

Article

System Dynamics Framework for Corporate Sustainability Performance Assessment Based on ESG Indicators

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Abstract

Corporate sustainability reporting has become a central component of corporate governance under the European Sustainability Reporting Standards (ESRS); yet organizations continue to face challenges in integrating sustainability data into decision-making processes. This study addresses this gap by developing a system dynamics (SD) model for analyzing corporate sustainability performance based on ESG indicators. The proposed framework integrates environmental, social, and governance variables into a unified dynamic structure, capturing feedback loops, time delays, and interdependencies among sustainability dimensions. The model is empirically tested using a ten-year dataset from a fuel retail company, enabling both historical validation and scenario-based analysis. The results demonstrate that the model successfully reproduces observed trends in resource efficiency, safety performance, and social indicators while highlighting trade-offs associated with business growth, particularly in energy consumption and CO₂ emissions. Sensitivity analysis demonstrates that the sustainability index remains stable under uncertainty in normalized ESG indicator values. Scenario simulations indicate that several sustainability targets for 2030 are achievable under current development trajectories; however, maintaining progress requires continuous investment and organizational commitment. The study contributes to sustainability research by integrating ESRS-based indicators into a dynamic modeling framework and provides a practical decision-support tool for corporate sustainability management, enabling more informed planning, performance evaluation, and strategic alignment with long-term sustainability goals.

Keywords: sustainability; system dynamics; modeling; corporate sustainability reporting



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1. Introduction

Sustainability reporting has evolved from a voluntary disclosure practice into a core element of corporate governance and strategic management. The implementation of the Corporate Sustainability Reporting Directive (CSRD) significantly expands the scope, standardization, and assurance of sustainability disclosures within the European Union (EU). Through the introduction of the European Sustainability Reporting Standards (ESRS), companies are required to provide consistent, verifiable, and comparable ESG information, applying the principle of double materiality—considering both financial impacts and societal and environmental effects [1,2]. Despite these regulatory advances, organizations continue to face challenges related to data availability, methodological consistency, and the integration of sustainability information into decision-making processes. These challenges highlight the need for analytical tools capable not only of aggregating sustainability indicators but also of analyzing their interactions and long-term dynamics [3,4]. Corporate

sustainability performance is shaped by complex, interdependent processes characterized by feedback loops, accumulations, and time delays [5]. Such dynamics cannot be adequately captured using static or linear approaches. System dynamics (SD) provides a robust methodological framework for modeling complex systems and analyzing their evolution over time. By integrating causal loop structures with stock-and-flow simulation, SD enables the identification of feedback mechanisms, trade-offs among sustainability dimensions, and leverage points for intervention. Although [6] SD has been widely applied in areas such as sustainable development policy, energy systems, the circular economy, and supply chains, the integration of ESRS-based corporate sustainability indicators into a unified dynamic modeling framework remains limited. This study addresses this gap by developing and empirically testing a system dynamics model for company-level sustainability performance. ESG indicators—such as carbon emissions, energy consumption, resource use, labor practices, and corporate transparency—serve as key instruments for evaluating organizational sustainability and its broader societal impact [7]. Beyond reporting, these indicators increasingly support strategic decision-making, risk management, and stakeholder engagement.

Given the dynamic nature of sustainability processes, there is a growing need for analytical frameworks that capture system complexity and support holistic analysis [8]. SD, rooted in systems thinking, enables the modeling of complex interactions through feedback structures and quantitative simulation. It allows exploration of how system structure drives behavior over time and supports the identification of mechanisms shaping sustainability outcomes [6,9,10]. Furthermore, it facilitates scenario analysis, policy evaluation, and integrated assessment across multiple domains. Its ability to capture non-linearities, delays, and cross-sectoral interactions makes it particularly suitable for addressing sustainability challenges, where unintended consequences and trade-offs are common.

The credibility of system dynamics models depends not only on their ability to reproduce observed behavior but also on the validity of their underlying structure and assumptions. Previous studies emphasize the importance of structure validation, behavior reproduction, dimensional consistency testing, sensitivity analysis, and expert review as complementary validation procedures. These approaches are widely recognized as essential components of system dynamics, model evaluation, and credibility assessment [5].

Recent studies highlight the benefits of integrating system dynamics with other analytical approaches, such as life cycle assessment (LCA), to improve the evaluation of sustainability impacts over time [11,12]. Empirical applications demonstrate SD's usefulness in areas such as circular construction, adoption, and sustainable supply chains [13,14]. Despite its advantages, SD faces challenges, including sensitivity to assumptions, data requirements, and model complexity. Nevertheless, ongoing developments—such as hybrid modeling approaches and participatory methods—are strengthening its applicability. Overall, SD offers significant potential to move corporate sustainability analysis beyond static reporting towards dynamic, decision-support-oriented modeling [14]. This research contributes by proposing a structured SD-based framework aligned with ESRS requirements for analyzing company sustainability performance over time [15]. Recent studies demonstrate that ESG indicators are increasingly used not only for sustainability reporting but also for performance measurement, investment evaluation, and risk management. The growing importance of ESG assessment has intensified the need for transparent and standardized sustainability metrics, although significant challenges remain regarding indicator selection, comparability, and aggregation methodologies [5,16,17]. ESG performance is also increasingly linked with corporate innovation capacity, financial outcomes, and long-term competitiveness [18].

This research aims to develop an SD framework for modeling corporate sustainability performance in alignment with the requirements of the ESRS. The proposed framework is intended to support the integration, analysis, and interpretation of sustainability-related data within a coherent and decision-oriented modeling environment. Currently, many companies have at least partially collected sustainability parameters or indicators, but there is a lack of unified systems or methodologies that would help interpret these data. This is also considered one of the most important tasks and aspects of this research: to interpret sustainability indicators using a sustainability model and to show trends and development directions.

To achieve this aim, the study pursues the following specific objectives:

- to identify and systematize key sustainability indicators relevant for corporate reporting under the ESRS framework;
- to assess the materiality of these indicators and analyze their causal interrelationships within a systemic context;
- to develop a dynamic sustainability performance index that captures the interactions and evolution of ESG dimensions over time;
- to test the operational validity and robustness of the proposed model using empirical data;
- to evaluate the feasibility of achieving corporate sustainability targets by 2030 under different strategic and operational scenarios.

The study emphasizes the validation of the analytical capability and practical applicability of the proposed modeling approach, rather than attempting to predict all possible future conditions. Instead, it seeks to provide a decision-support tool that enhances understanding of system behavior, supports scenario analysis, and facilitates more informed sustainability management and reporting practices. Although system dynamics models have been widely used in various sustainability characterizations, the aim of this study is to help generalize this approach by creating a model that can represent long-term data projections and forecasts without making it too complex or difficult to apply in real life. The aim is to motivate and encourage businesses to start analyzing sustainability data without being intimidated by the initially large amount of information and fragmentation that are usually associated with sustainability reporting issues.

2. Corporate Sustainability and the ESRS Reporting Logic

Corporate sustainability is increasingly conceptualized as a multidimensional performance construct integrating environmental, social, and governance (ESG) dimensions into core business strategy and decision-making [19]. Within the European Union, this integration is formalized through the Corporate Sustainability Reporting Directive (CSRD) and the European Sustainability Reporting Standards (ESRS) [20], which provide a harmonized structure for identifying, measuring, and disclosing sustainability impacts, risks, and opportunities [21].

