum_{j=1}^J \lambda_{kj} y^g_j \geq y^g_k \\ & h_k x^2_k - \sum_{j=1}^J \lambda'_{kj} x^2_j \leq 0 \\ & \sum_{j=1}^J \lambda'_{kj} y^b_j \leq y^b_k \\ & (\lambda_{k1}, \dots, \lambda_{kJ}), (\lambda'_{k1}, \dots, \lambda'_{kJ}) \in \Lambda(\tau), h_k \text{ free} \end{aligned} \quad (9)$$

When solving the above variant, one obtains the (optimal) radial reduction potential h_k^* for the emission-causing inputs of DMU k ; it is a type of technical input efficiency. The (optimal) intensity variables $(\lambda_{k1}^*, \dots, \lambda_{kJ}^*), (\lambda'_{k1}^*, \dots, \lambda'_{kJ}^*)$, if nonzero, provide information about the best practices used to determine this reduction potential. Given the above rationale—that carbon emission reduction is a consequence of input reduction— h_k^* does not directly measure the environmental performance of k 's activity. With this in mind, we define environmental performance based on the achieved emissions of the optimal benchmark references $(\lambda_{k1}^*, \dots, \lambda_{kJ}^*), (\lambda'_{k1}^*, \dots, \lambda'_{kJ}^*)$, which are selected according to the input reduction potential:

Definition 1. Let $h_k^*, (\lambda_{k1}^*, \dots, \lambda_{kJ}^*), (\lambda'_{k1}^*, \dots, \lambda'_{kJ}^*)$ be an optimal solution regarding Eq. (9). The environmental efficiency or eco-efficiency of DMU k is then defined by

$$eco_k = \frac{\mathbb{I}^T \left(\sum_{j=1}^J \lambda'_{kj} y^b_j \right)}{\mathbb{I}^T y^b_k} \in [0, 1] \quad (10)$$

with $\mathbb{I}$ being an all-one column vector.

Eq. (10) can vary in $[0, 1]$, where 0 implies a potential for a zero-emission activity (depending on the alternatives), and 1 means no reduction potential in emissions at all. Eq. (10) cannot be greater than 1 due to the restrictions in Eq. (9). However, Eq. (10) is only well defined if DMU k 's activity is nonzero, i.e., $y^b_k \geq 0$ with $y^b_k \neq 0$. If DMU k has a zero-emission activity, then $eco_k := 0$ because DMU k already performs ecologically efficient. The latter statement does not automatically imply $h_k^* = 1$, DMU k can be eco-efficient but still waste inputs.

In linear optimization problems, there may be multiple optima. That is, in the DEA domain, the optimal objective function value h_k^* is unique after solving Eq. (9), but the intensities $(\lambda_{k1}^*, \dots, \lambda_{kJ}^*)$ and $(\lambda'_{k1}^*, \dots, \lambda'_{kJ}^*)$ can be ambiguous—and hence eco_k too. There are several ways to deal

with such ambiguities in DEA. Here, most approaches are based on a two-stage procedure: first, optimize the efficiency objective; next, optimize a secondary objective, fixing the optimal value of the first stage. For some popular approaches, see Banker and Thrall [10], Doyle and Green [24], and Golany and Yu [30]. We can adapt such a philosophy, calculating the optimistic and pessimistic values for Eq. (10) via Eq. (11).

$$\begin{aligned} \min \quad & \mathbb{I}^T s_k \text{ and } \max \quad \mathbb{I}^T s_k \\ \text{s.t.} \quad & - \sum_{j=1}^J \lambda'_{kj} x^2_j \leq -h_k^* x^2_k \\ & \sum_{j=1}^J \lambda'_{kj} y^b_j + s_k = y^b_k \\ & (\lambda'_{k1}, \dots, \lambda'_{kJ}) \in \Lambda(\tau), s_k \geq 0 \end{aligned} \quad (11)$$

Using the objective functions of Eq. (11), we push the sum of the emission slacks—thus controlling the numerator of Eq. (10); the denominator is constant and can, therefore, be neglected. In this new optimization problem, the imperative max (min) corresponds to an optimistic (a pessimistic) estimate that gives the maximum (minimum) gap between both components of the fraction.

Proposition 1. Eq. (11) is a perfect surrogate model to fathom the limits of Eq. (10).

PROOF. To prove this statement, multiply the group of constraints $\sum_{j=1}^J \lambda'_{kj} y^b_j + s_k = y^b_k$ by $\mathbb{I}^T$ and rearrange. Furthermore, we can neglect the constraints corresponding to $\mathcal{T}^1(\tau)$ in Eq. (9) because $(\lambda_{k1}, \dots, \lambda_{kJ})$ is unaffected by the optimization of Eq. (11) due to the fixed h_k^* .

Remark 1. The minimization in Eq. (11) can be trivially solved; thus, the estimated pessimistic emission reduction potential is always zero.

PROOF. To prove this, one chooses the activity of k which leads to an optimal $s_k = 0$ regardless of the technology assumption.

In the following sections, we address eco-efficiency in food retail and identify corresponding reduction potentials for 25 grocery stores.

3. Eco-efficiency of grocery stores

Generally, the primary sources of carbon emissions in retail food buildings stem from heat and electricity consumption, as well as refrigeration, particularly when older refrigeration systems require frequent replenishment of harmful coolants [8]. This study analyzes data from 25 grocery stores, selected based on their participation in a third-party funded project focused on energy efficiency and emissions reduction in the retail sector. The data was collected through a structured questionnaire distributed to store operators as part of this initiative (<https://www.dbu.de/projektdatenbank/3741701>). The dataset, reflecting store conditions as of 2022, includes the following variables:

- Inputs:
 1. Total store area
 2. Electricity consumption
 3. Heat consumption
 4. Coolant refill quantity
- Bad outputs:
 5. CO₂ emissions from electricity consumption
 6. CO₂ emissions from heat consumption
 7. CO₂ emissions of the coolants

The selected stores vary in size, ranging from approximately 1400 m² to over 10,000 m² of total store area, as well as in location and operational characteristics. For instance, heating systems include natural gas, district heating, and heat pumps, with some stores also utilizing photovoltaic systems. Additionally, staffing levels range from 10 to 170

