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A systematic literature review of the logistics planning for sustainable bioenergy based on Forestry, Agricultural, and municipal solid waste value chains☆

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ABSTRACT

Sustainable bioenergy production is essential for mitigating greenhouse gas emissions and reducing dependence on fossil fuels. The logistics of managing dispersed and low-value biomass from forestry, agricultural, and municipal solid waste value chains pose significant challenges, including high transportation costs, seasonal availability, and storage limitations. This systematic literature review examines the critical operations, including collection, transportation, and preprocessing, necessary to optimize bioenergy supply chains. A central contribution of this paper is an analysis of integrating biomass value chains through collaborative models that leverage shared infrastructure and adaptive logistics to enhance cost efficiency and resource utilization. It also identifies critical gaps in optimization models, particularly the lack of comprehensive multi-biomass value chain integration frameworks and limited consideration of uncertainties in logistics planning. The analysis highlights that while mixed integer linear programming models dominate, they often overlook cross-chain synergies and logistics. By examining 112 articles, we show that integrating forestry, agricultural, and municipal solid waste value chains through shared infrastructure and collaborative planning can significantly reduce transportation costs, enhance supply stability, and improve resource utilization in bioenergy systems.

1. Introduction

Achieving the objectives set by the United Nations Sustainable Development Goals (SDGs), particularly those related to clean energy (SDG 7), responsible consumption and production (SDG 12), and climate action (SDG 13), requires the development of renewable energy systems, including sustainable biomass supply chains (SCs) that support bioenergy production [1]. Biomass value chains (VCs) are pivotal in supplying renewable feedstocks for bioenergy production. Among various biomass sources, forestry residues, agricultural byproducts, and municipal solid waste (MSW) are particularly significant due to their abundance, diversity, and potential to support sustainable resource utilization. Forestry residues offer high-energy–density feedstocks [2], agricultural byproducts are available in large quantities during harvest seasons [3], MSW provides a year-round supply while addressing urban waste management challenges [4]. These VCs represent a diverse spectrum of biomass resources with significant potential for bioenergy applications. However, these biomass sources are often studied in isolation despite their complementary logistics and supply stability characteristics. This systematic literature review explores the potential for integration, identifying synergies to enhance supply chain (SC) efficiency, reduce logistic costs, and improve resource utilization in bioenergy

Abbreviations: ABM, Agent-Based Modeling; AHP, Analytical Hierarchy Process; CE, Circular Economy; CHP, Combined Heat and Power; CvaR, Conditional Value at Risk; DES, Discrete Event Simulation; GHG, Greenhouse Gas; GIS, Geographic Information System; IoT, Internet of Things; LCA, Life Cycle Assessment; LHVs, Larger and Heavier Vehicles; LP, Linear Programming; MCDM, Multi-Criteria Decision Making; MILP, Mixed Integer Linear Programming; MINLP, Mixed Integer Non-Linear Programming; MSW, Municipal Solid Waste; NLP, Non-Linear Programming; NPV, Net Present Value; SC, Supply Chain; SCs, Supply Chains; SDGs, Sustainable Development Goals; ToSIA, Tool for Sustainability Impact Assessment; VRP, Vehicle Routing Problem; VC, Value Chain; VCs, Value Chains; WtE, Waste-to-Energy; XAI, Explainable Artificial Intelligence.

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systems.

Biorefineries are the key to biomass conversion into bioenergy. Bioenergy is an alternative to fossil fuels, helping reduce greenhouse gas emissions by utilizing renewable biomass resources that offset carbon emissions over their lifecycle. They use different types of biomass feedstock, including agricultural residues, forestry byproducts, energy crops, and MSW. The refineries produce biofuels and generate high-value chemicals, materials, and energy [5]. Biorefineries use many conversion technologies for these feedstock materials, including hydrolysis, fermentation, gasification, and pyrolysis, in contrast to traditional refineries dependent upon petroleum. The advantages of these technologies are that they use renewable and affordable feedstock, have a lower carbon footprint on products, and contribute to reducing the negative impacts [6].

In the use of biomass for energy, due to its cycle in natural carbon, the amount of carbon released by biomass combustion can be balanced with the amount absorbed in biomass growth. Then, its effect on the atmospheric CO2 level is neutral [7,8]. Forests and agricultural streams are the main bases of bioenergy supply and are among the primary sources of sustainable energy solutions. Up to 50 % of the primary energy supply globally could be derived from woody biomass fuel transformation. The sustainable exploitation of this resource is of utmost importance and should be efficient [9]. Forest residues, logging residues, and bark from forestry operations are valuable feedstocks for bioenergy and biochemical production that contribute to conformance with environmental concerns about energy generation [10]. Because the agricultural sector has a significant potential for waste biomass, this holds the prospect of producing biofuels. Agricultural wastes, including corn stover, sugarcane bagasse, and wheat straw, are used for fodder and as fuels at biorefineries. Energy crops, such as switchgrass, miscanthus, and willow, have been developed to produce high energy yields and have a low environmental impact [11].

Urban areas contribute to biomass through MSW. The fast-growing urbanization and growing populations in developing countries lead to an increase in solid waste generation, contributing to various environmental problems. Waste-to-Energy (WtE) technology could provide solutions for waste management combined with energy recovery. MSW, containing organic residues and other types of MSW, becomes a biomass resource. Organic items account for nearly 50 % of the total MSW content [12]. WtE technologies utilize this component to derive energy that will help control the city's garbage. Biomass feed-wood, lands, farms, and MSW contribute to green fuel generation, and play a role in the renewable aspect [13].

There are challenges in using biomass to produce bioenergy, including high process costs and unpredictable biomass availability. Differences in biomass sources, seasonal availability for agricultural biomass, storage stability for forestry residues, and the limited utilization of MSW in bioenergy production require varied logistic solutions for transportation and handling. These differences underscore a logistical innovation role in advancing bioenergy production [14].

Recent studies have developed models to evaluate regional production and distribution network decisions, address logistical challenges, and optimize the integration of new products into existing VCs. For instance, some studies use mixed integer linear programming (MILP) models to assess the integration of new products into the forest value chain (VC), incorporating manufacturing processes, distribution nodes, and a business-to-business circular economy (CE) approach [15].

Transitioning to sustainable energy requires logistical activities, including storage, transportation, and preprocessing activities like chipping and drying, which are crucial for transforming diverse biomass sources into sustainable energy. These logistical components significantly influence the bioenergy production process's efficiency, cost-effectiveness, and environmental sustainability [16,17]. Comparing forestry, agricultural, and MSW biomass VCs reveals unique and shared logistical challenges in advancing renewable energy. These challenges include high transportation costs, seasonal feedstock availability, and storage limitations, highlighting the importance of innovative logistical solutions in overcoming barriers to bioenergy production.

This paper advances the current understanding of bioenergy production by analyzing the integration of forestry, agricultural, and MSW VCs. It addresses four research questions to provide a comprehensive review.

- RQ1: What logistics operations are used and efficient in biomass procurement?
- RQ2: What are the analytical tools used for biomass logistics planning?
- RQ3: What optimization strategies facilitate the integration of forestry, agricultural, and MSW biomass SCs?
- RQ4: What methodological gaps and logistical challenges hinder the integration of multiple biomass VCs?

RQ1 examines the operational planning of biomass VCs, focusing on logistical operations like collection, storage, transportation, and preprocessing to identify similarities and differences between biomass VCs. RQ2 explores planning models for optimizing biomass VCs from diverse sources, highlighting effective logistical strategies. RQ3 investigates integrating forestry, agricultural, and MSW VCs to create a resilient, efficient SC, an underexplored area crucial for sustainable bioenergy systems. RQ4 explores challenges and research gaps in the literature related to integrating different biomass VCs.

Earlier reviews mainly focused on individual biomass VCs, such as forestry residues, agricultural byproducts, and MSW, without considering their potential synergies. A few considered a mix of forestry and agricultural biomass VCs and explored the integration, but with varying focuses on specific sectors. In 2013, Sharma et al. [18] focused on forestry and agricultural biomass SCs, reviewing articles published up to 2011 in logistical aspects such as storage, preprocessing, and transportation within individual SCs. While this review paper briefly mentioned the integration between biomass VCs, its main findings and core subject revolve around planning models for biomass SC optimization, addressing strategic, tactical, and operational decisions related to logistics and infrastructure. In 2014, Yue et al. [19] primarily examined the forestry and agricultural biomass VCs, discussing multi-scale modeling to optimize logistics and integrate biofuels into petroleum refinery SCs for cost reduction and efficiency improvement. Later, in 2021, Singh et al. [20] reviewed forestry, agricultural, and MSW biomass VCs, highlighting the role of policy and financial mechanisms in facilitating cross-sector collaboration and identifying gaps in incentives for biomass mobilization and harmonization. However, none of these studies investigated the logistical collaboration between forestry, agricultural, and MSW VCs. Instead, they addressed integration within specific biomass categories or through policy-level coordination rather than examining operational synergies and shared infrastructure for transportation and processing.

Some reviews, e.g., Wolfsmayr et al. [21], highlighted transportation challenges in forestry residue SCs, while others, like Mirkouei et al. [22], examined logistical optimizations for agricultural residues, often overlooking how these systems could complement each other. Similarly, studies on MSW-to-energy advancements like Chand Malav et al. [13] emphasized waste management technologies but did not explore how MSW could be integrated with forestry and agricultural residues to create more resilient and efficient SCs. These limitations in scope hinder the development of comprehensive solutions that leverage the strengths of multiple VCs.

Uncertainties in biomass SCs, such as variability in supply, storage degradation, market fluctuations, and policy changes, represent another significant challenge noted in prior reviews. Advanced modeling techniques, including stochastic programming and simulation, are often recommended to manage these risks and support more robust SC designs. Some reviews, such as those by Awudu et al. [23], Shabani et al. [24], and Yue et al. [19], explored these challenges and solutions.

Existing reviews have extensively analyzed individual VCs and their logistical challenges. However, they have not addressed the collaborative potential of integrating forestry, agricultural, and MSW VCs. Our review focuses on bridging these gaps by investigating strategies for collaboration, shared infrastructure, and multi-feedstock optimization. By emphasizing synergies and addressing inefficiencies through coordinated approaches, this review aims to enhance the sustainability and cost-effectiveness of biomass-to-bioenergy systems.

To better contextualize these gaps, Table A-1 in the Appendix provides a structured overview of 19 prior review papers examining the logistical aspects of biomass-to-bioenergy SCs. These studies are categorized by key parameters, including the time span of the literature reviewed, decision-making levels (strategic, tactical, operational), types of biomass VCs analyzed (forestry, agricultural, and MSW), and the specific logistical challenges addressed (such as transportation, collection, inventory management, preprocessing, and facility location). Additionally, the table outlines whether these reviews incorporate environmental, economic, or social dimensions, technological advancements, uncertainty analysis, and optimization approaches. This synthesis highlights that most earlier reviews have focused on one or two biomass types, often overlooking the complexities of integrating logistics across different sectors. This underscores the need for a comprehensive analysis emphasizing collaboration between forestry, agricultural, and MSW VCs, which is the focus of this study.

The main contribution of this review lies in identifying critical gaps in optimization models and collaborative frameworks while offering actionable insights into collective infrastructure, adaptive logistics, and multi-VC coordination. Additionally, it provides a comprehensive assessment of the current state of biomass logistics. It directly addresses the four key RQs, offering structured insights into logistics operations, analytical tools, optimization strategies, and integration challenges. It systematically answers these questions and presents a novel perspective on enhancing biomass-to-bioenergy systems through integrated VCs.

The remainder of this paper is organized as follows: Section 2 describes the systematic literature review methodology and criteria for selecting articles. Section 3 examines research trends and findings on biomass VCs and decision-making levels, categorizing articles by biomass VC types, geographical distribution, published year, optimization models, solution approaches, and uncertainty considerations. Sections 4–6 focus on strategic, tactical, and operational planning in forestry, agricultural, and mixed VCs, respectively, with Section 7 addressing the combination of decision-making levels. Section 8 mentions essential notes in the MSW VC. Section 9 discusses findings, emphasizing innovative logistical solutions for bioenergy logistics and the challenges of integrating different biomass types. Finally, Section 10 concludes with key findings. Moreover, tables in the Appendix show all articles investigated in this systematic literature review.

2. Systematic literature review methodology

The systematic literature review (SLR) method forms the basis of literature review research [17]. This structured approach can provide a comprehensive and focused review to help systematically categorize and analyze the literature using essential keywords, fundamental concepts, and relevant topics. For instance, a review paper in 2022 used the SLR approach to study energy conversion efficiency by biomass-based plants [25]. This paper presents an SLR of the complexity of biomass VC integration to increase biomass SC performance efficiency. Emphasis is placed on the nature of integration for efficiency. Forestry, agriculture, and MSW are the three primary biomass VCs selected for their critical role in providing abundant, diverse, and complementary feedstocks essential for advancing sustainable bioenergy solutions.

We followed a three-step search and screening process to ensure comprehensiveness and relevance. The review focuses on scientific peer-reviewed journal articles and conference proceedings in English published between 1997 and 2024. This timeframe begins with the first study in this field, focusing on agricultural biomass in the United States [26]. Critical issues in optimizing herbaceous biomass delivery systems, such as switchgrass, were addressed using linear programming (LP). This foundational work marked the start of systematic research in bioenergy logistics and serves as a fitting starting point for our review [26]. Book chapters, technical reports, and non-peer-reviewed studies were excluded to ensure consistency in peer-review standards and to avoid variability in methodological depth, quality control, and data accessibility. This decision supports the review's objective of analyzing models that meet recognized academic benchmarks regarding transparency, reproducibility, and scientific rigor. Our review was guided by four RQs designed to examine logistical operations, planning tools, and integration strategies across biomass VCs.

We searched Scopus, Web of Science, and ScienceDirect using the terms: "Bioenergy systems," "Biorefinery," and "Biomass-to-bioenergy SCs." These terms were applied across the "Title," "Abstract," and "Keywords" fields in scientific databases, yielding an initial pool of 94,508 articles. To narrow the scope, we added keywords "Forest biomass," "Agriculture biomass," and "Municipal solid waste biomass," which were specific to our focus on different biomass VCs, reducing the results to 1,526 articles. Studies focusing solely on feedstock conversion without logistical implications were excluded to refine the results further. Articles were included if they explicitly addressed logistics planning for biomass SCs or optimization models for bioenergy production. So, we incorporated additional terms related to logistics, integration, and collaboration, such as "Logistics," "Integrated," "Collaboration," and "Coordination," which led to 306 articles. A combination of Boolean operators ("or" and "and") was used to ensure precision in the search. For example, we searched for "Collaboration AND Forestry Value Chain" or "Biomass Logistics OR Bioenergy Logistics Optimization" combinations to identify relevant studies. This approach allowed us to refine the search results by including studies that specifically addressed collaboration within forestry VCs and broader studies focused on logistical and optimization aspects of biomass and bioenergy. By strategically combining keywords, we could cover various topics while excluding irrelevant results, ensuring a wide-ranging, focused literature review. A thorough screening process identified 112 articles deemed most relevant to our investigation. These include 93 articles focused on logistical operations, planning tools, and biomass optimization models, and 19 review articles offering insights into the broader context of biomass logistics and integration.

To categorize our analysis, we classify decision-making levels into strategic (long-term), tactical (mid-term), and operational (short-term), focusing on logistical and optimization models. This classification provides a structured understanding of SCs and their dynamics in biomass-to-bioenergy conversion. We explore decisions on SC structure, location planning, capacity, technology adoption, and market positioning at the strategic level. The tactical level bridges strategy and daily operations through logistics, risk management, distribution planning, and resource allocation. At the operational level, we focus on immediate actions, such as vehicle routing, scheduling, inventory control, and maintenance.

3. Descriptive analysis of reviewed literature

Research trends and findings on biomass VCs and decision-making levels are categorized based on biomass types, geographical distribution, publication years, optimization models, solution approaches, and methods for handling uncertainty.

3.1. Description of the identified VCs

Forest biomass VCs focus on forestry by-product residues from traditional harvesting, such as branches, treetops, low-quality logs, wood chips, and other residues [2]. Transporting diverse materials introduces logistical complexities, requiring innovative strategies like chipping to enhance economic efficiency and reduce environmental impact by less fuel consumption due to the decreasing biomass bulkiness and fewer truckloads. Chipping and pelletizing increase biomass energy density, requiring specialized logistics for efficient storage and transportation [27].

The Agricultural biomass VC focuses on producing, processing, and transforming agricultural biomass into energy and bio-based products, distinct from traditional agricultural VCs centered on food, feed, fiber, and industry materials [28]. It includes crop residues like straw and husks, energy crops like miscanthus and switchgrass, and by-products like animal manure and organic waste, offering energy production potential that supports renewable energy and CE goals [29].

MSW is valuable in biomass VCs, significantly influencing energy production and reducing greenhouse gas (GHG) emissions. Eco-centers, where MSW is collected and categorized into sets like wood, can be logistics' starting points in MSW biomass VC. Integrating MSW with forestry and agricultural biomass instead of considering it as a sole source of bioenergy demonstrates a growing trend toward multi-feedstock solutions. This integration underscores the complexity of optimizing biomass-to-bioenergy SCs while highlighting the potential of combining diverse biomass sources to enhance bioenergy systems [30].

Fig. 1 provides a detailed representation of biomass VCs, illustrating biomass flow from its sources, forests, farms, and eco-centers to its final conversion into bioenergy and bioproducts at biorefineries. It highlights key logistics operations such as biomass gathering, storage at different locations (e.g., source sites or terminals), and preprocessing steps like chipping and drying. The diagram also depicts alternative pathways, where biomass can be sent directly to the biorefinery or undergo preprocessing and storage before delivery. This visual emphasizes the interconnected stages and logistics required to manage biomass within SCs efficiently.

