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Review

Optimising Agricultural Waste Supply Chains for Sustainable Bioenergy Production: A Comprehensive Literature Review

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Abstract: One of the United Nations' 17 Sustainable Development Goals is to "Ensure access to affordable, sustainable, and clean energy for all." Additionally, the growing concerns about climate change and energy security have heightened the importance of exploring alternative energy sources to replace fossil fuels. The utilisation of agricultural waste for bioenergy production has acquired significant attention due to its potential to mitigate environmental impacts and provide renewable energy sources. However, the major obstacle to producing bioenergy is managing the supply chain while considering economic, environmental, and social factors in an optimal way. This paper presents a comprehensive overview of the literature on the management of agriculture waste supply chains, specifically related to the use of modelling and optimisation techniques for planning. The first section describes different stages of the supply chain and various technologies for converting biomass to bioenergy. This is followed by a synopsis of the literature reviewed based on decision levels, objective functions, modelling methodologies, and optimisation approaches. Finally, the review highlights limitations and gaps in current research and the areas with potential for further exploration.

Keywords: agricultural waste; optimisation; bioenergy; sustainability; bioeconomy

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1. Introduction

The demand for biomass grew at the start of this century when bioenergy was introduced on the assumptions that abundant biomass is available globally and the use of biomass for energy is carbon-neutral. In reality, the sustainability of biomass is dependent on the extent of land-use change [1]. Due to availability concerns, the cascading use of biomass is widely promoted to minimise resource use and reduce the competition between different applications in the bioeconomy [2]; biomass is used for its highest societal value, or highest economic value with the least damage to the environment in the first instance [3]. A value gap exists between biological waste streams that are used for low-value applications like animal feed and composting that may be valorised for high-value applications such as chemicals and energy [4].

AWCBs, or Agricultural Waste, Co-products, and By-products (AWCBs), are residues from farming activities, including materials like straw, husks, and manure [4]. As many AWCBs are rich in biochemicals, they have significant potential for biorefining, thereby maximising the potential value and impact of biomass used by processing it into a cascade of products, from high-added value chemicals to valuable energy. Europe's agri-sector is facing a sustainability crisis due to the combined challenges of depleting fossil resources and increasing environmental pressures through waste generation [3,5,6]. AWCBs as a type of biomass are readily available and can be valorised for energy generation in a useful manner, which otherwise leads to environmental pollution and causes health problems [7–9]. AWCBs play a key role in bioenergy generation in the European Union (EU) as they compete with energy and food like the first generation of biomass [10,11].

The potential use AWCBs for valorisation strongly depends on factors such as the location of the feedstock and the processing plant, the technology used, and economic and social factors [2,12]. While studies on biomass materials and conversion procedures have been well developed [13], decision-makers have identified logistics as a critical vulnerability in scaling up bioproduct production systems. Therefore, designing an effective supply chain is an important factor in applying biomass efficiently and converting it to high-value-added products at a lower cost [14]. It is essential to optimise the supply chain to improve sustainability factors, which are environmental, economic, and social. For designing an optimised Biomass Supply Chain (BSC), practitioners and researchers can make use of mathematical and optimisation models or techniques [15–17].

2. Methodology for Reviewing the Literature

To attain the research goal, different combinations of keywords were searched in Google Scholar, ISI Web of Science, Scopus, and Science Direct between the years 2000 and 2022. The publication selection was worldwide although only studies in English were chosen. The papers were sourced from a range of publishers, including ScienceDirect, Informs, Elsevier, Springer, Taylor & Francis, Wiley, IEEE, ACS, AIDIC, MDPI, and Inderscience. The first category of keywords included agriculture waste, agri-waste, agri-residue, agriculture residue, biomass, and biofuel. The second category comprised optimisation, optimising, optimal, and optimise. Finally, the last category comprised supply chain network design, supply chain, model, mathematical model, valorisation, and sustainability. After searching, the abstracts of papers were assessed to see whether they were related or not, and then papers that applied agricultural waste as feedstock were chosen. As a result, 71 papers were selected among about 200 papers in which agricultural waste was the main or part of the feedstock to valorise and produce bioproducts. The papers were investigated based on different categories such as decision levels (strategic, tactical, and operational), sustainability factors, modelling methodologies, uncertainty, etc. Moreover, the literature was classified based on the system presented by [7,14]. The primary subjects and categories utilised for organising the papers are displayed in Figure 1.