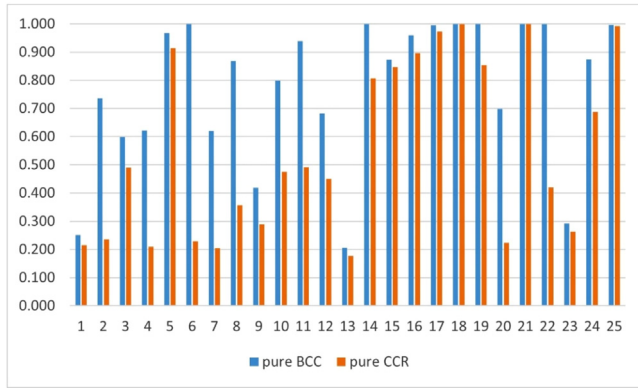


Fig. 1. Technical efficiencies for pure BCC and pure CCR regarding Eq. (9).

full-time equivalents (FTEs). These variations enable a comprehensive analysis of grocery store building operations, their associated carbon emission patterns, and potential mitigation strategies within the sector. For confidentiality reasons, neither the raw data nor detailed descriptive statistics of the seven variables can be published. However, the following matrix presents the correlations among them:

	Total Area	Elec Consum	Heat Consum	Coolant Refill	CO ₂ Electricity	CO ₂ Heat	CO ₂ Coolant
Total Area	1.00	0.79	0.77	0.18	0.68	0.73	0.39
Elec Consumption	0.79	1.00	0.80	0.14	0.97	0.76	0.47
Heat Consumption	0.77	0.80	1.00	0.14	0.75	0.97	0.60
Coolant Refill	0.18	0.14	0.14	1.00	0.07	0.23	0.14
CO₂ Electricity	0.68	0.97	0.75	0.07	1.00	0.72	0.42
CO₂ Heat	0.73	0.76	0.97	0.23	0.72	1.00	0.52
CO₂ Coolant	0.39	0.47	0.60	0.14	0.42	0.52	1.00

These correlations may facilitate the generation of correlated random numbers to validate the accuracy of our results, a common approach in empirical applications.

Furthermore, it is important to note that we do not have access to the total sales and staff numbers of the 25 grocery stores. Fortunately, we have a second data set; it contains more than 1000 entries with sales area (which is also available for the 25 grocery stores mentioned above), total sales, and number of employees in full-time equivalents; the corresponding correlations can be derived from the following matrix:

	Sales area	Total sales	Full-time equivalents
Sales area	1.0000	0.7494	0.6707
Total sales	0.7494	1.0000	0.6973
Full-time equivalents	0.6707	0.6973	1.0000

Based on the above correlations, we simulate 1000 data tuples per grocery store—with sales area as the independent variable—to obtain realistic sales figures and full-time equivalents. We thus complete the above list:

- Simulated input:
 - 8. Full-time equivalents of staff
- Simulated good output:
 - 9. Total sales

Averaging the stores' technical efficiencies, see again Eq. (10), over the 1000 simulations might show a more appropriate overview of the stores' improvement potentials. That is, Fig. 1 shows the histogram of the average technical efficiencies of the 25 DMUs and 1000 scenarios resulting from Eq. (9) for a BCC-only (the blue bars) and a CCR-only case (the red bars); i.e., we apply the same technology constraint for both the intended-production and the nature's residual-generation technology, namely, $(\lambda_{k1}, \dots, \lambda_{kj})$ and $(\lambda'_1, \dots, \lambda'_j) \in \Lambda(\tau = \text{BCC})$ or $(\lambda_{k1}, \dots, \lambda_{kj})$ and $(\lambda'_1, \dots, \lambda'_j) \in \Lambda(\tau = \text{CCR})$. Unsurprisingly, more cases are efficient in the BCC-only case—this naturally implies the more restrictive technology

structure in Eq. (9). In the BCC-only case, five grocery stores (Nos. 6, 14, 18, 19, 21) are technically efficient in all scenarios. Three grocery stores (Nos. 17, 22, 25) are weakly efficient only.

We also calculated efficiency scores under the mixed technology assumptions. However, these results did not provide additional insights, as they were numerically identical to the pure technology cases. This is reflected in the following correlation matrix:

	BCC-BCC	CCR-CCR	BCC-CCR	CCR-BCC
BCC-BCC	1.0000	0.7035	1.0000	0.7035
CCR-CCR	0.7035	1.0000	0.7035	1.0000
BCC-CCR	1.0000	0.7035	1.0000	0.7035
CCR-BCC	0.7035	1.0000	0.7035	1.0000

Although all constraint groups in Model (9) must be satisfied simultaneously, the first three—which govern the use of desirable inputs and the production of desirable outputs—define the primary production possibility set and impose the core structural restrictions. In contrast, the final two constraints, involving an auxiliary weight vector $(\lambda'_1, \dots, \lambda'_j)$, serve as additional environmental or regulatory filters. While they may further restrict the feasible region, they do not enlarge it. Thus, from a structural standpoint, the first three constraint groups are dominant and effectively determine the applicable production technology.

To keep the results transparent and because of their promising results to be discussed in Section 4.1, Table 1 presents respective numbers for the BCC-only and the CCR-only case; furthermore, we add the corresponding average optimistic values of the eco-efficiencies calculated via Eq. (11).

Table 1 shows that the last two columns provide lower bounds for the first two columns. Store No. 3, for example, can reduce its emissions to 0.262 of its current level on average—optimistically in the BCC-only case. In total, the second column of Table 1 reveals that five grocery stores (Nos. 6, 14, 18, 19, 21) have no potential to reduce energy-related inputs; this statement remains true even in the optimistic calculations for five grocery stores (see Nos. 14, 18, 19, 21, 25 in the fourth column) regarding energy-related carbon emissions. In the CCR-only case, as expected, nearly all stores' (eco-)efficiencies decrease. Still, Nos. 18 and 21 remain eco-efficient in all scenarios.

Table 1

Mean eco-efficiencies for 25 grocery stores and different models.