A central principle of the ESRS framework is double materiality, requiring organizations to assess both the financial effects of sustainability issues on corporate performance and the impacts of corporate activities on the environment and society. This bidirectional perspective shifts sustainability reporting from a descriptive exercise to a strategic management process. The introduction of the Corporate Sustainability Reporting Directive (CSRD) and the European Sustainability Reporting Standards (ESRS) represents a significant shift in sustainability reporting practices. The ESRS framework operationalizes the principle of double materiality, requiring organizations to evaluate both sustainability impacts on the company and the company's impacts on society and the environment [2,22,23]. As a result, sustainability indicators should be understood as interdependent elements within a

dynamic organizational system [2] rather than as isolated reporting variables. Within such a system, environmental performance influences operational costs and regulatory risks; social performance affects productivity, safety, and employee retention; and governance quality shapes investment decisions and organizational stability [10,24,25]. These interdependencies justify the application of systemic modeling approaches. Recent research emphasizes that double materiality should not be viewed solely as a reporting requirement but as a decision-support mechanism connecting sustainability performance indicators with corporate strategy and risk management. The translation of double materiality assessments into measurable sustainability indicators remains one of the key challenges in ESRS implementation [2,17,19]. It requires organizations to simultaneously assess how sustainability issues affect corporate performance and how corporate activities affect society and the environment. Recent studies identify double materiality assessment as a critical element of sustainability governance and strategic decision-making [26,27].

From a systems perspective, corporate sustainability performance is characterized by feedback loops, accumulations, time delays, and non-linear relationships. For example, investments in efficiency may lead to cost savings that enable further investments, while the effects of training on safety performance often occur with delays. Traditional static ESG assessment methods cannot capture these structural characteristics [26]. System dynamics provides a theoretical and methodological foundation for analyzing such behavior by linking system structure with performance over time. In the context of corporate sustainability, SD enables the integration of heterogeneous ESG indicators into a unified analytical framework, the analysis of trade-offs and synergies, the identification of leverage points, and the simulation of sustainability transition pathways [28].

Recent studies have shown that sustainability performance is influenced by complex interactions among environmental, social, governance, and financial variables. ESG-related risks can propagate across sectors and markets through dynamic and asymmetric relationships, highlighting the importance of analytical approaches that capture feedback mechanisms and systemic interactions [29]. These characteristics make system dynamics particularly well-suited to assessing sustainability performance.

System dynamics is widely applied in sustainability transition studies, energy systems, circular economy modeling, and policy analysis [30]. Its key theoretical contribution lies in explaining system behavior endogenously, meaning that outcomes are generated by internal system structure rather than by external shocks alone. In corporate sustainability analysis, this implies that long-term performance is driven by internal resource allocation and organizational learning; improvements in one sustainability dimension may generate reinforcing or balancing effects in others; and strategic targets can be evaluated using scenario simulation rather than simple extrapolation of historical trends. This study extends existing research by integrating ESRS-based indicators into a dynamic corporate sustainability performance index and empirically testing the model using longitudinal company data [31].

While previous studies have applied system dynamics to sustainability assessment, energy systems, and ESG performance evaluation, few studies have explicitly operationalized ESRS reporting requirements within a dynamic modeling environment. The novelty of this study lies in integrating ESRS-based indicator selection, double materiality assessment, and sustainability performance simulation into a unified framework. This approach transforms sustainability reporting information from a compliance-oriented disclosure process into a strategic decision-support mechanism.

Although substantial progress has been made in ESG measurement, sustainability reporting, and double materiality assessment, existing studies predominantly focus on static indicator evaluation, ESG ratings, or disclosure quality. Limited research has integrated

ESRS requirements, double materiality principles, and system dynamics modeling into a unified framework for assessing corporate sustainability performance. This study addresses this gap by combining ESG indicators, ESRS-based reporting logic, and dynamic simulation within a single decision-support framework [2,16,19,29,32].

3. Materials and Methods

The system dynamics (SD) model was developed using free online modeling platform Insight Maker. To ensure general applicability across industries, key sustainability indicators and datasets were first defined. The model focuses exclusively on internal resource and energy flows that can be directly influenced by company actions, excluding supply chain and downstream customer activities.

One of the largest fuel retailers in Riga (Latvia) was used for the validation of the model. The company is a strong market player operating in an industry with significant environmental impacts and has an annual turnover of over 560 million EUR. The company operates 80 gas stations in Latvia with around 750 employees; the business expands by 1–2 new stations each year. The company has its own development strategy, based on which sustainability targets for 2030 have been developed. Sustainability targets are set as a percentage reductions from the base year, which in this case is 2020. These data have also been used in model simulation [33].

The modeling process consisted of several stages. First, key performance indicators and their influencing variables were identified. To ensure relevance, indicators were aligned with the scope of company operations and their sustainability impacts. A dependency matrix based on the ESRS was constructed to capture relationships among indicators.

The materiality assessment was conducted to identify sustainability topics that are both relevant to company operations and suitable for inclusion in the system dynamics model. The assessment was based on a simplified ESRS-oriented double materiality approach, considering both the company's impacts on society and the environment (impact materiality) and the potential effects of sustainability issues on business performance (financial materiality). A 3×3 materiality matrix was applied using two evaluation dimensions: likelihood and impact (see Table 1). Likelihood reflects the probability that a sustainability issue may occur or influence company operations, while impact reflects the magnitude of potential environmental, social, governance, or financial consequences. Each sustainability topic was assigned a score from 1 to 3 for both dimensions: Low (1), Medium (2), and High (3) [34]. The overall materiality score was determined by combining likelihood and impact assessments. The evaluation was performed using expert judgment involving sustainability specialists, environmental managers, and company representatives familiar with operational and reporting processes. Internal historical company data, sustainability reports, internal audit findings, and regulatory requirements were used as supporting information during the assessment process.

Table 1. ESRS indicator materiality matrix.

ESRS	Impact Materiality	Financial Materiality	Final Materiality	Included
E1 Climate Change	High	High	High	Yes
E2 Pollution	High	Medium	High	Yes
E3 Water Resources	Medium	Medium	Medium	Yes
E5 Circular Economy	Medium	Medium	Medium	Yes
S1 Workforce	High	High	High	Yes
S4 Consumers	Medium	Medium	Medium	Yes
G1 Governance	High	High	High	Yes

Topics receiving high combined scores were considered material and included in the model structure. Topics with lower scores or insufficient historical data were excluded from quantitative modeling but remained relevant for reporting.

Within the context of the ESRS, the materiality assessment supports the identification of sustainability topics that require disclosure and management attention. Impact materiality is represented by indicators that reflect the company's environmental and social effects. In contrast, financial materiality is reflected in variables associated with operational efficiency, resource consumption, regulatory compliance, investment requirements, and business risks. The selected indicators therefore represent sustainability issues that are material from both organizational and stakeholder perspectives.

The empirical dataset consists of ten years of company data across all structural units, providing a comprehensive and longitudinal basis for analysis. Data were collected from various internal reporting systems, as well as from internal audits. To ensure comparability and eliminate inconsistencies between measurement units, all indicators were normalized relative to the baseline year (2020) using the ratio between the observed annual value and the corresponding baseline value. Such data interpretation also protects the company from leaking commercially important data.

Indicators representing positive sustainability performance (e.g., employee training, renewable energy use, sustainability investments and waste recycling) were transformed before aggregation so that lower normalized index values consistently represented improved sustainability performance across all indicators.

The dataset contained no missing observations for the selected indicators during the ten-year study period. Data quality was verified through consistency checks across internal reporting systems, sustainability reports, and audit records before model implementation.

Figure 1 illustrates both reinforcing (R) and balancing (B) feedback loops operating within the sustainability system. The R1 efficiency reinvestment loop represents a reinforcing mechanism in which efficiency improvements generate cost savings that can be reinvested into further sustainability initiatives. The R2 human capital loop demonstrates how employee training contributes to improved safety performance and productivity, which in turn support financial performance and additional investments in human capital. The R3 governance–finance loop reflects the relationship between governance quality, investor confidence, capital availability, and strategic investment decisions. The B1 environmental compliance loop represents a balancing mechanism whereby increasing emissions generate regulatory pressure, which stimulates investments in efficiency improvements and subsequently reduces environmental impacts. Positive (+) polarity indicates that variables move in the same direction, whereas negative (−) polarity indicates an inverse relationship between connected variables.

