International Journal of Hydrogen Energy 217 (2026) 153731

Contents lists available at ScienceDirect

International Journal of Hydrogen Energy

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

Circular supply chain design for biohydrogen recovery from perishable agri-food waste

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ARTICLE INFO

Keywords:
Biohydrogen
Perishable agri-food waste
Water-energy-food nexus
Circular supply chain
Sustainable supply chain

ABSTRACT

The increasing interdependencies between water, energy, and food systems highlight the urgency of integrated solutions for managing environmental and resource challenges. This study proposes a sustainable logistics framework for converting agri-food waste into biohydrogen, drawing on the Water-Energy-Food (WEF) Nexus to guide strategic planning. Focusing on Razavi Khorasan, Iran, a drought-prone region with substantial upstream food losses and declining groundwater reserves, the research explores how circular supply chain can support both waste reduction and clean energy generation. The proposed system is structured around a closed-loop supply chain that incorporates both forward delivery and reverse logistics to collect perishable food waste and redirect it for biohydrogen production. This approach prioritizes the recovery of high-water-footprint items such as fruits, vegetables, and cereals, thereby mitigating the loss of embedded resources. A scenario-based assessment of vehicle types and environmental policies highlights the operational and environmental trade-offs of different logistics strategies. The findings suggest that low-capital interventions, such as smart routing and shared logistics, can deliver significant environmental benefits without the infrastructure barriers of full fleet electrification. Ultimately, the framework supports resilient, low-carbon pathways for agri-food systems in water-stressed regions, contributing to circular economy goals and Sustainable Development Goals (SDGs) related to climate action, food security, and clean energy access.

1. Introduction

In recent years, the interconnection between water, energy, and food, commonly referred to as the Water-Energy-Food (WEF) Nexus, has emerged as a critical framework for understanding the complexity of sustainability challenges [1]. These three sectors are deeply intertwined: water is essential for food production, food systems require energy at every stage from farm to fork, and energy production, in turn, often relies heavily on water resources [2]. Climate change, population growth, and resource scarcity have amplified the urgency to address inefficiencies and losses across this nexus [3]. As illustrated in the Fig. 1a, food waste is one of the clearest symptoms of misalignment in the WEF nexus. Globally, more than 30 % of all food produced is lost or wasted, with the highest rates in fruits, vegetables, cereals, and dairy products [4]. This waste occurs at various stages, from production and storage to retail and consumption (Fig. 1b). In developing countries like Iran, a disproportionate share of food loss occurs in the early stages of the supply chain, primarily due to poor infrastructure, inadequate storage, and inefficient logistics [5]. For instance, Iran's national reports suggest that over 35 % of agricultural output is lost, especially in perishable products like cucumbers, apples, tomatoes, and grapes. These losses are higher than the global average in upstream segments such as post-harvest and distribution, signaling a structural challenge that exacerbates water scarcity and undermines food and energy security [6].

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https://doi.org/10.1016/j.ijhydene.2026.153731
Received 12 September 2025; Received in revised form 15 January 2026; Accepted 25 January 2026
Available online 13 February 2026

Addressing food loss is not only about reducing hunger or economic loss, it is also a strategic lever to conserve water and generate renewable energy [7]. In Iran, where over 15 billion cubic meters of water are wasted annually through lost perishable agri-food products, the issue becomes even more pressing. This invisible water loss embedded in wasted food, commonly referred to as the "virtual water footprint", represents a critical drain on one of the most vulnerable resources in arid and semi-arid climates [8]. Given that certain crops (e.g., oilseeds, pulses, and cereals) consume thousands of liters of water per kilogram, allowing such products to go uneaten results in massive environmental and economic costs [9]. Therefore, improving food system efficiency through a WEF lens not only supports Sustainable Development Goals (SDGs) but also unlocks new opportunities in circular energy recovery from unavoidable organic waste [2]. Unlike green hydrogen, which relies on electrolysis powered by renewable electricity [10], biohydrogen is derived from biomass through biochemical pathways [11], making it uniquely positioned to valorize organic waste streams while contributing to both energy and waste management goals [12]. In the face of escalating water scarcity in Iran, minimizing the water intensity of food production has become an urgent national priority [13]. Agricultural products such as beef (15,490 L/kg), rice (3,470 L/kg), wheat (1,470 L/kg), and onions (2,800 L/kg) consume vast quantities of water. When these water-intensive products are wasted along the supply chain, the associated "virtual water" is lost as well, water that was extracted, transported, and applied in vain [14]. This inefficiency is particularly problematic in arid regions like Iran, where agriculture consumes over 90 % of the total freshwater supply.

According to Fig. 2a, agricultural production in Razavi Khorasan is heavily concentrated in a small number of high-volume crops. The bar chart illustrates total production volume, while the line graph represents cultivated area. Products like wheat, sugar beet, and tomatoes dominate both indicators, suggesting a water- and land-intensive farming pattern. Given the high-water footprint of these crops their mismanagement or post-harvest loss can result in significant waste of embedded resources [15]. Much of Iran's waste occurs at the production and distribution stages, due to outdated harvesting machinery, inadequate storage, and inefficient logistics. Compounding this issue is the widespread drought, visualized on the Fig. 2b, which highlights Razavi Khorasan and other provinces experiencing extreme drought to abnormal dryness. These regions, already vulnerable due to water stress, cannot afford the additional loss of embedded water through food waste.

Given the dual challenges of rising perishable agri-food waste and increasing water stress, especially in arid regions like Iran, there is a pressing need for integrated supply chain solutions that transform waste into value while addressing environmental constraints [16]. This paper tries to introduce a framework that uses the WEF Nexus as the guiding principle in the conversion of perishable agricultural-feeding waste to bio-hydrogen through anaerobic digestion in a Closed-Loop Supply Chain (CLSC) manner. The framework for the logistics optimization of transportation routes as well as the actuation of depots, besides promoting the production of clean energy and minimizing the embedded water loss in the agricultural sector. The WEF Nexus, as opposed to the context, is more of an analytical framework that enunciates the boundaries and focus of the modeling process through the connection between the recovery of food waste in the agricultural sector and water scarcity, as well as the production of bio-hydrogen and the focus on emissions. The region chosen as the case study is Razavi Khorasan due to its strong vulnerability to drought as well as its heavy agricultural focus.

2. Literature review

2.1. Hydrogen supply chain and circular economy

A range of recent studies has explored the biohydrogen supply chain using techno-economic, environmental, and systemic approaches. Ganeshan, et al. [17] conducted a comparative techno-economic analysis and life cycle assessment (LCA) of biohydrogen production methods, concluding that biomass gasification was the most economical route ($1.2/kg H_2) and that eucalyptus wood gasification produced the lowest carbon footprint (−1.6 kg CO_2eq/kg H_2). Similarly, Kayan, et al. [18] employed a digital twin framework integrated with Monte Carlo simulation and network optimization to assess biohydrogen production from agricultural waste across 72 farms in India, demonstrating the potential for $34.54 billion in annual social savings. Goh, et al. [19] presented an integrated optimization of green hydrogen supply chains in Malaysia using mixed-integer programming, emphasizing safety, economic, and environmental factors. Their findings indicated that solar-powered electrolysis is economically viable only when hydrogen prices exceed $5.36/kg. Khalilpour, et al. [20] analyzed global hydrogen research using scientometric and collaboration network analysis, revealing a shift in innovation leadership toward Asian economies and identifying biohydrogen and photocatalysis as fast-growing fields. Amaya-Santos, et al. [21] applied LCA to compare biohydrogen produced from municipal solid waste in the UK with alternative hydrogen routes, concluding that biohydrogen with CCS delivers net-negative emissions and outperforms blue and green hydrogen in climate impact. Finally, Lee [22] developed a GTAP-based economic model incorporating circular economy principles, showing that Malaysia had the highest productivity in biohydrogen generation and that CE outperforms linear economy models in developed regions.

Besides, recent advances in CLSC modeling have contributed significantly to improving sustainability in the agri-food sector [23]. The term perishable agri-food waste is used to denote waste streams that, despite being classified as residual outputs, remain biologically active and reusable within a limited time window, and are therefore still subject to spoilage and quality degradation if recovery and valorization are delayed [24]. In this regard, Beheshti, et al. [25] examined the urban food supply chain in Iran and proposed a model using quantity flexibility

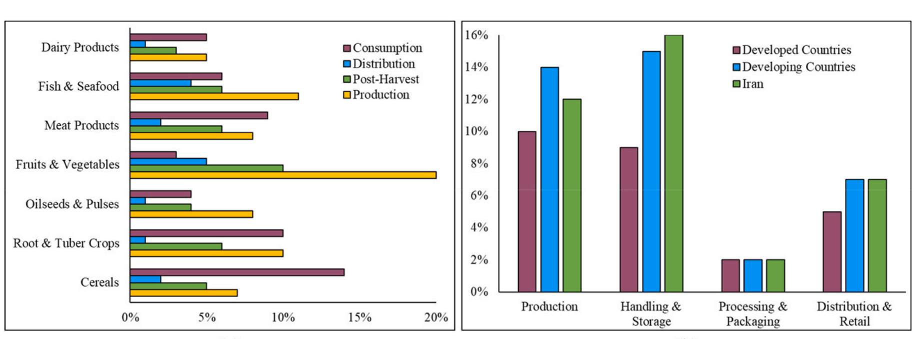
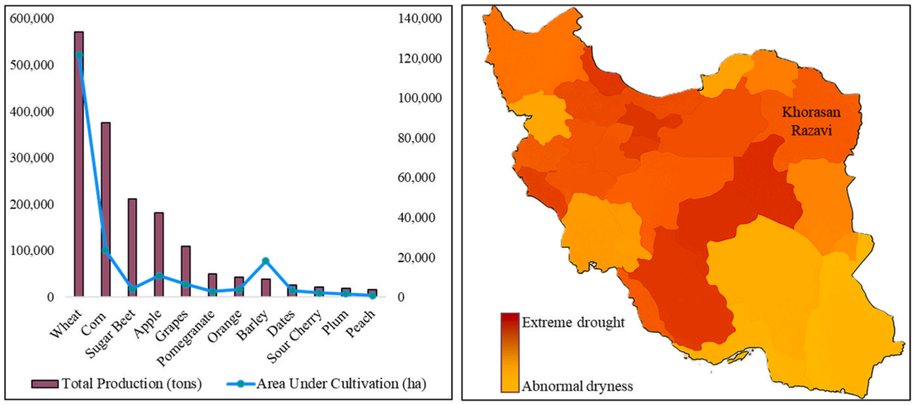


Fig. 1. Global and national comparison of food loss percentages across post-harvest stages (a) and supply chain actors (b), highlighting higher losses in Iran's upstream processes.