Store Number	BCC-BCC Eq. (10)	CCR-CCR Eq. (10)	BCC Eq. (11)	CCR Eq. (11)
1	0.251	0.216	0.205	0.071
2	0.736	0.235	0.728	0.130
3	0.598	0.491	0.262	0.112
4	0.622	0.209	0.585	0.078
5	0.968	0.914	0.972	0.914
6	1.000	0.229	0.425	0.080
7	0.620	0.205	0.576	0.079
8	0.869	0.356	0.651	0.189
9	0.419	0.289	0.388	0.289
10	0.799	0.474	0.402	0.193
11	0.939	0.491	0.948	0.491
12	0.682	0.450	0.971	0.899
13	0.206	0.177	0.088	0.043
14	1.000	0.807	1.000	0.968
15	0.873	0.847	0.942	0.900
16	0.959	0.897	0.952	0.644
17	0.995	0.973	0.994	0.337
18	1.000	1.000	1.000	1.000
19	1.000	0.854	1.000	0.735
20	0.698	0.224	0.224	0.038
21	1.000	1.000	1.000	1.000
22	0.999	0.420	0.998	0.256
23	0.293	0.263	0.317	0.171
24	0.874	0.688	0.752	0.514
25	0.997	0.993	1.000	0.993

Now, zooming in on grocery store No. 13, which has a high reduction potential (optimistic eco-efficiency 0.088), we find that it uses outdated refrigeration equipment with high levels of environmentally harmful refrigerants. DEA recommends replacing this technology with an ecologically better alternative—a CO₂ cooling system.

In addition to such technical conversions, however, there is also an avoidable waste of resources. Store No. 15 has about 14 percent more retail space than Store No. 18; when checking the remaining slack in the optimal solution of Eq. (9), however, Store No. 18 consumes more than 40 percent more electricity and more than 80 percent more heat energy with comparable technical equipment, which could indicate mismanagement.

The above results illustrate that eco-efficiency is, of course, a question of equipment and management. The results of the next section are linked to a new, emerging metric in the field of sustainability management, also known as the temperature alignment score.

4. Temperature alignment and eco-efficiency: a managerial link

4.1. Eco-efficiency and temperature alignment in food retail

The Paris Agreement, adopted in 2015, is a legally binding international treaty under the United Nations Framework Convention on Climate Change (UNFCCC). Its primary objective is to mitigate climate change by significantly reducing greenhouse gas emissions and achieving net-zero emissions globally by 2050. The 1.5 °C target is particularly crucial, as scientific research (e.g., IPCC reports) indicates that surpassing this threshold would lead to more severe climate-related impacts, including extreme weather events, rising sea levels, and biodiversity loss.

In our project, we also collected temperature alignment scores from the right based on science GmbH (see <https://www.right-basedonscience.de/>) for the 25 grocery stores. These scores, measured in degrees Celsius, indicate whether a building or business activity aligns with the Paris Agreement's goal of limiting global warming to well below 2 °C, preferably 1.5 °C, above pre-industrial levels. That is, temperature alignment scores serve as an operationalization of science-based targets, translating carbon emissions trajectories into corresponding global warming projections. By linking emissions performance to climate outcomes, these scores provide a meaningful assessment of an entity's alignment with long-term climate goals [12,13,50].

It is essential to note that the models presented in this section are intended as projection tools, rather than causal frameworks. Their purpose is to estimate the association between variations in observed eco-efficiency metrics and emission intensities, as well as temperature alignment scores, based on the available dataset. These models do not claim a causal relationship between operational changes and climate outcomes. Instead, they provide a data-driven, scenario-based approximation to support science-based target setting and informed decision-making. The temperature alignment scores used in this study indicate the degree to which the carbon footprints of the selected grocery stores align with the Paris Agreement's climate targets. A score above 1.5 °C suggests that the store's operations contribute to global warming beyond the target threshold, whereas a score below or at 1.5 °C indicates better climate alignment. These scores provide a science-based metric to assess the sustainability performance of retail food buildings and help identify potential areas for improvement in reducing emissions. This indicator is very appealing due to its straightforward design and is currently gaining more and more attention and popularity. Before we turn to the details, we show the correlations between these temperature values and the eco-efficiencies from the previous section in Table 2.

Unsurprisingly, our eco-efficiencies are negatively correlated with the temperature ratings; i.e., if the eco-efficiency score worsens (the number decreases), so does the temperature rating (the number increases). They are not perfectly correlated because the focus of the temperature rating is on CO₂ emissions; additionally, eco-efficiencies consider both inputs and good outputs of the transformation processes.

Table 2

Correlations between eco-efficiencies and temperature alignment.

	BCC-BCC Eq. (10)	CCR-CCR Eq. (10)	BCC Eq. (11)	CCR Eq. (11)	Temperature alignment
BCC-BCC Eq. (10)	1.000	0.8049	0.9673	0.7726	−0.7604
CCR-CCR Eq. (10)	0.8049	1.000	0.8032	0.9631	−0.7660
BCC Eq. (11)	0.9673	0.8032	1.000	0.8021	−0.7327
CCR Eq. (11)	0.7726	0.9631	0.8021	1.000	−0.7209
Temperature alignment	−0.7604	−0.7660	−0.7327	−0.7209	1.000

Although the highest correlation with temperature ratings is observed in the CCR-only case, the corresponding number is unreliable due to the presence of multiple optima. When examining the correlations associated with the optimistic eco-efficiencies derived from Eq. (11), the highest correlation is observed in the BCC-only case (e.g., fourth row and last column).

Information that is easily interpreted and relates directly to an action outcome is needed to achieve acceptance of change. A significant strand of literature addresses the measurement of (perceived) efficacy relative to the information available; see Angill-Williams and Davis [6] and the references therein. DEA, as a mathematical tool, is incapable of providing this insight since it requires an understanding of linear programming. Even if this understanding is present, the relationships between coefficients, constraints, and objective functions are not always fully comprehensible in large problem structures. Additionally, the eco-efficiency indicator calculated in this manner may remain abstract, as it reflects the potential for resource reduction rather than a direct measure of environmental outcomes. Therefore, combining DEA as a planning tool with temperature assessment can help illustrate and communicate the effects of changes in degrees Celsius. Fig. 2 illustrates the association between eco-efficiency scores and temperature alignment, using projected temperature scores derived from the optimization results of our DEA models. Specifically, the CCR temperature and BCC temperature (temp) values represent the estimated temperature alignment scores obtained after applying efficiency improvements suggested by the CCR and BCC pollution-generating DEA models, respectively.

To better understand the logic behind Fig. 2, we outline the estimation and calculation steps as follows:

- The original temperature alignment scores for the 25 grocery stores were obtained from the right based on science GmbH and serve as the baseline values (red dots) in Fig. 2(a). These scores indicate the expected contribution of each store's operations to global warming in degrees Celsius based on current carbon emissions.
- We applied a linear regression model to estimate the relationship between carbon intensity (CO₂ emissions per store area) and temperature alignment scores (represented by blue dots in Fig. 2(a)). This regression function is used to estimate the association between emission reductions and temperature alignment within the observed dataset.
- Next, we calculated eco-efficiency scores using our pollution-generating DEA models (Eqs. 9–11). These were based on two technology constellations:
 - BCC—where each of the two intersecting technologies applies the convexity restriction.
 - CCR—neither of the two intersecting technologies applies the convexity restriction.