Logistical operations for biomass collection and harvesting differ based on the type of biomass. Agricultural residues are typically collected in bales or chopped forms, while forestry residues are transported either as unprocessed material or as wood chips directly from harvest sites. Implementing efficient methods in these processes ensures maximum utility and reduces logistical inefficiencies [31]. The unpredictable nature of biomass harvesting, such as seasonality, quality, and quantity of biomass, impacts storage strategies. Agricultural biomass requires timely storage on farms due to harvesting seasons, while forestry residues benefit from on-site open-air drying over several months to reduce moisture content. Intermediate storage facilities (terminals) can help balance supply and demand, but add transportation and handling costs, increasing overall logistics expenses [32,33].

Transportation, one of the most significant costs in biomass logistics, is mainly influenced by transport mode, distance, biomass volume, and type. The flexibility needed to handle different biomass types further adds complexity to the process, requiring careful planning to optimize efficiency and cost [34,35] Preprocessing steps such as sorting, chipping, drying, and densification prepare biomass for energy conversion by reducing its size, compacting it, and controlling its moisture content. These processes enhance logistics performance by improving transport efficiency, reducing storage space requirements, and ensuring consistency in biomass quality for conversion [36,37].

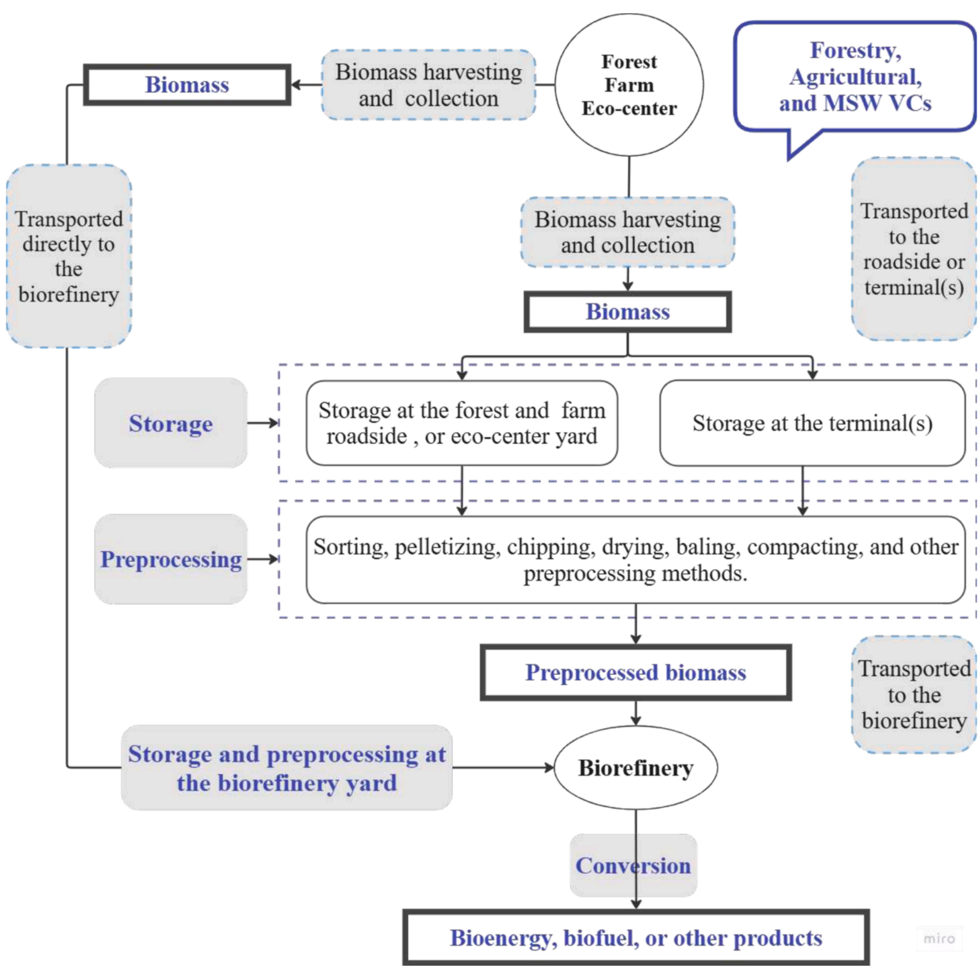

Fig. 1. Key logistics operations in the biomass value chains.

3.2. Distribution of articles based on the types of biomass VCs and decision-making levels

This analysis shows that the forest biomass VC has the highest literature share, with 44 articles, the agricultural biomass VC has 22 articles, and the MSW biomass VC has 5 articles. Notably, 22 studies discuss integrating different VCs, including MSW. MSW VC has not been considered as a separate SC in logistics optimization. It has always been considered with other biomass from forest and agricultural biomass VCs. The research on MSW, with 5 articles introducing the role of MSW in bioenergy production, underscores the need for further study on integrating MSW into broader bioenergy VCs. In addition to these 93 articles, 19 review papers were considered in this study.

Fig. 2 highlights the distribution of research across different decision-making levels in bioenergy logistics. Strategic and mixed levels dominate the focus, with 26 and 30 articles emphasizing long-term planning and integrated strategies to optimize SCs. The tactical level, represented by 20 articles, underscores the importance of process-driven solutions that enhance intermediate SC efficiency. With 12 articles, the operational level addresses short-term logistics challenges, reflecting its targeted and context-driven nature.

3.3. Distribution of articles based on the geography of the case study

Countries for articles are assigned based on the location of the case study. The United States and Canada lead research on forest biomass VCs, with 10 and 13 articles, respectively. This focus is driven by their vast forested areas, which provide abundant feedstock, and their commitment to sustainable forestry practices. The United States also shows strong interest in agricultural biomass, with 7 studies reflecting its large agricultural sector and the potential to repurpose residues for bioenergy, reducing waste, and promoting rural sustainability. The focus for MSW VCs spans multiple countries, including the United States, Iran, and China. In Iran, integrating MSW with forestry and agricultural biomass helps address environmental challenges, such as waste accumulation, while creating jobs and supporting rural economies. China's focus on MSW reflects its efforts to manage growing urban waste and support renewable energy goals. The United States leads with 26 articles, followed by Canada and Finland, illustrating a global attempt to use different types of biomass VCs together. Each country's emphasis reflects its unique resources and priorities, whether leveraging forests, agriculture, or urban waste to advance bioenergy systems (Fig. 3).

3.4. Distribution of articles based on the published year

The evolution of research on biomass-to-bioenergy logistics, as shown in Fig. 4, began with a 1997 USA study using an LP model to address uncertainties in agricultural biomass production, optimizing transportation and storage. LP models, valued for simplicity and efficiency, laid the groundwork for bioenergy SC research [26]. In 2004, Sweden advanced the field with a MILP model for forest biomass logistics, integrating terminal logistics and preprocessing with heuristic approaches for near-optimal solutions. This reflects the shift to more sophisticated models [38].

In 2009, a USA study introduced a MILP model integrating forestry and agricultural biomass VCs, marking a breakthrough in optimizing multi-biomass SCs [39]. This pivotal moment prompted increased research activity, peaking in 2021 with 14 articles, possibly influenced by the COVID-19 pandemic's focus on bioenergy. The pandemic may have heightened interest in bioenergy by emphasizing the importance of resilient and sustainable energy systems, as disruptions to traditional energy SCs and increased environmental awareness could have drawn attention to renewable energy sources like bioenergy. During this pandemic, research shifted towards agricultural and MSW biomass, with fewer forest biomass studies, highlighting the growing need for diverse biomass sources to improve SC resilience and sustainability.

Since 2019, research on agricultural and mixed biomass VCs has doubled compared to forestry-focused studies, reflecting a shift toward integrating multiple biomass sources to optimize bioenergy systems and enhance sustainability. This trend aligns with goals to reduce GHG emissions and fossil fuel reliance. However, a decline in publications post-2021, from 8 in 2022 to 3 in 2023, with a slight rebound to 4 in 2024, indicates a possible shift in research focus within the energy sector, influenced by evolving policies and technological advancements.

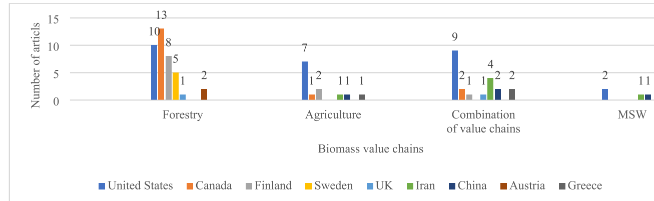

Fig. 3. Distribution of articles by biomass value chain type across countries.

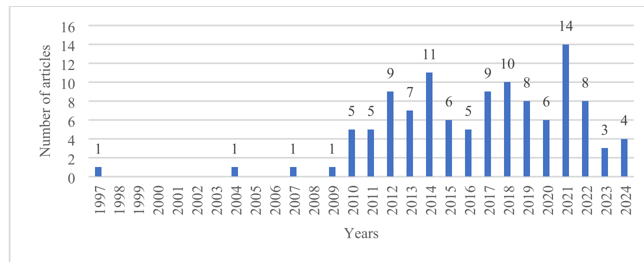

Fig. 4. Distribution of articles by publication year.

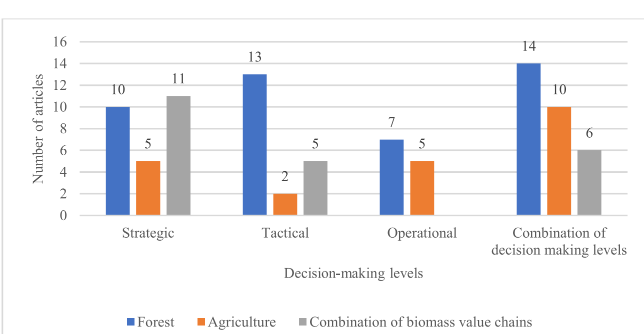

Fig. 2. Distribution of articles by biomass value chain type and decision-making level.

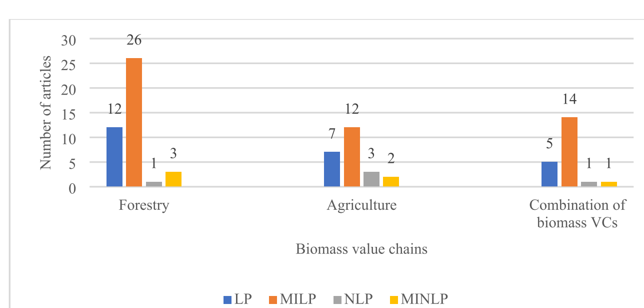

Fig. 5. Distribution of articles by programming model across biomass value chains.

3.5. Distribution of articles based on the modeling approach

The distribution of optimization models in biomass-to-bioenergy systems (Fig. 5) reflects the complexity of biomass SC modeling. MILP is widely used in 26 forestry, 12 agricultural, and 14 combined VC studies. Its popularity stems from its ability to handle continuous and discrete decision variables, making it suitable for addressing complex logistics like facility location, harvesting schedules, transportation planning, and seasonal variations. LP, used in 12 forestry and 7 agricultural VC studies, is often applied in large-scale problems, focusing on continuous decision variables such as transportation flows or resource allocation and offering computational efficiency. non-linear programming (NLP) [40] and mixed-integer non-linear programming (MINLP) [41] are less commonly applied, mainly in forestry and agricultural VCs. These approaches are used for cases with non-linear constraints. Still, their computational intensity limits their practicality for medium to large-scale studies. Researchers favor MILP and LP for their ability to balance model complexity, computational efficiency, and applicability to real-world SC challenges [42,43].

3.6. Distribution of articles based on the solution approach

The distribution of solution approaches in biomass VC optimization (Fig. 6) highlights the diverse methods used to tackle the varying complexities and data sizes of forestry, agricultural, and combined biomass systems. Exact methods dominate the research in 34 forestry, 19 agricultural, and 19 combined biomass studies. Often paired with optimization models like LP and MILP, these methods effectively solve problems with clearly defined parameters and constraints [41,44]. They excel in optimizing logistics such as facility location, transportation planning, and resource allocation when computational requirements remain manageable.

Meta-heuristic methods (7 forestry, 4 agricultural, 3 combined) and heuristic methods (7 forestry, 1 agricultural, 7 combined) are preferred for larger and more complex problems where exact methods become computationally infeasible. These approaches suit large datasets such as vehicle routing, scheduling, or integrating diverse biomass types with varying logistical needs. Meta-heuristics, such as genetic algorithms or simulated annealing, are effective for exploring large solution spaces in complex problems [45,46]. Heuristics, by contrast, follow simplified rule-based methods and offer quick, near-optimal solutions. These approaches are practical when computational efficiency is more important than achieving exact solutions [32]. Some studies combine multiple solution methods to address the complexities of biomass VCs more effectively. In 2024, Yunusoglu et al. [47] proposed a two-stage approach combining a heuristic and an exact method to optimize the location of facilities in the biomass-to-bioenergy SC. The first stage applies k-means clustering to group candidate sites based on ecological characteristics, reducing problem complexity. The second stage employs pre-emptive goal programming, prioritizing environmental and economic objectives by minimizing their negative environmental impact on nearby populations while maximizing profitability. This hybrid approach enhances efficiency in handling large datasets and conflicting objectives in biomass logistics. The model was implemented on a real-world biomass SC network in Izmir, Turkey, demonstrating its effectiveness in optimizing facility location while balancing economic and environmental concerns.

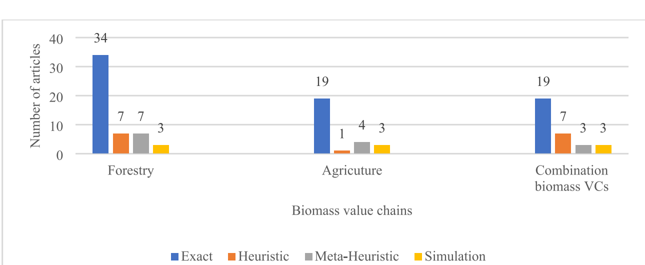

Fig. 6. Distribution of articles by solution approaches across biomass value chains.

Simulation methods (3 studies in each VC) are primarily used for problems with high uncertainty, such as seasonal supply variations or fluctuating demand, regardless of dataset size. While they do not directly optimize, simulations allow researchers to test strategies and evaluate system performance under various scenarios. They are particularly valuable for analyzing large-scale systems with dynamic variables that are difficult to model deterministically. For example, a 2020 study used a MILP model to address logistical aspects, including facility location, transportation planning, and biomass flows. Additionally, it integrates a discrete event simulation (DES) model to account for uncertainties, such as machine availability, productivity, and weather-related delays, ensuring the feasibility and practicality of the proposed solutions [48].

3.7. Distribution of articles based on the uncertainty status

Fig. 7 highlights stochastic programming and robust optimization to address uncertainties in biomass VCs. In forest biomass VCs, 9 articles employ stochastic programming to model uncertainties in biomass availability, transportation costs, and market demand, incorporating probabilistic scenarios to improve decision-making under variability. Additionally, 4 articles use robust optimization to account for worst-case disruptions, particularly transportation. This approach ensures resilience by optimizing feasible decisions across a defined range of uncertainty in critical parameters, such as transportation costs. For instance, in transportation disruptions, robust optimization considers transportation costs as uncertain parameters within predefined bounds, identifying solutions that maintain feasibility under all potential variations within the specified uncertainty set [43,49]. In 2016, Shabani et al. [50] combined both methods to address supply and quality uncertainties for a forest-based biomass power plant. Stochastic programming models scenarios like seasonal supply variations, enabling flexible decisions, while robust optimization ensures resilience by focusing on parameters like moisture content and heating value within defined ranges.

In agricultural biomass VCs, 7 articles utilize stochastic programming to tackle uncertainties such as weather-dependent feedstock supply and fluctuating market prices. These models enable more resilient SC planning by considering variable yields and market volatility. Although less common (applied in 3 articles for agricultural biomass and 2 for combined biomass VCs), robust optimization effectively handles disruptions, such as delayed transportation, by ensuring that solutions remain feasible under worst-case parameter variations [15,51].

Deterministic models dominate biomass SC studies, with 31 forestry-focused, 11 agricultural, and 12 combined biomass articles. However, the increasing use of stochastic programming and robust optimization underscores the importance of managing logistics uncertainties,

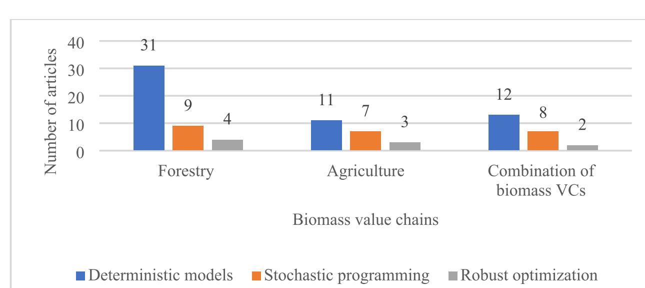

Fig. 7. Distribution of articles by uncertainty considerations across biomass value chains.

particularly in fluctuating biomass availability and market conditions.

This study systematically compiles and analyzes optimization-based approaches for managing biomass SCs, focusing on logistical operations and decision-making frameworks. To support this analysis, Tables A-2 to A-4 in the Appendix summarize 93 optimization-focused studies reviewed in this paper. These tables categorize the studies based on key parameters, including logistical operations (such as facility location, transportation, preprocessing, storage, and inventory management), decision-making levels (strategic, tactical, operational), objective functions (single or multiple), modeling approaches, solution methods, and geographic regions.

Specifically, Table A-2 compiles studies related to forestry biomass VCs, Table A-3 focuses on agricultural biomass VCs, and Table A-4 examines studies involving the integration of forestry, agricultural, and MSW biomass VCs, offering insights into collaborative SC strategies. These tables provide a comprehensive reference for identifying research trends, methodological gaps, and opportunities for advancing biomass SC optimization across different biomass sectors.

Sections 4 through 8 extend on these classifications, discussing representative studies from Tables A-2 to A-4, organizing them according to decision-making levels (strategic, tactical, operational) and biomass types (forestry, agricultural, MSW, and multi-biomass), and highlighting key logistical operations and modeling approaches within each category.