(a) (b)

Fig. 2. Per capita food waste distribution across provinces in Iran (a) and spatial drought intensity map (b), showing correlation between food waste generation and areas of extreme dryness.

contracts and rented recycling facilities, showing enhanced profitability and real-world feasibility. Several studies have focused on valorization of food waste through technological and systemic innovations. Tian, et al. [26] conducted an experimental LCA on a decentralized micro-AD system in Singapore, finding that energy neutrality and even negative emissions (−77 kg CO_2-eq/t) are feasible with higher food waste loading and engine efficiency. Tomić and Schneider [27] explored energy recovery in circular economy frameworks, showing that up to 60 % of energy needs could be met through waste recovery, thereby improving the sustainability of recycled materials. Stillitano, et al. [23] proposed a multi-cycle LCA integrated with economic and social indicators for the olive oil supply chain, enabling a more holistic assessment of circular strategies.

2.2. WEF nexus and governance strategies

The WEF Nexus has been hailed as a system approach to cope with the interrelations in core resource sectors but also noted to risk being a 'catch phrase in policy processes if referred to only at a conceptual level' [28]. In this respect, Allouche [28] underlines that the nexus is not only and primarily a technical task of integrating resource sectors into one system unit but a political process driven by governance and power dynamics and feasibility realities; while Hussein and Ezbakhe [29] add to this line of thought by noting that nexus technologies lead to very limited policy contributions if not developed into decision tools and learning by doing practices.

In this regard, numerous studies have tackled the complexity of the WEF nexus using both qualitative and quantitative approaches to support sustainable planning and policy. Naderi, et al. [30] applied a system dynamics model in Iran's Qazvin Plain to simulate water-energy dynamics under future demand and climate conditions, concluding that without integrated demand- and supply-side policies, the region faces severe groundwater depletion. Similarly, Samadi-Foroushani, et al. [31] combined system dynamics with social network analysis to evaluate Iran's water governance structures, showing that strategic interventions improved irrigation efficiency by 16 % and reduced food losses by 5 %, all while mapping institutional reform pathways. Expanding on systemic trade-offs, You, et al. [32] used a MILP model to design a bioethanol supply chain in Jeju, Korea, under a WEF-Land nexus lens, achieving notable reductions in resource usage across land, water, and energy. Complementing these modeling efforts, Rubinsin, et al. [33] optimized oil palm biomass value chains in Malaysia and showed that a 34 % profit trade-off could lead to 91 % carbon and 97 % water use reductions, emphasizing the utility of integrated multi-objective strategies.

On the governance side, Yuan and Lo [34] proposed a conceptual WEF nexus framework based on nine governance principles including innovation, equity, and stakeholder participation, with case applications in Taiwan. Meanwhile, Pereira Ribeiro, et al. [35] offered a Balanced Scorecard for Brazilian food policies that aligns WEF metrics with the SDGs, identifying several overlaps and inconsistencies in national policy. In addition, Itayi, et al. [36] highlighted that many WEF studies neglect social and gender dimensions, proposing a household-level framework to incorporate these gaps. Addressing pandemic-related challenges, Al-Saidi and Hussein [37] analyzed COVID-19's disruptive effects on the WEF nexus and urged the inclusion of spatial risk assessments in planning. Finally, several researchers developed novel modeling frameworks to operationalize nexus insights. Afkhami and Zarrinpoor [38] integrated GIS and multi-objective modeling to optimize a biofuel supply chain in Iran, finding that increased use of used cooking oil reduces land and water stress compared to reliance on Jatropha. Li, et al. [39] explored sectoral transmission of energy-water nexus pressures in China using MRIO and betweenness analysis.

2.3. Gaps and novelties

Despite its width in literature related to food waste valorization, hydrogen supply chain optimization, or WEF nexus analysis, current research within this area proves particularly methodologically incongruous. To the best of our knowledge, multi-objective methods for supply chain optimization commonly attempt to minimize costs, emissions, or optimize for improved energy efficiency. By contrast, these objectives hardly ever integrate an evident nexus-driven framework that connects food system resource inefficient practices to water savings or optimal use of available resource energies. In this regard, while CLSC for similar Agrifood supply chain contexts prove decidedly inclusive of municipal or industrial solid waste sources for recycling or repurposing in model frameworks, such an approach hardly distinguishes among largely diverse solid WEF sources according to practical imbedded water intensities or relevant WEF sources for similar water scarcity analysis considerations. In somewhat related context, MARCOS as a multi-criteria decision-making (MCDM) tool confirm decisively prevalent trends for sustainability strategies ranking assessments, the same hardly ever definitively integrating or building directly from relevant supply chain network optimized logistics configurations or addressing particularly pertinent feasibility implications in both developing countries studies or studies focusing related electric or hybrid truck adoption assessments.

The research fills this gap by integrating WEF-focused problem formulation, CLSC optimization, and grey MARCOS strategic evaluation within a unified framework. The WEF Nexus has a direct influence on determining the scope of the systems, waste stream prioritization, and scenario characterization, where a focus on reducing food loss will clearly drive water conservation and low-carbon energy recovery via biohydrogen. The contribution thus goes beyond the implementation of existing techniques. On a conceptual level, this framework thus moves beyond viewing circular supply chain thinking as a mere means for achieving WEF-based transitions by providing an operational entry point for this purpose, as opposed to conceptualizing circular thinking as a strictly technological and/or policy-oriented challenge. On a methodological level, implementing bi-objective MILP and Grey MARCOS thus helps to close a hitherto underdeveloped gap existing in circular supply chain and nexus research by enabling transition pathways adapted to feasibility that result from optimized logistics solutions.

3. Methods and materials

This study adopts a solution-oriented, applied research philosophy aimed at designing an implementable logistics model for circular bioenergy production from perishable agri-food waste [40]. Recognizing the multi-dimensional nature of sustainability challenges [41], the methodology integrates both quantitative optimization modeling and qualitative decision analysis to support informed and context-sensitive planning [42]. The rationale for combining these approaches stems from the dual necessity of achieving technical feasibility through cost-emission optimization, while also evaluating strategic adaptability under real-world constraints such as infrastructure readiness, regulatory uncertainty, and stakeholder alignment. In this regard, the research builds upon a systemic understanding of the WEF Nexus, emphasizing the closed-loop flow of materials and information as the foundation for circular economy transitions in the agri-food sector [43].

The WEF Nexus approach explicitly informs both the structure of the optimization models and scenario design [44]. In terms of dimension of water, it focuses on waste streams of high virtual water content and views logistics alternatives based on avoidance of non-productive losses associated with transportation [45]. For the dimension of energy, biohydrogen production is considered in terms of valorization options that can transform non-avoidable food waste into a low-carbon fuel, but vehicle technology scenarios correspond to constraints of freight sector energy transitions. For the dimension of food systems, service constraints are applied that ensure all sources of perishable waste types are fully accounted for so that targeted or partial recovery does not effectively drive upstream losses of food products [46].

To operationalize this vision, a structured multi-phase framework was designed, as shown in Fig. 3. The process begins with system framing through literature review and WEF Nexus analysis, followed by the identification of the research problem, objectives, scope, and stakeholders [47]. The biohydrogen supply chain is then conceptualized by designing node types and flow structures to capture perishable agri-food waste (mainly fruits, vegetables, and bakery discards) from customer locations and route them to selected depots for conversion via anaerobic digestion [48], A bi-objective mathematical model is formulated to minimize both logistics costs and carbon emissions across this reverse logistics network [49]. Next, scenario development incorporates relevant transportation and policy considerations to examine electric and conventional vehicle strategies. For implementation planning, nine candidate strategies are evaluated using the grey MARCOS method [50], which integrates expert-informed criteria across economic, environmental, and operational dimensions. The process concludes with a

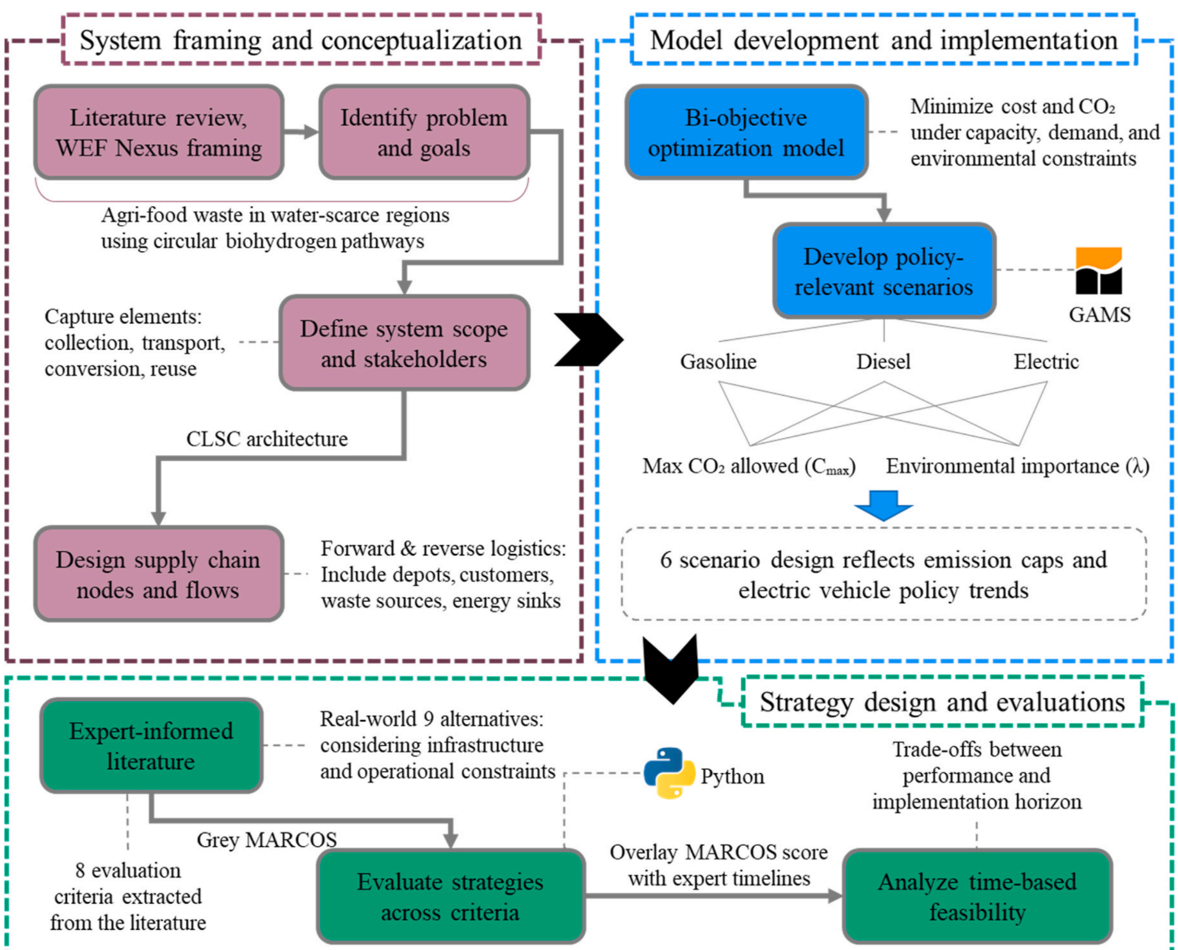


Fig. 3. Stepwise methodological process including system framing, model development, and multi-criteria strategy evaluation.

time-based feasibility analysis that assesses the practicality of each strategy under different emission constraints [51].