The SD model integrates environmental, social, and governance variables into a unified structure, allowing simulation of dynamic interactions and identification of key drivers affecting overall sustainability performance. The stock-flow structure represents the accumulation and depletion mechanisms of operational resources, human capital, and sustainability performance, together with policy-controlled inflows and outflows. The model is used to evaluate sustainability targets set for 2030. Scenario simulations assess whether current development trajectories are sufficient to achieve these targets and identify required adjustments in resource use, investment, and operational strategies.

The threshold values used to interpret the sustainability index were developed to support managerial assessment of sustainability performance within the analyzed company. These thresholds were not derived from regulatory requirements or universally accepted ESG benchmarks, as no standardized ESRS-based sustainability index classification currently exists. Instead, the interpretation ranges were established using three

considerations: (1) historical sustainability performance observed during the study period; (2) internal sustainability targets defined by company management; and (3) the need to distinguish between substantial improvement, moderate improvement, limited progress, and performance deterioration relative to the baseline year. Because all indicators were normalized relative to the baseline value of 1.0, the threshold categories were defined around this reference point. Values below 1.0 indicate improvement relative to baseline conditions, whereas values above 1.0 indicate deterioration. In Table 2, the category “very good” (0–0.5) represents substantial improvement relative to baseline performance. The category “good” (0.5–1.0) indicates a measurable improvement in sustainability. Values between 1.0 and 1.5 indicate limited progress or stagnation, while values above 1.5 indicate significant deterioration requiring management attention.

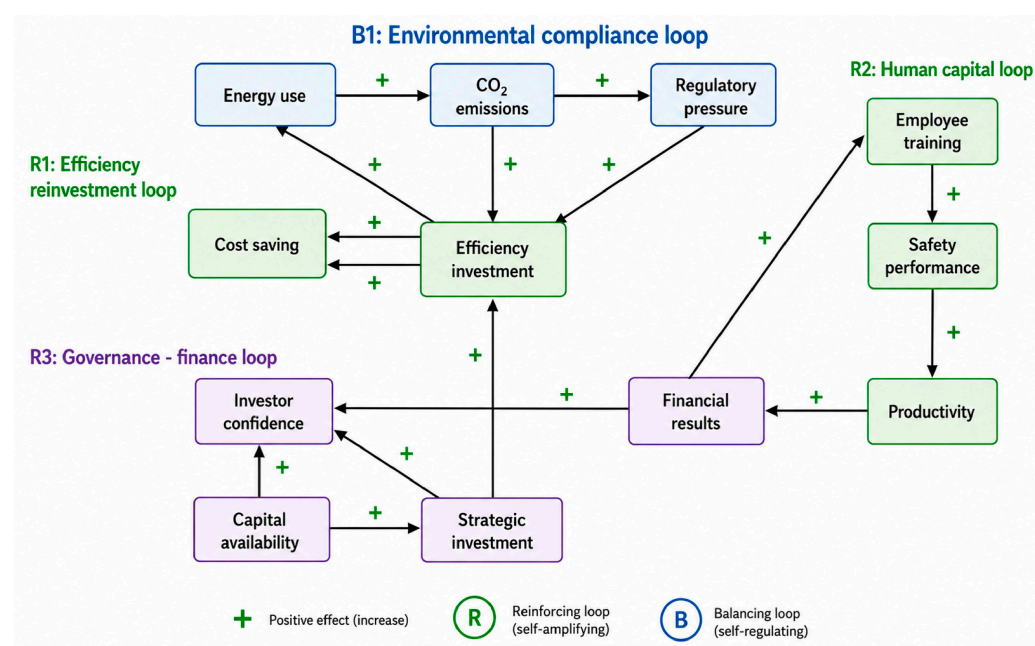


Figure 1. Causal loop diagram of corporate sustainability performance.

Table 2. Sustainability index interpretation thresholds.

Sustainability Index	Interpretation	Meaning
0.0–0.5	Very good	Substantial improvement relative to baseline
0.5–1.0	Good	Improvement relative to baseline
1.0–1.5	Moderate	Limited progress or stagnation
>1.5	Critical	Significant deterioration requiring intervention

The proposed threshold values should be interpreted as company-specific decision-support ranges rather than universal sustainability benchmarks. Different industries, reporting frameworks, or organizational contexts may require alternative threshold definitions based on sector-specific targets, regulatory requirements, or statistical performance distributions.

The unweighted arithmetic mean was selected as the primary aggregation method because it provides a transparent and easily interpretable representation of overall sustainability performance. This approach avoids subjective weighting decisions and facilitates communication of results to managers and stakeholders. However, the arithmetic mean allows compensability between indicators, meaning that strong performance in one dimension may offset weaker performance in another. Therefore, alternative aggregation approaches were also evaluated.

To be able to replicate a similar model:

- Sustainability data or industry-specific indicators that can significantly affect overall sustainability performance need to be collected.
- Next, to avoid discrepancies in measurement units or descriptive parameters, absolute values should be converted into indexed values.
- Indicator values by year should be entered into the model as “Conver”, with each of them named after the corresponding sustainability indicator, for example, CO₂ volume.
- To designate indexes, “Stock” should be selected. Then, all indicators related to a specific index should be connected using the “Link” arrows.
- Next, each specific index should create its own “Stock” section, which is connected to the Link.
- Once all sustainability indicators and indices have been identified in the model and their own Stock blocks have been created, they are added to the overall sustainability index, which is also selected as “Stock”, using the “Flow” arrows.

A sensitivity analysis was used to evaluate the stability and responsiveness of the developed system dynamics (SD) model under parameter uncertainty. In SD modeling, sensitivity analysis is a critical validation step, as model behavior may be influenced by assumptions regarding input data, parameter values, and structural relationships within the system [5,10]. The analysis was performed using a Monte Carlo simulation approach with a varying number of runs, ensuring statistical reliability and convergence of the results. Increasing the number of simulation runs did not significantly alter the confidence intervals, confirming the stability of the simulation outcomes, and 1000 runs were deemed appropriate. A uniform probability distribution was used for parameter variation. During each Monte Carlo simulation run, individual normalized indicators were multiplied by independently generated random coefficients ranging from 0.7 to 1.3, representing a $\pm 30\%$ variation relative to baseline values. The randomization procedure was applied exclusively to the ESG indicator values included in the sustainability index calculations. No uncertainty was introduced into the causal structure, feedback loops, model equations, or functional relationships between variables.

Consequently, the sensitivity analysis evaluates how input uncertainty propagates through the indicator aggregation structure rather than the structural validity of the complete system dynamics model. The analysis, therefore, provides insights into index stability and uncertainty propagation but should not be interpreted as a standalone test of the model’s stability or of the sustainability index under indicator-level uncertainty.

4. Model Validation

The credibility of a system dynamics (SD) model depends on its ability to represent real system structure and to reproduce observed behavior. In this study, model validation was conducted using a multi-method approach consisting of structure validation, behavior validation, and sensitivity analysis. Structure validation assessed the consistency between the conceptual model and the real-world system. This included verification of causal relationships based on ESRS logic, consistency checks of stock-and-flow structures, dimensional consistency of variables, and expert-based evaluation of the dependency matrix. The selected system boundary is limited to internally controllable resource flows, ensuring that all model relationships reflect managerial decision-making processes. Structural validity was evaluated independently from the sensitivity analysis through expert review of causal relationships, consistency checks of indicator interactions, verification of model assumptions, and comparison with established sustainability reporting logic under the ESRS framework. The use of empirical company data further strengthens structural validity. Behavior validation was performed by comparing simulated outputs with historical company data over a ten-year period. The model reproduces key observed trends,

including: decreasing resource consumption intensity, reduction in occupational safety incidents, gradual improvement in social indicators, and slower changes in electricity consumption and CO₂ emissions. The model's ability to replicate these patterns indicates that its feedback structure adequately captures the dominant mechanisms of corporate sustainability performance. Extreme-condition tests confirmed logical consistency under boundary conditions. Sensitivity analysis was conducted using Monte Carlo simulation to evaluate model stability and identify influential variables. Simulations were performed with 1000 runs. Increasing the number of runs did not significantly change the confidence intervals, confirming convergence.