4. Strategic decision-making level

4.1. Forest biomass value chain

Early strategic models for forest biomass VCs primarily addressed facility location and basic SC configurations. For example, in 2010, Leduc et al. [52] contributed a foundational framework that integrated feedstock availability, transportation costs, and energy demands to optimize methanol plant location in Sweden. This approach laid the groundwork for coupling biofuel production with district heating in biomass logistics. Extending the system boundary, Rauch et al. [53] changed the focus from production plant locations to the intermediate steps in the biomass SC. Their work introduced a MILP model to optimize terminal locations for storing and chipping forest biomass before delivery to energy plants. It emphasized the importance of including intermediate nodes and multi-actor coordination, a notable advancement in handling seasonal supply fluctuations.

As research progressed, models incorporated multi-period planning to capture long-term dynamics of biomass availability, market fluctuations, and technology deployment. Cambero et al. [54] introduced a dynamic multi-period MILP model that optimized bioenergy and biofuel SCs over a 20-year horizon, demonstrating the scientific contribution of adaptive SC design in response to uncertain market conditions. The model determined when and where to install technologies, how to allocate biomass, and the best mix of heat, electricity, pellets, and bio-oil. Similarly, Campanella et al. [55] advanced the field by integrating multiple facilities into cohesive networks, including sawmills, ethanol plants, and pellet production. The model determined the optimal location, capacity, and material flows between these facilities to enhance economic feasibility. Instead of explicitly modeling uncertainties, the study evaluated different production scenarios to assess the impact of facility configurations and material allocation strategies. Their work emphasized resource efficiency and residue valorization, showcasing how production clustering can improve economic and environmental performance.

More recent studies addressed uncertainty management and national-scale planning. In 2016, Marufuzzaman et al. [56] integrated supply and cost uncertainties into a syngas SC, applying sensitivity analysis to evaluate system robustness, an essential step toward resilient SC design. This study optimized the location and capacity of bio-gasification facilities and chipping terminals, minimizing costs across the Southeast U.S. The model considered uncertainty in biomass supply, transportation costs, and operational efficiency, using sensitivity analysis to assess how fluctuating factors impact system viability. Implemented in a real-world case study, the model incorporated data from a bio-gasification facility at Mississippi State University, showing how logistical efficiency affects the economic feasibility of syngas. Expanding the geographical scope, Calderón et al. [57] introduced a geospatially explicit model for the BioSNG SC, integrating policy incentives and scenario analysis. Their multi-period MILP model integrated geospatially explicit data, optimizing feedstock procurement, facility location, and product distribution. This framework accounted for government incentives, such as feed-in tariffs and Renewable Obligation Certificates, showing their impact on economic viability. Uncertainty in energy prices, feedstock availability, and demand growth was incorporated through scenario analysis, revealing the role of policy support in driving investment. The model was implemented using real-world data from UK government reports, demonstrating how domestic resources could meet the projected gas demand under specific conditions.

4.2. Agricultural biomass value chain

Strategic planning models for agricultural biomass SCs have progressively evolved to incorporate sustainability, risk management, and uncertainty considerations. One of the early advancements in this area was introduced in 2012 by Čuček et al. [28], who developed a multi-criteria optimization model balancing economic, environmental, and social impacts in regional bioenergy SCs. By integrating total footprint metrics, including carbon, energy, water, land, and pollution, and a food-to-energy footprint to address food competition concerns, this model contributed a sustainability-focused framework to SC design. Formulated as a MINLP, it optimized biomass collection, processing, and distribution under various scenarios, demonstrating that incorporating environmental trade-offs leads to more sustainable outcomes than purely economic approaches.

As the field matured, stochastic modeling emerged as a key contribution to address supply and market uncertainties. Kazemzadeh et al. [58] advanced SC resilience by introducing a two-stage stochastic programming model that optimized biorefinery locations, capacities, and transportation flows under feedstock yields, fuel prices, and fluctuations in logistics costs. Their use of Conditional Value at Risk (CVaR) provided a structured approach to managing supply shortage risks, contributing a risk-aware framework that balanced profit maximization with long-term SC stability. This model, applied to the Iowa biomass SC, highlighted how stochastic approaches can mitigate fuel shortages and enhance economic performance over time.

Building on these advancements, Serrano et al. [59] refined strategic planning by incorporating probabilistic supply variations into biorefinery location models. Using a stochastic MILP formulation, their model considered the impacts of climate variability, competition, and alternative uses on biomass availability, representing these factors through triangular and uniform probability distributions. This risk-based planning approach contributed to robust facility location decisions, ensuring SC resilience against fluctuating resource conditions. Their application across 94 candidate sites in Navarre, Spain, identified the most stable biorefinery location under various risk scenarios. This marked a shift towards scenario-based decision-making in agricultural biomass SCs.

4.3. Multi-biomass value chains

In deterministic models addressing multi-biomass systems, one of the key strategic challenges is coordinating diverse feedstock sources with varying geographical availability, seasonal patterns, and logistical requirements. While models such as those developed by Ekşioğlu et al. [39] and Huang et al. [60] optimize long-term decisions like facility location and capacity planning, they often assume feedstocks can be centrally planned and substituted without fully capturing the complexity of feedstock-specific constraints, such as harvest timing, moisture content, or preprocessing compatibility. This becomes increasingly problematic when integrating agricultural residues, forestry biomass, and MSW within a single infrastructure plan. Furthermore, strategic models tend to simplify or exclude institutional fragmentation across sectors, which presents a real barrier to joint planning and investment decisions. Another limitation lies in the models' limited capacity to assess the interdependency between infrastructure design and future flexibility, for instance, how choices made about depot placement or blending configurations may lock the system into rigid logistics paths, hindering long-term resilience. While models like Roni et al. [61] account for feedstock diversification, few offer mechanisms to prioritize infrastructure investments based on the joint evolution of supply availability, demand growth, and regional development constraints.

Uncertainty-based models for multi-biomass systems have advanced strategic planning by incorporating variability in feedstock supply, demand, and policy conditions. However, challenges remain in how these models handle strategic infrastructure decisions under uncertainty. A key limitation lies in the reliance on scenario-based representations that may not fully capture the dynamic evolution of SCs over long horizons. For instance, while models by Chen and Fan [62] and Gebreslassie et al. [63] integrate uncertainties in supply and demand, their frameworks typically assume a static set of facility options and do not explore how infrastructure can adapt as uncertainties unfold over time. This restricts their capacity to support flexible investment strategies, such as phased expansions or modular facility designs. Furthermore, while robust optimization approaches, as seen in Razm et al. [64], they can hedge against worst-case scenarios but often do so without incorporating cross-sectoral coordination mechanisms at the strategic level. The absence of frameworks for shared infrastructure planning across biomass sectors limits the models' ability to optimize multi-biomass integration holistically. Additionally, most models lack mechanisms to evaluate long-term policy risks or regulatory shifts, which are critical for investment planning in multi-sectoral biomass systems. This gap reduces the relevance of such models for guiding resilient infrastructure development that aligns with evolving market and policy landscapes.

Resource assessment and multi-criteria decision-making (MCDM) studies provide critical support for early-stage strategic planning in multi-biomass SCs, particularly by identifying feedstock availability and prioritizing resource utilization across regions. However, these approaches face limitations when transitioning from resource evaluation to actionable infrastructure planning. For instance, the GIS-based assessments by Pande et al. [65] map biomass distribution across agricultural, forestry, and wasteland sectors, but do not link these spatial insights to infrastructure design decisions such as facility locations or capacity allocations. Without integrating logistical or investment models, such assessments offer limited guidance for strategic location or scaling of biorefinery networks. Similarly, while Firouzi et al. [66] apply hybrid MCDM methods to rank biomass feedstocks based on environmental and economic criteria; these rankings remain disconnected from SC design models and do not account for system-wide trade-offs such as transport feasibility or preprocessing requirements. This disconnect creates challenges for aligning resource prioritization with infrastructure investments in multi-biomass systems. Furthermore, these studies often overlook cross-sectoral integration dynamics, failing to assess how combining different biomass types might influence long-term infrastructure flexibility or investment sequencing.

Strategic planning models for multi-biomass SCs, whether based on deterministic optimization, stochastic programming, or resource assessment frameworks, have advanced the design of infrastructure and supply integration across biomass types. Yet, these models consistently overlook how infrastructure decisions can adapt alongside evolving feedstock landscapes and sectoral interactions. Cross-sector collaboration mechanisms, such as shared infrastructure investment or joint capacity planning, remain largely absent from strategic formulations. Moreover, few models embed long-term policy uncertainty or institutional fragmentation into infrastructure decisions, leaving gaps in supporting robust, integrated multi-biomass systems.

5. Tactical decision-making level

5.1. Forest biomass value chain

Tactical planning for forest biomass SCs initially focused on optimizing procurement, storage, and transportation decisions to ensure a steady supply for energy production. Early contributions, such as a study in 2004 by Gunnarsson et al. [38], introduced one of Sweden's first tactical models, applying a MILP framework to plan biomass procurement and logistics over a yearly horizon. Their integration of monthly planning periods captured seasonal supply variations, while a heuristic rolling-horizon approach improved computational efficiency in large-scale problems. This study marked an essential step in aligning tactical decisions with seasonal dynamics in biomass availability.

Subsequent models refined regional supply networks by incorporating infrastructure configurations and operational trade-offs. Gronalt et al. [32] expanded the tactical framework by modeling Austria's forest fuel supply network, comparing centralized industrial chipping with mobile chippers at regional terminals. Their iterative heuristic approach contributed valuable insights into balancing terminal investments, transport distances, and supply reliability, highlighting the importance of terminal operations in tactical decision-making.

Advancements in model complexity emerged by introducing nonlinear constraints to capture operational realities. In 2013, Shabani et al. [41] developed a MINLP model for a forest biomass power plant in Canada, integrating energy production constraints, biomass mixing effects, and ash management. A key contribution was the explicit consideration of biomass quality factors, such as moisture content and ash levels, improving tactical coordination between procurement and energy production. This model, implemented in a real-world case, demonstrated the operational benefits of fuel blending strategies.

As the need for handling uncertainty grew, models evolved toward stochastic programming. In 2014, Shabani et al. [67] transitioned from MINLP to MILP to improve computational efficiency, introducing a two-stage stochastic model that managed supply uncertainties in biomass availability. Integrating bi-objective risk management and balancing profit maximization with SC stability marked a key scientific contribution to resilient tactical planning.

Further refinement came with the development of hybrid stochastic-robust models. In 2016, Shabani et al. [50] extended their framework by incorporating both biomass quantity and quality uncertainties, including moisture content and energy value fluctuations. Using a scenario tree structure enabled dynamic adjustments in procurement and scheduling, enhancing resilience in energy supply operations. This hybrid approach demonstrated the benefits of integrating robust optimization into stochastic planning for forest biomass systems.

Attention to biomass quality dynamics and infrastructure flexibility continued with Gautam et al. [68], who assessed the tactical role of terminals between forests and biorefineries in Quebec in 2017. Their multi-period MILP model accounted for moisture content tracking, seasonality, and weather-related restrictions. It shows that terminals could act as decoupling points to reduce transportation inefficiencies and stabilize supply–demand mismatches. This study emphasized the strategic role of terminals in improving SC resilience, although their benefits were sensitive to infrastructure and operational costs.

In recent years, robust optimization has gained prominence for managing SC uncertainties. In 2022, Ahmadvand et al. [69] applied a robust model to forest-based biomass SCs in British Columbia, integrating uncertainties across procurement, transportation, storage, and preprocessing. Using Monte Carlo simulations and sensitivity analyses, this work identified transportation costs as the dominant logistical expense, reinforcing the critical role of transport decisions in tactical planning. Their model enhanced supply risk management under uncertainty, offering a comprehensive framework for stable biomass logistics.

5.2. Agricultural biomass value chain

Tactical planning models for agricultural biomass remain relatively limited, with few studies addressing short-to medium-term logistics coordination in this sector. In 2024, Ogunrewo et al. [70] made a notable recent contribution by presenting an LP model to optimize biomass SCs for bioethanol and bio-digestate production in Southwest Nigeria. Their model focused on multiple agricultural residues, including cassava peel, maize husk, rice straw, and sorghum bran, offering a rare tactical-level analysis of multi-feedstock logistics in agricultural systems. The model optimized biomass procurement, transportation, storage, and energy conversion planning to maximize revenue and minimize production costs.

A key scientific contribution was the integration of single and multi-feedstock strategies, allowing the exploration of feedstock blending options within tactical decision-making, a topic often underexplored in agricultural biomass chains. Additionally, sensitivity analysis assessed the influence of feedstock availability, transport costs, and market prices on profitability, providing insights into operational flexibility and risk factors.

While real-world implementation was not explicitly detailed, the framework offered practical decision-making support for industry stakeholders and policymakers, highlighting the economic benefits of coordinated multi-feedstock SCs in agricultural biomass logistics. This study fills the tactical-level gap in agricultural biomass SC research, where models frequently focus on strategic planning or resource assessments, but rarely on operational logistics coordination.

5.3. Multi-biomass value chains

Integrating multiple biomass types at the tactical level introduces several challenges, including coordinating logistics across heterogeneous feedstocks, synchronizing harvest and transport schedules, and aligning supplier incentives. While Wang et al. [71] addressing multi-biomass logistics for forest residues, willow, switchgrass, and Miscanthus. The MILP model optimizes cost minimization without incorporating interdependencies between feedstocks, such as joint transport or preprocessing synergies, leaving gaps in cross-sectoral logistics integration. Fan et al. [72] introduce contract coordination mechanisms involving farmers, middlemen, and manufacturers to manage supply uncertainty in solid biomass fuels. However, their model focuses on single-sector coordination (agricultural residues) without extending contractual frameworks to integrate the forestry or MSW sectors. This limits the applicability of their approach in multi-biomass settings, where sectoral diversity requires harmonized risk-sharing mechanisms.

Salehi et al. [15] contribute by integrating robust optimization for demand uncertainty and disruption resilience. Still, their focus remains at a network design level and does not address tactical logistics adjustments such as adaptive transport routing or harvest scheduling across biomass types. This leaves a gap in operationalizing resilience strategies at the mid-term tactical layer. Finally, Mirkouei et al. [22] explore mobile versus stationary bio-refineries for mixed biomass systems, offering tactical flexibility in facility deployment. However, their model emphasizes economic and environmental trade-offs without integrating real-time logistics coordination across feedstocks or addressing multi-modal transport planning.

Overall, these studies highlight that while tactical models manage biomass-specific logistics flows and supplier coordination, they seldom address the complexities of integrating logistics networks across different biomass types. The absence of joint routing and preprocessing strategies, which could harmonize transport modes, storage requirements, and processing constraints for forestry, agricultural residues, and MSW, remains a key limitation. Additionally, dynamic contractual mechanisms that adapt to fluctuating supply availability and sector-specific risks are rarely extended beyond single biomass sectors, leaving inter-sectoral coordination frameworks underdeveloped. Furthermore, while models optimize for cost, environmental, or resilience objectives independently, they often lack mechanisms for prioritizing or balancing these objectives across biomass types in real-time. This disconnect between logistics coordination, supplier engagement, and risk mitigation strategies reduces the system's ability to respond flexibly to disruptions, seasonal variations, or market shifts in multi-biomass SCs at the tactical level.

6. Operational decision-making level

6.1. Forest biomass value chain

Operational planning models for forest biomass SCs have evolved from transport scheduling to addressing biomass quality dynamics and real-time adaptability. Early efforts concentrated on optimizing truck operations to reduce costs and improve delivery efficiency. In 2012, Han and Murphy [46] developed a MILP-based truck scheduling model for woody biomass transport in Oregon, incorporating fleet allocation, routing, and load distribution under time-window and working-hour constraints. Their integration of a Simulated Annealing heuristic addressed computational complexity, enhancing scheduling efficiency across multiple truck types and destinations. Implemented with real-world data, this model demonstrated significant cost and time reductions, showcasing the impact of route optimization in operational logistics.

Beyond transport coordination, biomass quality management emerged as a key operational focus. Also, Acuna et al. [73] introduced an LP model that integrated moisture dynamics into harvesting schedules, storage durations, and delivery plans for various biomass assortments in Finland. Their approach contributed by linking moisture content to logistics decisions, revealing that optimized drying and storage strategies can reduce harvesting volumes and improve cost efficiency in bioenergy SCs. This marked a shift toward quality-driven operational planning.

Expanding this focus in 2018, Marques et al. [74] advanced operational models by incorporating energy content variability as a central decision factor. Their MILP framework synchronized chipping and transportation operations while optimizing biomass allocation based on energy yield rather than volume. Tracking moisture variation over time and aligning chip production with delivery targets ensured consistent energy content in biomass supply, a critical requirement for energy conversion efficiency.

More recently, operational planning has integrated real-time adaptability and uncertainty management. In 2020, Panoutsou et al. [75] introduced a hybrid optimization-simulation framework combining MILP with DES to address dynamic SC disruptions, seasonal variability, and market fluctuations. Their use of Benders decomposition enabled efficient large-scale optimization, while DES provided the flexibility to test performance under real-world uncertainties. This model contributed by balancing operational efficiency with resilience, emphasizing adaptive storage, flexible sourcing, and synchronized logistics in volatile bioenergy markets.

6.2. Agricultural biomass value chain

Operational planning in agricultural biomass SCs has predominantly focused on transport logistics optimization and coordination mechanisms to improve efficiency in residue collection and energy production. In 2014, Gracia et al. [76] contributed one of the early operational models targeting fleet routing and vehicle scheduling for pruning residues in Mediterranean agricultural systems. Their approach, formulated as a Vehicle Routing Problem (VRP) with capacity constraints, integrated Hybrid Genetic Algorithms with local search methods, optimizing the collection routes for chippers, trucks, and tractors. Applied to a case study in Valencia, Spain, this model significantly reduced travel distance and transportation costs, marking a key advancement in cost-effective biomass transport at the operational level.

Beyond routing optimization, coordination between SC actors has emerged as a critical area of research. In 2021, Vazifeh et al. [77] introduced a game-theoretic framework to optimize SC coordination among suppliers, hubs, and energy converters in remote Canadian communities. Their bi-level NLP model incorporated wholesale pricing, procurement quantities, and energy generation decisions, accounting for leadership structures and incentive mechanisms such as quantity discounts and side payments. This approach highlighted the economic benefits of community-led coordination, demonstrating that collaborative structures can reduce energy costs and increase biomass-based electricity generation, especially in remote or isolated regions.