These models estimate potential CO₂ reductions by optimizing emissions related to inputs from electricity, heating, and refrigeration systems.

- Using the regression-derived formula, we projected new temperature alignment scores based on the efficiency improvements suggested by the DEA models. The CCR temp and BCC temp values in Fig. 2(b) represent the estimated temperature alignment scores after applying the

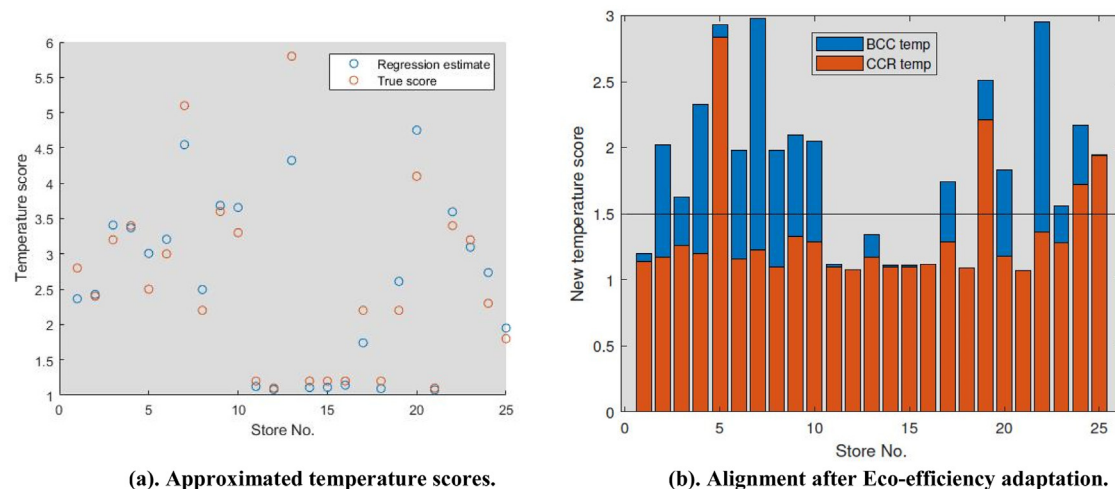


Fig. 2. Temperature score estimation.

optimized CO₂ reductions from the CCR and BCC models, respectively.

Fig. 2(a) demonstrates that the temperature function can be effectively approximated using a linear regression model, due to the nearly proportional relationship between global temperature change and cumulative CO₂ emissions (for further justification, see [60]). In this model, temperature alignment (dependent variable) is predicted using carbon intensity (CO₂ emissions per store area, independent variable), achieving an R^2 of approximately 0.886, indicating a strong correlation.

Using this relationship, we estimated new temperature scores based on the average optimistic eco-efficiencies derived from the DEA models. Fig. 2(b) presents these results, with the horizontal line at 1.5 °C indicating the upper limit set by the Paris Agreement. Several stores demonstrate the potential to align their operations with this threshold by adopting practices observed in more energy-efficient peers, such as upgrading equipment and implementing improved management approaches. It is worth noting that the temperature scores based on efficiency improvements from the BCC model are equal to or slightly higher than those from the CCR model. This reflects the BCC model's generally higher efficiency scores, which indicate equal or lower potential for further improvement. In some cases, such as stores 16, 18, 21, and 25, these differences are minor and may appear as overlapping values in Fig. 2(b).

Although achieving the 1.5 °C target appears more challenging in the BCC-only case, it is essential to note that the regression model tends to overestimate high-temperature scores (as seen in Fig. 2(b)). This suggests that even more stores could potentially align with the 1.5 °C target under BCC assumptions after efficiency improvements. Furthermore, Ferreira et al. [26] classify a best-in-class food retail building as one with a carbon intensity of less than 115 kg CO₂ per square meter per year. However, when applying our regression model to this benchmark, it yields a temperature alignment score of approximately 3.8 °C, which is far above the Paris Agreement threshold. This finding challenges existing classifications of “best-in-class” retail buildings and further highlights the value of integrating DEA-based eco-efficiency assessments with temperature alignment modeling.

The following section examines the defining characteristics of Paris Agreement-compatible grocery stores and explores how targeted operational improvements can enhance climate alignment.

4.2. Projected results of management measures on temperature alignment

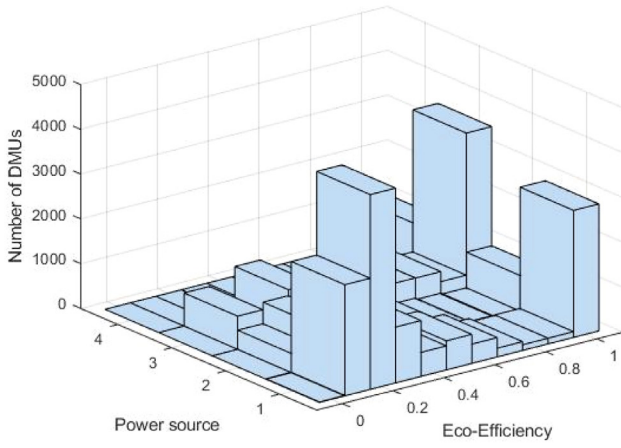
Fig. 2(a) shows that seven grocery stores are already operating below 1.5 °C. Fig. 2(b) illustrates that most grocery stores can achieve this goal if they optimize eco-efficiency using a CCR-based, pollution-generating technology. However, the complete transformation of a gro-

cery store can imply high investments in new technologies, such as CO₂ cooling or photovoltaic systems. To understand the break-even point concerning the 1.5 °C limit, we examine how investments in replacing old technologies with new ones are associated with projected outcomes by comparing our simulated scenarios. Due to data confidentiality constraints, the original values for total sales and full-time equivalents could not be disclosed. To overcome this, we implemented a simulation procedure based on a larger proprietary dataset, using k-means clustering to identify similar entities. For each store, we repeatedly sampled 30 observations from its cluster and re-estimated simple linear regressions to project sales and staffing figures. This procedure was repeated 1000 times, generating a distribution of plausible values that preserves the observed correlation structure and variability of the original dataset. To test the robustness of the efficiency scores to the simulated data, we performed a sensitivity analysis through random subsampling and repeated regression re-estimation. Specifically, for each simulation run, the sales and personnel variables were recalculated using a new sub-sample, and the entire DEA procedure was repeated. We then examined the variability in DEA scores and rankings across simulations.