WEF Nexus is modeled in this research primarily in terms of logistics-related decision variables rather than flow equations involving multiple resources. Water-related aspects are also included in a rather indirect manner, prioritizing agricultural food processing waste streams as well as focusing on upstream food losses, as they are identified as a significant source of embedded water wastage in arid environments in general [52]. The empirical aspect of energy is included in terms of the choice of bio-hydrogen as the valorization option as well as transport-related emissions from vehicles [53]. The specific water and energy-related process flows within this research remain exogenous in order to keep the research tractable in terms of resolution. The particular bi-objective formulation of the model is specific regarding its size as a proof-of-concept within a data-constrained region like the case region of this research. However, it can be adapted in a rather flexible manner in terms of the different product categories of the agri-food industry in general. The application case of this research in the province of Razavi Khorasan is rather representative in a demonstrative rather than a limiting framework regarding its applicability conditions.

3.1. Assumptions

To effectively design a sustainable, CLSC for converting perishable agri-food waste into biohydrogen, a mathematical model was developed with specific assumptions related to network structure, parameters, vehicle characteristics, emissions, and operational constraints [54]. These assumptions guide the formulation of the optimization problem and enable scenario-based analysis under different vehicle types and environmental standards [55]. The methodological contribution of this study lies not in proposing new algorithms, but in the structured integration of established methods within a WEF-oriented decision logic that links system framing, operational optimization, and implementation planning.

1. All customers must be served exactly once by a vehicle.
2. Vehicles can only operate between open depots and assigned customer nodes.
3. Each vehicle starts and ends its route at the same depot (round-trip logic).
4. The total pickup and delivery demand served by any vehicle must not exceed its capacity.
5. The total pickup and delivery assigned to each depot must respect the depot's capacity limit.
6. Each customer is assigned to only one depot.
7. Delivery and pickup flows must satisfy customer-specific demand exactly.
8. Travel is only allowed between customers if they are assigned to the same depot.
9. Binary decision variables ensure discrete choices for depot openings and route assignments.
10. Emissions per route are calculated based on distance and an emission factor validated in Ref. [56] for Iranian vehicles, specifically in Razavi Khorasan; total emissions must remain below a scenario-dependent threshold.
11. The model includes a risk factor penalty when emissions exceed predefined sustainability thresholds (based on vehicle type).
12. Environmental impacts (CO_2 emissions) are integrated into the objective function to enable multi-objective optimization.
13. The system is designed to support closed-loop flow: waste collected from customers is routed back to depots.
14. Travel cost, fixed facility costs, and fixed vehicle costs are included in the cost-minimization objective.
15. The model supports scenario-based sensitivity analysis based on vehicle fuel type (gasoline, diesel, electric), each with distinct emission profiles and risk weights.
16. No transshipment is allowed between customers; only direct routes from/to depots are permitted.
17. The conversion rates and hydrogen yields used in the model for fruit, vegetable, and cereal waste are based on experimental values reported in the literature. Specifically, average yields from anaerobic digestion processes under mesophilic conditions were adopted, as validated in studies such as [57,58].

3.2. Model description

The mathematical model developed in this study involves a two-echelon logistics network consisting of multiple customer locations and potential depot sites [59]. To formally represent the structure and behavior of the system, a set of indices, parameters, and decision variables is defined. These elements serve to capture the spatial layout, capacity constraints, cost elements, and operational decisions (e.g., routing, depot opening, and delivery/pickup assignments) [60]:

Indices	
i	Index for all nodes (i.e., locations); the model considers 12 nodes in total.
j	Subset of nodes, used as destination or intermediate nodes.
k	Subset of nodes, used to index depot candidates.
m	Subset of nodes, used for depot/customer linkage in constraints.
N	The full set of nodes: $N = N_0 \cup N_1$
N_0	Set of depot nodes (e.g., nodes 4, 5, and 6).
N_1	Set of customer nodes (e.g., nodes 1, 2, 3, 7, 8, 9, 10, 11, 12).
Parameters	
DC_{ij}	Distance between node i and node j.
$DELD_i$	Delivery demand at customer i.
$PDEL_i$	Pickup demand at customer i.
$PEDFC$	Fixed cost of opening depot k.
$CAPD$	Capacity of depot k.
$CAPV$	Capacity of each vehicle.
Vfc	Fixed cost of assigning a vehicle.
Variables	
Q_{ij}	Binary variable: 1 if a vehicle travels from node i to node j, 0 otherwise.
T_{ij}	Quantity of delivery transported from node i to node j.
S_{ij}	Quantity of pickup transported from node i to node j.
U_k	Binary variable: 1 if depot k is opened, 0 otherwise.

3.3. Mathematical model

This model adopts a bi-objective optimization approach. The first objective function (Equation (1)) aims to minimize the total economic costs, including the cost of opening distribution facilities, the fixed cost of deploying vehicles, and the travel costs associated with vehicle routing across the delivery and pickup network [60]. The second objective (Equation (2)) incorporates environmental considerations by minimizing the total carbon emissions from vehicle operations [61]. A weighted risk factor is included to reflect regulatory or strategic penalties for exceeding CO_2 emission thresholds.

$$Min\ z_1 = \sum_{i \in N} \sum_{j \in N} DC_{ij} Q_{ij} + \sum_{K \in N_0} DEPFC_K U_k + \sum_{K \in N_0} \sum_{i \in N_1} Vfc.Q_{ki} \tag{1}$$

$$Min\ z_2 = \sum_{K \in N_0} \sum_{i \in N_1} e_{ik} z_{ik} + \lambda.risk\ factor \tag{2}$$

To ensure comprehensive service coverage, Constraint (3) enforces that each customer must be visited exactly once by a vehicle [60]. Constraint (4) guarantees routing consistency by ensuring that the number of trips entering a node equals those leaving it, this prevents isolated loops and ensures feasible tours. Constraint (5) enforces that each customer is assigned to exactly one depot [62]. Constraints (6) and (7) further ensure that if a customer is allocated to a depot, actual travel must occur between them, maintaining logical connectivity [63].

$$\sum_{j \in N} Q_{ij} = 1 \qquad \forall i \in N_1 \tag{3}$$

$$\sum_{j\in N} Q_{ij} = \sum_{j\in N} Q_{ji} \quad \forall i \in N \tag{4}$$

$$\sum_{k\in N_0} Z_{ik} = 1 \quad \forall i \in N_1 \tag{5}$$

$$Q_{ik} \le Z_{ik} \quad \forall k \in N_0, \forall i \in N_1 \tag{6}$$

$$Q_{ki} \le Z_{ik} \quad \forall k \in N_0, \forall i \in N_1 \tag{7}$$

Constraint (8) limits the total CO_2 emissions resulting from vehicle movements to stay within a specified environmental cap. This constraint promotes the selection of cleaner routes and fewer trips, supporting climate-conscious logistics planning [60].

$$\sum_{K\in N_0}\sum_{i\in N_1} e_{ik} z_{ik} \le C_{\max} \tag{8}$$

Constraint (9) ensures that the combined pickup and delivery volumes on any route segment do not exceed the vehicle's capacity [60]. Constraints (10) and (11) break this down further by applying limits individually to pickup and delivery volumes [64]. Constraints (12) and (21) ensure the realism of shipment flow, vehicles cannot carry more than requested, and customers receive exactly what is needed [65].

$$T_{ij} + S_{ij} \le CAPV.Q_{ij} \quad \forall i,j \in N, i \ne j \tag{9}$$

$$S_{ij} \le (CAPV - PDEL_i).Q_{ij} \quad \forall i \in N, \forall j \in N_1 \tag{10}$$

$$T_{ij} \le (CAPV - DELD_i).Q_{ij} \quad \forall i \in N_1, \forall j \in N \tag{11}$$

$$S_{ij} \ge PDEL_i.Q_{ij} \quad \forall i \in N_1, \forall j \in N \tag{12}$$

Constraints (13) and (14) ensure that the total assigned delivery and pickup volumes to each depot remain within that depot's operational capacity [60]. This prevents depot overloading and enables efficient resource use.

$$\sum_{i\in N_1} DELD_i Z_{ik} \le CAPD_k.U_k \quad \forall k \in N_0 \tag{13}$$

$$\sum_{i\in N_1} PDEL_i Z_{ik} \le CAPD_k.U_k \quad \forall k \in N_0 \tag{14}$$

Constraints (15) and (16) ensure the delivery and pickup flow balance at each customer node, the total load entering or leaving must match the exact delivery or pickup demand [60]. Similarly, Constraints (17) through (20) ensure load conservation and balance at depots: all outgoing/incoming vehicle flows match the total assigned customer volumes, and vehicles do not carry excess load back to the depot.

$$\sum_{j\in N} T_{ji} - \sum_{j\in N} T_{ij} = DELD_i \quad \forall i \in N_1 \tag{15}$$

$$\sum_{j\in N} S_{ij} - \sum_{j\in N} S_{ji} = PDEL_i \quad \forall i \in N_1 \tag{16}$$

$$\sum_{j\in N_1} T_{kj} = \sum_{j\in N_c} DELD_j Z_{jk} \quad \forall k \in N_0 \tag{17}$$

$$\sum_{j\in N_1} T_{jk} = 0 \quad \forall k \in N_0 \tag{18}$$

$$\sum_{j\in N_1} S_{jk} = \sum_{j\in N_c} PDEL_j Z_{jk} \quad \forall k \in N_0 \tag{19}$$

$$\sum_{j\in N_1} S_{kj} = 0 \quad \forall k \in N_0 \tag{20}$$

Constraint (22) ensures that if two customers are on the same route, they must be assigned to the same depot, this maintains coherence in route planning and avoids fragmented deliveries [60].