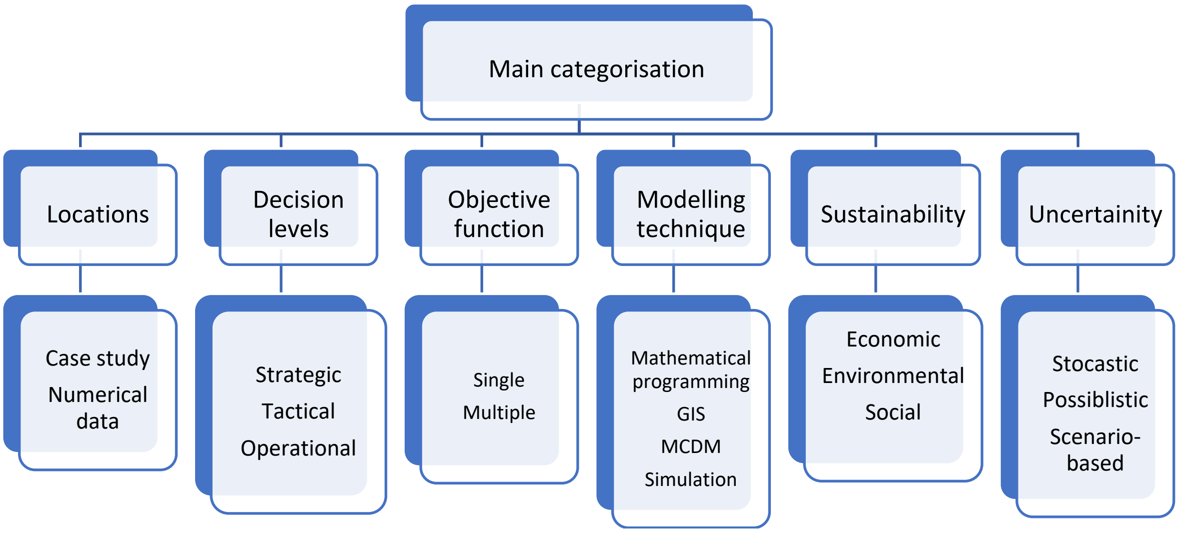

Figure 1. Categorisation of the reviewed literature.

3. Results

In terms of the year published, about 90% of papers (n = 64) had been published in the last 12 years (Figure 2), with most of the studies having been carried out in the US (31%, n = 22), followed by Europe (28%, n = 20). Figure 3 displays the number of locations that have been chosen as case studies.