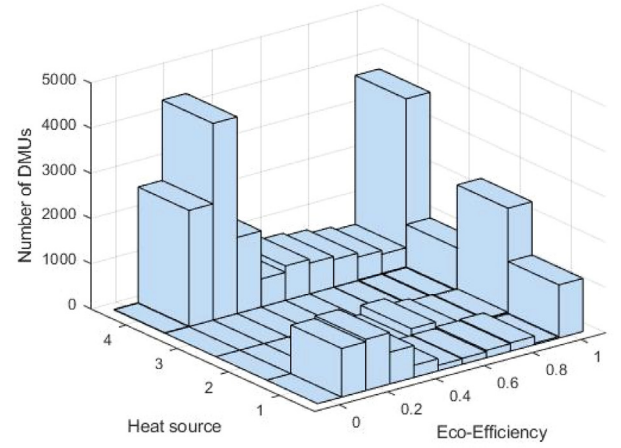
The following figures illustrate the eco-efficiency assessment in combination with different energy sources and technology systems, providing an impression of the effectiveness of various management measures. Fig. 3(a) shows the histogram of the eco-efficiency scores as a function of the four electricity source categories: 1 $\hat{=}$ purchased conventional electricity, 2 $\hat{=}$ purchased conventional electricity in combination with an on-site photovoltaic system, 3 $\hat{=}$ purchased green electricity, and 4 $\hat{=}$ purchased green electricity in combination with a photovoltaic system. This figure shows that the less green the electricity source, the higher the frequencies with little eco-efficiency. In the case of pure conventional electricity, we have a considerable increase in cases with an eco-efficiency of less than 0.5.

Fig. 3(b) displays the corresponding histogram regarding the four heating source categories: 1 $\hat{=}$ district heating, 2 $\hat{=}$ heat pump, 3 $\hat{=}$ heat recovery unit, 4 $\hat{=}$ natural gas. Using a heat pump or a heat recovery unit corresponds to high eco-efficiencies in our case. In contrast, there is a wide spread of frequencies for natural gas; in addition, there are more inefficient than efficient cases. Fig. 3(c) summarizes the eco-efficiency histogram for the three types of refrigerants: 1 $\hat{=}$ CO₂, 2 $\hat{=}$ R404, 3 $\hat{=}$ R449A. Interestingly, although the first refrigerant is the most environmentally friendly, there is also widespread use of other refrigerants. This could be an initial indication that we need to examine pairs of actions rather than individual actions to achieve eco-efficiency.

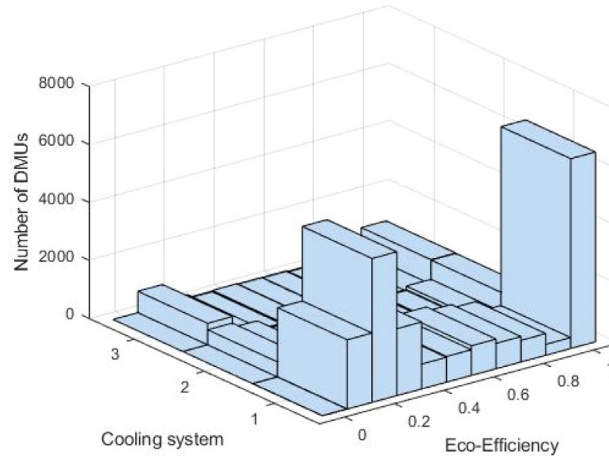
We will now evaluate the results conditioned under more than one measure to assess the above presumption better. Thus, Fig. 4 illustrates



(a). Eco-eff. and power source.



(b). Eco-efficiency and heat source.



(c). Eco-efficiency and cooling system.

Fig. 3. Eco-efficiency assessment grouped by supermarket equipment.

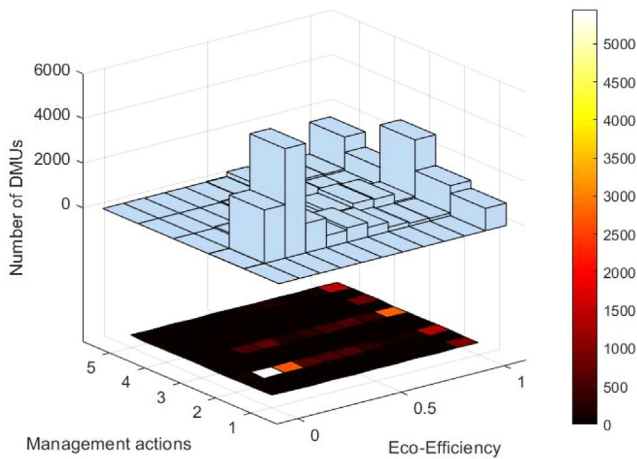


Fig. 4. Eco-efficiency histogram and intensity map.

an eco-efficiency histogram and intensity map regarding five management actions: $1 \triangleq \{\text{purchased green electricity}\} \wedge (\{\text{heat pump}\} \vee \{\text{heat recovery unit}\}) \wedge \{\text{CO}_2 \text{ refrigerants}\}$, $2 \triangleq \{\text{purchased conventional elec-$

tricity}\} \wedge (\{\text{district heating}\} \vee \{\text{natural gas}\}) \wedge \{\text{CO}_2 \text{ refrigerants}\}, $3 \triangleq \{\text{purchased green electricity}\} \wedge (\{\text{district heating}\} \vee \{\text{natural gas}\}) \wedge \{\text{CO}_2 \text{ refrigerants}\}$, $4 \triangleq \{\text{purchased conventional electricity}\} \wedge (\{\text{heat pump}\} \vee \{\text{heat recovery unit}\}) \wedge (\{\text{R404 refrigerants}\} \vee \{\text{R449A}\})$, $5 \triangleq \{\text{purchased conventional electricity}\} \wedge (\{\text{heat pump}\} \vee \{\text{heat recovery unit}\}) \wedge \{\text{CO}_2 \text{ refrigerants}\}$.