$$T_{ij} \ge DELD_j.Q_{ij} \quad \forall i \in N, \forall j \in N_1 \tag{21}$$

$$Q_{ij} + Z_{ik} + \sum_{\substack{m\in N_0\\ m\ne k}} Z_{jm} \le 2 \quad \forall k \in N_0, \forall i,j \in N_1, i \ne j \tag{22}$$

Constraints (23) and (24) enforce that all delivery and pickup volumes must be non-negative. Constraint (25) ensures that route decisions are binary, either a vehicle travels a route segment or it does not. Constraints (26) and (27) define binary decisions for depot assignment and facility activation, respectively, ensuring operational clarity and preventing partial service logic [66].

$$T_{ij} \ge 0 \quad \forall i,j \in N \tag{23}$$

$$S_{ij} \ge 0 \quad \forall i,j \in N \tag{24}$$

$$Q_{ij} \in \{0,1\} \quad \forall i,j \in N \tag{25}$$

$$Z_{ik} \in \{0,1\} \quad \forall i \in N_1, \forall k \in N_0 \tag{26}$$

$$U_k \in \{0,1\} \quad \forall k \in N_0 \tag{27}$$

3.4. Grey MARCOS

In this study, to rank the formulated scenarios and comprehensively evaluate the alternatives under multiple criteria, the MARCOS method was adopted in a grey environment [67]. It has gained attention in solving diverse decision-making problems due to its structured process and ability to deliver stable and consistent rankings [68]. The method determines the utility functions of alternatives based on their relationship to the ideal and anti-ideal reference points. Compared to other classical MCDM techniques, MARCOS offers several advantages, including higher computational efficiency, a more straightforward structure, enhanced robustness under changing scale conditions, and immunity to the rank reversal problem [69].

In MARCOS, m alternatives are evaluated against n criteria, and each entry in the decision matrix represents the performance score of an alternative with respect to a specific criterion [70]. Alternatives are denoted by A_i and criteria by C_j, as shown in Equation (28). In this study, the method was implemented in a grey context to better handle linguistic evaluations and uncertainty in expert judgments, making it well-suited for complex, real-world decision problems.

$$X = \begin{array}{c c} & \begin{array}{cccc} C_1 & C_2 & \cdots & C_n \end{array} \\ \begin{array}{c} A_1 \\ A_2 \\ \cdots \\ A_m \end{array} & \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{21} & \cdots & x_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \end{array} \tag{28}$$

In the second step, the crisp values X obtained in the decision matrix from Step 1 are converted into grey numbers based on the predefined linguistic. As a result, the decision matrix is transformed into a grey decision matrix where each entry is represented by a grey number [71]. This transformation allows the incorporation of uncertainty and ambiguity inherent in expert evaluations, enabling a more realistic and flexible modeling of decision-makers' preferences [72]. The grey representation captures not only the estimated performance value but also the degree of hesitation and confidence around it, a crucial aspect for complex and qualitative criteria.

$$\tilde{X} = \begin{array}{c} \\ A_1 \\ A_2 \\ \dots \\ A_m \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \dots & C_n \end{array} \\ \begin{bmatrix} (x_{11}^l, x_{11}^u) & (x_{12}^l, x_{12}^u) \dots & (x_{1n}^l, x_{1n}^u) \\ (x_{21}^l, x_{21}^u) & (x_{22}^l, x_{22}^u) \dots & (x_{2n}^l, x_{2n}^u) \\ \dots & \dots \quad \dots & \dots \\ (x_{m1}^l, x_{m1}^u) & (x_{m2}^l, x_{m2}^u) \dots & (x_{mn}^l, x_{mn}^u) \end{bmatrix} \end{array} \tag{29}$$

Step 3: In this section, based on equations (30) and (31), the ideal values of A_{id} and the anti-ideal values of A_{ai} are determined [71].

$$A_{ai} = \min_{1 \le i \le m} x_{ij}, j\epsilon B^{max}, \max_{1 \le i \le m} x_{ij}, j\epsilon C^{min} \tag{30}$$

$$A_{id} = \max_{1 \le i \le m} x_{ij}, j\epsilon B^{max}, \min_{1 \le i \le m} x_{ij}, j\epsilon C^{min} \tag{31}$$

The term B means the criteria that have a profit aspect and the term C means the criteria that have a cost aspect.

Step 4: In this step, the decision matrix is normalized. Using equation (32), normalization is done for the criteria of the profit type and using equation (33), normalization is done for the criteria of the cost type [73].

$$n_{ij} = \frac{x_{id}}{x_{ij}} \ \ if \quad j\epsilon C \tag{32}$$

$$n_{ij} = \frac{x_{ij}}{x_{id}} \ \ if \quad j\epsilon B \tag{33}$$

Step 5: The normalized matrix is multiplied by the weights of the criteria using equation (34) to form the weighted normal matrix [74].

$$v_{ij} = n_{ij} * w_j \tag{34}$$

Step 6: In this step, the ideal K_i^+ and anti-ideal K_i^- degree of desirability of the options are calculated using equations (35) and (36) [74].

$$K_i^- = \frac{S_i}{S_{ai}} \tag{35}$$

$$K_i^+ = \frac{S_i}{S_{id}} \tag{36}$$

In the above equation, S_i is the sum of the values of each row in the weighted matrix, which is obtained from the following equation.

$$S_i = \sum_{i=1}^{n} v_{ij} \tag{37}$$

Step 7: Finally, the desired performance of each option is calculated using equation (38).

$$f(k_i) = \frac{K_i^+ + K_i^-}{1 + \frac{1 - f(K_i^+)}{f(K_i^+)} + \frac{1 - f(K_i^-)}{f(K_i^-)}} \tag{38}$$

In the above equation, $f(K_i^-)$ is the anti-ideal utility function and $f(K_i^+)$ is the ideal utility function for the infinitesimal, which is calculated from equations (39) and (40).

$$f(K_i^-) = \frac{K_i^+}{K_i^+ + K_i^-} \tag{39}$$

$$f(K_i^+) = \frac{K_i^-}{K_i^+ + K_i^-} \tag{40}$$

Then, based on the numbers obtained from $f(k_i)$ of each option, ranking is done in descending order.

The grey MARCOS assessment uses expert judgment to evaluate non-optimized dimensions such as the risk of implementation, organizational misalignment, and social acceptability. The panel of experts consisted of 9 domain experts with at least 8 years of experience and actual experience related to perishable agri-food or supply chain logistics, waste management, energy planning, and sustainability policy in Iran. To counter potential biases, this method uses a grey multi-criteria assessment and evaluation process and uses a grey interval evaluation method, treating uncertainties and discrepancies in expert judgments. The CPLEX solver and GAMS 33 software were used for the optimization modeling. In contrast, the grey MARCOS method used a Python 3.10 platform with standard numerical libraries and house-designed grey mathematical algorithms.

4. Results

4.1. *Case of perishable agri-food in Razavi Khorasan*

The Razavi Khorasan province is experiencing critical water stress, which makes it a significant case for water-resource-related research. As shown in the rainfall data (Fig. 4a), precipitation levels in 2024 have drastically declined across most counties compared to both the previous five-year average and long-term climatic norms. For instance, Mashhad recorded only 98 mm of rainfall in 2024, a sharp drop from the five-year average of 170.6 mm and the long-term average of 132.3 mm. Similar reductions are evident in other counties like Sabzevar (65.5 mm vs. long-term 128.6 mm) and Nishapur (124.3 mm vs. long-term 132 mm), indicating a persistent downward trend in precipitation across the region (Fig. 4b).

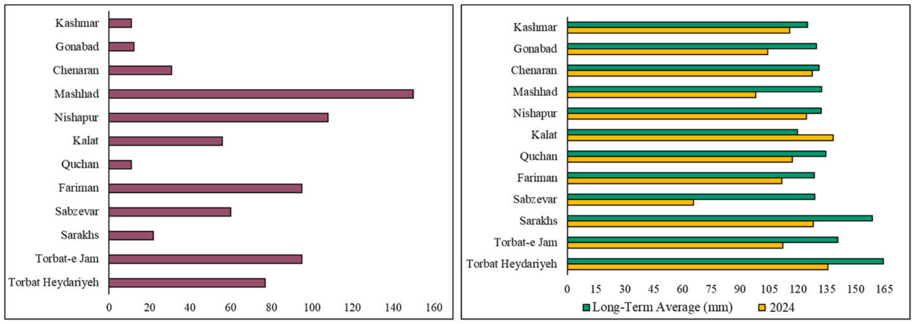
Simultaneously, the province is facing an alarming groundwater crisis. The groundwater critical storage ratios underscore the severity: Mashhad (150 MCM), Nishapur (108 MCM), and Torbat-e Jam (95 MCM) are among the most critical zones. These reflect the cumulative overextraction of groundwater resources beyond natural recharge rates.

In addition to hydro-climatic stress, the context of institutional and operational framework of agrico-food waste management in Razavi Khorasan adds further reason for the defined modeling framework. In the region, the collection and valorization of agrico-food waste are largely driven by the municipal government and related state agencies, with little involvement from for-profit logistics companies or horizontal coordination between food producers themselves. The logistics systems for collecting agrico-food waste are mostly focused on environmentally sound disposal rather than recovery, with inadequate source separation, refrigerated transport of organic materials, and decentralized transfer points for agrico-food waste. Policies are currently more focused on environmental protection and public service provision, whereas there are no drivers or policies to induce the involvement of producers, wholesalers, and for-profit logistics service providers to make a proactive contribution to closed-loop recovery of agrico-food waste.

4.2. *Defining scenarios and data structure*

To evaluate the impacts of vehicle type and environmental policy factors, six scenarios were formulated and labeled to reflect the combination of fuel type and environmental weighting (Table 1). The first group (SG5, SD5, and SE5) examines the simultaneous influence of both the CO_2 emission limit (C_{max}) and the environmental importance coefficient (λ), with each scenario representing gasoline, diesel, and electric truck configurations respectively. The second group (SG7, SD7, and SE7) isolates the effect of increasing the environmental priority (λ) while keeping the CO_2 cap constant. This structured comparison enables a robust understanding of trade-offs between environmental regulation and vehicle technology in sustainable logistics planning.

Appendix A presents the pairwise Euclidean distances between the



(a) (b)

Fig. 4. (a) Rainfall comparison across counties in Razavi Khorasan: 2024 vs. 5-year and long-term averages. (b) Groundwater critical storage levels (Million Cubic Meters) across counties in Razavi Khorasan.

Table 1
Scenario definitions based on vehicle type (gasoline, diesel, electric), maximum allowable CO_2 emissions (C_{max}), and environmental importance coefficient (λ).