Operational planning for synchronized logistics and machine scheduling was further advanced with the work of An [78], who developed an MILP model to optimize biomass transportation from satellite storage to bioenergy plants in 2022. This model integrates truck and loader routing, addressing multi-trips, synchronized operations, and workload balancing, features often overlooked in earlier frameworks. By combining closed routes for trucks with open routes for loaders, the study introduced a novel synchronized multi-vehicle routing methodology. Implemented in Southwestern Ontario, Canada, the model demonstrated practical feasibility and cost efficiency for large-scale operations, supported by a heuristic-based solution approach tailored for complex, real-world logistics networks.

Despite these advancements, a critical gap remains in operational planning for multi-biomass integration. No existing model has unified forestry, agricultural, and MSW biomass within a single short-term logistics framework, limiting opportunities for cost reduction, supply stability, and infrastructure utilization across sectors. Moreover, while routing, storage, and preprocessing decisions are often modeled, they are typically treated as isolated layers, preventing system-wide synchronization. Although studies acknowledge potential disruptions such as equipment failures, weather variability, and dynamic routing needs, few apply robust or resilient optimization frameworks capable of managing these uncertainties effectively. This highlights the need for integrated, adaptive operational models coordinating biomass types and SC layers.

7. Combination of decision-making levels

7.1. Forest biomass value chain

Integrating strategic, tactical, and operational decisions in forest biomass SCs has improved logistics coordination, facility investment decisions, and SC resilience. Early efforts to connect these levels focused on network design and logistics integration. In 2017, Abasian et al. [79] contributed a MILP framework that addressed strategic facility location (e.g., sorting yards and biorefineries) and tactical-level logistics improvements, such as fiber allocation and backhaul transportation. Their Newfoundland case study demonstrated how shared terminals and backhauling strategies could improve profitability, marking an important step toward multi-level SC coordination.

Building on this in 2018, Palander et al. [80] explored the integration of larger and heavier vehicles (LHVs) into forest SCs, aligning tactical vehicle selection with strategic energy-efficiency and carbon-neutrality goals. Their multi-objective dynamic biofuel cycle model optimized transport distances and fuel choices, demonstrating that vehicle innovations can significantly reduce emissions and logistics costs. However, this contribution highlighted regulatory and infrastructure constraints limiting the adoption of such integrated solutions.

Recognizing the impact of market uncertainties in 2019, Abasian et al. [2] expanded their earlier work by introducing demand and price fluctuations into forest bioenergy network design. Their two-stage stochastic optimization model incorporated risk management techniques, allowing flexible coordination between strategic investments and tactical logistics decisions under uncertain conditions. This contribution underscored the importance of adaptive decision-making frameworks that can respond to market volatility, reinforcing the need for flexible integration across decision levels.

Further advancing the integration of preprocessing, transportation, and facility investment decisions, Zamora-Cristales et al. [45] applied a MILP-simulation approach to optimize preprocessing locations, equipment configurations, and transport strategies. Their model connected strategic facility selection with tactical equipment utilization by structuring biomass sites as network nodes. Tested in Oregon and Washington, this study revealed operational barriers, such as high preprocessing costs and machine underutilization due to road constraints, emphasizing the need for SC designs that account for operational realities.

Incorporating environmental assessment into SC integration in 2020, Raghu et al. [81] combined life cycle assessment (LCA) with agent-based modeling (ABM) and GIS tools to evaluate GHG emissions in forest biomass logistics. This model contributed a multi-layered analytical framework that assessed how imported biomass and real-time fuel quality monitoring influenced emissions and logistics efficiency. Their findings highlighted the trade-offs between local and imported biomass sourcing, demonstrating how real-time monitoring can optimize fuel selection and reduce unnecessary transport.

A more comprehensive integration of decision levels and simulation feedback was introduced in 2020 by Akhtari et al. [48], who developed a hybrid optimization-simulation model linking strategic, tactical, and operational planning. Their recursive optimization-simulation approach combined an MILP model with DES to iteratively adjust biomass flows, facility selection, and inventory strategies based on operational feedback. Tested in British Columbia, this framework revealed that short-term operational variations could significantly influence long-term investment profitability, favoring smaller-scale, flexible production facilities capable of adapting to supply fluctuations.

7.2. Agricultural biomass value chain

Finding optimal locations for bioenergy facilities is crucial for improving SC efficiency in rural areas. In 2019, Laasasenaho et al. [82] developed a GIS-based approach to identify suitable sites for farm and centralized biogas plants and terminals by minimizing transportation needs. The study applied hierarchical clustering and location optimization for biogas plants and kernel density estimation in ArcGIS for wood terminals. The solution approach used route optimization and spatial clustering to allocate biomass efficiently. The model was tested in Finland, identifying viable locations for distributed bioenergy production.

Designing a resilient bioenergy SC requires optimizing facility locations, production levels, and material flows while accounting for economic and environmental factors. In 2022. Abdali et al. [83] developed a robust optimization model to configure a sugarcane-based bioenergy network under uncertainty. The study first employed fuzzy data envelopment analysis to identify suitable cultivation sites based on climatic, ecological, and social criteria. A robust MILP model was applied to optimize strategic and tactical decisions, integrating sustainability concerns such as CO_2 emissions, water consumption, and energy use. The model was tested in Iraq, determining optimal facility placements and production levels.

7.3. Multi-biomass value chains

Despite the contributions of integrated planning models across decision-making levels, critical gaps remain in managing multi-biomass SCs. For instance, Fattahi et al. [84] proposed a two-stage stochastic programming model that integrates strategic decisions (facility location, capacity, technology selection) with tactical (inventory, transportation) and operational (emissions control) layers, accounting for environmental risks and social life cycle impacts. However, the model's complexity and reliance on scenario-based uncertainty modeling restrict its scalability to larger, more diverse biomass systems, particularly where cross-sectoral collaboration and real-time flexibility are essential.

Similarly, Rentizelas et al. [4] employed a deterministic MILP model to optimize facility location, fuel mix allocation, and annual fuel use for a combined MSW and biomass system. While this multi-level framework bridges planning horizons, it remains static, handling variability only through sensitivity analysis, which does not fully capture the dynamics of biomass supply and demand across sectors or seasons. Machani et al. [85] introduced a multi-period MILP framework integrating forest residues, agricultural residues, and MSW into pulp and paper mills, coordinating investment timing, feedstock allocation, and production scheduling. Despite addressing flexibility in feedstock integration and facility utilization, the model does not incorporate uncertainty handling or adaptive logistics coordination, leaving gaps in responding to market fluctuations and supply disruptions.

On the other hand, Väisänen et al. [86] applied a multi-method approach, combining LCA and analytical hierarchy process (AHP), to evaluate sustainability trade-offs in distributed energy systems. While this approach supports qualitative integration of environmental and social criteria at the strategic level, it lacks quantitative mechanisms for tactical and operational coordination, such as resource allocation, logistics routing, or real-time decision adjustments. Fan et al. [87] incorporated clustering and environmental optimization for biomass integration in the Tomsk region, managing GHG emissions and land use across planning levels. However, their focus remains on environmental performance, without embedding economic trade-offs or adaptive logistics adjustments at tactical or operational stages.

These studies collectively demonstrate progress in aligning strategic, tactical, and operational decisions within multi-biomass SCs, yet they expose persistent limitations in fully synchronizing these layers. Integrating diverse biomass types with unique spatial distributions, seasonal availabilities, and processing requirements remains a key challenge in cohesive SC networks. While models coordinate infrastructure planning and feedstock allocation, they frequently operate under fixed or scenario-based assumptions, lacking mechanisms for continuous recalibration as system conditions evolve. The disconnect between long-term decisions (e.g., facility location, capacity sizing) and short-term logistical adjustments (e.g., transport flows, inventory management) constrains system adaptability, especially under market volatility or supply disruptions. Furthermore, cross-sectoral synchronization remains underdeveloped for harmonizing logistics and resource sharing across forestry, agriculture, and MSW sectors. Most models do not incorporate feedback mechanisms that allow operational data to influence upstream planning decisions, limiting the capacity for real-time adjustments across decision levels. Additionally, while environmental and economic objectives are often integrated, social dimensions, such as labor conditions, stakeholder coordination, and community impacts, are rarely embedded into tactical or operational planning. These limitations collectively hinder the realization of flexible, resilient, and cohesive multi-biomass SCs capable of adjusting to the complexities inherent in diverse biomass systems.

8. MSW biomass value chain

8.1. MSW biomass characteristics and logistics

MSW logistics are defined by centralized urban collection, variable composition, and regulatory complexity, all of which affect their integration into bioenergy systems. WtE technologies, including incineration, gasification, pyrolysis, and anaerobic digestion, present distinct logistical demands that differ from those of forestry and agricultural biomass.

Thermal WtE systems, such as incineration and RDF production, are widely used in the U.S. and Europe. They require dry, energy-dense waste streams and robust emission control systems. Gasification and pyrolysis, while offering higher energy recovery and lower residues, are more sensitive to feedstock uniformity and require sophisticated sorting and pretreatment steps. In contrast, anaerobic digestion is suitable for the organic, high-moisture fraction of MSW and demands separate collection or advanced separation systems [30].

These conversion pathways shape MSW SC design. Collection must be frequent and adaptable to urban density and waste generation variability. Transfer stations and preprocessing facilities must accommodate a range of material characteristics. Logistics depend on zoning policies, vehicle routing constraints, and facility permitting. As noted by Malav et al. (2020), up to 70 % of the total cost of MSW management in India arises from collection and transportation alone, highlighting the logistics intensity of urban waste valorization [13].

Understanding the compatibility between MSW fractions and WtE technologies is crucial to planning efficient SCs. Thermal technologies require low-moisture content and energy-dense inputs, while biological processes depend on high organic content and stable moisture levels. These factors must be addressed in logistics modeling for MSW to function as a reliable component of integrated biomass systems.

It is essential to highlight that MSW is rarely modeled as a standalone logistics system in the reviewed literature. Instead, it is predominantly integrated with forestry and agricultural biomass in multi-feedstock models to improve supply consistency, diversify input streams, and share infrastructure. This integration approach is consistently observed across decision-making levels, strategic (Section 4.3), tactical (Section 5.3), and combined levels (Section 7.3). This modeling trend reflects the practical advantages of incorporating MSW as a complementary base-load feedstock alongside seasonal or spatially dispersed biomass sources. The following section (8.2) examines a selection of studies that, while limited in number, offer unique insights into the role of MSW within independent and integrated SCs.

8.2. Optimization models involving MSW biomass: Logistics planning

Research on MSW biomass logistics remains limited but provides essential contributions to understanding and optimizing waste-to-energy SCs. In 2010, early foundational work by Gregg [88] developed a global modeling framework to estimate national and regional MSW biomass availability, using macro-level data such as trade volumes, product lifespans, and discard rates. Although not directly focused on logistics, this study laid the groundwork for long-term supply assessments, providing critical inputs for planning MSW-based energy systems.

In 2014, Rentizelas et al. [4] introduced a tactical MILP model that combined MSW and agricultural residues to supply a district energy system in Greece as interest in biomass co-utilization grew. While transportation and collection logistics were not explicitly modeled, their approach highlighted MSW's role as a base-load feedstock, complementing the seasonal nature of agricultural biomass. This contribution demonstrated how feedstock blending can stabilize facility utilization rates and enhance SC reliability.

Further advancing MSW energy logistics in 2021, Barros et al. [89] conducted a techno-economic assessment of two MSW-to-energy pathways, landfill gas recovery and anaerobic digestion, in Brazil's Minas Gerais region. Although lacking a formal optimization model, their study emphasized the importance of shared infrastructure and regional coordination in improving logistics efficiency for MSW systems. This highlighted the role of collaborative planning in enhancing the feasibility of MSW energy projects.

At the process optimization level, Khalilarya et al. [90] developed an optimized CHP system using gasified MSW sourced from a university campus. Employing Taguchi design and ANOVA analysis, their work focused on gasification conditions to maximize energy output. While not addressing broader logistics, this study showcased how decentralized MSW conversion systems can support distributed energy networks when integrated with flexible logistics and preprocessing infrastructure.

The most comprehensive MSW logistics framework was introduced by Xu et al. [91], who developed a multi-objective mixed-integer dynamic model for reverse logistics of MSW. Integrating soft-path strategies (policy-driven waste sorting) and hard-path strategies (technology deployment), their model optimized collection routing, preprocessing, facility allocation, and cascading technology selection under uncertainty. Applied to Shanghai, this framework balanced cost, emissions, employment, energy output, and system resilience, offering a flexible architecture that, while focused on MSW, provides a potential foundation for broader biomass integration across sectors.

9. Discussions

This section synthesizes the findings from the reviewed literature to critically address the four research questions guiding this study. The discussion integrates insights across planning levels and biomass types by building on the analysis of logistics operations, decision-making frameworks, and optimization models across forestry, agricultural, and MSW biomass VCs. The following subsections explore the distinct logistical operations of each biomass sector (RQ1), assess the analytical tools and methods employed in biomass logistics planning (RQ2), examine the integration strategies and challenges in coordinating multiple biomass VCs (RQ3), and identify methodological gaps that hinder effective multi-biomass collaboration (RQ4). This structure ensures a comprehensive evaluation of the current state of biomass-to-bioenergy logistics, highlighting opportunities for improving efficiency, resilience, and integration across sectors.

9.1. Logistics operations in biomass-to-bioenergy SCs

The logistics operations within forestry, agricultural, and MSW biomass SCs exhibit distinct characteristics and constraints that shape their efficiency and scalability in bioenergy systems. Transportation remains a central logistical concern across all biomass types, but operational conditions vary widely. In forestry biomass, transport is challenged by remote locations, requiring route optimization and on-site chipping to reduce bulk and minimize costs. In contrast, agricultural biomass collection is highly seasonal and dispersed, demanding timely routing strategies to align with harvest windows, while MSW biomass benefits from consistent year-round availability. However, urban transport networks introduce routing complexity linked to waste collection schedules and site congestion.

Preprocessing operations similarly reflect biomass-specific constraints. Forestry residues require moisture management through chipping and drying to prevent degradation and improve transportability, while agricultural residues rely on baling and drying to maintain quality and reduce volume. In MSW systems, preprocessing emphasizes sorting and densification to enhance energy recovery and minimize contamination risks. However, contamination variability in MSW streams and moisture fluctuations in forestry and agricultural feedstocks challenge preprocessing consistency, limiting logistics predictability.

Storage practices further differentiate these chains. Forestry biomass faces self-ignition and quality degradation risks during long storage periods, requiring well-designed storage systems, often proximal to harvesting sites. Agricultural biomass, subject to seasonal harvesting cycles, depends on covered storage solutions to preserve feedstock integrity across collection intervals. In contrast, MSW storage is closely tied to preprocessing capacity and urban facility location decisions, aiming to balance collection frequency and processing throughput.

At the coordination level, aligning tactical and operational planning remains a critical yet unresolved challenge, particularly given feedstock variability and distinct logistical frameworks across these chains. Tactical decisions, such as facility utilization rates and transport network configurations, must contend with operational realities, including real-time scheduling and supply fluctuations. While advances in stochastic and hybrid models have improved planning under uncertainty, the fragmented infrastructure, regulatory divergence, and data gaps across sectors hinder broader coordination.

This lack of coordination is further compounded by the absence of integrated operational models synchronizing short-term logistics decisions across biomass sectors. Despite extensive strategic and tactical planning research, no existing framework unifies routing, storage, and preprocessing operations for forestry, agricultural, and MSW biomass within a single real-time logistics system. Current models typically focus on single-biomass chains or treat operational layers in isolation, restricting system-wide synchronization and cross-sector efficiency. Additionally, although SC disruptions, such as weather variability, equipment failures, and dynamic routing needs, are frequently acknowledged, few models incorporate robust or resilient optimization frameworks capable of adapting to these uncertainties in real-time.

Overall, logistical challenges arise from biomass heterogeneity, spanning moisture content, bulk density, and contamination levels, and are compounded by transportation costs, particularly in remote or dispersed regions. The seasonality of agricultural residues, the composition variability of MSW, and the remote sourcing of forestry biomass require flexible logistics strategies, including adaptive procurement, feedstock blending, and localized infrastructure investments. Addressing these operational distinctions demands region-specific logistics planning and enhanced cross-sector collaboration to unlock the full potential of biomass-to-bioenergy SCs.

Despite advances in modeling logistics operations across forestry, agricultural, and MSW biomass SCs, a significant gap remains in the practical validation of these models. While several studies incorporate real-world datasets (e.g., California, Quebec, Kansas), reflecting actual transport routes, facility locations, and feedstock characteristics, their applications are typically scenario-based rather than validated through long-term operational deployment. This limits the ability to assess model robustness under dynamic, real-world conditions such as policy shifts, market volatility, and supply disruptions. Future research should prioritize pilot-scale implementations and industry collaborations to validate logistics strategies in operational environments. This step is crucial for refining models, enhancing their credibility, and supporting effective decision-making in integrated biomass-to-bioenergy systems.

9.2. Planning tools and methods in biomass logistics

Early biomass logistics models primarily used LP to optimize fundamental operations such as transportation and facility location. However, as SC complexity increased, MILP models became the dominant approach, representing 57 % of reviewed studies. In contrast, nonlinear models (MINLP, NLP) account for only 12 %, reflecting the computational challenges of solving such models, particularly for large-scale and multi-biomass systems.

Since 2020, MILP has been the preferred method for mixed biomass VCs, with only one LP and one MINLP model published in this period. This trend underscores MILP's flexibility and scalability in addressing diverse logistical challenges, including transportation, preprocessing, and facility location decisions. Despite their potential, multi-objective models remain less common due to the complexity of modeling and solving trade-offs, such as balancing economic and environmental goals. WtE systems integrating multi-objective programming are scarce but crucial for addressing sustainability concerns.