The climate index is calculated as an unweighted arithmetic mean of five environmental indicators:

$$\text{Climate index} = \frac{(\text{Fuel} + \text{Gas} + \text{Electricity} + \text{Waste} + \text{CO}_2)}{5}$$

All indicators are expressed as relative values (base year = 1). Uncertainty in each indicator was modeled using multiplicative scaling:

$$\text{Indicator}_{eff} = \text{Indicator} \times \text{Fix}(0.7; 1.3)$$

This introduces $\pm 30\%$ variability while maintaining consistency within each simulation run. Results indicate that a $\pm 30\%$ variation in individual indicators leads to limited changes.

The theoretical maximum influence of a single indicator is: $0.3 \times 0.2 = 6\%$. This confirms that the index structure distributes influence evenly across components, resulting in high stability but reduced sensitivity. Alternative aggregation methods were evaluated:

$$\text{WeightedMean} = w_1 \times \text{Fuel} + w_2 \times \text{Gas} + w_3 \times \text{Electricity} + w_4 \times \text{Waste} + w_5 \times \text{CO}_2$$

$$\text{GeometricMean} = (\text{Fuel} \times \text{Gas} \times \text{Electricity} \times \text{Waste} \times \text{CO}_2)^{0.2}$$

where w_1, w_2, w_3, w_4 , and w_5 —indicator-specific weighted indicators, 0–1;

Fuel, Gas, Electricity, Waste, and CO₂—normalized indicator values.

The geometric mean reduces compensability and increases sensitivity to extreme values. A stress-test scenario, where one indicator was significantly reduced (e.g., CO₂ = 0.2), showed a lower index value than the arithmetic mean, indicating improved detection of critical under-performance. Overall, the model demonstrates the stability of the sustainability index under indicator-level uncertainty and adequate sensitivity for sustainability performance analysis.

Compared with the arithmetic mean (see Table 3), the geometric mean reduces compensability and increases sensitivity to poor performance in individual indicators. Consequently, it provides a more conservative assessment of sustainability performance and may be particularly useful when management seeks to identify critical weaknesses within specific ESG dimensions. Weighted aggregation methods may also be appropriate when materiality assessments indicate that certain sustainability topics are strategically more important than others. However, the selection of weights introduces additional subjectivity and may reduce transparency. For this reason, the unweighted arithmetic mean was retained as the primary aggregation method in the present study.

Table 3. Comparison of aggregation methods.

Method	Advantages	Limitations
Arithmetic mean	Transparent, simple, easy to interpret	Allows compensability
Weighted mean	Reflects materiality priorities	Requires subjective weights
Geometric mean	Sensitive to weak indicators	Less intuitive for practitioners

5. Results

5.1. Conceptual Model

Figure 2 presents the proposed system dynamics framework for corporate sustainability assessment. The model integrates the most relevant environmental, social, and governance (ESG) indicators identified through the ESRS materiality assessment into a hierarchical structure consisting of input indicators, sustainability sub-indices, and an aggregated sustainability index.

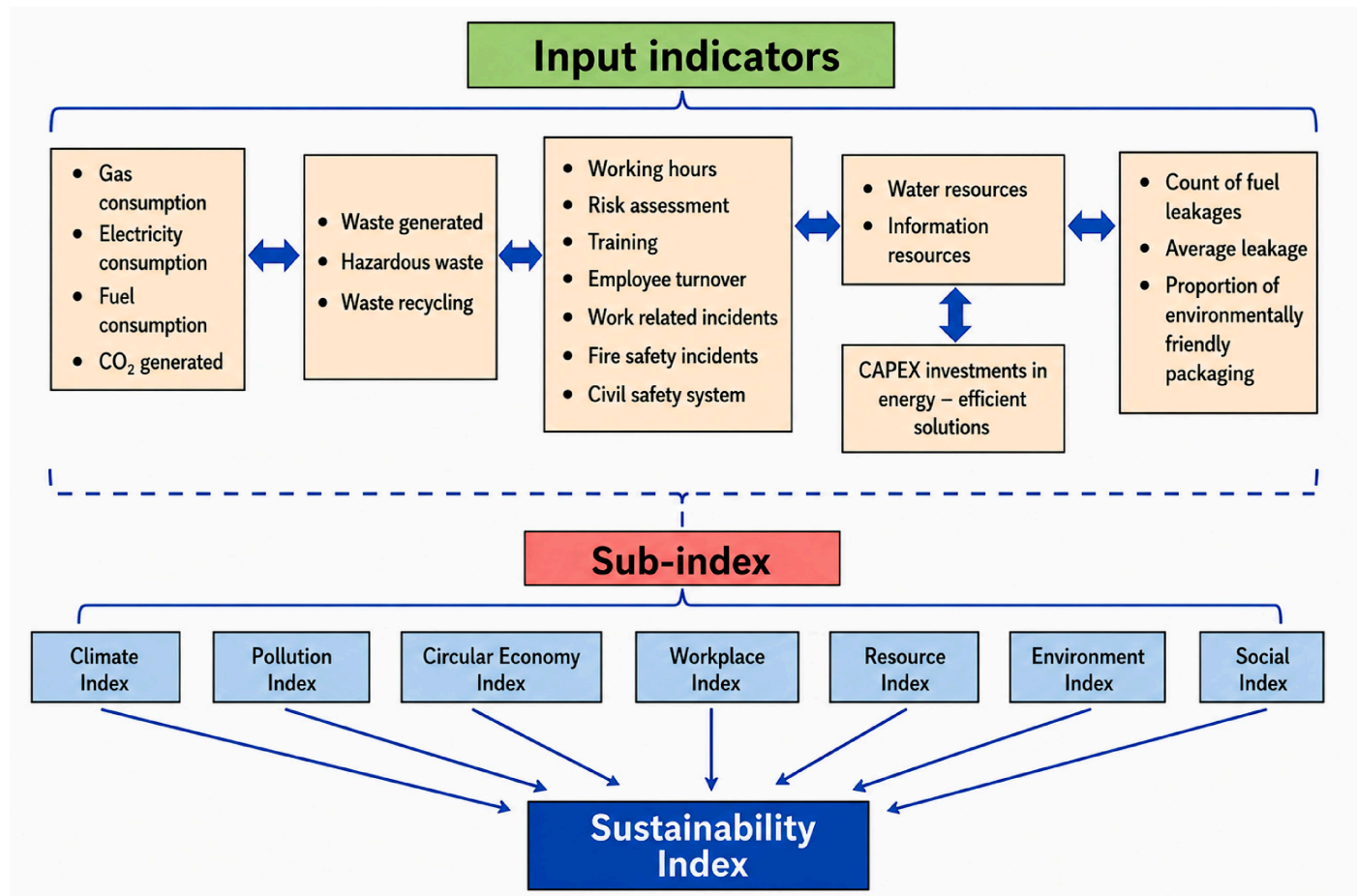


Figure 2. Company sustainability model architecture created using Insight Maker (2026).

The model was implemented using annual time steps over the period 2014–2030. The simulation period was selected to allow both historical validation (2014–2024) and future scenario analysis (2025–2030). Sustainability performance is represented through a hierarchy of stock variables, sub-indices, and an aggregated sustainability index.

Composite sustainability indicators are widely used to aggregate complex environmental, social, and governance information into a manageable form for decision-making. However, the construction of composite indices requires careful consideration of normalization procedures, weighting approaches, compensability effects, and aggregation methods. The choice of aggregation technique may significantly influence sustainability performance interpretation [35,36].

The model structure consists of: (1) input indicators (Converters); (2) ESG sub-indices (Stocks); (3) overall sustainability index (Stock); (4) Information links representing causal relationships; and (5) flows representing changes in sustainability performance over time.

All indicators were normalized relative to the baseline value:

$$I_n = \frac{I_t}{I_{base}},$$

where

I_n —normalized indicator;

I_t —observed indicator value;

I_{base} —baseline year value.

The general stock-flow equation used for each sustainability sub-index is:

$$Stock_t = Stock_{t-1} + Inflow - Outflow,$$

where

Inflow represents sustainability improvements generated through investments, operational efficiency measures, employee training, and governance actions.