Scenario	Vehicle type	Max CO_2 allowed (C_{max})	Environmental importance (λ)
SG5	Gasoline	200	0.5
SD5	Diesel	180	0.5
SE5	Electric	120	0.5
SG7	Gasoline	200	0.7
SD7	Diesel	180	0.7
SE7	Electric	120	0.7

12 service points (C, D) used in the model. These distances were calculated based on geographic coordinates and reflect the realistic spatial distribution of customer and depot locations. The values are symmetric, and only the upper triangle of the matrix is displayed to avoid redundancy. These distance inputs play a critical role in evaluating routing efficiency and minimizing total transportation costs in the optimization model.

To support the optimization model, several key input parameters are defined (Table 2). $DELD_i$ and $PDEL_i$ vary across 9 customers (C1 to C9). These values reflect the expected volume of goods that must be delivered to and collected from each customer node. Three depots (D1 to D3) are considered as potential facility locations, each with an equal capacity of 1500 units. The fixed cost associated with opening each depot is also specified and varies by location. The vehicle fleet used in the model assumes a fixed capacity of 400 units and a fixed cost of 40 per vehicle used.

In terms of environmental modeling, CO_2 emissions are incorporated based on average emission rates per vehicle-kilometer. For gasoline vehicles, the model assumes an average emission rate of 0.15 $^{kgCO_2}/_{km}$ (equivalent to 150 $^{g}/_{km}$). This is used to compute the total emissions on each route segment using the formula $e_{ik} = DC_{ik} \times 0.15$, where DC_{ik} is the distance between nodes [56]. For other vehicle types such as diesel or electric, the emission rate and consequently the C_{max} (maximum allowable $^{CO_2}/_{trip}$) differ and are adjusted accordingly in scenario analysis [75].

Table 2
Input parameters for the optimization model.

Parameter	Description	Values
$DELD_i$	Demand at customer nodes C1 to C9	[112, 120, 62, 145, 125, 120, 71, 54, 128]
$PDEL_i$	Reverse logistics at customer nodes C1 to C9	[25, 100, 15, 100, 29, 100, 17, 98, 100]
PEDFC	Fixed cost of opening depots D1 to D3	[35,53,45]
CAPD	Maximum capacity per depot	[1500, 1500, 1500]
CAPV	Maximum load per vehicle	400
vfc	Fixed cost per vehicle	40
Emission rate	CO_2 emission per km for gasoline vehicle ($^{kg}/_{km}$)	0.15

4.3. Base scenario implementation

In the base scenario labeled SD5, the model simulates a logistics network for biohydrogen supply chain operations using diesel-powered vehicles, under a moderate carbon cap ($C_{max} = 180$) and a baseline environmental priority coefficient ($\lambda = 0.5$). The bi-objective optimization aims to minimize both total logistics cost (Z_1) and carbon emissions (Z_2). The results reveal a total system cost of 656.66 units and an associated emission of 36.23 kg CO_2, demonstrating a balanced trade-off between economic and environmental objectives.

The model's route assignments and flow allocations are presented in Tables 3 and 4. Table 3 illustrates the quantity of delivery transported between nodes. Key delivery flows are observed from C3 to C1 (112 units), C4 to C9 (128 units), and C6 to C4 (273 units), suggesting that these customer pairs are spatially and logistically aligned for efficient forward logistics. Depots D1, D2, and D3 are selectively activated based on proximity and load-balancing: D1 services C8; D2 covers C2 and C6; and D3 handles C7.

Table 4 illustrates the reverse logistics flows under Scenario SD5, revealing not only operational efficiency but also strategic depot utilization patterns. Notably, D3 handles a significant inbound load from both C1 (57 units) and C9 (300 units), positioning it as a critical hub in the circular network. This clustering suggests potential for economies of scale in energy conversion infrastructure at D3, making it a high-priority location for future investment or expansion. Meanwhile, the isolated link between C2 and D2 (100 units) reflects the need for targeted routing to ensure coverage of less-connected zones without overburdening depots. The presence of lateral flows, such as waste moved from C3 to C1 or C6 to C4, signals spatial imbalances in waste availability versus depot proximity, reinforcing the importance of flexible routing algorithms in minimizing empty trips and enhancing backhaul efficiency. Overall, the configuration optimally balances depot capacities, travel distances, and collection demand, ensuring a resilient and resource-efficient reverse

Table 3
Optimal delivery routes and transported quantities (T_{ij}) under Scenario SD5, showing active links between customers and depots based on spatial proximity and demand volume.

	C1	C2	C3	C4	C5	C6	C7	C8	C9
C3	112	0	0	0	0	0	0	0	0
C4	0	0	0	0	0	0	0	0	128
C6	0	0	0	273	0	0	0	0	0
C7	0	0	174	0	0	0	0	0	0
C8	0	0	0	0	125	0	0	0	0
D1	0	0	0	0	0	0	0	179	0
D2	0	120	0	0	0	393	0	0	0
D3	0	0	0	0	0	0	245	0	0

Table 4
Reverse logistics flows (S_{ij}) for food waste collection in Scenario SD5, indicating effective backhaul operations and depot utilization for circular supply chain performance.

	C1	C3	C4	C5	C9	D1	D2	D3
C1	0	0	0	0	0	0	0	57
C2	0	0	0	0	0	0	100	0
C3	32	0	0	0	0	0	0	0
C4	0	0	0	0	200	0	0	0
C5	0	0	0	0	0	127	0	0
C6	0	0	100	0	0	0	0	0
C7	0	17	0	0	0	0	0	0
C8	0	0	0	98	0	0	0	0
C9	0	0	0	0	0	0	300	0

logistics system that supports both environmental goals and logistical feasibility.

Fig. 5 illustrates the optimized flow of perishable agri-food waste in the closed-loop supply chain model under the base scenario. Each node represents either a customer location (waste source) or an activated depot (conversion facility), and the directed arrows indicate the optimized routing of waste materials for biohydrogen production. The model identifies the most efficient transportation paths based on cost and emission constraints, enabling the dynamic allocation of waste flows between customer nodes and depots. Interestingly, certain customer nodes act as intermediate collection points, redistributing waste to downstream depots, a reflection of spatial clustering and routing efficiency.

4.4. Scenario-based sensitivity analysis

In sensitivity analysis through this model, the anaerobic digestion process parameters are considered fixed, reflecting the current technological setup of state-operated biohydrogen facilities in Iran. These plants are not expected to undergo substantial changes in the short to medium term. As such, instead of analyzing internal conversion dynamics, our scenario analysis concentrates on the transportation segment of the supply chain, where tangible shifts are emerging. Given the growing national emphasis on electrifying logistics fleets, we examined alternative vehicle-fuel strategies, emissions thresholds, and environmental prioritization, offering realistic insights into how the system might evolve under plausible policy-driven transitions.

To assess the trade-offs between cost efficiency and environmental performance, Fig. 6 illustrates the results of six logistics scenarios (SG5, SG7, SD5, SD7, SE5, SE7), each representing a unique combination of vehicle type (gasoline, diesel, electric) and environmental weighting factor ($\lambda = 0.5$ vs. 0.7). Fig. 6a corresponds to the first objective, total system cost (Z_1), while the Fig. 6b shows the second objective, carbon emissions (Z_2). From Fig. 6a, it is evident that scenarios using electric trucks (SE5 and SE7) significantly outperform others in terms of cost reduction, with the lowest total cost of 600.83 units. In contrast, diesel (SD5, SD7: 656.66 units) and gasoline (SG5, SG7: 640.83 units) scenarios incur higher costs. Interestingly, increasing the environmental weighting from 0.5 to 0.7 (e.g., SG5 → SG7) has no impact on total cost, indicating that financial outcomes remain static under these policy shifts.

Fig. 6b presents a sharper contrast in environmental impact. Electric scenarios (SE5: 13.04 kg CO_2, SE7: 12.99 kg CO_2) dramatically reduce emissions compared to diesel (SD5: 36.23, SD7: 36.27) and gasoline scenarios (SG5: 42.87, SG7: 42.93). Notably, raising λ slightly improves emissions performance (e.g., SD7 slightly better than SD5), showing that higher environmental prioritization does shift marginal allocation decisions to cleaner routes or depot configurations.

From an absolute perspective, it is observable that there are visible economic and environment-related variations for different vehicles. When Compared to the Gasoline-based scenarios (SG5 and SG7), the diesel variants (SD5 and SD7) offer a cumulative decrease of around 15 %–16 % in overall CO_2 emissions while incurring comparable logistical costs of transportation owing to not only policy-related factors but also their increased payload efficiency and lower emissions per waste transported per unit of fuel consumed. The gasoline vehicles attain their maximum emissions earlier in their lifespan and are therefore less fuel-efficient for route consolidation and incur higher marginal costs, while the electric vehicles (SE5 and SE7) offer maximum reductions of over 65 % relative to the gasoline variants and also incur the lowest cumulative system cost owing to reduced energy consumption and improved route optimization owing to binding emissions limits.

4.5. Grey MARCOS analysis of strategic alternatives

Following the optimization and scenario analysis, the study advances toward evaluating how these theoretical configurations translate into actionable strategies under real-world conditions. While the model outputs define cost-optimal and emission-compliant logistics structures, successful implementation hinges on managerial feasibility, technological readiness, and policy alignment. To navigate this complexity, nine strategic alternatives (O1–O9) were identified through a synthesis of expert input and prior studies, encompassing a blend of vehicle upgrades, phased electrification, and process innovations. These strategies aim to enhance sustainability while acknowledging infrastructure, economic, and behavioral constraints specific to Iran's agri-food sector. The use of the grey MARCOS method allows the incorporation of uncertainty and subjectivity into the assessment process, enabling a nuanced ranking of options based on eight criteria covering economic, environmental, operational, and social dimensions. For instance, while O3 (full electrification) promises long-term decarbonization benefits, its feasibility is hampered by high upfront costs and limited charging

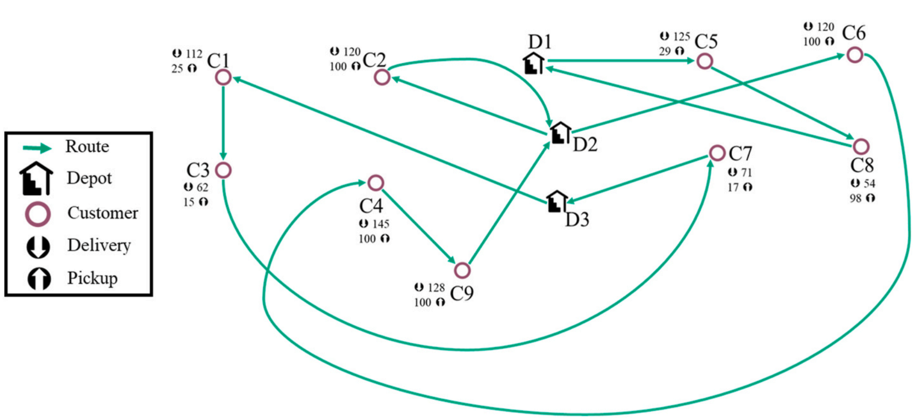


Fig. 5. Optimized reverse logistics network of perishable agri-food waste flows across customer and depot nodes under the base scenario.