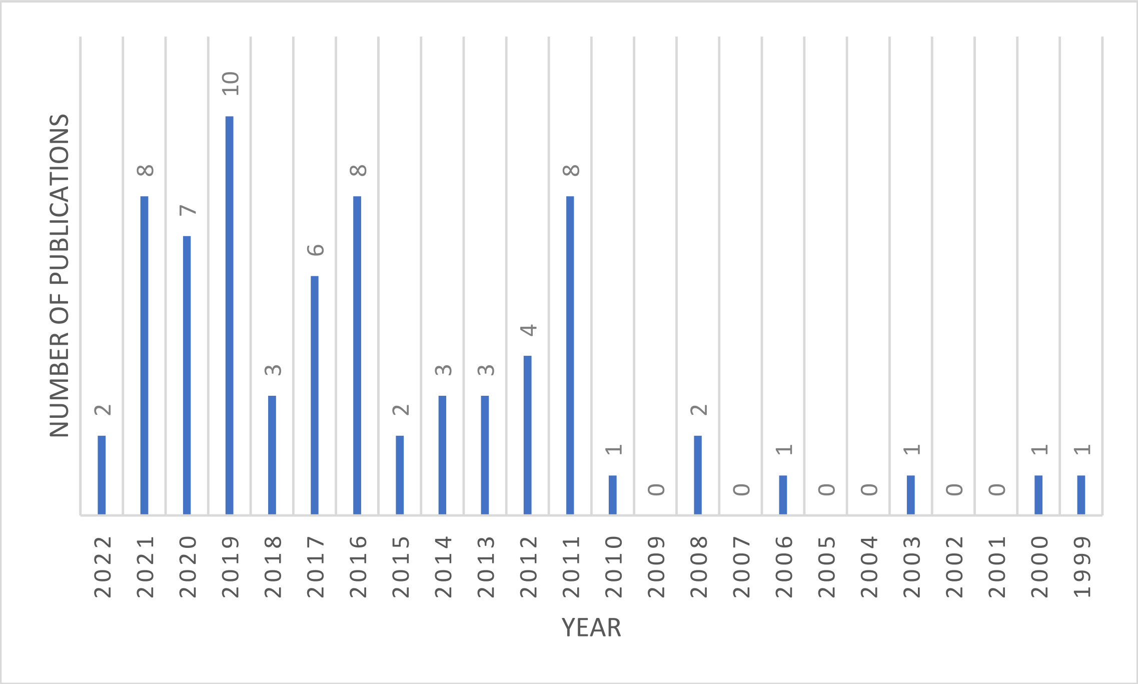

Figure 2. Number of studies between 1999 and 2022.

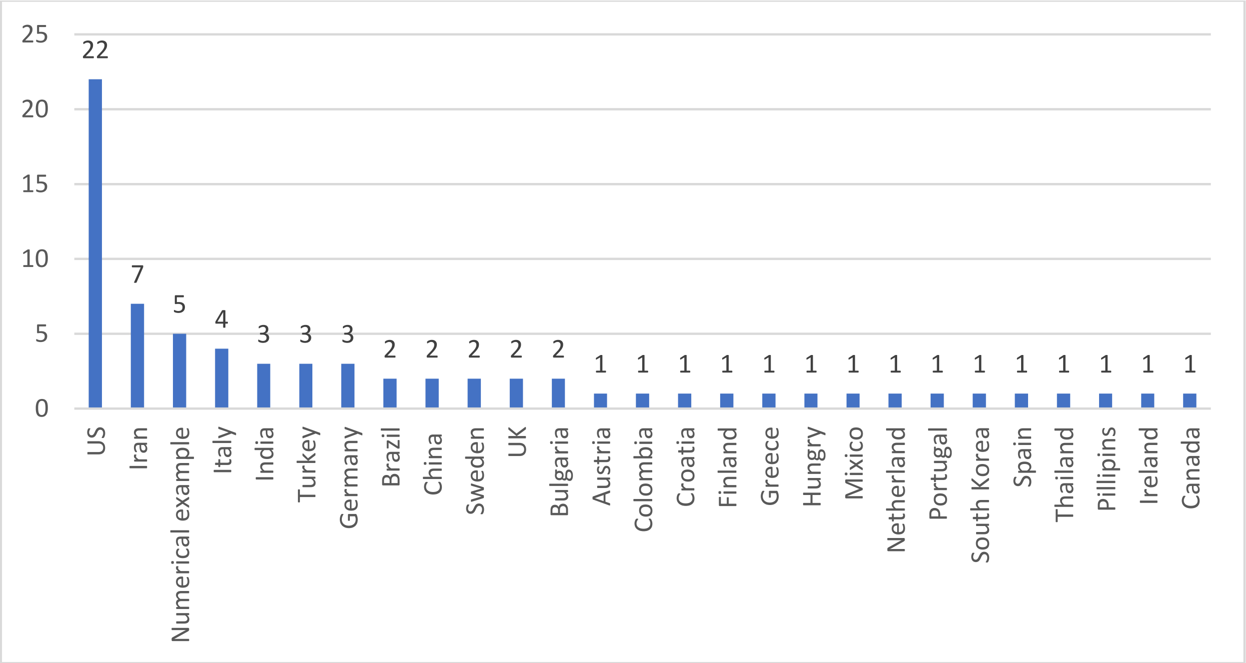

Figure 3. Numbers of papers based on locations of case studies.

3.1. Decision Levels in Supply Chain Management

Similar to how decisions are categorised within production management and industrial logistics, the decision-making processes within biomass supply chains can also be systematically classified into strategic, tactical, and operational levels based on the time frame, as shown in Figure 4 [16].