Outflow represents deterioration caused by resource consumption, emissions, incidents, compliance failures, and operational inefficiencies.

The overall sustainability index is calculated as:

$$SI = \frac{\sum_{i=1}^n Index_i}{n},$$

where

$Index_i$ —represents individual sustainability sub-indices;

n —the number of sub-indices included in the assessment.

To represent organizational adaptation processes, time delays were introduced into selected feedback loops. Employee training effects were assumed to influence safety performance with a one-year delay, while energy-efficiency investments affected resource-consumption indicators after a two-year delay. These delays reflect implementation periods observed in corporate sustainability management practices.

5.2. Quantitative Model Specification

The quantitative model was developed by selecting ESG indicators relevant to corporate sustainability assessment under the ESRS framework. Indicator selection was based on the materiality assessment presented in Section 3, data availability, and their suitability for dynamic simulation. The selected indicators are organized according to the ESRS reporting structure. Table 4 identifies general ESRS standard requirements and possible applications in the fuel retail industry. Collecting and understanding such information helps us to understand which data can be obtained and reflected in the context of a specific company or industry.

Table 4. General ESRS standard requirements.

ESRS 1—General Requirements		ESRS 2—General Disclosures	
Requirement	Application to a Fuel Retail Business	Requirement	Application to a Fuel Retail Business
Reporting limits	One site/whole network	Management structure	ESG responsible
Double significance	Environmental risks + financial impact	Strategy	Energy efficiency, emission reduction
Data consolidation	Individual site network level	Policies	Environmental protection, safety
Reporting period	Annual report	Goals and KPIs	Reduction data
		Internal control	Environmental audit, incident logs

The general ESRS requirements provide the reporting framework within which industry-specific indicators were identified. Environmental indicators represent the largest

group of variables incorporated into the model. Table 5 presents ESRS environmental standards regarding climate change and pollution.

Table 5. ESRS environmental indicators and applications in fuel retail operations.

ESRS E1—Climate Change		ESRS E2—Pollution	
Requirement	Application to a Fuel Retail Business	Requirement	Application to a Fuel Retail Business
Emissions generated	Tons	Leakage monitoring	Count
Energy consumption	kWh	Pollution incidents	Count and size
Climate risks	Percentage of renewable energy use	Preventive measures	HSE requirements
Transition plan	Percentage of alternative fuels	Compliance with HSE norms	Count of incidents

These indicators mainly describe energy use, greenhouse gas emissions and pollution prevention. Resource-related indicators capture the efficiency of water use and circular resource management.

Table 6 presents the ESRS environmental standard requirements from a resource perspective.

Table 6. ESRS resource-related indicators and applications in fuel retail operations.

ESRS E3—Water and Marine Resources		ESRS E5—Resource Use and Circular Economy	
Requirement	Application to a Fuel Retail Business	Requirement	Application to a Fuel Retail Business
Water consumption	m ³	Waste volume	Hazardous/non-hazardous and volume
Wastewater control	m ³	Recycling rate	Percentage
Risk assessment	Count of incidents	Plastic reduction	Percentage of recycled waste

Social indicators represent workforce performance and customer-related sustainability outcomes.

Table 7 shows ESRS social standard requirements as well as their application to the fuel retail industry.

Table 7. ESRS social indicators and applications in fuel retail operations.

ESRS S1—Own Workforce		ESRS S4—Consumers and End-Users	
Requirement	Application to a Fuel Retail Business	Requirement	Application to a Fuel Retail Business
Number of employees	Count	Customer Safety	Count of incidents
Work safety	Injuries	Complaints	Count
Training	Training hours	Product Liability	Fuel Quality
Employee turnover	Percentage	Clarity of Information	Labeling
Equality	Gender distribution		

Governance indicators describe organizational control mechanisms and compliance performance.

Table 8 presents the most important ESRS governance standard requirements.

Not all ESRS indicators were suitable for quantitative modeling. Indicators were included only when historical data were available, the issue was material to company operations, and the variable could be influenced by management decisions. Indicators were included if (1) data were available for at least ten consecutive years, (2) the variable reflected a material sustainability issue identified through the materiality assessment, and (3) the indicator could be directly influenced by management decisions. Indicators lacking

historical consistency or relevance to company operations were excluded (see indicator mapping in Table 9).

Table 8. ESRS governance indicators and applications in fuel retail operations.

ESRS G1—Business Conduct	
Requirement	Application to a Fuel Retail Business
Compliance with norms	Work inspection/fire inspection cases
Corruption risk procurement	Procurement process
Internal control	Audits
Incident reporting	Customer complaints

Table 9. ESRS indicator mapping and model inclusion criteria.

ESRS	Company Variable	Model Variable	Data Source	Included
E1	CO ₂ emissions	Climate index	Environmental reports	Yes
E1	Electricity consumption	Climate index	Energy database	Yes
E2	Fuel Leakage incidents	Pollution index	HSE reports	Yes
E3	Water consumption	Resource index	Utility reports	Yes
E5	Waste generation	Circular economy index	Waste reports	Yes
S1	Work accidents	Workplace index	HR/HSE reports	Yes
S1	Employee training	Workplace index	HR records	Yes
S4	Customer complaints	Social index	CRM database	Yes
G1	Compliance audits	Governance index	Internal audits	Yes
ESRS biodiversity indicators	Not available	-	No historical data	Excluded

5.3. Sustainability Performance Analysis

Figures 3–5 illustrate historical trends in the selected ESG indicators and the aggregated sustainability index.

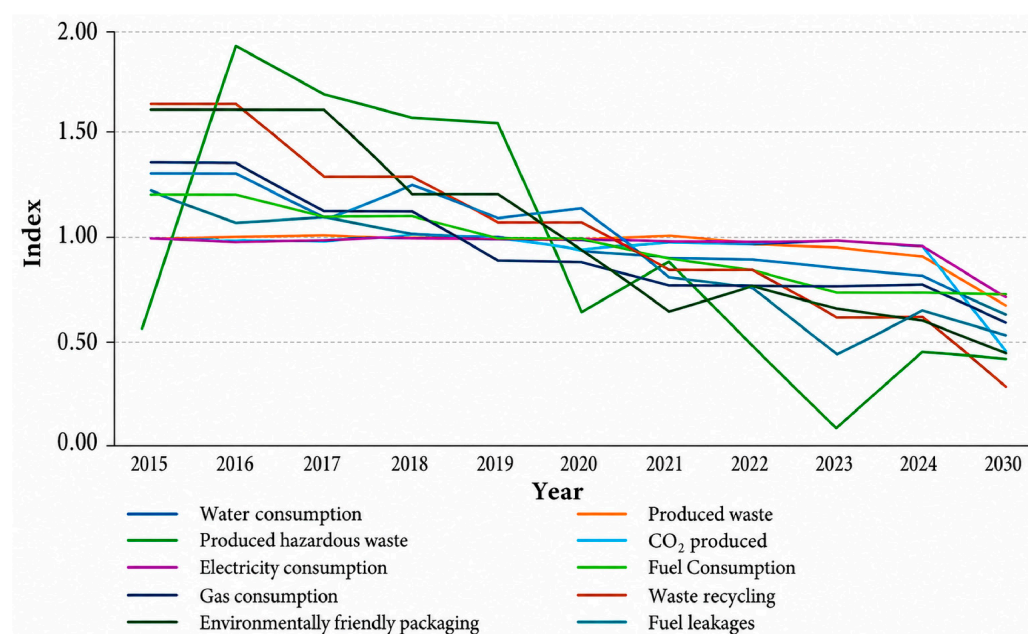


Figure 3. Environmental ESG indicator trends and 2030 projections.