Researchers have explored alternative solution methods to tackle the computational intensity of large-scale problems. Exact methods, such as branch-and-bound algorithms, are the most prevalent, appearing in 65 % of studies. While they provide optimal solutions, their computational burden limits their applicability to large and complex problems. Heuristic (15 %) and metaheuristic (13 %) approaches have gained traction, particularly for large-scale and mixed biomass systems. Metaheuristic techniques, including Genetic Algorithms and Particle Swarm Optimization, offer near-optimal solutions within reasonable computational times, making them suitable for practical implementation.

8 % of studies use simulation methods to capture dynamic system behaviors and uncertainties in biomass logistics. These approaches are beneficial for modeling real-time transportation and storage dynamics where SC conditions fluctuate. The increasing adoption of heuristics, metaheuristics, and simulation-based approaches reflects their growing importance in solving large-scale, complex optimization problems.

Despite the inherent variability in biomass SCs, 68 % of reviewed models remain deterministic, with only 32 % incorporating uncertainty factors such as moisture content fluctuations, crop yield variations, and seasonal waste generation. Scenario analysis and stochastic programming have been the primary tools for capturing probabilistic uncertainty, allowing planners to model yield, price, or demand variations through scenario-based frameworks. For instance, two-stage [51] and multi-stage [50] stochastic models have improved adaptability in SCs with seasonal supply shifts or market fluctuations. However, the computational burden of scenario generation and expansion in multi-period models limits their scalability.

In contrast, robust optimization offers an alternative by handling uncertainty within bounded sets, without relying on probability distributions. This method ensures solution feasibility across uncertain parameters, such as biomass availability or quality ranges, but often leads to conservative solutions prioritizing feasibility over cost-efficiency. Studies have applied uncertainty budgets within robust frameworks to balance performance and conservatism [69].

Some recent contributions have explored hybrid models, combining stochastic and robust optimization to capture probabilistic and bounded uncertainties. While offering flexibility, these models increase computational complexity and remain challenging to implement in large-scale, multi-biomass systems. ABM has also emerged as a complementary tool for simulating dynamic disruptions, but its integration with optimization frameworks remains limited [81].

While deterministic models remain prevalent due to their computational efficiency, they fail to capture the real-world volatility of biomass SCs. Stochastic programming suits systems with quantifiable uncertainties, whereas robust optimization is preferred in data-scarce environments where feasibility under worst-case scenarios is critical. The choice between these approaches should be guided by data availability, risk tolerance, and computational capacity, with hybrid models offering potential for systems facing both uncertainties.

The selection of planning tools and methods varies across decision-making levels in biomass logistics, reflecting differences in time horizons, problem complexity, and uncertainty management:

- Strategic planning primarily employs MILP, GIS, and MCDM methods (e.g., TOPSIS, AHP, WASPAS) for biorefinery and terminal location, long-term feedstock allocation, and policy evaluation.
- Tactical planning integrates MILP, MINLP, and heuristic methods to optimize biomass procurement, storage, blending, and transportation. Game theory models support contractual coordination, while GIS-based decision support systems enhance logistics network design.
- Operational planning addresses real-time fleet routing, truck scheduling, and preprocessing, using VRP hybrid simulation–optimization approaches, and metaheuristic techniques (e.g., Genetic Algorithms, Simulated Annealing) to minimize transportation costs and improve SC efficiency. Monte Carlo simulation and Bender's decomposition are also employed to assess SC disruptions and enhance logistics resilience.

9.3. Integration and collaboration in biomass value chains: Challenges and opportunities

Integrating forestry, agricultural, and MSW biomass VCs offers notable opportunities to enhance feedstock availability, logistics efficiency, and conversion flexibility. However, realizing these opportunities is constrained by systemic barriers arising from the distinct characteristics of each biomass sector. These barriers manifest differently across individual VCs and become more complex in integrated, multi-biomass systems. Fig. 8 provides a comparative overview of key challenges, including seasonal availability, moisture variability, preprocessing compatibility, and contamination risk, and assesses their severity (low, medium, or high) across various sectors. While some challenges, like spatial alignment in forestry or contamination risk in MSW, are sector-specific, integrating multiple biomass sources amplifies medium-level challenges across categories, reflecting the compounded complexity in logistics coordination, quality management, and infrastructure planning.

This comparative assessment also highlights the critical trade-offs and synergies that arise from combining these biomass sources. For example, MSW provides a continuous, year-round supply, but it introduces high contamination risks that require specialized preprocessing. In contrast, forestry biomass offers stable quality with low contamination; however, it is constrained by seasonality and spatial dispersion. Similarly, agricultural residues are abundant post-harvest but suffer from moisture variability and limited storage stability. Despite these trade-offs, synergistic opportunities arise from blending feedstocks (e.g., pairing high-energy–density forestry residues with MSW to improve fuel quality) and shared logistics infrastructures that stabilize feedstock flows across sectors. These interlinked challenges and synergies underscore the need for adaptive logistics, blending-aware optimization, and coordinated infrastructure planning, which are further explored in Section 9.4.

The following challenges, synthesized from the literature, represent key obstacles to effective integration:

- **Feedstock heterogeneity and incompatible logistics systems**

The inherent differences in feedstock characteristics, including moisture content, bulk density, particle size, and contamination levels, necessitate sector-specific logistics and preprocessing infrastructures. Forestry residues demand specialized harvesting and chipping equipment, agricultural residues require seasonal collection systems, and MSW relies on urban waste networks. This divergence in logistics design impedes shared infrastructure utilization, reinforcing operational terminals and complicating the alignment of transport and preprocessing activities across sectors.

- **Temporal and spatial supply mismatch**

The asynchronous availability patterns of biomass sources exacerbate SC coordination. Forestry residues are tied to logging seasons and road access windows, agricultural residues follow crop harvest cycles, and MSW is continuously produced but exhibits quality variability. These seasonal and spatial disparities make it difficult to maintain consistent feedstock flows, particularly for blended SCs. Simple storage solutions are insufficient due to feedstock degradation risks, such as moisture-induced spoilage and microbial activity, demanding more sophisticated coordination mechanisms.

- **Institutional fragmentation and sectoral terminals**

Each biomass sector operates under regulatory frameworks, market structures, and stakeholder networks. Forestry, agriculture, and urban waste management follow different governance protocols, with little incentive to pursue collaborative logistics or shared investments. This

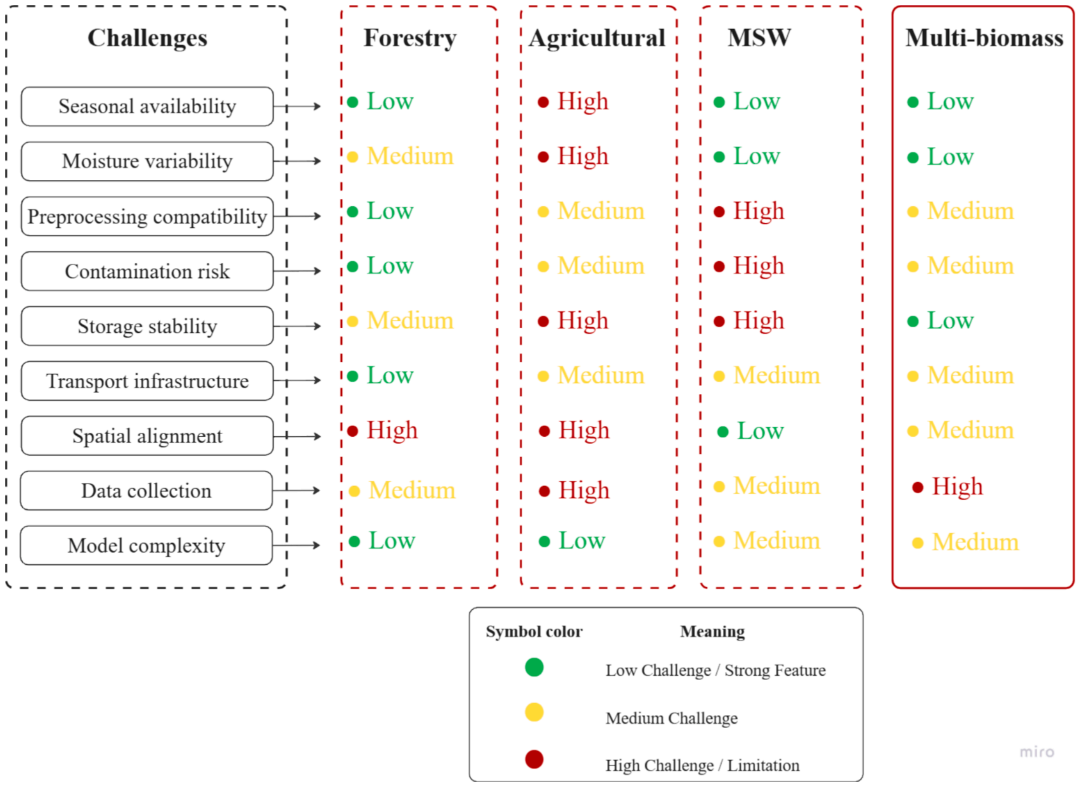

Fig. 8. Comparative overview of integration challenges across forestry, agricultural, and MSW biomass value chains.

institutional separation obstructs the formation of joint strategies and coordinated infrastructure planning, leaving each sector to optimize independently.

- **Quality control and feedstock compatibility issues**

Integrating biomass types requires meeting strict quality standards across the SC, but inconsistent feedstock properties pose substantial barriers. Contamination risks are particularly acute with MSW, where non-biomass materials (e.g., plastics, metals) can compromise conversion processes and regulatory compliance. Meanwhile, forestry and agricultural residues vary in energy content, ash levels, and moisture content, complicating blending strategies. Cross-sector blending remains risky and inefficient without harmonized preprocessing protocols, real-time quality monitoring, and contamination mitigation measures.

- **Lack of data integration and real-time coordination**

Biomass sectors maintain isolated data systems, independently tracking supply volumes, logistics schedules, and quality metrics. The absence of standardized, interoperable data platforms hinders real-time visibility and coordination, resulting in misaligned forecasts, inefficient logistics, and delayed responses to disruptions. Data-sharing hesitations due to trust and confidentiality concerns further exacerbate these issues, stalling collaborative efforts.

- **Economic misalignment and contractual barriers**

Divergent economic priorities across sectors discourage joint investments and shared logistics operations. While forestry and agriculture often prioritize cost minimization for their feedstock streams, MSW management focuses on waste diversion mandates. The lack of coordinated contractual mechanisms, such as revenue-sharing, risk-pooling, or performance-based agreements, prevents incentive alignment, undermining collaboration on shared infrastructure or integrated logistics systems.

- **Underrepresentation of environmental and social integration metrics**

Although models frequently optimize for economic or logistical efficiency, they rarely comprehensively integrate environmental and social sustainability metrics across sectors. GHG emissions, land use impacts, labor conditions, and community engagement are often considered secondary or external factors, weakening the sustainability case for multi-biomass integration and limiting stakeholder buy-in.

- **Model complexity and limited scalability:**

Efforts to integrate the logistical, environmental, and economic dimensions of multi-biomass systems into comprehensive models often lead to high computational complexity. These models, which attempt to handle feedstock variability, uncertainty, and cross-sector coordination, can become data-intensive and challenging to scale, restricting their applicability to real-world scenarios. As a result, many models remain theoretical exercises, validated on simplified case studies, rather than operational tools adaptable to the complex dynamics of biomass SCs.

9.4. Modeling strategies and logistics recommendations for multi-biomass integration

Integrating forestry, agricultural, and MSW biomass VCs has been extensively modeled using a range of strategic, tactical, and operational techniques. As highlighted in Section 9.3, these models address key integration challenges arising from the distinct characteristics of each biomass type and the complexity of coordinating their respective logistics systems. To address these issues, prior studies have employed MILP for facility location and logistics coordination, stochastic and robust optimization for uncertainty management, and multi-method frameworks such as LCA and AHP for evaluating sustainability trade-offs. Additional contributions include contractual coordination models and spatial clustering techniques designed to align actors across biomass sectors.

While these frameworks provide valuable insights, they often address individual barriers in isolation and fall short of capturing the broader, systemic synergies required for multi-biomass integration. Effective integration requires a holistic approach that balances sector-specific limitations with shared opportunities across logistics, infrastructure, and governance. To illustrate this, Fig. 9 synthesizes a set of synergistic elements that enable integration across forestry, agricultural, and MSW SCs. These elements, ranging from complementary seasonality and multimodal transport to coordinated preprocessing and terminal infrastructure, are categorized based on their feasibility and impact, offering a conceptual foundation for developing cohesive, cross-sector integration strategies.

Achieving effective integration across forestry, agricultural, and MSW biomass VCs requires coordinated logistics, shared infrastructure, and stakeholder alignment. The following synergy strategies outline key elements that can enable such integration in practice.

- **Flexible preprocessing infrastructure**

In multi-biomass systems, feedstocks such as forestry residues, agricultural byproducts, and MSW differ significantly in moisture content, particle size, contamination levels, and energy density. Configurable machinery, capable of adjusting drying rates, chipping sizes, or densification pressures, is essential to ensure that preprocessing operations are compatible with these varying characteristics. Without such flexibility, processing infrastructure becomes feedstock-specific, leading to underutilization or increased downtime when switching between biomass types. For instance, agricultural residues may require different drying conditions than forest biomass, while MSW introduces contamination risks requiring specialized handling.

- **Coordinated multimodal transportation networks**

The spatial dispersion of biomass sources poses significant logistical challenges. MSW is concentrated in urban areas, agricultural residues are distributed across rural landscapes, and forestry residues are often located in remote regions. Multimodal transport systems, combining road, rail, and waterways, can optimize cost-efficiency and reduce the environmental footprint of biomass transport. These networks must account for feedstock-specific logistics, such as moisture-related weight penalties for wet biomass or contamination risks during transit. Coordinated transport scheduling also enables backhauling opportunities, where empty vehicles returning from deliveries transport other biomass types, enhancing overall system efficiency.

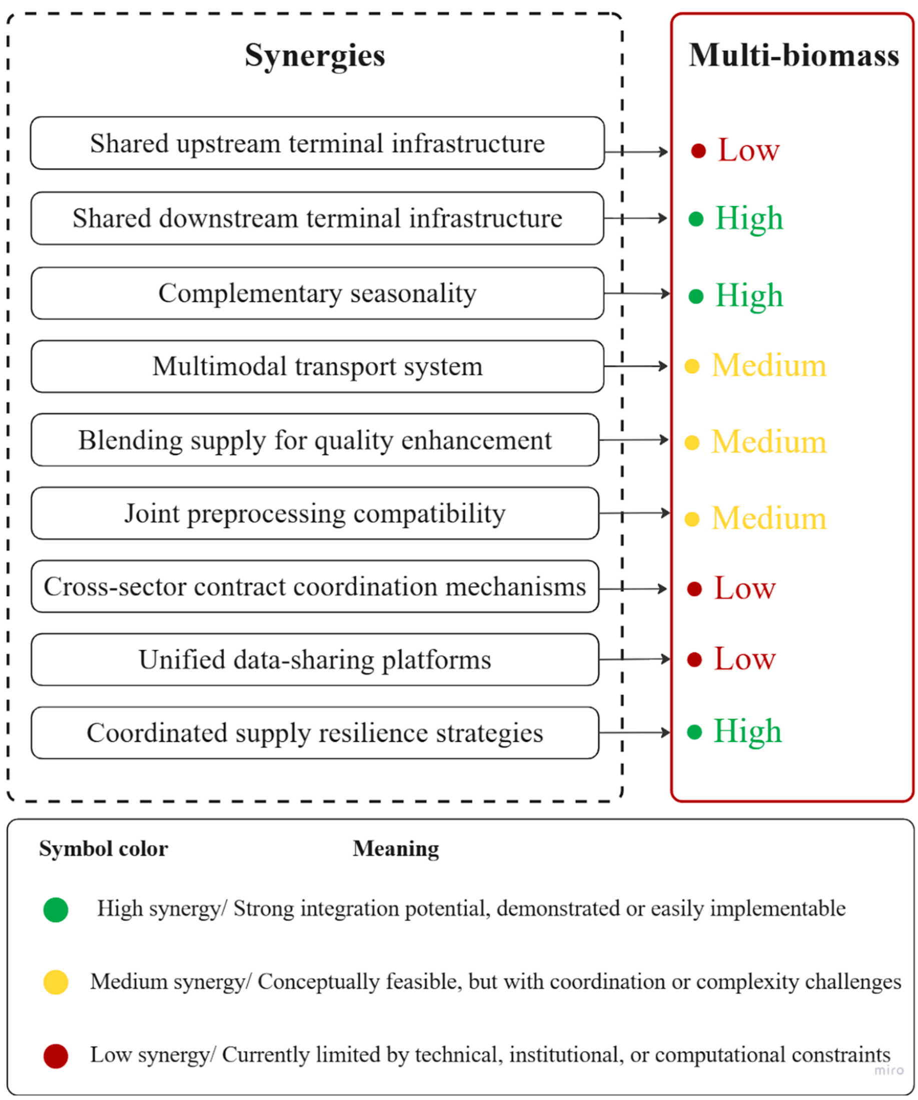

Fig. 9. Comparative assessment of synergy enablers in multi-biomass value chains.

- **Adaptive storage management**

Storage requirements vary widely among biomass types; forestry residues can be stored for longer periods with minimal degradation, while agricultural residues and MSW can degrade rapidly due to their sensitivity to moisture and microbial activity. Adaptive storage systems must therefore accommodate varying storage durations, ventilation requirements, and moisture control measures. Integrated inventory models can dynamically allocate biomass to storage locations that best match its preservation needs, minimizing energy content and quality losses across the SC.

- **Blending-aware optimization frameworks**

Biomass blending is crucial for feedstock standardization prior to conversion, particularly when integrating low-quality MSW with high-energy–density forestry biomass or agricultural residues. Optimization models must explicitly account for blending constraints, such as achieving target moisture content or contamination thresholds. Without blending-aware frameworks, SCs risk delivering heterogeneous feedstocks that reduce conversion efficiency or increase processing costs at biorefineries.