The first action implies the most environmentally friendly measures—and hence, all scenarios lead to eco-efficient solutions; see the intensity map below the histogram in Fig. 4. However, these may require significant investments in new technologies, such as heat pumps and CO₂ cooling systems, as well as additional costs for purchasing green electricity. The second measure does not require additional investment in heating technology, but rather a CO₂ cooling system that can be operated without purchasing green electricity. In such cases, the eco-efficiencies in the corresponding scenarios vary significantly. Action three demonstrates that an additional purchase of green electricity results in high eco-efficiency frequencies and low frequencies in eco-inefficient scenarios. Actions four and five are interesting, as they show that investing in heat pumps or a heat recovery system in combination with a CO₂ cooling system is nearly a guarantee for eco-efficient scenarios.

However, eco-efficiency is only one side of the coin; we also need to focus on temperature alignment, as discussed in the preceding section.

Table 3
Temperature alignments for the five management actions.

Actions	Average temperature alignment
1	1.10 °C
2	3.09 °C
3	1.18 °C
4	2.35 °C
5	2.00 °C

In the next step, we calculate the effects on temperature by inferring the temperature scores that result when management actions one to five are implemented. Table 3 summarizes the results:

Table 3 shows that if we apply all measures via Action 1, we can achieve an average temperature value of 1.10 °C, well below the limit of 1.5 °C set in the Paris Agreement. From an investment perspective, investing in heat pumps or a heat recovery system in combination with a CO₂ cooling system is the most cost-intensive. Still, from an environmental perspective, it is only a good deal if it is combined with green electricity. Otherwise, we have only come close to 2.0 °C. Interestingly, combining a CO₂ cooling system and purchasing green electricity (Action 3) is associated with the most favorable projected temperature alignment and requires less investment than Action 5. This result is plausible—as long as the green electricity is composed of renewables only—because of the enormous amount of electricity required in supermarkets for lighting and refrigeration. It would also be interesting to isolate the pure temperature effect of green electricity; however, our data do not yet allow us to answer this question.

4.3. Limitations of the proposed approach

While this study provides valuable insights into the integration of eco-efficiency analysis with temperature alignment ratings, several limitations must be acknowledged.

While our simulation approach is grounded in a structured empirical process, we acknowledge that using generated data introduces inherent uncertainty. To address this, we applied random subsampling with repeated regression estimation across 1000 iterations, allowing us to examine the sensitivity of DEA results to fluctuations in the simulated variables, supporting the internal consistency of our findings. Nevertheless, we caution that point efficiency estimates may be sensitive to simulation assumptions. As such, interpretations should emphasize general trends and comparative insights rather than exact numerical values. Future work with full access to primary operational data could further enhance the precision of this analysis.

A primary limitation of this study is the reliance on data collected from a relatively small sample of 25 grocery stores. While the dataset provides meaningful insights into the relationship between eco-efficiency and temperature alignment, its generalizability to the broader food retail sector may be limited. Additionally, some variables, such as total sales and staff numbers, were imputed based on correlations rather than directly observed, which introduces potential biases.

The Data Envelopment Analysis (DEA) model applied in this study is inherently a static efficiency assessment tool. It evaluates performance based on a single period and does not account for dynamic changes in store operations, technology adoption, or market conditions over time. Future research could extend this approach using dynamic DEA models to capture longitudinal improvements in eco-efficiency and sustainability measures. While the DEA-based application employs a pollution-generating technology approach to integrate undesirable outputs into DEA, which ensures adherence to the Material Balance Principle, it does not account for uncertainties in environmental performance evaluations. Stochastic or fuzzy DEA models could be explored in future studies to enhance robustness under data uncertainty, particularly in emissions reporting and energy use variations resulting from seasonal effects.

Lastly, the temperature alignment scores were estimated using a linear regression model that linked carbon intensity to global temperature outcomes. While this approach provides a useful approximation and exhibits a high correlation with real temperature scores, it does not account for non-linear climate feedback mechanisms. Future research should consider integrating more complex climate models directly into DEA frameworks—such as bilevel programming and counterfactual analysis, as suggested by Bogetoft et al. [14]—to refine temperature alignment assessments.

Despite these limitations, this study presents a novel first application that links eco-efficiency analysis with climate alignment metrics. Addressing the identified limitations through improved data collection, dynamic modeling approaches, and a broader range of sustainability measures can enhance the relevance and applicability of this research for informing corporate sustainability strategies.

5. Conclusions

This paper presents a pioneering application that integrates eco-efficiency analysis with temperature alignment ratings, providing a comprehensive approach to assessing the environmental performance of grocery stores. By linking eco-efficiency scores to temperature alignment, our study presents a novel approach to evaluate how operational efficiency improvements contribute to climate objectives, particularly the 1.5 °C target established by the Paris Agreement.

From a practical perspective, our findings indicate that most of the 25 grocery stores analyzed can enhance their temperature alignment with this target through strategic operational adjustments, such as upgrading refrigeration systems, optimizing energy consumption, and transitioning to greener electricity sources. These insights offer actionable guidance for store operators, policymakers, and sustainability managers aiming to reduce carbon emissions in the retail sector. On a theoretical level, our study extends the application of pollution-generating technology within a DEA framework, demonstrating its effectiveness in linking efficiency metrics with climate policy objectives. Unlike conventional DEA models, our approach considers temperature alignment as an additional sustainability criterion, broadening the scope of eco-efficiency analysis in the food retail sector.

Future research could explore model enhancements, such as incorporating stochastic variations in energy consumption or integrating multi-objective optimization methods, to further refine the robustness and applicability of this approach. By advancing the intersection of efficiency analysis and climate alignment, this study provides a solid foundation for future sustainability assessments in the food retail industry.

Declaration of competing interest

The above 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.

CRedit authorship contribution statement

Andreas Dellnitz: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Formal analysis, Conceptualization. **Madjid Tavana:** Writing – review & editing, Writing – original draft, Validation, Methodology, Formal analysis. **Salome Dellnitz:** Writing – original draft, Validation, Investigation, Formal analysis. **Andreas Kleine:** Writing – original draft, Methodology, Formal analysis. **Lukas Dalhoff:** Validation, Methodology, Investigation.

Acknowledgments

This work was supported by the Deutsche Bundesstiftung Umwelt (DBU), Osnabrück, in the context of the research fund 37417/01.