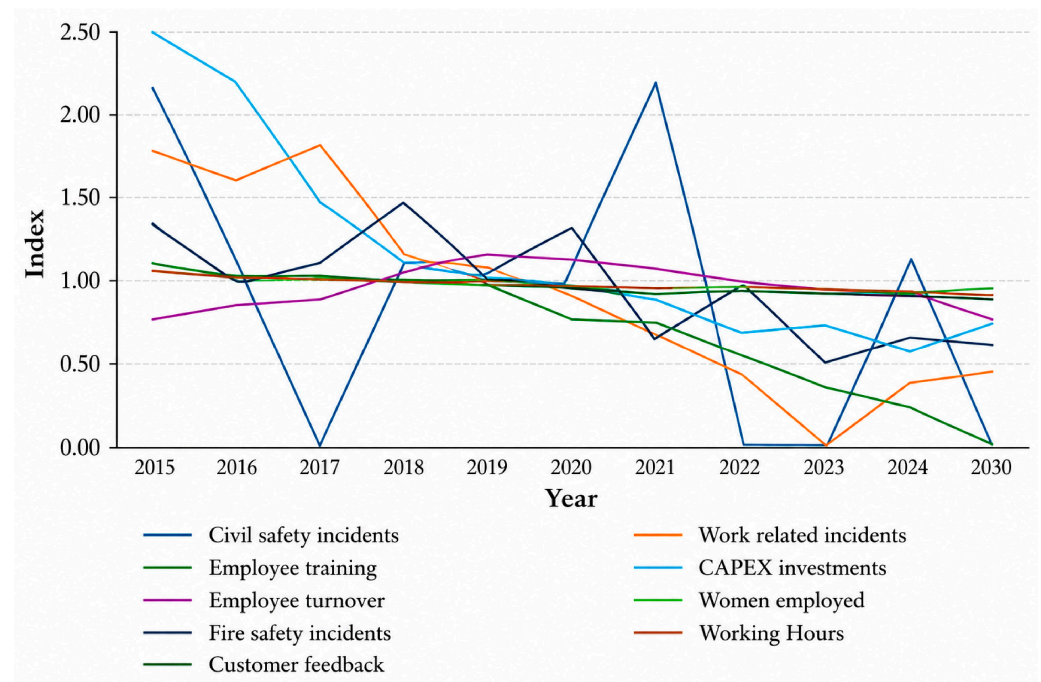


Figure 4. Social and governance ESG indicator trends and 2030 projections.

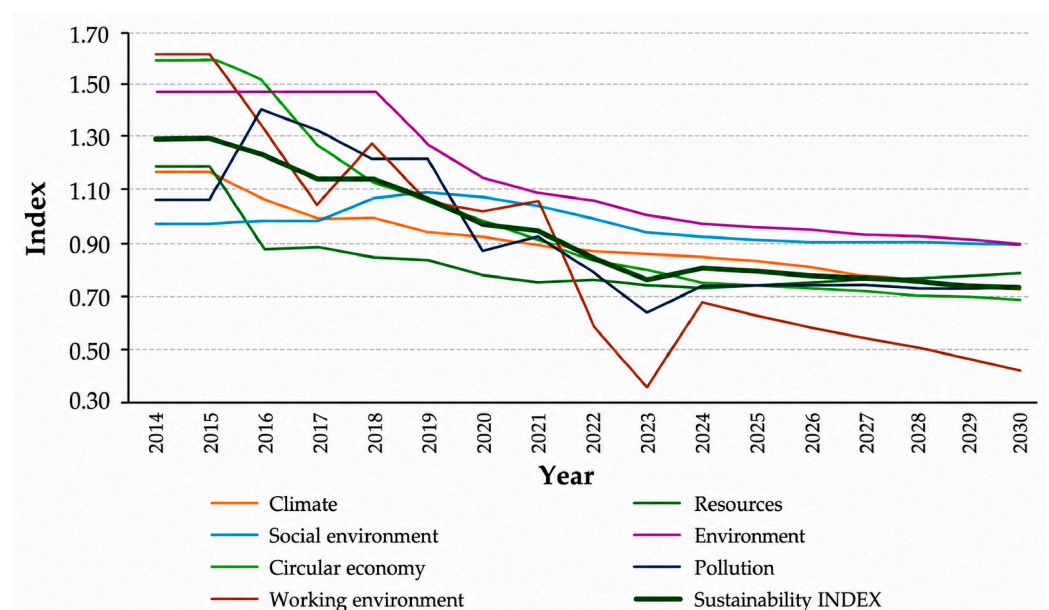


Figure 5. General Sustainability indicators and sustainability index.

Overall, the ten-year dataset demonstrates a positive sustainability trajectory characterized by declining resource consumption, fewer occupational safety incidents, improved employee-related indicators, and better environmental performance. These improvements reflect increasing operational efficiency and the gradual implementation of sustainability measures.

Not all indicators improved at the same pace. Electricity consumption and CO₂ emissions showed slower reductions, primarily due to continued business expansion and rising technological requirements. This illustrates the trade-offs frequently observed between operational growth and environmental performance.

The aggregated sustainability index shows a continuous long-term decline from 2014 to 2024, indicating overall improvement in corporate sustainability performance. During

this period, the index decreased by approximately 38%, suggesting that the company has already achieved substantial progress toward its sustainability objectives.

5.4. Baseline Scenario Analysis

The simulation in this study serves as a baseline, assuming the continuation of current operational practices, investment patterns, and sustainability management activities. No major technological innovations, regulatory changes, or strategic interventions were introduced into the simulation. Consequently, the projected sustainability performance reflects the continuation of historical development trends observed during the study period.

The company's sustainability strategy defines quantitative targets for 2030 relative to the baseline year (2020). These targets were normalized and incorporated into the model to assess whether the current development trajectory is sufficient to achieve the planned sustainability objectives.

The simulation results indicate that the company has already made substantial progress in several sustainability dimensions during the historical observation period. Improvements are particularly evident in occupational safety, employee development, and investments supporting energy efficiency. At the same time, environmental indicators such as electricity consumption and CO₂ emissions continue to improve at a slower rate, reflecting the effects of continued business expansion and increased operational activity.

The aggregated sustainability index demonstrates a continuous downward trend throughout the analyzed period, indicating overall improvement in corporate sustainability performance. Between 2014 and 2024, the sustainability index decreased by approximately 38%. According to the baseline simulation, the index is projected to decline further from 0.81 in 2024 to approximately 0.74 by 2030, corresponding to an additional improvement of approximately 9%. These results suggest that the company's current sustainability strategy is generally consistent with achieving its planned 2030 targets, provided that existing investment levels and management practices are maintained.

To demonstrate the flexibility of the proposed framework, four additional scenario types were conceptually defined: (1) low-investment, (2) high energy-efficiency, (3) business expansion, and (4) regulatory pressure scenarios. These scenarios illustrate potential applications of the framework under alternative strategic conditions but were not quantitatively simulated in the present study because the necessary empirical data were unavailable. Their implementation therefore represents an important direction for future research.

Overall, the baseline scenario confirms that the proposed system dynamics framework can support long-term sustainability planning by integrating historical performance with strategic sustainability targets and by providing a structured basis for future scenario evaluation.

5.5. Sensitivity Analysis

A Monte Carlo sensitivity analysis (see Figure 6) was performed to evaluate the propagation of uncertainty in the normalized ESG indicators and their influence on the sustainability index. A total of 1000 simulation runs were carried out, with independent random variation of $\pm 30\%$ for each normalized indicator. The uncertainty was introduced only into the input indicator values, while the stock-flow structure, causal relationships, feedback loops, and model equations remained unchanged. Consequently, the analysis evaluates the stability of the sustainability index under indicator-level uncertainty rather than the structural validity of the system dynamics model.

The simulation results demonstrate stable long-term behavior across all analyzed indicators despite stochastic variation in the input values. Although the widths of the uncertainty intervals differ across indicators, all simulation trajectories remain convergent

throughout the simulation period, indicating that uncertainty in individual ESG indicators does not substantially alter the overall sustainability trajectory.