- **Scenario-based decision-making across scales**

The variability in biomass supply, driven by seasonality (e.g., agricultural harvest cycles), market dynamics, and policy shifts (e.g., MSW regulations), necessitates robust scenario planning. Incorporating stochastic and robust optimization techniques allows SC models to assess multiple uncertain conditions while maintaining coordination across strategic, tactical, and operational levels. This approach ensures SCs remain resilient and adaptive, even as conditions fluctuate across spatial regions and time horizons.

- **Shared infrastructure and contractual coordination**

Integrating multiple biomass sectors requires shared logistics assets (e.g., transport fleets, preprocessing hubs) and coordinated contractual agreements that align incentives across forestry, agriculture, and urban waste management stakeholders. Without such frameworks, sector-specific terminals persist, which prevents resource sharing and increases system costs. Shared infrastructure reduces capital expenditures and fosters synergistic planning, while contractual models (e.g., revenue sharing, risk pooling) stabilize supply flows and distribute uncertainty burdens equitably among participants.

- **Integrated data sharing platforms**

Fragmented data systems hinder the coordination of forestry, agriculture, and MSW biomass VCs, each tailored to sector-specific needs such as harvest schedules, yield patterns, or collection rates. The lack of standardized, interoperable data exchange mechanisms leads to misaligned supply forecasts, inefficient logistics, and delays in resource allocation. Establishing integrated data platforms, leveraging cloud-based technologies or blockchain frameworks, can facilitate real-time visibility of feedstock availability, quality parameters (e.g., moisture content, contamination), and logistics status across all sectors. This enables dynamic procurement, transport, and inventory coordination, ensuring efficient biomass flows across geographically dispersed regions. Implementing standardized data protocols and confidentiality agreements is crucial to ensure data integrity, foster stakeholder trust, and facilitate collaborative decision-making, thereby reducing transaction costs and enhancing system-wide integration.

10. Concluding remarks

This review presents a novel and comprehensive synthesis of logistics planning and optimization strategies across forestry, agricultural, and MSW biomass VCs, with a focus on collaboration and multi-biomass integration. Earlier review papers have primarily focused on individual biomass types or limited logistical aspects; this study addresses that gap by examining the operational synergies, infrastructure needs, and decision-making frameworks required for cohesive biomass-to-bioenergy systems.

The study analyzes 112 articles, including 19 prior reviews, to identify trends in optimization approaches, decision levels, modeling tools, and integration challenges. Shared infrastructure, such as co-located preprocessing facilities and multimodal transportation networks, emerges as a key enabler for collaborative logistics. These systems can leverage the complementary characteristics of forestry residues, agricultural byproducts, and MSW to reduce costs, improve supply resilience, and enhance system efficiency.

Despite these opportunities, integration remains limited by several persistent challenges. These include variability in biomass quality, contamination risks in mixed streams, the complexity of synchronizing SCs with different seasonality and logistics profiles, and limited scalability of shared systems. Preprocessing compatibility, adaptive transportation planning, and better coordination across stakeholders remain critical for advancement.

The findings also emphasize the importance of advanced modeling approaches, such as MILP and scenario-based analysis, to support logistics decisions under uncertainty. While spatial and temporal constraints have been addressed in some models, uncertainty related to biomass availability, degradation, and policy shifts remains insufficiently explored. Future work should expand stochastic and robust optimization frameworks, ideally supported by GIS and life-cycle assessment tools.

In parallel, policy and institutional mechanisms must support integration efforts. Incentives for shared infrastructure, grants for preprocessing innovation, and cross-sector partnerships between industry, municipalities, and academia can accelerate adoption.

Key future research directions include:

- Developing flexible preprocessing systems that accommodate diverse biomass properties,
- Designing adaptive, multimodal transportation systems to manage dispersed biomass flows and seasonal variability,
- Expanding stakeholder collaboration models to manage operational complexity across sectors,
- Enhancing uncertainty modeling through robust and stochastic optimization methods,
- Supporting integration with regional and national policy tools,
- Building integrated operational frameworks that enable real-time coordination of routing, storage, and preprocessing across forestry, agricultural, and MSW biomass VCs,
- Validating optimization models through real-world pilot projects and collaborative implementation with industry, municipalities, and bioenergy producers,

Developing interoperable data-sharing platforms (e.g., cloud-based or blockchain-enabled) is essential to support dynamic logistics coordination, real-time supply visibility, and quality tracking across forestry, agricultural, and MSW sectors. In parallel, the integration of emerging technologies such as the Internet of Things (IoT) and Explainable Artificial Intelligence (XAI) presents a promising avenue for advancing operational responsiveness and transparency. IoT-enabled sensors and tracking systems can provide continuous data on biomass availability, location, and quality (e.g., moisture content, contamination), forming the basis for real-time decision-making. Meanwhile, XAI can enhance the interpretability of complex optimization models, enabling decisionmakers to better understand the underlying trade-offs and model logic. Future research should explore how the combination of IoT for data acquisition and XAI for model transparency can bridge the gap between theoretical models and practical implementation in integrated multi-biomass logistics systems.

This review highlights the opportunities and limitations of current biomass logistics systems and outlines a path toward more integrated, cost-effective, and resilient SCs that support sustainable bioenergy goals.

CRediT authorship contribution statement

Seyyedeh Rozita Ebrahimi: Writing – original draft, Methodology. **Mikael Rönnqvist:** Writing – review & editing, Supervision. **Mustapha Ouhimmou:** Writing – review & editing, Supervision. **Paul Stuart:** Supervision.

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.

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Appendix A

Table A1
Overview of earlier review papers on biomass-to-bioenergy SCs.

Reference	Authors and publication year	Time span	Decision-making levels			Biomass value chains			Logistical aspects								Programming approaches	Solution methods	Collaboration and integration	Case Study Region Classification
			Strategic	Tactical	Operational	Forest	Agriculture	MSW	Transportation	Collection and availability	Inventory management	Preprocessing	Facility location	Environmental, economic, and social	Technological investigations	Uncertainty status				
[92]	(Gold & Seuring, 2011)	2000- 2009				✓	✓		✓	✓	✓	✓		✓	✓					
[23]	(Awudu & Zhang, 2012)	2000- 2011	✓	✓	✓	✓								✓		✓	✓	✓		
[24]	(Shabani et al., 2013)	2000- 2013	✓	✓	✓	✓			✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		
[18]	(Sharma et al., 2013)	Published up to 2011	✓	✓	✓	✓	✓		✓	✓	✓	✓	✓	✓		✓	✓	✓	✓	✓
[19]	(Yue et al., 2014)	2000-2013	✓	✓	✓	✓	✓		✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
[21]	(Wolfsmayr, Ulrich J., 2014)	1989-2011	✓	✓	✓	✓			✓	✓	✓	✓								
[93]	(Mafakheri & Nasiri, 2014)	2000-2013	✓	✓	✓	✓	✓		✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		
[14]	(Cambero & Sowlati, 2014)	2000-2014	✓	✓	✓	✓			✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		
[94]	(Ba et al., 2016)	1989- 2014	✓	✓	✓	✓	✓		✓	✓	✓	✓	✓	✓		✓	✓	✓		
[95]	(Li et al., 2017)	2000-2017						✓						✓						
[33]	(Malladi & Sowlati, 2017)	1989-2017			✓	✓			✓			✓				✓	✓	✓		
[96]	(Ko et al., 2018)	1990- 2016				✓	✓		✓					✓						
[30]	(Mukherjee et al., 2019)	2000- 2019						✓				✓		✓	✓		✓	✓		
[13]	(Chand Malav et al., 2020)	2000-2020						✓		✓		✓		✓	✓					
[20]	(Singh et al., 2021)	1990-2020				✓	✓	✓		✓				✓					✓	
[97]	(Mobtaker et al., 2021)	2000-2019		✓		✓			✓	✓				✓						
[16]	(Yana et al., 2022)	2007-2020				✓	✓	✓		✓		✓		✓	✓					
[98]	(Chidozie et al., 2023)	2011-2023	✓	✓	✓	✓	✓			✓		✓		✓	✓			✓		
[99]	(Longo et al., 2024)	2000-2022				✓	✓	✓						✓	✓					✓

Table A2
Forest biomass value chain studies and logistical aspects of their optimization models.

Reference.	Authors and publication year	Logistic operations in optimization models								Uncertainty	Decision-making level			Objective function		Modeling approach				Solution Method				Case study's location
		Preprocessing	Transportation	Location-Allocation	Supply Network Design	Economic study	Storage and Inventory management	Biomass availability	Environmental aspects	Stochastic programming or Robust optimization	Strategic	Tactical	Operational	Single	Multiple Obj.	LP	NLP	MILP	MINLP	Exact	Heuristic	Meta-Heuristic	Simulation	
[38]	(Gunnarsson et al., 2004)		✓		✓			✓				✓		✓				✓			✓			Sweden
[32]	(Gronalt et al., 2007)	✓			✓							✓		✓				✓			✓			Austria
[52]	(Leduc et al., 2010)		✓	✓	✓						✓			✓				✓		✓				Sweden
[100]	(Kim et al., 2011)	✓	✓	✓	✓			✓	✓	✓	✓	✓		✓				✓		✓				USA
[101]	(Svensson et al., 2011)				✓	✓		✓	✓	✓	✓			✓				✓		✓				No case study
[102]	(Flisberg et al., 2012)	✓	✓	✓				✓			✓	✓		✓		✓				✓				Sweden
[73]	(Acuna et al., 2012)	✓	✓		✓		✓	✓					✓	✓		✓				✓				Finland
[103]	(Karhunen et al., 2012)							✓			✓	✓		✓		✓				✓				Finland
[104]	(Tay et al., 2013)			✓	✓			✓	✓	✓	✓	✓		✓					✓	✓				USA
[46]	(Han et al., 2012)		✓					✓					✓		✓			✓				✓		USA
[53]	(Rauch et al., 2010)	✓		✓			✓				✓			✓				✓		✓				Austria
[41]	(Shabani et al., 2013)		✓				✓	✓	✓			✓		✓					✓	✓				Canada
[67]	(Shabani et al., 2014)				✓		✓	✓		✓		✓		✓				✓		✓				Canada

Table A2
(Cont.).

Reference..	Authors and publication year	Logistic operations in optimization models								Uncertainty	Decision-making level			Objective function		Modeling approach				Solution Method				Case study's location
		Preprocessing	Transportation	Location-Allocation	Supply Network Design	Economic study	Storage and Inventory management	Biomass availability	Environmental aspects	Stochastic programming or Robust optimization	Strategic	Tactical	Operational	Single	Multiple Obj.	LP	NLP	MILP	MINLP	Exact	Heuristic	Meta-Heuristic	Simulation	
[105]	(Yeh et al., 2014)				✓	✓			✓			✓			✓			✓		✓				Not-Mentioned
[106]	(Natarajan et al., 2014)		✓	✓	✓				✓		✓			✓				✓		✓				Finland
[42]	(Akhtari et al., 2014)		✓		✓			✓				✓		✓		✓				✓				Canada
[107]	(Huang et al., 2014)		✓		✓			✓		✓	✓	✓		✓				✓		✓				USA
[54]	(Cambero et al., 2015)		✓	✓				✓	✓		✓			✓				✓		✓				Canada
[31]	(Zamar et al., 2015)				✓			✓		✓		✓		✓		✓					✓		✓	No case study
[40]	(Yeh et al., 2015)			✓	✓				✓	✓	✓				✓		✓			✓				No case study
[45]	(Zamora-Cristales et al., 2015)	✓		✓	✓						✓	✓		✓				✓				✓		USA
[108]	(Cambero et al., 2016)		✓		✓	✓			✓			✓			✓			✓		✓				Canada
[50]	(Shabani et al., 2016)		✓		✓			✓		✓		✓		✓		✓					✓			Canada
[109]	(F. Zhang et al., 2016)	✓	✓				✓				✓	✓		✓				✓		✓		✓		USA
[56]	(Marufuzzaman et al., 2016)	✓	✓		✓				✓		✓				✓			✓		✓				USA
[79]	(Abasian et al., 2017)	✓	✓					✓			✓	✓		✓				✓		✓		✓		Canada

Table A2
(Cont.).

Reference.	Authors and publication year	Logistic operations in optimization models								Uncertainty	Decision-making level			Objective function		Modeling approach				Solution Method				Case study's location
		Preprocessing	Transportation	Location-Allocation	Supply Network Design	Economic study	Storage and Inventory management	Biomass availability	Environmental aspects	Stochastic programming or Robust optimization	Strategic	Tactical	Operational	Single	Multiple Obj.	LP	NLP	MILP	MINLP	Exact	Heuristic	Meta-Heuristic	Simulation	
[68]	(Gautam et al., 2017a)		✓		✓			✓				✓		✓				✓		✓				Canada
[110]	(W. Y. Liu et al., 2017)		✓		✓			✓	✓			✓		✓				✓		✓				No case study
[43]	(Osmani et al., 2017)		✓	✓					✓	✓	✓				✓	✓				✓		✓		USA
[111]	(Zamar et al., 2017)		✓		✓			✓		✓		✓		✓		✓						✓		USA
[44]	(Björheden, 2017)	✓	✓	✓	✓			✓			✓	✓		✓		✓				✓				Finland and Sweden
[55]	(Campanella et al., 2018)		✓	✓	✓						✓			✓				✓		✓				Argentina
[112]	(Calderón et al., 2018)	✓	✓					✓	✓		✓			✓				✓		✓				UK
[113]	(Malladi et al., 2018)		✓	✓			✓	✓					✓	✓				✓			✓			Canada
[114]	(Akhtari et al., 2018)	✓			✓		✓	✓			✓	✓		✓				✓		✓		✓		Canada
[74]	(Marques et al., 2018)		✓		✓		✓	✓	✓				✓	✓				✓		✓				Finland
[80]	(Palander et al., 2018)		✓	✓		✓		✓	✓		✓	✓			✓	✓				✓				Finland
[2]	(Abasian et al., 2019)	✓	✓		✓			✓		✓	✓	✓		✓				✓		✓				Canada
[115]	(Akhtari et al., 2019)		✓		✓		✓		✓				✓	✓									✓	No case study

Table A2
(Cont.).

Reference..	Authors and publication year	Logistic operations in optimization models								Uncertainty	Decision-making level			Objective function		Modeling approach				Solution Method				Case study's location
		Preprocessing	Transportation	Location-Allocation	Supply Network Design	Economic study	Storage and Inventory management	Biomass availability	Environmental aspects	Stochastic programming or Robust optimization	Strategic	Tactical	Operational	Single	Multiple Obj.	LP	NLP	MILP	MINLP	Exact	Heuristic	Meta-Heuristic	Simulation	
[48]	(Akhtari et al. 2020)	✓	✓	✓			✓		✓	✓	✓	✓	✓	✓				✓					✓	Canada
[27]	(Battuvshin et al., 2020)				✓			✓			✓			✓		✓				✓	✓			Japan
[81]	(Raghu et al., 2020)		✓	✓	✓			✓	✓		✓	✓		✓		✓				✓				Finland
[75]	(Panoutsou et al., 2020)		✓		✓		✓			✓			✓		✓			✓		✓		✓	✓	Greece
[69]	(Ahmadvand & Sowlati, 2022)		✓		✓					✓		✓		✓					✓	✓	✓			Canada

Table A3
Agricultural biomass value chain studies and logistical aspects of their optimization models.

Reference..	Authors and publication year	Logistic operations in optimization models								Uncertainty	Decision-making level			Objective function		Modeling approach				Solution Method				Case study's location
		Preprocessing	Transportation	Location-Allocation	Supply Network Design	Economic study	Storage and Inventory management	Biomass availability	Environmental aspects	Stochastic programming or Robust optimization	Strategic	Tactical	Operational	Single	Multiple Obj.	LP	NLP	MILP	MINLP	Exact	Heuristic	Meta-Heuristic	Simulation	
[26]	(Cundiff et al., 1997)	✓			✓		✓					✓			✓			✓		✓				USA
[28]	(Čuček et al., 2012)	✓				✓	✓	✓			✓								✓	✓				Slovenia
[58]	(Kazemzadeh et al., 2013)		✓	✓	✓			✓		✓	✓					✓				✓				USA
[116]	(J. Zhang et al., 2013)		✓	✓	✓						✓				✓			✓		✓				USA
[51]	(Osmani et al., 2013)		✓	✓	✓	✓				✓	✓	✓	✓			✓				✓				USA
[76]	(Gracia et al., 2014)		✓					✓					✓	✓				✓				✓		Spain
[59]	(Serrano et al., 2015)		✓	✓	✓			✓		✓	✓				✓			✓		✓				Spain
[117]	(Ren et al., 2015)					✓				✓	✓	✓	✓		✓			✓		✓				No case study
[118]	(Asadi et al., 2018)		✓				✓		✓	✓	✓	✓	✓	✓			✓					✓		Iran
[119]	(He-Lambert et al., 2019)		✓	✓			✓			✓	✓	✓		✓	✓			✓		✓				USA
[120]	(Soren et al., 2019)			✓	✓		✓			✓	✓				✓			✓		✓		✓	✓	Greece
[82]	(Laasasenaho et al., 2019)		✓	✓	✓	✓		✓			✓	✓		✓		✓				✓				Finland
[121]	(Morales Chavez et al., 2021)		✓	✓			✓		✓	✓	✓	✓	✓	✓			✓			✓		✓		USA

Table A3
(Cont.).

.Reference.	Authors and publication year	Logistic operations in optimization models								Uncertainty	Decision-making level			Objective function		Modeling approach				Solution Method				Case study's location
		Preprocessing	Transportation	Location-Allocation	Supply Network Design	Economic study	Storage and Inventory management	Biomass availability	Environmental aspects	Stochastic programming or Robust optimization	Strategic	Tactical	Operational	Single	Multiple Obj.	LP	NLP	MILP	MINLP	Exact	Heuristic	Meta-Heuristic	Simulation	
[122]	(Benjamin et al., 2021)				✓	✓							✓	✓				✓			✓	✓		Philippines
[123]	(Allman et al., 2021)		✓	✓						✓	✓	✓		✓		✓		✓		✓				USA
[77]	(Vazifeh et al., 2021)	✓		✓	✓	✓							✓				✓		✓	✓				Canada
[83]	(Abdali et al., 2022)			✓	✓				✓	✓	✓	✓	✓			✓				✓				Iraq
[124]	(J. Zhang et al., 2022)		✓	✓					✓			✓	✓		✓	✓		✓		✓			✓	China
[78]	(An, 2022)		✓										✓	✓				✓		✓	✓			Canada
[125]	(Ollila et al., 2023)		✓	✓	✓		✓	✓					✓	✓				✓		✓				Finland
[47]	(Yunusoglu et al., 2024)		✓	✓			✓	✓	✓			✓	✓			✓				✓	✓			Turkey
[70]	(Ogunrewo et al., 2024)		✓	✓	✓		✓					✓			✓			✓		✓			✓	Nigeria

Table A4
Multi-biomass value chain studies and logistical aspects of their optimization models.