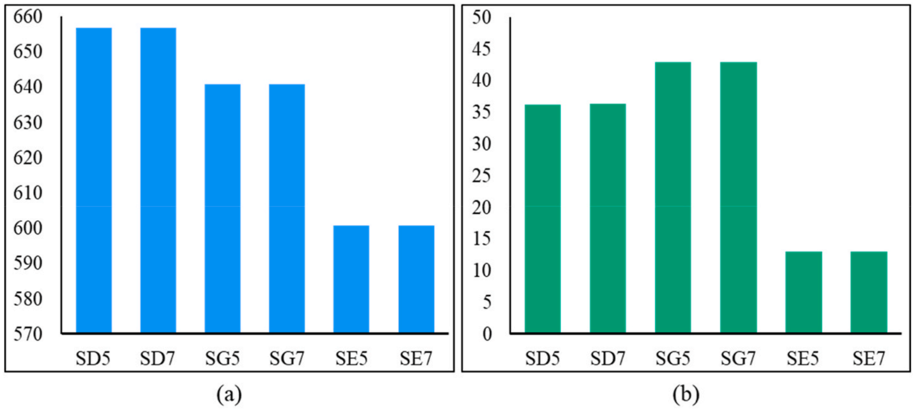


Fig. 6. Scenario comparison of six vehicle-based strategies in terms of (a) total cost (Z_1) and (b) total CO_2 emissions (Z_2).

infrastructure. Conversely, O7–O9, which focus on routing optimization, logistics collaboration, and maintenance improvements, offer near-term gains with minimal investment. Table 5 outlines these strategies, providing decision-makers with a menu of context-sensitive options that can be prioritized based on regional readiness and resource availability.

To incorporate expert uncertainty in qualitative evaluations, linguistic terms were translated into grey number intervals based on predefined scales (Appendix B). This allowed the integration of imprecise expert judgments into the grey MARCOS analysis. The evaluation was based on eight grey-weighted criteria, categorized as either positive (beneficial when maximized) or negative (preferably minimized), as shown in Table 6. These include food spoilage risks, energy reliability, infrastructure costs, regulatory alignment, and social acceptance. The grey weight intervals reflect expert uncertainty and judgment imprecision, capturing a more realistic decision-making environment.

Appendix C provides the mean (μ) and standard deviation (σ) of expert assessments for each strategic alternative across all evaluation criteria, offering a statistical summary of judgment variability and consistency. Table 7 summarizes the normalized performance scores derived using the grey MARCOS method. The key performance indicators, anti-ideal closeness (K^-), ideal closeness (K^+), and their associated utility functions, are used to calculate the final compromise score f(k) for each strategy. A higher f(k) value indicates a more desirable alternative. According to the results, O7 (smart routing and capacity planning) ranked first, followed by O8 (shared logistics) and O9 (preventive maintenance). These top-ranked options share a common feature: they require lower capital investment while achieving operational and environmental gains, aligning well with both cost constraints and system sustainability goals.

Table 7 presents the grey MARCOS rankings of nine strategic logistics alternatives, incorporating performance across eight sustainability criteria. The analysis reveals that O7 (smart routing and capacity planning) outperforms all others with the highest utility score (f(K) = 0.464), highlighting the immediate impact of operational optimization without major infrastructure changes. O8 (shared logistics participation) and O9 (preventive maintenance practices) follow closely, offering cost-effective, low-disruption pathways for emissions and cost reduction. In contrast, O3 (full electrification), despite its environmental benefits, ranks lowest due to high capital costs, technological uncertainty, and long lead times, issues particularly relevant in the context of developing regions like Iran. These results underline a critical insight: high-impact does not always equate to high-feasibility. Alternatives like O1–O6, focused on vehicle upgrades, present moderate utility due to trade-offs between long-term sustainability and short-term implementation challenges. The grey MARCOS approach captures these nuances by incorporating expert-based uncertainty and weighting sensitivity, making the framework more aligned with dynamic policy environments. Overall, this prioritization supports a tiered strategy, starting with collaborative and operational reforms (O7–O9) while gradually preparing for technology-driven transitions (O4–O6). These insights can guide policymakers in allocating resources and designing phased interventions that align with circular economy principles and WEF nexus goals.

Table 5
Strategic alternatives evaluated for sustainable logistics transitions.

Code	Strategy description	Reference
O1	Maintain current diesel truck fleet	[76]
O2	Replace old diesel trucks with newer, fuel-efficient diesel models	[77]
O3	Full replacement of diesel fleet with electric trucks	[76]
O4	Mixed deployment of electric and diesel trucks based on route characteristics	[78]
O5	Phased electrification over time (gradual replacement)	[79]
O6	Adoption of plug-in hybrid electric vehicles (PHEVs)	[80]
O7	Operational optimization through smart routing and capacity planning	[81]
O8	Participation in shared logistics or freight pooling	[82]
O9	Enhancing preventive maintenance practices to improve fuel efficiency	[83]

Table 6
Decision criteria and grey weights for evaluating logistics strategies.

Code	Criterion description	Grey weight	Type	Reference
CR1	Risk of food spoilage due to inadequate logistics in temperature-sensitive shipments	[0.72, 0.84]	Negative	[3]
CR2	Energy reliability required for charging/refueling	[0.65, 0.77]	Positive	[84]
CR3	Food delivery lead time consistency (impact on food system resilience)	[0.61, 0.73]	Positive	[85]
CR4	Alignment with local/regional sustainability regulations on emissions and land use	[0.56, 0.68]	Positive	[86]
CR5	Trade-off flexibility between emissions and operational cost	[0.49, 0.60]	Positive	[87]
CR6	Initial capital investment required for fleet transition, infrastructure, or technology upgrades	[0.68, 0.80]	Negative	[88]
CR7	Operational risk due to time delays, disruptions, or downtime in transportation logistics	[0.66, 0.78]	Negative	[82]
CR8	Social acceptability and stakeholder alignment, including public perception and policy support	[0.70, 0.82]	Positive	[89]

Table 7
Grey MARCOS ranking of strategic logistics alternatives based on eight evaluation criteria.

Code	K^-	K^+	$F(K^-)$	$F(K^+)$	$(1-f(K^-))/f(K^-)$	$(1-f(K^+))/f(K^+)$	f(K)	Ranking
O1	2.049	0.392	0.149	0.777	5.726	0.286	0.348	4
O2	1.850	0.399	0.152	0.702	5.599	0.424	0.320	8
O3	1.625	0.370	0.140	0.616	6.125	0.623	0.257	9
O4	1.853	0.421	0.160	0.703	5.267	0.423	0.340	5
O5	1.835	0.416	0.158	0.696	5.336	0.436	0.332	6
O6	1.838	0.410	0.155	0.697	5.433	0.434	0.327	7
O7	2.152	0.484	0.183	0.817	4.451	0.225	0.464	1
O8	1.975	0.450	0.171	0.749	4.860	0.334	0.392	2
O9	1.986	0.426	0.162	0.753	5.181	0.327	0.371	3

5. Discussion

This study has combined multi-objective mathematical optimization with scenario ranking using the grey MARCOS method to provide an actionable decision-support framework for perishable agri-food logistics decarbonization. The optimization model enabled the identification of feasible configurations for biohydrogen supply chains under varying vehicle types and carbon thresholds, while the grey MARCOS method helped assess nine implementation strategies based on multiple qualitative and operational criteria. Among the evaluated options, operational optimization through smart routing (O7), shared logistics (O8), and preventive maintenance improvements (O9) emerged as the most desirable strategies in terms of combined performance, according to the ranking scores derived from the utility functions.

Fig. 7 offers a two-part visual synthesis of the scenario evaluation. Fig. 7a illustrates a strategic map where each option is plotted based on its MARCOS score (Y-axis) and its average time-to-implementation horizon (X-axis) as assessed by experts. The color-coded zones, short-term, medium-term, and long-term, indicate practical feasibility over time. The dashed line represents the equal-weight trade-off frontier, where higher utility aligns proportionally with ease of implementation. O7 stands out in the upper-left quadrant, indicating both high desirability and near-term feasibility. In contrast, options like O3 (full electrification) fall into the bottom-right region, suggesting high implementation barriers despite long-term value. Fig. 7b complements this analysis by offering a direct comparison of strategy rankings, helping stakeholders visually prioritize interventions.

5.1. Managerial implications

In the present study, the emphasis on operational or logistics-focused strategies can be understood within the limitations of existing governance structures and policies. In a situation like Razavi Khorasan, with the current division of responsibilities on managing waste among concerned local authority structures, producers, and transportation organizations, overall institutional or incentive-driven changes within the marketplace cannot easily happen on a large scale. Strategies like smart routes, logistics pools, or proactive maintenance, therefore, are more governance-friendly and do not necessarily demand changes on a short notice scale.

The findings highlight a delicate balance between sustainability ambition and real-world feasibility. Electrification-focused strategies such as O3 and phased hybrid adoption in O5 offer promising long-term decarbonization outcomes but require significant upfront investments, grid upgrades, and behavioral adaptation, making them less viable for immediate deployment in regions like Razavi Khorasan. In contrast, strategies like O7 (co-loading logistics), O8 (existing vehicle reallocation), and O9 (shared depot use) can deliver meaningful environmental and economic benefits within a short timeframe (1–2 years), with minimal disruption to current operations. Managers should thus consider sequencing their implementation efforts, first addressing low-cost coordination-based improvements, then gradually shifting toward infrastructure-intensive transitions. This ensures early emissions reductions while maintaining financial and logistical realism.