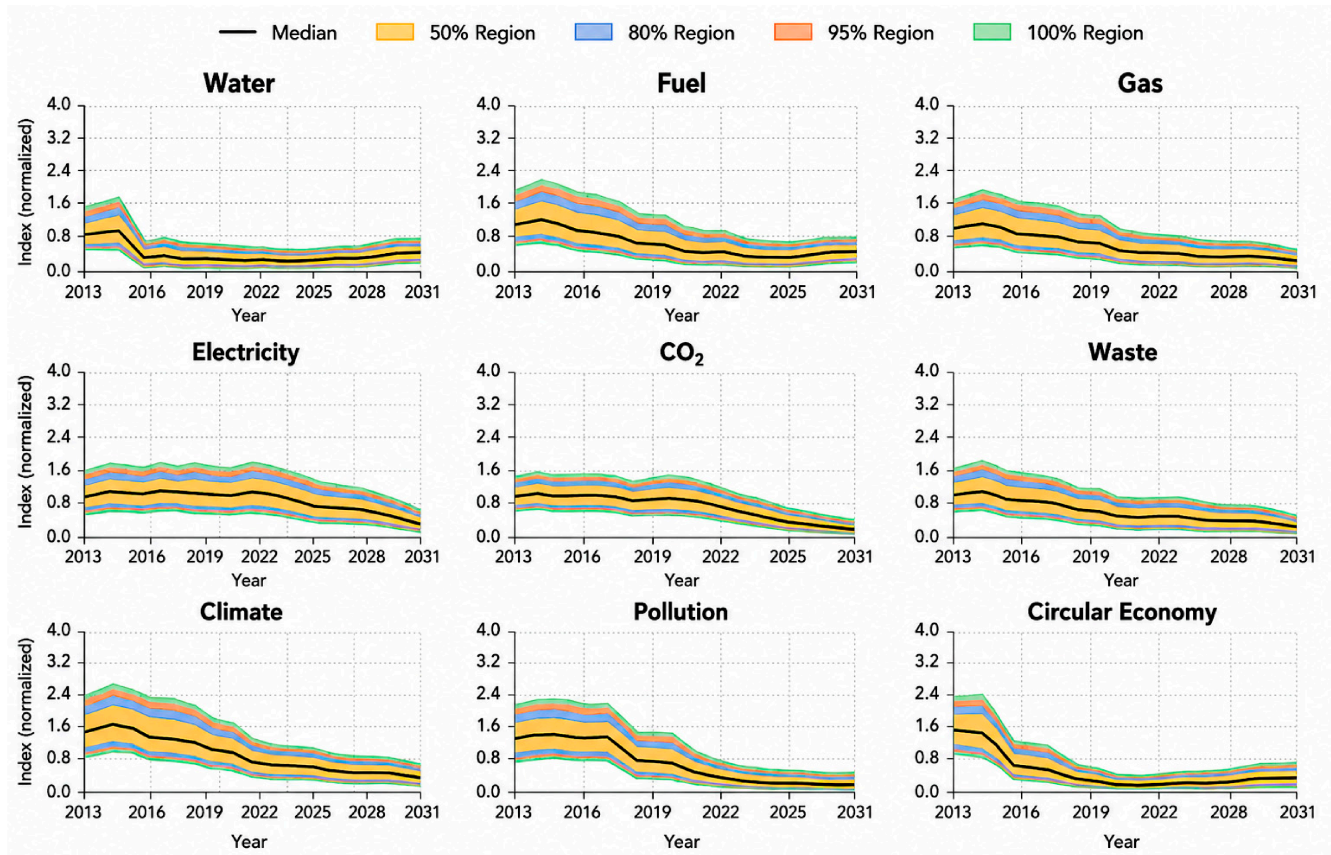


Figure 6. Monte Carlo sensitivity analysis results for selected indicators. The figure shows the median trajectory (black line) and uncertainty regions corresponding to the 50% (yellow), 80% (blue), 95% (orange) and 100% (green) confidence intervals.

Indicators directly related to energy consumption and climate performance, including Fuel, Gas, and the Climate Index, exhibit the narrowest uncertainty intervals, indicating relatively low sensitivity to input variation. In contrast, Water, Waste, and the Pollution Index show moderately wider confidence intervals, reflecting greater variability associated with operational processes and resource use. Nevertheless, none of the analyzed indicators exhibits unstable or divergent behavior during the simulation period.

The composite sustainability indices demonstrate progressively narrowing uncertainty intervals over time. This behavior suggests that the aggregation of multiple ESG indicators reduces the influence of random fluctuations in individual variables while preserving the overall development trend. As a result, the sustainability index provides a stable representation of long-term corporate sustainability performance despite uncertainty in individual indicator values.

Overall, the sensitivity analysis confirms that the proposed framework is robust with respect to indicator-level uncertainty. The limited dispersion of simulation trajectories indicates that moderate variation in normalized ESG indicators has only a minor influence on the aggregated sustainability index. These results support the application of the proposed framework as a practical decision-support tool for sustainability assessment and long-term strategic planning.

5.6. Summary of Results

The empirical application demonstrates that the proposed system dynamics framework successfully integrates ESRS-based environmental, social, and governance indicators into a coherent sustainability assessment model. The selected indicator structure allows sustainability performance to be evaluated using a unified sustainability index while preserving the relationships among individual ESG dimensions.

Analysis of the historical dataset indicates a generally positive sustainability trajectory over the ten-year observation period. Most indicators show gradual improvement, particularly in resource efficiency, occupational safety, employee development, and governance practices. Slower progress in electricity consumption and CO₂ emissions reflects the influence of continued business expansion and increased operational activity.

The baseline scenario simulation suggests that the company is likely to achieve its planned 2030 sustainability targets if current operational practices, investment patterns, and sustainability management activities are maintained. The projected decline of the sustainability index indicates continued improvement in overall sustainability performance under existing development conditions.

The Monte Carlo sensitivity analysis further demonstrates that the sustainability index remains stable under uncertainty in normalized ESG indicator values. Although individual indicators exhibit different levels of variability, uncertainty propagation has only a limited influence on the aggregated sustainability assessment. These findings support the suitability of the proposed framework as a practical decision-support tool for monitoring corporate sustainability performance, evaluating long-term development trends, and supporting sustainability-related strategic planning.

Overall, the results confirm that the proposed framework provides a transparent and adaptable approach for integrating sustainability reporting data into dynamic performance assessment and may serve as a useful analytical tool for organizations implementing ESRS-based sustainability management.

6. Discussion

This study contributes to the growing body of research on corporate sustainability modeling by integrating ESG indicators within a system dynamics framework. The findings confirm that performance is driven by complex interdependencies, feedback loops, and time delays, which cannot be adequately captured by static analytical approaches. This aligns with previous research emphasizing the importance of dynamic modeling in sustainability analysis [5,6].

The observed improvements in resource efficiency and safety indicators are consistent with studies suggesting that sustainability-oriented investments lead to both environmental and economic benefits. However, the slower progress in electricity consumption and CO₂ emissions reflects structural constraints associated with business growth and technological expansion. Similar trade-offs have been identified in energy transition and industrial sustainability studies, where efficiency gains are partially offset by increased operational demand [9].

The results also highlight the importance of internal organizational mechanisms, such as employee training and capital allocation, in shaping sustainability outcomes. This supports the view that corporate sustainability performance is largely determined by endogenous system structures rather than external pressures alone [10]. In particular, the reinforcing relationship between training, safety, and productivity demonstrates how social investments contribute to long-term organizational performance.

The application of system dynamics in this study confirms its suitability for analyzing sustainability transitions at the company level. Previous studies have shown similar

advantages of SD in capturing feedback effects, identifying leverage points, and supporting policy evaluation [11]. The integration of ESRS-based indicators into a dynamic modeling framework represents a novel contribution, addressing a gap in current research on ESG reporting and decision-support tools.

The empirical validation presented in this study is based on a single fuel retail company operating in Latvia. Consequently, the observed sustainability trajectories reflect not only general sustainability dynamics but also company-specific characteristics, including management strategy, investment priorities, operational practices, market position, and compliance with national regulatory requirements. For example, the observed reductions in resource consumption intensity and the slower decline in CO₂ emissions may be influenced by the company's expansion strategy, technological investments, and local regulatory conditions. Therefore, these patterns should not be interpreted as representative of all fuel retail companies or other industrial sectors.