Reference..	Authors and publication year	Type of Biomass VCs			Logistic operations in optimization models								Uncertainty	Decision-making level			Objective function		Modeling Approach				Solution Approach				Case study's location
		Forestry	Agricultural	MSW	Transportation	Preprocessing	Location-Allocation	Supply Network Design	Economic study	Storage and Inventory management	Biomass availability	Environmental aspects	Stochastic programming or Robust optimization	Strategic	Tactical	Operational	Single	Multiple Obj.	LP	NLP	MILP	MINLP	Exact	Heuristic	Meta-Heuristic	Simulation	
[39]	(Ekşioğlu et al., 2009)	✓	✓		✓			✓		✓				✓			✓				✓		✓				USA
[126]	(Parker et al., 2010)	✓	✓	✓	✓		✓	✓			✓			✓			✓				✓		✓				USA
[60]	(Huang et al., 2010)	✓	✓	✓				✓	✓		✓			✓			✓				✓		✓				USA
[127]	(Santibañez-Aguilar et al., 2011)	✓	✓			✓		✓	✓		✓			✓				✓			✓		✓				USA
[62]	(Chen et al., 2012)	✓	✓	✓			✓	✓			✓	✓	✓	✓			✓			✓			✓				USA
[63]	(Gebreslassie et al., 2012)	✓	✓						✓	✓		✓	✓	✓			✓				✓		✓				USA
[4]	(Rentizelas et al., 2014)		✓	✓			✓	✓	✓					✓	✓		✓		✓				✓			✓	Greece
[85]	(Machani et al., 2014)	✓	✓	✓				✓			✓	✓		✓	✓		✓		✓				✓				Canada
[86]	(Väisänen et al., 2016)	✓	✓		✓	✓	✓			✓	✓			✓	✓			✓	✓				✓				Finland
[57]	(Calderón et al., 2017)	✓	✓	✓	✓	✓					✓			✓			✓				✓		✓				UK
[22]	(Mirkouei et al., 2017)	✓	✓		✓		✓				✓		✓		✓		✓				✓				✓		USA
[72]	(Fan et al., 2019)	✓	✓				✓		✓				✓		✓		✓		✓					✓			China
[61]	(Roni et al., 2019)		✓	✓	✓		✓				✓			✓			✓				✓		✓	✓			USA

Table A4
(cont.).

Reference..	Authors and publication year	Type of Biomass VCs			Logistic operations in optimization models								Uncertainty	Decision-making level			Objective function		Modeling Approach				Solution Approach				Case study's location
		Forestry	Agricultural	MSW	Transportation	Preprocessing	Location-Allocation	Supply Network Design	Economic study	Storage and Inventory management	Biomass availability	Environmental aspects	Stochastic programming or Robust optimization	Strategic	Tactical	Operational	Single	Multiple Obj.	LP	NLP	MILP	MINLP	Exact	Heuristic	Meta-Heuristic	Simulation	
[71]	(Y. Wang et al., 2020)	✓	✓		✓	✓				✓	✓				✓		✓				✓		✓	✓			USA
[84]	(Fattahi et al., 2021)	✓	✓	✓				✓				✓	✓	✓	✓		✓				✓		✓				Iran
[65]	(Pande et al., 2021)	✓	✓						✓		✓		✓	✓												✓	India
[64]	(Razm et al., 2021)	✓	✓				✓	✓	✓			✓	✓	✓			✓				✓		✓	✓			Iran
[66]	(Firouzi et al., 2021)	✓	✓	✓					✓		✓	✓		✓			✓							✓			Iran
[87]	(Fan et al., 2021)	✓	✓		✓		✓				✓			✓	✓	✓	✓				✓		✓				Russia
[15]	(Salehi et al., 2022)	✓	✓	✓				✓			✓		✓		✓		✓					✓	✓	✓			Iran
[128]	(B. Liu et al., 2022)	✓	✓	✓			✓	✓		✓		✓	✓	✓			✓				✓		✓				China
[129]	(Abdel-Aal, 2024)	✓	✓		✓		✓	✓		✓				✓	✓	✓	✓				✓		✓		✓		No case study

Data availability

No data was used for the research described in the article.

References

[1] Blair MJ, Gagnon B, Klain A, Kulišić B. Contribution of biomass SCs for bioenergy to sustainable development goals. Land (Basel) 2021;10:1–28. https://doi.org/10.3390/land10020181.

[2] Abasian F, Rönnqvist M, Ouhimmou M. Forest bioenergy network design under market uncertainty. Energy 2019;188. https://doi.org/10.1016/j.energy.2019.116038.

[3] Khandelwal C, Singhal M, Gaurav G, Dangayach GS, Meena ML. Agriculture SC Management: A Review (2010–2020). Mater Today Proc 2021;47:3144–53. https://doi.org/10.1016/j.matpr.2021.06.193. Elsevier Ltd.

[4] Rentizelas AA, Tolis AI, Tatsiopoulos IP. Combined Municipal Solid Waste and biomass system optimization for district energy applications. Waste Manag 2014;34:36–48. https://doi.org/10.1016/j.wasman.2013.09.026.

[5] Ubando AT, Felix CB, Chen WH. Biorefineries in circular bioeconomy: A comprehensive review. Bioresour Technol 2020;299. https://doi.org/10.1016/j.biortech.2019.122585.

[6] Zhu L. Biorefinery as a promising approach to promote microalgae industry: An innovative framework. Renew Sustain Energy Rev 2015;41:1376–84. https://doi.org/10.1016/j.rser.2014.09.040.

[7] Wall AAJ, Rabemanolontsoa H, Venus J. Bioprocessing and Fermentation Technology for Biomass Conversion. Appl Sci (Switzerland) 2024;14. https://doi.org/10.3390/app14010005.

[8] Yogalakshmi KN, Mohamed MU, Kavitha S, Sachdeva S, Thakur S, Adish Kumar S, et al. Lignocellulosic Biorefinery Technologies: A Perception into Recent Advances in Biomass Fractionation, Biorefineries, Economic Hurdles and Market Outlook. Fermentation 2023;9. https://doi.org/10.3390/fermentation9030238.

[9] Pan Y, Birdsey RA, Phillips OL, Jackson RB. The structure, distribution, and biomass of the world's forests. Annu Rev Ecol Evol Syst 2013;44:593–622. https://doi.org/10.1146/annurev-ecolsys-110512-135914.

[10] Alam MB, Pulkki R, Shahi C. Woody biomass availability for bioenergy production using forest depletion spatial data in northwestern ontario. Can J For Res 2012;42:506–16. https://doi.org/10.1139/X2012-011.

[11] Pasinszki T, Krebsz M. Agricultural waste valorization for sustainable biofuel production. Valorization of Agri-Food Wastes and By-Products: Recent Trends. Innov Sustain Challen, Elsevier 2021:913–26. https://doi.org/10.1016/B978-0-12-824044-1.00021-0.

[12] Karak T, Bhagat RM, Bhattacharyya P. Municipal solid waste generation, composition, and management: The world scenario. Crit Rev Environ Sci Technol 2012;42:1509–630. https://doi.org/10.1080/10643389.2011.569871.

[13] Chand Malav L, Yadav KK, Gupta N, Kumar S, Sharma GK, Krishnan S, et al. A review on municipal solid waste as a renewable source for waste-to-energy project in India: Current practices, challenges, and future opportunities. J Clean Prod 2020;277. https://doi.org/10.1016/j.jclepro.2020.123227.

[14] Cambero C, Sowlati T. Assessment and optimization of forest biomass SCs from economic, social and environmental perspectives – A review of literature. Renew Sustain Energy Rev 2014;36:62–73. https://doi.org/10.1016/j.rser.2014.04.041.

[15] Salehi S, Zare Mehrjerdi Y, Sadegheih A, Hosseini-Nasab H. Designing a resilient and sustainable biomass SC network through the optimization approach under uncertainty and the disruption. J Clean Prod 2022;359. https://doi.org/10.1016/j.jclepro.2022.131741.

[16] Yana S, Nizar M, Irhamni MD. Biomass waste as a renewable energy in developing bio-based economies in Indonesia: A review. Renew Sustain Energy Rev 2022;160. https://doi.org/10.1016/j.rser.2022.112268.

[17] Durach CF, Kembro J, Wieland A. A New Paradigm for Systematic Literature Reviews in SC Management. J SC Manage 2017;53:67–85. https://doi.org/10.1111/jscm.12145.

[18] Sharma B, Ingalls RG, Jones CL, Khanchi A. Biomass SC design and analysis: Basis, overview, modeling, challenges, and future. Renew Sustain Energy Rev 2013;24:608–27. https://doi.org/10.1016/j.rser.2013.03.049.

[19] Yue D, You F, Snyder SW. Biomass-to-bioenergy and biofuel SC optimization: Overview, key issues and challenges. Comput Chem Eng 2014;66:36–56. https://doi.org/10.1016/j.compchemeng.2013.11.016.

[20] Singh A, Christensen T, Panoutsou C. Policy review for biomass value chains in the European bioeconomy. Glob Transit 2021;3:13–42. https://doi.org/10.1016/j.glt.2020.11.003.

[21] Wolfsmayr UJ, Rauch P. The primary forest fuel SC: A literature review. Biomass Bioenergy 2014;60:203–21. https://doi.org/10.1016/j.biombioe.2013.10.025.

[22] Mirkouei A, Haapala KR, Sessions J, Murthy GS. A mixed biomass-based energy SC for enhancing economic and environmental sustainability benefits: A multi-criteria decision making framework. Appl Energy 2017;206:1088–101. https://doi.org/10.1016/j.apenergy.2017.09.001.

[23] Awudu I, Zhang J. Uncertainties and sustainability concepts in biofuel SC management: A review. Renew Sustain Energy Rev 2012;16:1359–68. https://doi.org/10.1016/j.rser.2011.10.016.

[24] Shabani N, Akhtari S, Sowlati T. Value chain optimization of forest biomass for bioenergy production: A review. Renew Sustain Energy Rev 2013;23:299–311. https://doi.org/10.1016/j.rser.2013.03.005.

[25] van den Oever AEM, Costa D, Cardellini G, Messagie M. Systematic review on the energy conversion efficiency of biomass-based Fischer-Tropsch plants. Fuel 2022;324. https://doi.org/10.1016/j.fuel.2022.124478.

[26] Cundiff JS, Dias N, Sherali HD. A LINEAR PROGRAMMING APPROACH FOR DESIGNING A HERBACEOUS BIOMASS DELIVERY SYSTEM. vol. 59. 1997.

[27] Battuvshin B, Matsuoka Y, Shirasawa H, Toyama K, Hayashi U, Aruga K. Supply potential and annual availability of timber and forest biomass resources for energy considering inter-prefectural trade in Japan. Land Use Policy 2020;97. https://doi.org/10.1016/j.landusepol.2020.104780.

[28] Čuček L, Varbanov PS, Klemeš JJ, Kravanja Z. Total footprints-based multi-criteria optimisation of regional biomass energy SCs. Energy 2012;44:135–45. https://doi.org/10.1016/j.energy.2012.01.040.

[29] Paschalidou A, Tsatiris M, Kitikidou K, Papadopoulou C. Green Energy and Technology Using Energy Crops for Biofuels or Food: The Choice. n.d.

[30] Mukherjee C, Denney J, Mbonimpa EG, Bhowmik R. A review on municipal solid waste-to-energy trends in the USA. 2019.

[31] Zamar DS, Gopaluni B, Sokhansanj S, Newlands NK. Robust optimization of competing biomass SCs under feedstock uncertainty. IFAC-PapersOnLine 2015;28:1222–7. https://doi.org/10.1016/j.ifacol.2015.09.135.

[32] Gronalt M, Rauch P. Designing a regional forest fuel supply network. Biomass Bioenergy 2007;31:393–402. https://doi.org/10.1016/j.biombioe.2007.01.007.

[33] Malladi KT, Sowlati T. Optimization of operational level transportation planning in forestry: a review. Int J For Eng 2017;28:198–210. https://doi.org/10.1080/14942119.2017.1362825.

[34] Rentizelas AA, Tolis AJ, Tatsiopoulos IP. Logistics issues of biomass: The storage problem and the multi-biomass SC. Renew Sustain Energy Rev 2009;13:887–94. https://doi.org/10.1016/j.rser.2008.01.003.

[35] Sosa A, Acuna M, McDonnell K, Devlin G. Controlling moisture content and truck configurations to model and optimise biomass SC logistics in Ireland. Appl Energy 2015;137:338–51. https://doi.org/10.1016/j.apenergy.2014.10.018.

[36] Malladi KT, Sowlati T. Biomass logistics: A review of important features, optimization modeling and the new trends. Renew Sustain Energy Rev 2018;94:587–99. https://doi.org/10.1016/j.rser.2018.06.052.

[37] Memişoğlu G, Üster H. Integrated bioenergy SC network planning problem. Transp Sci 2016;50:35–56. https://doi.org/10.1287/trsc.2015.0598.

[38] Gunnarsson H, Rönnqvist M, Lundgren JT. SC modelling of forest fuel. Eur J Oper Res 2004;158:103–23. https://doi.org/10.1016/S0377-2217(03)00354-0.

[39] Ekşioğlu SD, Acharya A, Leightley LE, Arora S. Analyzing the design and management of biomass-to-biorefinery SC. Comput Ind Eng 2009;57:1342–52. https://doi.org/10.1016/j.cie.2009.07.003.

[40] Yeh K, Whittaker C, Realff MJ, Lee JH. Two stage stochastic bilevel programming model of a pre-established timberlands SC with biorefinery investment interests. Comput Chem Eng 2015;73:141–53. https://doi.org/10.1016/j.compchemeng.2014.11.005.

[41] Shabani N, Sowlati T. A mixed integer non-linear programming model for tactical value chain optimization of a wood biomass power plant. Appl Energy 2013;104:353–61. https://doi.org/10.1016/j.apenergy.2012.11.013.

[42] Akhtari S, Sowlati T, Day K. Optimal flow of regional forest biomass to a district heating system. Int J Energy Res 2014;38:954–64. https://doi.org/10.1002/er.3099.

[43] Osmani A, Zhang J. Multi-period stochastic optimization of a sustainable multi-feedstock second generation bioethanol SC − A logistic case study in Midwestern United States. Land Use Policy 2017;61:420–50. https://doi.org/10.1016/j.landusepol.2016.10.028.

[44] Björheden R. Development of Bioenergy from Forest Biomass-a Case Study of Sweden and Finland. vol. 38. 2017.

[45] Zamora-Cristales R, Sessions J, Boston K, Murphy G. Economic optimization of forest biomass processing and transport in the Pacific Northwest USA. For Sci 2015;61:220–34. https://doi.org/10.5849/forsci.13-158.

[46] Han SK, Murphy GE. Solving a woody biomass truck scheduling problem for a transport company in Western Oregon, USA. Biomass Bioenergy 2012;44:47–55. https://doi.org/10.1016/j.biombioe.2012.04.015.

[47] Yunusoglu P, Ozsoydan FB, Bilgen B. A machine learning-based two-stage approach for the location of undesirable facilities in the biomass-to-bioenergy SC. Appl Energy 2024;362. https://doi.org/10.1016/j.apenergy.2024.122961.

[48] Akhtari S, Sowlati T. Hybrid optimization-simulation for integrated planning of bioenergy and biofuel SCs. Appl Energy 2020;259. https://doi.org/10.1016/j.apenergy.2019.114124.

[49] Pishvaee MS, Rabbani M, Torabi SA. A robust optimization approach to closed-loop SC network design under uncertainty. App Math Model 2011;35:637–49. https://doi.org/10.1016/j.apm.2010.07.013.

[50] Shabani N, Sowlati T. A hybrid multi-stage stochastic programming-robust optimization model for maximizing the SC of a forest-based biomass power plant considering uncertainties. J Clean Prod 2016;112:3285–93. https://doi.org/10.1016/j.jclepro.2015.09.034.

[51] Osmani A, Zhang J. Stochastic optimization of a multi-feedstock lignocellulosic-based bioethanol SC under multiple uncertainties. Energy 2013;59:157–72. https://doi.org/10.1016/j.energy.2013.07.043.

[52] Leduc S, Lundgren J, Franklin O, Dotzauer E. Location of a biomass based methanol production plant: A dynamic problem in northern Sweden. Appl Energy 2010;87:68–75. https://doi.org/10.1016/j.apenergy.2009.02.009.

[53] Rauch P, Gronalt M. The Terminal Location Problem in the Forest Fuels Supply Network. Int J For Eng 2010;21:32–40. https://doi.org/10.1080/14942119.2010.10702596.