From a supply chain improvement perspective, the results suggest that enhancing the reliability and spatial coverage of organic waste collection, especially from high-yield clusters such as urban fruit markets or bakery nodes, can significantly increase bioconversion potential. Policymakers should support route consolidation between neighboring customer nodes, invest in modular pretreatment units at depots, and promote digital platforms for coordinating waste availability. Moreover, emissions caps and environmental weights in our scenarios show that prioritizing cleaner transport technologies must go hand-in-hand with optimizing depot activation schedules to avoid underutilized trips. A

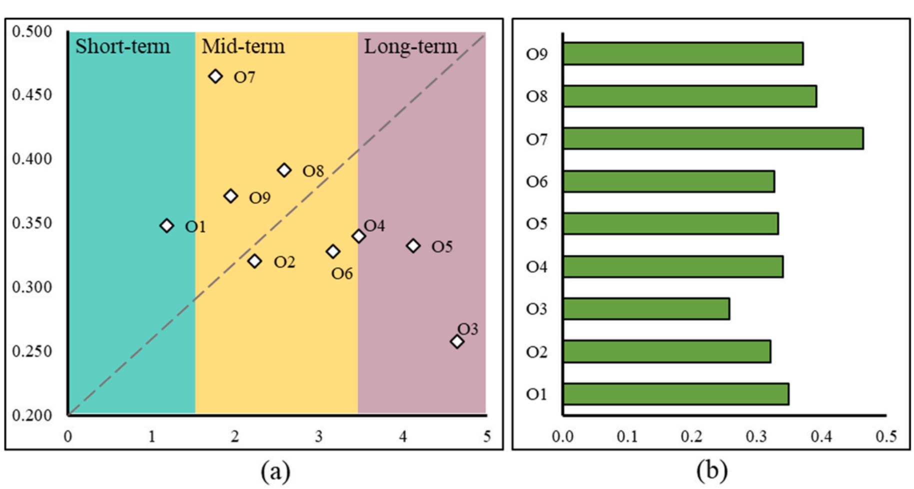


Fig. 7. (a) Strategic positioning of implementation strategies based on expert-elicited time horizon and MARCOS performance scores, and (b) Ranking of all nine strategies based on final utility scores derived from the grey MARCOS method.

smart integration of logistics coordination, phased EV deployment, and localized infrastructure investments offers the most robust pathway toward scalable, circular biohydrogen systems tailored to Iran's drought-prone and resource-constrained context.

6. Conclusion

This research developed an integrated decision-support framework for the optimization of the biohydrogen supply chain from perishable agri-food waste, merging a WEF-oriented problem framing with closed-loop supply chain optimization and grey MARCOS-based strategy evaluation. Results show that low-capital operational measures, such as smart routing and shared logistics, are the most feasible and preferred by stakeholders when compared to capital-intensive options, at least for baseline adoption, while presenting some clear trade-offs between near-term implementable strategies and longer-term transitions such as full fleet electrification. The empirical application focuses on one province and a limited network size, but by its very nature, the proposed framework is scalable and transferable. This bi-objective optimization structure, scenario design, and evaluation logic can easily be adapted to other regions, agri-food systems, or organic waste streams simply by recalibrating parameters, policy constraints, and stakeholder criteria, without changing the model structure. This is supportive for immediate applications within diverse contexts of institutional capacity, infrastructure maturity, and product mixes where large-scale infrastructure investments are not directly feasible.

Several of these limitations point at obvious avenues for future research. The water and energy dimensions are represented indirectly, in that water use is only accounted for in terms of virtual water loss, and the performance of the biohydrogen conversion is treated exogenously, while investment costs and ownership structures are excluded under the assumption of pre-existing facilities. Future work should, therefore, focus on incorporating explicit water-use and energy-consumption constraints, expand the nexus to include land and waste, and socio-economic and governance factors such as investment incentives and heterogeneity among stakeholders. Further, behavioral modeling and pilot-scale validation of selected strategies would help to strengthen the empirical grounding and support the development of actionable transition pathways to circular bioenergy systems.

CRediT authorship contribution statement

Moein Khazaei: Writing – original draft, Validation, Investigation, Conceptualization. **Maryam Mehrparvar:** Writing – original draft, Methodology, Conceptualization. **Kannan Govindan:** Writing – review & editing, Supervision, Project administration, Methodology. **Saeid Barazandeh:** Writing – review & editing, Formal analysis, Conceptualization. **Amirhossein Mostofi:** Writing – review & editing, Validation, Investigation, Formal analysis. **Zahra Mohemmi:** Writing – review & editing, Validation, Formal analysis.

Declaration of competing interest

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

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ijhydene.2026.153731.

References

[1] Ali SM, Acquaye A. An examination of water-energy-food nexus: from theory to application. Renew Sustain Energy Rev 2024;202:114669.
[2] Verma N, et al. Food-energy-water nexus in compliance with sustainable development goals for integrating and managing the core environmental verticals for sustainable energy and circular economy. Sci Total Environ 2024;930:172649.
[3] Varjani S, et al. Nexus of food waste and climate change framework: unravelling the links between impacts, projections, and emissions. Environ Pollut 2024;344: 123387.
[4] Chen C, Chaudhary A, Mathys A. Nutritional and environmental losses embedded in global food waste. Resour Conserv Recycl 2020;160:104912.
[5] Heydari M. Cultivating sustainable global food supply chains: a multifaceted approach to mitigating food loss and waste for climate resilience. J Clean Prod 2024;442:141037.
[6] Barrett CB. Overcoming global food security challenges through science and solidarity. Am J Agric Econ 2021;103(2):422–47.
[7] Kuiper M, Cui HD. Using food loss reduction to reach food security and environmental objectives–A search for promising leverage points. Food Policy 2021;98:101915.
[8] Deihimfard R, Rahimi-Moghaddam S, Collins B, Azizi K. Future climate change could reduce irrigated and rainfed wheat water footprint in arid environments. Sci Total Environ 2022;807:150991.
[9] Mrabet R. Sustainable agriculture for food and nutritional security. In: Sustainable agriculture and the environment. Elsevier; 2023. p. 25–90.
[10] Bag S, Routray S, Rahman MS, Shrivastav SK. Investigate the effect of green hydrogen supply chain integration on supply chain resilience: organization information processing theory perspective. Int J Prod Econ 2025;284:109613.
[11] Do Q, Ramudhin A, Colicchia C, Creazza A, Li D. A systematic review of research on food loss and waste prevention and management for the circular economy. Int J Prod Econ 2021;239:108209.
[12] Paraskevopoulou C, Vlachos D, Bechtsis D, Tsolakis N. An assessment of circular economy interventions in the peach canning industry. Int J Prod Econ 2022;249: 108533.
[13] Barati AA, Pour MD, Sardooei MA. Water crisis in Iran: a system dynamics approach on water, energy, food, land and climate (WEFLC) nexus. Sci Total Environ 2023;882:163549.
[14] Mekonnen MM, et al. Trends and environmental impacts of virtual water trade. Nat Rev Earth Environ 2024:1–16.
[15] Agnusdei GP, Coluccia B, Pacifico AM, Miglietta PP. Towards circular economy in the agrifood sector: water footprint assessment of food loss in the Italian fruit and vegetable supply chains. Ecol Indic 2022;137:108781.
[16] Yang M, et al. Circular economy strategies for combating climate change and other environmental issues. Environ Chem Lett 2023;21(1):55–80.
[17] Ganeshan P, et al. How does techno-economic analysis and lifecycle assessment help in commercializing the biohydrogen supply chain? Fuel 2023;341:127601.
[18] Kayan RR, Jauhar SK, Kamble SS, Belhadi A. Optimizing bio-hydrogen production from agri-waste: a digital twin approach for sustainable supply chain management and carbon neutrality. Comput Ind Eng 2025;204:111021.
[19] Goh QH, Tan W-S, Ho YK, Chew IML. Integrated optimisation of biowaste-based green hydrogen supply chains from economic, environmental, and safety perspectives. Comput Chem Eng 2025;199:109120.
[20] Khalilpour KR, Pace R, Karimi F. Retrospective and prospective of the hydrogen supply chain: a longitudinal techno-historical analysis. Int J Hydrogen Energy 2020;45(59):34294–315.
[21] Amaya-Santos G, Chari S, Sebastiani A, Grimaldi F, Lettieri P, Materazzi M. Biohydrogen: a life cycle assessment and comparison with alternative low-carbon production routes in UK. J Clean Prod 2021;319:128886.
[22] Lee D-H. Building evaluation model of biohydrogen industry with circular economy in Asian countries. Int J Hydrogen Energy 2019;44(6):3278–89.
[23] Stillitano T, Falcone G, Iofrida N, Spada E, Gulisano G, De Luca AI. A customized multi-cycle model for measuring the sustainability of circular pathways in agri-food supply chains. Sci Total Environ 2022;844:157229.
[24] Bolívar J, Cantillo V, Miranda P. Agri–food supply chain design for perishable products: application to small-scale farmers. Operational Research 2025;25(2):26.
[25] Beheshti S, Heydari J, Sazvar Z. Food waste recycling closed loop supply chain optimization through renting waste recycling facilities. Sustain Cities Soc 2022;78: 103644.
[26] Tian H, et al. A closed loop case study of decentralized food waste management: system performance and life cycle carbon emission assessment. Sci Total Environ 2023;899:165783.
[27] Tomić T, Schneider DR. The role of energy from waste in circular economy and closing the loop concept–energy analysis approach. Renew Sustain Energy Rev 2018;98:268–87.
[28] Allouche J. Nexus framing of sustainability issues: feasibility, synergies, and trade-offs in terms of water-energy-food. Annu Rev Environ Resour 2024;49(1):501–18.
[29] Hussein H, Ezbakhe F. The water–employment–migration nexus: buzzword or useful framework? Dev Policy Rev 2023;41(3):e12676.
[30] Naderi MM, Mirchi A, Bavani ARM, Goharian E, Madani K. System dynamics simulation of regional water supply and demand using a food-energy-water nexus approach: application to Qazvin Plain, Iran. J Environ Manag 2021;280:111843.
[31] Samadi-Foroushani M, Keyhanpour MJ, Musavi-Jahromi SH, Ebrahimi H. Integrated water resources management based on water governance and water-food-energy nexus through system dynamics and social network analyzing approaches. Water Resour Manag 2022;36(15):6093–113.
[32] You C, Han S, Kim J. Integrative design of the optimal biorefinery and bioethanol supply chain under the water-energy-food-land (WEFL) nexus framework. Energy 2021;228:120574.