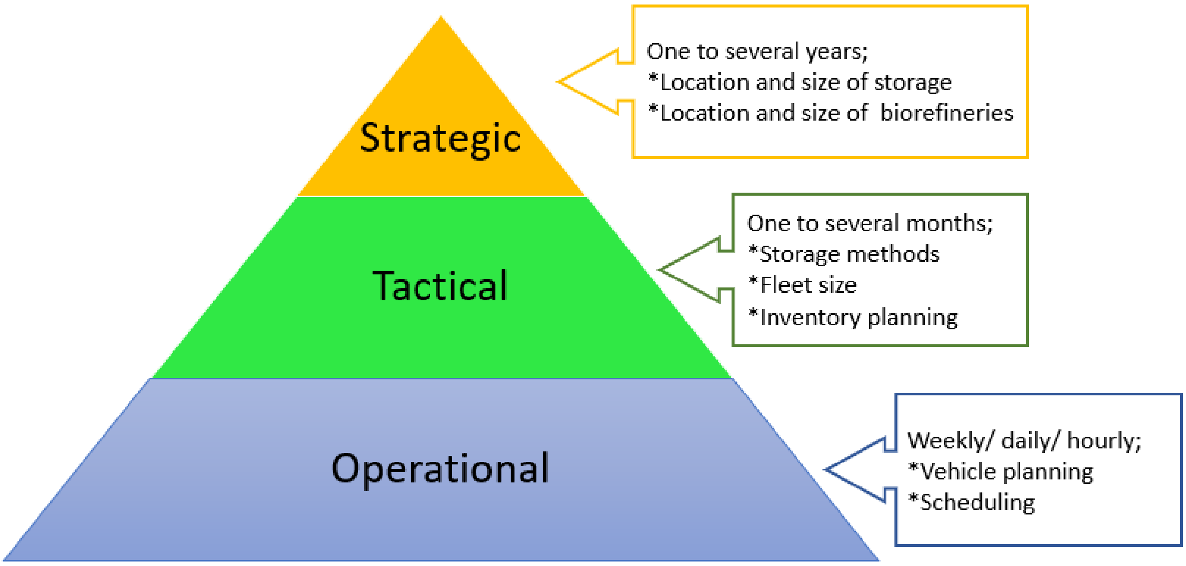

Figure 4. Features and examples of different decision levels in a biomass supply chain design.

3.1.1. Strategic Decisions

Strategic decisions have an impact of more than one year and are long-term decisions that are very unlikely to be changed in a short time. The most important strategic decision is the designing of a supply chain network. Examples of strategic decisions in an AWCB supply chain are the locations and sizes of biorefineries, storage, pre-processing facilities; the selection of feedstock; and transportation types and routes that link the distribution of feedstocks and AWCB/bioproducts over the supply chain network [16]. Most researchers consider planning a single period [18] although multi-period horizons can be helpful sometimes for modelling demand fluctuations in the long term, like eight periods of four years [19].

The balance between the cost of constructing conversion facilities and transportation is the main trade-off in designing the AWCB supply chain network since transportation costs play an important role in the AWCB supply chain. Therefore, optimising the location and number of these facilities against the backdrop of transportation logistics becomes a central challenge in ensuring that the AWCB supply chain is both economically viable and sustainable. In addition, selecting valorisation technologies is a significant strategic decision as different technologies may have different investment and operational costs and levels of bioproduct productivity and need different types of feedstock. The best selection of valorisation technologies can depend on the availability and distribution of AWCBs, bioproduct demand, and the national regulation at the biorefinery locations, which can affect technology selection. This regulation consist of the laws, guidelines, and standards set by governmental authorities that govern bioenergy production and waste management. Regulations can affect every stage of the AWCB supply chain, from how agricultural waste is collected and treated to how bioenergy products are produced, marketed, and used. They might encompass environmental protections, safety standards, and sustainability criteria that valorisation technologies must meet [20]. The analysed literature shows (Table 1) a significant preference towards strategic decision-making models in the literature, with sixty-two papers focusing on strategic aspects compared to only nine papers addressing both tactical and operational dimensions. This considerable difference may imply a predominant research interest in the long-term planning and policy development aspects of the field. Strategic models are typically concerned with higher-level, long-range planning, which includes setting objectives, determining action plans to achieve those goals, and allocating resources.

Table 1. Different characteristics of the reviewed papers.