References

- [1] A. Abad, W. Brieç, On the axiomatic of pollution-generating technologies: non-parametric production analysis, *Eur. J. Oper. Res.* 277 (1) (2019) 377–390.
- [2] A. Abad, P. Ravelojaona, An unified framework for measuring environmentally-adjusted productivity change: theoretical basis and empirical illustration, *Eur. J. Oper. Res.* 320 (3) (2025) 642–654.
- [3] G.A. Amahnu, M. Vanegas, L. Verchot, A. Castro-Nunez, Achieving the Paris Agreement goals by transitioning to low-emissions food systems: A comprehensive review of countries' actions, *Environ. Sci. Policy* 163 (2025) 103968, doi:10.1016/j.envsci.2024.103968.
- [4] A. Amirteimoori, T. Allahviranloo, M. Zadmiraee, F. Hasanzadeh, On the environmental performance analysis: a combined fuzzy data envelopment analysis and artificial intelligence algorithms, *Expert Syst. Appl.* 224 (2023) 119953.
- [5] A. Amirteimoori, A. Cezar, M. Zadmiraee, A. Susaeta, Environmental performance evaluation in the forest sector: an extended stochastic data envelopment analysis approach, *Socio-Econ. Plan. Sci.* 94 (2024) 101943.
- [6] A. Angill-Williams, C. Davis, Increasing climate efficacy is not a surefire means to promoting climate commitment, *Think. Reason.* 28 (3) (2022) 375–395.
- [7] B. Arabi, S.M. Doraisamy, A. Emrouznejad, A. Khoshroo, Eco-efficiency measurement and material balance principle: an application in power plants Malmquist Luenberger Index, *Ann. Oper. Res.* 255 (2017) 221–239.
- [8] B. Arabi, M. Toloo, Z. Yang, P. Zhang, B. Xu, Sustainable refrigeration technology selection: an innovative DEA-TOPSIS hybrid model, *Environ. Sci. Policy* 158 (2024) 103780.
- [9] R.D. Banker, A. Charnes, W.W. Cooper, Some models for estimating technical and scale inefficiencies in data envelopment analysis, *Manag. Sci.* 30 (1984) 1078–1091.
- [10] R.D. Banker, R.M. Thrall, Estimation of returns to scale using data envelopment analysis, *Eur. J. Oper. Res.* 62 (1992) 74–84.
- [11] W.J. Baumol, W. Oates, *The Theory of Environmental Policy*, 2nd Ed., Cambridge University, Cambridge, 1988.
- [12] A. Björn, S. Lloyd, U. Schenker, M. Margni, A. Levasseur, M. Agez, H.D. Matthews, Differentiation of greenhouse gases in corporate science-based targets improves alignment with Paris temperature goal, *Environ. Res. Lett.* 18 (8) (2023) 084007.
- [13] A. Björn, J.P. Tilsted, A. Addas, S.M. Lloyd, Can science-based targets make the private sector Paris-aligned? A review of the emerging evidence, *Curr. Clim. Change Rep.* 8 (2022) 53–69.
- [14] P. Bogetoft, J. Ramirez-Ayerbe, D. Romero Morales, Technical Report, in: Technical Report, 88, IMUS, Sevilla, Spain, 2022, pp. 831–850.
- [15] V. Caritte, S. Acha, N. Shah, Enhancing corporate environmental performance through reporting and roadmaps, *Bus. Strategy Environ.* 24 (5) (2015) 289–308.
- [16] A. Cattaneo, G. Federighi, S. Vaz, The environmental impact of reducing food loss and waste: a critical assessment, *Food Policy* 98 (2021) 101890 food Loss and Waste: Evidence for effective policies.
- [17] A. Charnes, W.W. Cooper, E. Rhodes, Measuring the efficiency of decision making units, *Eur. J. Oper. Res.* 2 (1978) 429–444.
- [18] K.H. Dakpo, P. Jeanneaux, L. Latruffe, Modelling pollution-generating technologies in performance benchmarking: recent developments, limits and future prospects in the non-parametric framework, *European J. Oper. Res.* 250 (2) (2016) 347–359.
- [19] A. Dellnitz, RTS-mavericks in data envelopment analysis, *Oper. Res. Lett.* 44 (5) (2016) 622–624.
- [20] A. Dellnitz, A. Kleine, W. R'odder, CCR or BCC: what if we are in the wrong model? *J. Bus. Econ.* 88 (2018) 831–850.
- [21] A. Dellnitz, W. R'odder, Returns to scale as an established scaling indicator: always a good advisor? *Jahrbuch für Natl. Stat.* 241 (2) (2021) 173–186.
- [22] A. Dellnitz, M. Tavana, R. Banker, A novel median-based optimization model for eco-efficiency assessment in data envelopment analysis, *Ann. Oper. Res.* 322 (2023) 661–690.
- [23] D. Deprins, L. Simar, H. Tulkens, Measuring labor-efficiency in post offices, in: M. Marchand, P. Pestieau, H. Tulkens (Eds.), *The Performance of Public Enterprises: Concepts and Measurement*, Springer-Verlag, Amsterdam, 1984, pp. 243–268.
- [24] J.R. Doyle, R.H. Green, Cross-evaluation in DEA: improving discrimination among DMUs, *INFOR* 32 (1994) 205–222.
- [25] A. Ferreira, M. Pinheiro, J. de Brito, R. Mateus, Relating carbon and energy intensity of best-performing retailers with policy, strategy and building practice, *Energy Effic.* 13 (2020).
- [26] A. Ferreira, M. Pinheiro, J. de Brito, R. Mateus, Assessing the sustainability of retail buildings: the portuguese method lidera, *Sustainability* 14 (23) (2022).
- [27] F.R. Forsund, Good modelling of bad outputs: pollution and multiple-output production, *Int. Rev. Environ. Resour. Econ.* 3 (1) (2009) 1–38.
- [28] G. Gebresenbet, I. Nordmark, T. Bosona, D. Ljungberg, Potential for optimised food deliveries in and around Uppsala city, Sweden, *J. Transp. Geogr.* 19 (6) (2011) 1456–1464.
- [29] B. Gimeno-Frontera, M. Mainar-Toledo, A. de Guinoa, D. Zambrana-Vasquez, I. Zabalza-Bribi'an, Sustainability of non-residential buildings and relevance of main environmental impact contributors' variability. A case study of food retail stores buildings, *Renew. Sustain. Energy Rev.* 94 (2018) 669–681.
- [30] B. Golany, G. Yu, Estimating returns to scale in DEA, *Eur. J. Oper. Res.* 103 (1997) 28–37.
- [31] M.C. Gouveia, C.O. Henriques, L.C. Dias, Eco-efficiency changes of the electricity and gas sectors across 28 European countries: A value-based data envelopment analysis productivity approach, *Socio-Econ. Plan. Sci.* 87 (2023) 101609.