[33] Rubinsin NJ, et al. Modelling and optimisation of oil palm biomass value chains and the environment–food–energy–water nexus in peninsular Malaysia. Biomass Bioenergy 2021;144:105912.
[34] Yuan M-H, Lo S-L. Principles of food-energy-water nexus governance. Renew Sustain Energy Rev 2022;155:111937.
[35] Pereira Ribeiro JM, et al. A proposal of a balanced scorecard to the water, energy and food nexus approach: brazilian food policies in the context of sustainable development goals. Stoch Environ Res Risk Assess 2021;35:129–46.
[36] Itayi CL, Mohan G, Saito O. Understanding the conceptual frameworks and methods of the food–energy–water nexus at the household level for development-oriented policy support: a systematic review. Environ Res Lett 2021;16(3):033006.
[37] Al-Saidi M, Hussein H. The water-energy-food nexus and COVID-19: towards a systematization of impacts and responses. Sci Total Environ 2021;779:146529.
[38] Afkhami P, Zarrinpoor N. The energy-water-food-waste-land nexus in a GIS-based biofuel supply chain design: a case study in Fars province, Iran. J Clean Prod 2022;340:130690.
[39] Li Y, et al. Identifying the critical transmission sectors with energy-water nexus pressures in China's supply chain networks. J Environ Manag 2021;289:112518.
[40] Romero-Perdomo F, González-Curbelo MÁ. Integrating multi-criteria techniques in life-cycle tools for the circular bioeconomy transition of agri-food waste biomass: a systematic review. Sustainability 2023;15(6):5026.
[41] Bui T-D, Rosiana R, Tsai F-M, Chiu AS, Tseng M-L. Circular economy challenges under uncertainty in the Indonesian fashion industry: a causal hierarchical model. Int J Prod Econ 2025:109719.
[42] Chakraborty S, Ji S. A review of integrating space syntax analysis into heritage impact assessment: a comprehensive framework for sustainable historic urban development. Int J Unity Sci 2025;29(1):123–50.
[43] Poponi S, Arcese G, Pacchera F, Martucci O. Evaluating the transition to the circular economy in the agri-food sector: selection of indicators. Resour Conserv Recycl 2022;176:105916.
[44] Vrachioli M, et al. WEFE nexus unveiled: a comprehensive review of monitoring and modelling methods in the water-energy-food-ecosystems nexus. Environ Res Lett 2025.
[45] Duncan AJ, Ayantunde A, Blummel M, Amole T, Padmakumar V, Moran D. Applying circular economy principles to intensification of livestock production in Sub-Saharan Africa. Outlook Agric 2023;52(3):327–38.
[46] Kashyap A, Yadav D, Shukla OJ, Kumar R. Unraveling barriers to food loss and waste in perishable food supply chain: a way toward sustainability. Environ Dev Sustain 2024;26(10):26817–37.
[47] Izadian AB, Pasandideh SHR, Abad ARKK. A new approach for reliability modeling in green closed-loop supply chain design under post-pandemic conditions: a case study. Comput Chem Eng 2024;189:108803.
[48] Abbas H, Zhao L, Gong X, Faiz N. The perishable products case to achieve sustainable food quality and safety goals implementing on-field sustainable supply chain model. Soc Econ Plann Sci 2023;87:101562.
[49] Yang H, et al. Optimal planning of local biomass-based integrated energy system considering anaerobic co-digestion. Appl Energy 2022;316:119075.
[50] Mahéo A, Rossit DG, Kilby P. Solving the integrated bin allocation and collection routing problem for municipal solid waste: a Benders decomposition approach. Ann Oper Res 2023;322(1):441–65.
[51] Nguyen P-H, Nguyen L-AT, Nguyen T-HT, Vu T-G. Exploring complexities of innovation capability in Vietnam's IT firms: insights from an integrated MCDM model-based grey theory. J Open Innov Technol Mark Complex 2024:100328.
[52] Heal K, et al. Water quality: the missing dimension of water in the water–energy–food nexus. Hydrol Sci J 2021;66(5):745–58.
[53] Chi Y, Xu W, Xiao M, Wang Z, Zhang X, Chen Y. Fuel-cycle based environmental and economic assessment of hydrogen fuel cell vehicles in China. Energy 2023;282:128773.
[54] Ahmed R, He Q, Garza-Reyes JA. The sustainable configuration of a circular economy in the agri-food supply chain: a case study of the sugar cane supply chain. Manag Environ Qual Int J 2025;36(4):1013–33.
[55] Zhu B, Sun Y, Zhao J, Han J, Zhang P, Fan T. A critical scenario search method for intelligent vehicle testing based on the social cognitive optimization algorithm. IEEE Trans Intell Transport Syst 2023;24(8):7974–86.
[56] Heidari E, Bikdeli S, Mansouri Daneshvar MR. A dynamic model for CO2 emissions induced by urban transportation during 2005–2030, a case study of Mashhad, Iran. Environ Dev Sustain 2023;25(5):4217–36.
[57] Vijayaraghavan K, Ahmad D, Soning C. Bio-hydrogen generation from mixed fruit peel waste using anaerobic contact filter. Int J Hydrogen Energy 2007;32(18):4754–60.
[58] Soltan M, Elsamadony M, Mostafa A, Awad H, Tawfik A. Nutrients balance for hydrogen potential upgrading from fruit and vegetable peels via fermentation process. J Environ Manag 2019;242:384–93.
[59] Wang Y, Wang X, Wei Y, Sun Y, Fan J, Wang H. Two-echelon multi-depot multi-period location-routing problem with pickup and delivery. Comput Ind Eng 2023;182:109385.
[60] Yu VF, Lin S-Y. Solving the location-routing problem with simultaneous pickup and delivery by simulated annealing. Int J Prod Res 2016;54(2):526–49.
[61] Ehsani M, Ahmadi A, Fadai D. Modeling of vehicle fuel consumption and carbon dioxide emission in road transport. Renew Sustain Energy Rev 2016;53:1638–48.
[62] Chen X, Wang T, Thomas BW, Ulmer MW. Same-day delivery with fair customer service. Eur J Oper Res 2023;308(2):738–51.
[63] Orenstein I, Raviv T. Parcel delivery using the hyperconnected service network. Transport Res E Logist Transport Rev 2022;161:102716.
[64] Ancele Y, Hà MH, Lersteau C, Matellini DB, Nguyen TT. Toward a more flexible VRP with pickup and delivery allowing consolidations. Transport Res C Emerg Technol 2021;128:103077.
[65] Azad T, Rahman HF, Chakrabortty RK, Ryan MJ. Optimization of integrated production scheduling and vehicle routing problem with batch delivery to multiple customers in supply chain. Memetic Computing 2022;14(3):355–76.
[66] Reihaneh M, Ghoniem A. A branch-and-price algorithm for a vehicle routing with demand allocation problem. Eur J Oper Res 2019;272(2):523–38.
[67] Ali J. A q-rung orthopair fuzzy MARCOS method using novel score function and its application to solid waste management. Appl Intell 2022;52(8):8770–92.
[68] Foukolaei PZ, Asari FA, Khazaei M, Gholian-Jouybari F, Hajiaghaei-Keshteli M. From responsible sourcing of wastes to sustainable energy consumption in the blue hydrogen supply chain: case of nearshoring in Nuevo Leon. Int J Hydrogen Energy 2024;77:1387–400.
[69] Shekhovtsov A, Kizielewicz B, Sałabun W. Advancing individual decision-making: an extension of the characteristic objects method using expected solution point. Inf Sci 2023;647:119456.
[70] Ali J. A novel score function based CRITIC-MARCOS method with spherical fuzzy information. Comput Appl Math 2021;40(8):280.
[71] Abdulla A, Baryannis G, Badi I. An integrated machine learning and MARCOS method for supplier evaluation and selection. Decis Anal J 2023;9:100342.
[72] Younis M, Ashraf S, Abdullah S, Shahid T, KC G. Strategic MARCOS model for optimizing renewable energy investments under pythagorean hesitant fuzzy assessments. Advances in Fuzzy Systems 2025;2025(1):6193403.
[73] Fan J, Wang S, Wu M. An integrated FMEA approach using best-worst and MARCOS methods based on D numbers for prioritization of failures. J Intell Fuzzy Syst 2021;41(2):2833–46.
[74] Majumder P. An integrated trapezoidal fuzzy FUCOM with single-valued neutrosophic fuzzy MARCOS and GMDH method to determine the alternatives weight and its applications in efficiency analysis of water treatment plant. Expert Syst Appl 2023;225:120087.
[75] Liu Y, Huang W, Lin X, Xu R, Li L, Ding H. Variation of spatio-temporal distribution of on-road vehicle emissions based on real-time RFID data. J Environ Sci 2022;116:151–62.
[76] Cheng X, Lin J. Is electric truck a viable alternative to diesel truck in long-haul operation? Transport Res Transport Environ 2024;129:104119.
[77] Gao Z, et al. The evaluation of developing vehicle technologies on the fuel economy of long-haul trucks. Energy Convers Manag 2015;106:766–81.
[78] García A, Monsalve-Serrano J, Martinez-Boggio S, Gaillard P. Impact of the hybrid electric architecture on the performance and emissions of a delivery truck with a dual-fuel RCCI engine. Appl Energy 2021;301:117494.
[79] Borlaug B, et al. Heavy-duty truck electrification and the impacts of depot charging on electricity distribution systems. Nat Energy 2021;6(6):673–82.
[80] Singh H, Ambikapathy A, Logavani K, Arun Prasad G, Thangavel S. Plug-in hybrid electric vehicles (PHEVs). Electric vehicles: modern technologies and trends. 2021. p. 53–72.
[81] Jayachandran M, Reddy CR, Padmanaban S, Milyani A. Operational planning steps in smart electric power delivery system. Sci Rep 2021;11(1):17250.
[82] Hu S, et al. Sustainable impact analysis of freight pooling strategies on city crowdsourcing logistics platform. Transport Res Transport Environ 2024;130:104167.
[83] Kattan IA, Hassan AK. A case study on improving the effectiveness of preventive maintenance. Int J Manag Sci Eng Manag 2010;5(5):353–61.
[84] Chen X, Pang Z, Zhang M, Jiang S, Feng J, Shen B. Techno-economic study of a 100-MW-class multi-energy vehicle charging/refueling station: using 100% renewable, liquid hydrogen, and superconductor technologies. Energy Convers Manag 2023;276:116463.
[85] Cole MB, Augustin MA, Robertson MJ, Manners JM. The science of food security. npj Science of Food 2018;2(1):14.
[86] Colocci A, Gioia E, Casareale C, Marchetti N, Marincioni F. The role of sustainable energy and climate action plans: synergies with regional sustainable development strategies for a local 2030 agenda. Environ Dev 2023;47:100894.
[87] Guo S, Kutanoglu E, Goodarzi S, Singh M. Exploring the cost–carbon trade-off in using a mixed fleet of hydrogen trucks and diesel trucks. Decis Sci J 2024.
[88] Comello S, Glenk G, Reichelstein S. Transitioning to clean energy transportation services: life-cycle cost analysis for vehicle fleets. Appl Energy 2021;285:116408.
[89] Sugihara C, Hardman S, Kurani K. Social, technological, and economic barriers to heavy-duty truck electrification. Research in Transportation Business & Management 2023;51:101064.