Several alternative approaches are available for assessing sustainability performance, including scorecard-based methods, linear trend extrapolation, statistical forecasting models, and ESG rating systems (see Table 10). Scorecard approaches provide a simple and transparent overview of sustainability indicators but generally do not represent interactions among environmental, social, and governance dimensions. Similarly, linear trend extrapolation can estimate future indicator values but assumes that historical trends continue unchanged and does not account for feedback effects or policy interventions. Regression-based approaches can identify statistical relationships among sustainability variables but are typically limited in representing dynamic feedback structures, implementation delays, and nonlinear interactions. In contrast, system dynamics models explicitly represent causal relationships, feedback loops, and long-term behavioral responses to management interventions.

Table 10. Comparison of sustainability assessment approaches.

Method	Advantages	Limitations
Scorecard	Simple, transparent	No dynamic interactions
Linear trend extrapolation	Easy forecasting	Assumes unchanged trends
Regression analysis	Quantifies statistical relationships	Limited representation of feedback mechanisms
System dynamics	Captures feedback, delays, scenarios	Higher complexity and data requirements

Consequently, the primary advantage of the proposed framework is not necessarily improved predictive accuracy but rather the ability to evaluate alternative sustainability strategies, identify indirect effects, and explore long-term consequences of management decisions within an integrated sustainability system.

From a methodological perspective, the results of the sensitivity analysis demonstrate that the climate index is structurally robust but exhibits limited responsiveness due to its aggregation method. This finding is consistent with previous studies highlighting the trade-off between stability and sensitivity in composite indicators [23]. While the arithmetic mean ensures transparency and comparability, alternative approaches such as weighted or geometric means may improve responsiveness in specific analytical contexts.

The Monte Carlo analysis evaluates uncertainty propagation in indicator values rather than validating the causal structure of the system dynamics model.

Overall, the study confirms that system dynamics modeling provides a valuable tool for integrating sustainability data, analyzing system behavior, and supporting strategic decision-making. The findings contribute to both academic research and practical applications by offering a structured approach to modeling corporate sustainability performance under ESRS requirements. This approach, by integrating SD and ESRS, promotes the

dynamic assessment of ESG issues, which, in today's changing environment, can become a significant contribution to helping businesses make correct and sustainable decisions much more quickly.

While the empirical findings are company-specific, the proposed modeling architecture is designed to be transferable across organizations. The transferability of the framework lies in its methodological structure rather than in the numerical results obtained from the case study.

The proposed framework can support several categories of sustainability-related managerial decisions. First, the model can be used to evaluate alternative investment priorities, including energy-efficiency improvements, renewable energy adoption, waste reduction initiatives, and sustainability-related infrastructure upgrades. Second, the model can support workforce-related decisions by assessing the potential long-term effects of employee training, occupational safety programs, and human capital development initiatives. Third, the framework can assist sustainability planning by identifying indicators that contribute most strongly to overall sustainability performance and therefore deserve priority management attention.

For example (see Table 11), if simulation results indicate that energy consumption and greenhouse gas emissions contribute disproportionately to sustainability index deterioration, managers may prioritize investments in energy-efficiency technologies or low-carbon operational practices. Conversely, if workforce-related indicators show the strongest influence on sustainability performance, additional investments in training and safety programs may be more effective.

Table 11. Examples of management decisions supported by the model.

Sustainability Issue	Decision Option	Model Output
High energy consumption	Increase energy-efficiency investments	Change in sustainability index
Rising CO ₂ emissions	Implement emission reduction measures	Change in climate index
Increasing accidents	Expand training programs	Change in social index
High waste generation	Improve recycling initiatives	Change in circular economy index
Regulatory pressure	Increase compliance investments	Change in governance index

The framework does not prescribe optimal investment levels or specific budget allocations. Instead, it enables comparison of alternative sustainability strategies and assessment of their potential long-term consequences under different assumptions and scenarios.

7. Limitations and Future Research

Although the proposed framework provides a practical approach for integrating ESG indicators and ESRS reporting requirements into a system dynamics environment, several limitations should be acknowledged. First, the empirical validation was conducted using data from a single fuel retail company operating in Latvia. While the general modeling framework may be transferable to other industries, the selected indicators, parameter values, and sustainability priorities may differ substantially across sectors. Therefore, the results should not be interpreted as universally representative of all organizations.

Second, the model boundary was intentionally limited to sustainability aspects that can be directly influenced by company management. Consequently, supply chain effects, upstream environmental impacts, and downstream customer-related impacts were not included in the analysis. These factors may significantly influence overall sustainability performance and should be incorporated into future model extensions.

Third, the framework relies primarily on internally generated company data. Although data quality checks and validation procedures were applied, the accuracy of model

outputs remains dependent on the completeness and reliability of company reporting systems. Future studies should consider integrating external data sources and independent sustainability benchmarks.

Fourth, the use of aggregated sustainability indices inevitably simplifies the complexity of sustainability performance. While index aggregation improves interpretability and communication, it may mask poor performance in individual indicators when stronger performance in other dimensions compensates for weaker results. Alternative aggregation approaches, such as weighted or geometric indices, may provide complementary insights.

Finally, sustainability reporting indicators do not necessarily capture all dimensions of actual sustainability performance. ESG and ESRS indicators serve as measurable proxies for sustainability outcomes, but some environmental and social impacts remain difficult to quantify. Consequently, improvements in reported sustainability indicators should not automatically be interpreted as equivalent improvements in overall sustainability performance.

Future research should validate the framework using multiple companies, different industrial sectors, and broader datasets. Development could also incorporate supply chain sustainability indicators, dynamic weighting procedures, and stakeholder-specific materiality assessments, and alternative sustainability index formulations.

The greatest practical value of the framework lies in scenario comparison. Managers can evaluate how alternative investment strategies, operational changes, or regulatory requirements influence long-term sustainability performance before committing organizational resources to implementation.

8. Conclusions

This study developed and empirically validated a system dynamics framework for modeling corporate sustainability performance in alignment with ESRS requirements. The results confirm that corporate sustainability is driven by complex, interdependent processes characterized by feedback loops, time delays, and non-linear relationships, which cannot be adequately captured using static analytical approaches.

The proposed model demonstrates its capability to integrate heterogeneous ESG indicators into a unified analytical structure and to reproduce observed sustainability trends based on real company data. The findings show that improvements in sustainability performance are strongly linked to internal organizational mechanisms, such as resource allocation, investment in efficiency, and employee training. At the same time, the analysis reveals inherent trade-offs between business growth and environmental performance, particularly in energy use and emissions.

The sensitivity analysis confirms that the developed Insight Maker system dynamics model is structurally robust and behaviorally stable, as the selected quantitative ESG indicators demonstrated statistically significant convergence and decreasing uncertainty over time despite $\pm 30\%$ stochastic parameter variation.

The strongest long-term stabilization effects were observed for the pollution, gas, fuel, and circular economy indicators, indicating that sustainability-oriented operational improvements and circular economy practices generate dominant balancing feedback mechanisms and support reliable long-term ESG transition pathways.

From a practical perspective, the model provides a decision-support tool that enables companies to evaluate sustainability performance, test strategic scenarios, and assess the feasibility of achieving long-term targets. It is particularly valuable in the context of ESRS implementation, where organizations must integrate complex sustainability data into coherent management processes.

The study contributes to the literature by bridging sustainability reporting and system dynamics modeling and demonstrates the potential of dynamic approaches in advancing corporate sustainability analysis.

Future research should focus on extending the model to include supply chain effects, integrating weighted sustainability indicators, and applying the framework across different industries to enhance its generalizability. The framework should therefore be interpreted as a strategic planning and scenario evaluation tool rather than an optimization model. Its primary contribution lies in supporting structured sustainability decision-making under uncertainty by revealing the potential long-term consequences of alternative management actions.

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