- [32] C. Guerlain, S. Renault, F. Ferrero, Understanding construction logistics in urban areas and lowering its environmental impact: a focus on construction consolidation centres, *Sustainability* 11 (21) (2019).
- [33] Y. Guo, W. Liu, J.P. Tian, R.A. He, L.J. Che, Eco-efficiency assessment of coal-fired combined heat and power plants in Chinese eco-industrial parks, *J. Clean. Prod.* 168 (2017) 963–972.
- [34] M. Hasannasab, D. Margaritis, I. Roshdi, P. Rouse, Hyperbolic efficiency measurement: A conic programming approach, *Eur. J. Oper. Res.* 278 (2) (2019) 401–409.
- [35] H. Helander, M. Bruckner, S. Leipold, A. Petit-Boix, S. Bringezu, Eating healthy or wasting less? Reducing resource footprints of food consumption, *Environ. Res. Lett.* 16 (5) (2021) 054033.
- [36] Y. Jiang, X. Liu, L. Yang, T. Hu, H. Pan, H. Luo, W. Han, S. Xiao, Moving towards sustainable development in China's rural counties: ecological efficiency evaluation based on DEA-Malmquist-Tobit model, *J. Clean. Prod.* 442 (2024) 141093.
- [37] A. Kleine, W. R'odder, A. Dellnitz, Returns to scale revisited – towards Cross-RTS, in: H. Ahn, M. Clermont, R. Souren (Eds.), *Nachhaltiges Entscheiden: Beiträge zum Multiperspektivischen Performancemanagement Von Wertschöpfungsprozessen*, Springer-Verlag, 2016, pp. 385–404.
- [38] T.C. Koopmans, An analysis of production as an efficient combination of activities, in: T.C. Koopmans (Ed.), *Activity Analysis of Production and Allocation*, John-Wiley and Sons, New York, London, 1951, pp. 33–97.
- [39] T. Kuosmanen, Duality theory of non-convex technologies, *J. Product. Anal.* 20 (3) (2003) 273–304.
- [40] T. Kuosmanen, R.K. Matin, Duality of weakly disposable technology, *Omega* 39 (2011) 504–512.
- [41] F.H. Lotfi, R.F. Saen, Z. Moghaddas, M. Vaez-Ghasemi, Using an SBM-NDEA model to assess the desirable and undesirable outputs of sustainable supply chain: A case study in wheat industry, *Socio-Econ. Plan. Sci.* 87 (2023) 101699.
- [42] S. Lozano, Technical and environmental efficiency of a two-stage production and abatement system, *Ann. Oper. Res.* 255 (2017) 199–219.
- [43] S. Maki, A. Ohnishi, M. Fujii, N. Goto, L. Sun, Using waste to supply steam for industry transition: selection of target industries through economic evaluation and statistical analysis, *J. Ind. Ecol.* 26 (2022) 1475–1486.
- [44] S. Murty, R.R. Russell, S.B. Levkoff, On modeling pollution-generating technologies, *J. Environ. Econ. Manag.* 64 (2012) 117–135.
- [45] S. Nikolicic, M. Kilibarda, M. Maslaric, D. Mircetic, S. Bojic, Reducing food waste in the retail supply chains by improving efficiency of logistics operations, *Sustainability* 13 (12) (2021).
- [46] H. Niu, Z. Li, C. Zhang, M. Li, Sustainable food systems under environmental footprints: the delicate balance from farm to table, *Sci. Total Environ.* 954 (2024) 176761, doi:10.1016/j.scitotenv.2024.176761.
- [47] M.N. Nodin, Z. Mustafa, S.I. Hussain, Eco-efficiency assessment of Malaysian rice self-sufficiency approach, *Socio-Econ. Plan. Sci.* 85 (2023) 101436.
- [48] S. Pan, E. Ballot, F. Fontane, D. Hakimi, Environmental and economic issues arising from the pooling of smes' supply chains: case study of the food industry in western France, *Flex. Serv. Manuf. J.* 26 (2014) 92–118.
- [49] K.H. Rankin, A. Arceo, K. Isin, S. Saxe, Embodied GHG of missing middle: residential building form and strategies for more efficient housing, *J. Ind. Ecol.* (2024) 1–14.
- [50] S. Rekker, M.C. Ives, B. Wade, L. Webb, C. Greig, Measuring corporate Paris compliance using a strict science-based approach, *Nat. Commun.* 13 (2022) 4441.
- [51] H. Scheel, S. Scholtes, Continuity of dea efficiency measures, *Oper. Res.* 51 (1) (2003) 149–159.
- [52] R.W. Shephard, *The Theory of Cost and Production Functions*, Princeton University Press, Princeton, 1970.
- [53] A.A. Sidhoum, C. Canessa, J. Sauer, Effects of agri-environment schemes on farm-level eco-efficiency measures: empirical evidence from EU countries, *J. Agric. Econ.* 74 (2023) 551–569.
- [54] M. Taleb, A. Emrouznejad, V. Charles, R. Khalid, R. Ramli, An extended-directional mix-efficiency measure: performance evaluation of OECD countries considering Net-Zero, *Comput. Ind. Eng.* 189 (2024) 109967.
- [55] A. Torres-Ruiz, A.R. Ravindran, Use of interval data envelopment analysis, goal programming and dynamic eco-efficiency assessment for sustainable supplier management, *Comput. Ind. Eng.* 131 (2019) 211–226.
- [56] N.T. Trang, V.H. Tu, L.T. Son, N.P. Son, Environmental efficiency assessment in shrimp farming: an application of the Material Balance Principle, *Environ. Dev. Sustain.* 25 (2023) 2670–2687.
- [57] H. Tulkens, On FDH efficiency analysis: some methodological issues and applications to Retail banking, courts, and urban transit, *J. Product. Anal.* 4 (1993) 183–210.
- [58] X. Wang, S. Zhang, N. Schneider, Evaluating the carbon emissions of alternative food provision systems: A comparative analysis of recipe box and supermarket equivalents, *Technol. Forecast. Soc. Change* 173 (2021) 121099.
- [59] M. Zadmiraee, F. Hasanzadeh, A. Susaeta, E. Gutiérrez, A novel integrated fuzzy DEA-artificial intelligence approach for assessing environmental efficiency and predicting CO₂ emissions, *Soft Comput.* 28 (2024) 565–591.
- [60] K. Zickfeld, A. MacDougall, H. Damon Matthews, On the proportionality between global temperature change and cumulative CO₂ emissions during periods of net negative CO₂ emissions, *Environ. Res. Lett.* 11 (5) (2016) 055006.