[54] Cambero C, Sowlati T, Marinescu M, Röser D. Strategic optimization of forest residues to bioenergy and biofuel SC. Int J Energy Res 2015;39:439–52. https://doi.org/10.1002/er.3233.
[55] Campanella S, Corsano G, Montagna JM. A modeling framework for the optimal forest SC design considering residues reuse. Sustain Prod Consum 2018;16:13–24. https://doi.org/10.1016/j.spc.2018.06.003.
[56] Marufuzzaman M, Li X, Yu F, Zhou F. SC Design and Management for Syngas Production. ACS Sustain Chem Eng 2016;4:890–900. https://doi.org/10.1021/acssuschemeng.5b00944.
[57] Calderón AJ, Agnolucci P, Papageorgiou LG. An optimisation framework for the strategic design of synthetic natural gas (BioSNG) SCs. Appl Energy 2017;187:929–55. https://doi.org/10.1016/j.apenergy.2016.10.074.
[58] Kazemzadeh N, Hu G. Optimization models for biorefinery SC network design under uncertainty. J Renew Sustain Energy 2013;5. https://doi.org/10.1063/1.4822255.
[59] Serrano A, Faulin J, Astiz P, Sánchez M, Belloso J. Locating and designing a biorefinery SC under uncertainty in Navarre: A stochastic facility location problem case. Transp Res Procedia 2015;10:704–13. https://doi.org/10.1016/j.trpro.2015.09.024. Elsevier.
[60] Huang Y, Chen CW, Fan Y. Multistage optimization of the SCs of biofuels. Transp Res E Logist Transp Rev 2010;46:820–30. https://doi.org/10.1016/j.tre.2010.03.002.
[61] Roni MS, Thompson DN, Hartley DS. Distributed Biomass SC Cost Optimization to Evaluate Multiple Feedstocks for a Biorefinery. 2019.
[62] Chen CW, Fan Y. Bioethanol SC system planning under supply and demand uncertainties. Transp Res E Logist Transp Rev 2012;48:150–64. https://doi.org/10.1016/j.tre.2011.08.004.
[63] Gebreslassie BH, Yao Y, You F. Design under uncertainty of hydrocarbon biorefinery SCs: Multiobjective stochastic programming models, decomposition algorithm, and a Comparison between CVaR and downside risk. AIChE J 2012;58:2155–79. https://doi.org/10.1002/aic.13844.
[64] Razm S, Dolgui A, Hammami R, Brahimi N, Nickel S, Sahebi H. A two-phase sequential approach to design bioenergy SCs under uncertainty and social concerns. Comput Chem Eng 2021;145. https://doi.org/10.1016/j.compchemeng.2020.107131.
[65] Pande CB, Moharir KN, Kumar Singh S, Varade AM, Elbeltagi A, Khadri SFR, et al. Estimation of crop and forest biomass resources in a semi-arid region using satellite data and GIS. J Saudi Soc Agric Sci 2021;20:302–11. https://doi.org/10.1016/j.jssas.2021.03.002.
[66] Firouzi S, Allahyari MS, Isazadeh M, Nikkhah A, Van Haute S. Hybrid multi-criteria decision-making approach to select appropriate biomass resources for biofuel production. Sci Total Environ 2021;770. https://doi.org/10.1016/j.scitotenv.2020.144449.
[67] Shabani N, Sowlati T, Ouhimmou M, Rönnqvist M. Tactical SC planning for a forest biomass power plant under supply uncertainty. Energy 2014;78:346–55. https://doi.org/10.1016/j.energy.2014.10.019.
[68] Gautam S, LeBel L, Carle MA. SC model to assess the feasibility of incorporating a terminal between forests and biorefineries. Appl Energy 2017;198:377–84. https://doi.org/10.1016/j.apenergy.2017.01.021.
[69] Ahmadvand S, Sowlati T. A robust optimization model for tactical planning of the forest-based biomass SC for syngas production. Comput Chem Eng 2022;159. https://doi.org/10.1016/j.compchemeng.2022.107693.
[70] Ogunrewo OF, Nwulu NI. Optimisation framework of biomass SC in southwest Nigeria. Clean. Eng Technol 2024;18. https://doi.org/10.1016/j.clet.2023.100711.
[71] Wang Y, Wang J, Schuler J, Hartley D, Volk T, Eisenbies M. Optimization of harvest and logistics for multiple lignocellulosic biomass feedstocks in the northeastern United States. Energy 2020;197. https://doi.org/10.1016/j.energy.2020.117260.
[72] Fan K, Li X, Wang L, Wang M. Two-stage SC contract coordination of solid biomass fuel involving multiple suppliers. Comput Ind Eng 2019;135:1167–74. https://doi.org/10.1016/j.cie.2019.01.016.
[73] Acuna M, Anttila P, Sikanen L, Prinz R, Asikainen A. Predicting and Controlling Moisture Content to Optimise Forest Biomass Logistics. vol. 33. 2012.
[74] Marques A, Rasinmäki J, Soares R, Amorim P. Planning woody biomass supply in hot systems under variable chips energy content. Biomass Bioenergy 2018;108:265–77. https://doi.org/10.1016/j.biombioe.2017.11.016.
[75] Panoutsou C, Singh A, Christensen T, Pelkmans L. Competitive priorities to address optimisation in biomass value chains: The case of biomass CHP. Glob Transit 2020;2:60–75. https://doi.org/10.1016/j.glt.2020.04.001.
[76] Gracia C, Velázquez-Martí B, Estornell J. An application of the vehicle routing problem to biomass transportation. Biosyst Eng 2014;124:40–52. https://doi.org/10.1016/j.biosystemseng.2014.06.009.
[77] Vazifeh Z, Mafakheri F, An C. Biomass SC coordination for remote communities: A game-theoretic modeling and analysis approach. Sustain Cities Soc 2021;69. https://doi.org/10.1016/j.scs.2021.102819.
[78] An H. The closed-open truck and loader routing problem for biomass transportation from satellite storage locations to a bioenergy plant. Comput Electron Agric 2022;194. https://doi.org/10.1016/j.compag.2022.106764.
[79] Abasian F, Rönnqvist M, Ouhimmou M. Forest fibre network design with multiple assortments: A case study in newfoundland. Can J For Res 2017;47:1232–43. https://doi.org/10.1139/cjfr-2016-0504.
[80] Palander T, Haavikko H, Kärhä K. Towards sustainable wood procurement in forest industry – The energy efficiency of larger and heavier vehicles in Finland. Renew Sustain Energy Rev 2018;96:100–18. https://doi.org/10.1016/j.rser.2018.07.043.
[81] Raghu KC, Aalto M, Korpinen OJ, Ranta T, Proskurina S. Lifecycle assessment of biomass SC with the assistance of agent-based modelling. Sustainability (Switzerland) 2020;12. https://doi.org/10.3390/su12051964.
[82] Laasasenaho K, Lensu A, Lauhanen R, Rintala J. GIS-data related route optimization, hierarchical clustering, location optimization, and kernel density methods are useful for promoting distributed bioenergy plant planning in rural areas. Sustainable Energy Technol Assess 2019;32:47–57. https://doi.org/10.1016/j.seta.2019.01.006.
[83] Abdali H, Sahebi H, Pishvaee M. A sustainable robust optimization model to design a sugarcane-based bioenergy supply network: A case study. Chem Eng Res Des 2022;180:265–84. https://doi.org/10.1016/j.cherd.2022.02.028.
[84] Fattahi M, Govindan K, Farhadkhani M. Sustainable SC planning for biomass-based power generation with environmental risk and supply uncertainty considerations: a real-life case study. Int J Prod Res 2021;59:3084–108. https://doi.org/10.1080/00207543.2020.1746427.
[85] Machani M, Nourelfath M, D'Amours S. A mathematically-based framework for evaluating the technical and economic potential of integrating bioenergy production within pulp and paper mills. Biomass Bioenergy 2014;63:126–39. https://doi.org/10.1016/j.biombioe.2014.02.024.
[86] Väisänen S, Mikkilä M, Havukainen J, Sokka L, Luoranen M, Horttanainen M. Using a multi-method approach for decision-making about a sustainable local distributed energy system: A case study from Finland. J Clean Prod 2016;137:1330–8. https://doi.org/10.1016/j.jclepro.2016.07.173.
[87] Van FY, Romanenko S, Gai L, Kupressova E, Varbanov PS, Klemeš JJ. Biomass integration for energy recovery and efficient use of resources: Tomsk Region. Energy 2021;235. https://doi.org/10.1016/j.energy.2021.121378.
[88] Gregg JS. National and regional generation of municipal residue biomass and the future potential for waste-to-energy implementation. Biomass Bioenergy 2010;34:379–88. https://doi.org/10.1016/j.biombioe.2009.11.009.
[89] de Brito RC, Barros RM, dos Santos IFS, Tiago Filho GL, da Silva SPG. Municipal solid waste management and economic feasibility for electricity generation from landfill gas and anaerobic reactors in a Brazilian state. Environ Technol Innov 2021;22. https://doi.org/10.1016/j.eti.2021.101453.
[90] Khalilarya S, Chitsaz A, Mojaver P. Optimization of a combined heat and power system based gasification of municipal solid waste of Urmia University student dormitories via ANOVA and taguchi approaches. Int J Hydrogen Energy 2021;46:1815–27. https://doi.org/10.1016/j.ijhydene.2020.10.020.
[91] Xu J, Huang Y, Shi Y, Li R. Reverse SC management approach for municipal solid waste with waste sorting subsidy policy. Socioecon Plann Sci 2022;81. https://doi.org/10.1016/j.seps.2021.101180.
[92] Gold S, Seuring S. SC and logistics issues of bio-energy production. J Clean Prod 2011;19:32–42. https://doi.org/10.1016/j.jclepro.2010.08.009.
[93] Mafakheri F, Nasiri F. Modeling of biomass-to-energy SC operations: Applications, challenges and research directions. Energy Policy 2014;67:116–26. https://doi.org/10.1016/j.enpol.2013.11.071.
[94] Ba BH, Prins C, Prodhon C. Models for optimization and performance evaluation of biomass SCs: An Operations Research perspective. Renew Energy 2016;87:977–89. https://doi.org/10.1016/j.renene.2015.07.045.
[95] Li Y, Zhou LW, Wang RZ. Urban biomass and methods of estimating municipal biomass resources. Renew Sustain Energy Rev 2017;80:1017–30. https://doi.org/10.1016/j.rser.2017.05.214.
[96] Ko S, Lautala P, Handler RM. Securing the feedstock procurement for bioenergy products: a literature review on the biomass transportation and logistics. J Clean Prod 2018;200:205–18. https://doi.org/10.1016/j.jclepro.2018.07.241.
[97] Mobtaker A, Ouhimmou M, Rönnqvist M, Paquet M. Development of an economically sustainable and balanced tactical forest management plan: A case study in Quebec. Can J For Res 2018;48:197–207. https://doi.org/10.1139/cjfr-2017-0232.
[98] Chidozie BC, Ramos AL, Ferreira JV, Ferreira LP. Residual Agroforestry Biomass SC Simulation Insights and Directions: A Systematic Literature Review. Sustainability (Switzerland) 2023;15. https://doi.org/10.3390/su15139992.
[99] Longo S, Cellura M, Luu LQ, Nguyen TQ, Rincione R, Guarino F. Circular economy and life cycle thinking applied to the biomass SC: A review. Renew. Energy 2024;220. https://doi.org/10.1016/j.renene.2023.119598.
[100] Kim J, Realff MJ, Lee JH. Optimal design and global sensitivity analysis of biomass SC networks for biofuels under uncertainty. Comput Chem Eng 2011;35:1738–51. https://doi.org/10.1016/j.compchemeng.2011.02.008.
[101] Svensson E, Strömberg AB, Patriksson M. A model for optimization of process integration investments under uncertainty. Energy 2011;36:2733–46. https://doi.org/10.1016/j.energy.2011.02.013.
[102] Flisberg P, Frisk M, Rönnqvist M. FuelOpt: A decision support system for forest fuel logistics. J Oper Res Soc 2012;63:1600–12. https://doi.org/10.1057/jors.2011.157.
[103] Karhunen A, Laihanen M, Ranta T. Supply and Demand of a Forest Biomass in Application to the Region of South-East Finland. Smart Grid Renew Energy 2012;03:34–42. https://doi.org/10.4236/sgre.2012.31005.
[104] Tay DHS, Ng DKS, Tan RR. Robust optimization approach for synthesis of integrated biorefineries with supply and demand uncertainties. Environ Prog Sustain Energy 2013;32:384–9. https://doi.org/10.1002/ep.10632.
[105] Yeh K, Realff MJ, Lee JH, Whittaker C. Analysis and comparison of single period single level and bilevel programming representations of a pre-existing timberlands SC with a new biorefinery facility. Comput Chem Eng 2014;68:242–54. https://doi.org/10.1016/j.compchemeng.2014.05.025.
[106] Natarajan K, Leduc S, Pelkonen P, Tomppo E, Dotzauer E. Optimal locations for second generation Fischer Tropsch biodiesel production in Finland. Renew Energy 2014;62:319–30. https://doi.org/10.1016/j.renene.2013.07.013.

[107] Huang Y, Fan Y, Chen CW. An integrated biofuel SC to cope with feedstock seasonality and uncertainty. Transp Sci 2014;48:540–54. https://doi.org/10.1287/trsc.2013.0498.
[108] Cambero C, Sowlati T, Pavel M. Economic and life cycle environmental optimization of forest-based biorefinery SCs for bioenergy and biofuel production. Chem Eng Res Des 2016;107:218–35. https://doi.org/10.1016/j.cherd.2015.10.040.
[109] Zhang F, Johnson DM, Wang J. Integrating multimodal transport into forest-delivered biofuel SC design. Renew Energy 2016;93:58–67. https://doi.org/10.1016/j.renene.2016.02.047.
[110] Liu WY, Lin CC, Yeh TL. SC optimization of forest biomass electricity and bioethanol coproduction. Energy 2017;139:630–45. https://doi.org/10.1016/j.energy.2017.08.018.
[111] Zamar DS, Gopaluni B, Sokhansanj S, Newlands NK. A quantile-based scenario analysis approach to biomass SC optimization under uncertainty. Comput Chem Eng 2017;97:114–23. https://doi.org/10.1016/j.compchemeng.2016.11.015.
[112] Calderón AJ, Papageorgiou LG. Key aspects in the strategic development of synthetic natural gas (BioSNG) SCs. Biomass Bioenergy 2018;110:80–97. https://doi.org/10.1016/j.biombioe.2018.01.004.
[113] Malladi KT, Quirion-Blais O, Sowlati T. Development of a decision support tool for optimizing the short-term logistics of forest-based biomass. Appl Energy 2018;216:662–77. https://doi.org/10.1016/j.apenergy.2018.02.027.
[114] Akhtari S, Sowlati T, Griess VC. Integrated strategic and tactical optimization of forest-based biomass SCs to consider medium-term supply and demand variations. Appl Energy 2018;213:626–38. https://doi.org/10.1016/j.apenergy.2017.10.017.
[115] Akhtari S, Sowlati T, Siller-Benitez DG, Roeser D. Impact of inventory management on demand fulfilment, cost and emission of forest-based biomass SCs using simulation modelling. Biosyst Eng 2019;178:184–99. https://doi.org/10.1016/j.biosystemseng.2018.11.015.
[116] Zhang J, Osmani A, Awudu I, Gonela V. An integrated optimization model for switchgrass-based bioethanol SC. Appl Energy 2013;102:1205–17. https://doi.org/10.1016/j.apenergy.2012.06.054.
[117] Ren J, Dong L, Sun L, Goodsite ME, Tan S, Dong L. Life cycle cost optimization of biofuel SCs under uncertainties based on interval linear programming. Bioresour Technol 2015;187:6–13. https://doi.org/10.1016/j.biortech.2015.03.083.
[118] Asadi E, Habibi F, Nickel S, Sahebi H. A bi-objective stochastic location-inventory-routing model for microalgae-based biofuel SC. Appl Energy 2018;228:2235–61. https://doi.org/10.1016/j.apenergy.2018.07.067.
[119] He-Lambert L, Shylo O, English BC, Eash NS, Zahn JA, Lambert DM. SC and logistic optimization of industrial Spent Microbial Biomass distribution as a soil amendment for field crop production. Resour Conserv Recycl 2019;146:218–31. https://doi.org/10.1016/j.resconrec.2019.03.028.
[120] Soren A, Shastri Y. Resilient design of biomass to energy system considering uncertainty in biomass supply. Comput Chem Eng 2019;131. https://doi.org/10.1016/j.compchemeng.2019.106593.
[121] Morales Chavez MM, Costa Y, Sarache W. A three-objective stochastic location-inventory-routing model for agricultural waste-based biofuel SC. Comput Ind Eng 2021;162. https://doi.org/10.1016/j.cie.2021.107759.
[122] Benjamin MFD, Ventura JRS, Sangalang KPH, Adorna JA, Belmonte BA, Andiappan V. Optimal synthesis of Philippine agricultural residue-based integrated biorefinery via the P-graph method under supply and demand constraints. J Clean Prod 2021;308. https://doi.org/10.1016/j.jclepro.2021.127348.
[123] Allman A, Lee C, Martín M, Zhang Q. Biomass waste-to-energy SC optimization with mobile production modules. Comput Chem Eng 2021;150. https://doi.org/10.1016/j.compchemeng.2021.107326.
[124] Zhang J, Zhang X, Rentizelas A, Dong C, Li J. Optimisation of Logistic Model Using Geographic Information Systems: A Case Study of Biomass-based Combined Heat & Power Generation in China. Appl Energy Combust Sci 2022;10. https://doi.org/10.1016/j.jaecs.2022.100060.
[125] Ollila K, Kotavaara O. Measuring Accessibility and Optimising Logistics of Marginal Land Grass Biomass in the Case of Northern Ostrobothnia, Finland. Eur Countryside 2023;15:542–62. https://doi.org/10.2478/euco-2023-0029.
[126] Parker N, Tittmann P, Hart Q, Nelson R, Skog K, Schmidt A, et al. Development of a biorefinery optimized biofuel supply curve for the Western United States. Biomass Bioenergy 2010;34:1597–607. https://doi.org/10.1016/j.biombioe.2010.06.007.
[127] Santibañez-Aguilar JE, González-Campos JB, Ponce-Ortega JM, Serna-González M, El-Halwagi MM. Optimal planning of a biomass conversion system considering economic and environmental aspects. Ind Eng Chem Res 2011;50:8558–70. https://doi.org/10.1021/ie102195g.
[128] Liu B, Ge X, Liu B, Yuan X. Distributionally robust optimization of non-fossil fuels processing network under uncertainty. Chem Eng J 2022;445. https://doi.org/10.1016/j.cej.2022.136756.
[129] Abdel-Aal MAM. Matheuristic approach and a mixed-integer linear programming model for biomass SC optimization with demand selection. Int J Ind Eng Comput 2024;15:235–54. https://doi.org/10.5267/j.ijiec.2023.10.001.