Reference	Type of Biomass	Uncertainty	Decision Level		Objective		Technology		Seasonality	Sustainability	Modelling Technique			Case Study
			Strategic	Tactical and Operational	Single	Multiple	Single	Multiple			Mathematical Model	LCA	GIS	
Ivanov et al. (2022) [21]	Dairy waste scum		*			*	*				*			Bulgaria
Fattahi et al. (2021) [22]	Biomass	*	*			*		*		*	*	*		Iran
Cooper et al. (2019) [23]	Wheat straw, barley straw, and corn stover		*		*			*			*		*	Hungry
Aranguren et al. (2021) [24]	Corn, wheat, switchgrass, Miscanthus, Sorghum	*	*		*		*				*			US
Ghani et al. (2018) [25]	Corn stover		*	*		*					*			US
Esmaeili et al. (2020) [26]	Corn and corn stover		*		*						*			US
Duc et al. (2021) [27]	Rice husk	*	*	*		*	*				*			Thailand
Wu et al. (2021) [28]	Agri-biomass (straw)		*		*						*		*	China
Ge et al. (2021) [29]	Agricultural residues (corn stover) and urban waste wood (discarded furniture)		*	*	*			*	*		*			US
Aboytes-Ojeda et al. (2020) [30]	Lignocellulosic	*	*	*	*			*			*			US
Espinoza-Vázquez et al. (2021) [19]	Agricultural residues (corn, sorghum, wheat, and barley)				*		*				*			Mexico
Zhu and Yao (2011) [31]	Switchgrass, corn stalk, and wheat straw													US
Abriyantoro et al. (2019) [32]	Biomass	*	*								*			
Cobuloglu and Büyüktahtakın (2017) [33]	Switchgrass, corn	*	*	*		*					*			US
Castillo-Villar et al. (2017) [23]	Switchgrass		*											US
Fattahi and Govindan (2018) [34]	Agricultural residues (corn Stover, wheat straw, and rice straw) and forest biomass	*	*	*					*	*	*			Iran
Nilsson (1999) [35]	Straw	*	*											Sweden
Nilsson (2000) [36]	Straw	*	*											Sweden
Kim et al. (2011b) [37]	Thinnings, prunings, grasses, chips/shavings	*			*						*			US
Čuček et al. (2012) [38]	Corn, corn stover, wood chips, MSW (municipal solid waste), manure, and timber		*			*		*			*	*		Numerical data
Bairamzadeh et al. (2016) [39]	Corn stover, wheat straw	*	*	*		*		*	*	*	*	*		Iran
Yue and You (2014) [40]	Corn stover		*		*						*			US

Table 1. *Cont.*

Reference	Type of Biomass	Uncertainty	Decision Level		Objective		Technology		Seasonality	Sustainability	Modelling Technique			Case Study
			Strategic	Tactical and Operational	Single	Multiple	Single	Multiple			Mathematical Model	LCA	GIS	
Akgul et al. (2014) [41]	Woody biomass		*			*		*			*			UK
Bruglieri and Liberti (2008) [42]	Agricultural products, biological waste				*		*				*			Italy
Roni et al. (2017) [43]	Cellulosic biomass					*	*			*	*			US
Akgul et al. (2011) [44]	Corn stover		*		*						*			Italy
Leão et al. (2011) [45]	Vegetable oil		*		*						*			Brazil
Bowling et al. (2011) [46]	Vegetable oil		*								*			Numerical
Morrow et al. (2006) [47]	Corn and switchgrass		*		*		*				*			US
Ren et al. (2013) [48]	Multiple		*	*							*			China
You and Wang (2011) [49]	Corn stover, energy crops, wood residues		*			*			*	*	*	*		US
Tatsiopoulos and Tolis (2003) [50]	Chopped cotton-plant stalks		*		*						LP		*	Greece
Albashabsheh and Stamm (2019) [51]	Corn stover and switchgrass			*	*		*		*		*			US
Laasasenaho et al. (2019) [52]	Manures, biowastes, Sewage sludge		*				*		*				*	Finland
Razm et al. (2019) [53]	Forest residues, woodwork factory residues, agricultural residues, switchgrass	*	*		*			*			*			Iran/Armenia
Ng and Maravelias (2017) [54]	Corn stover, switchgrass		*		*			*			*			US
Sarker et al. (2019) [55]	Crops, grass, wood residue, and livestock waste		*		*		*		*		*			US
Jonkman et al. (2019) [56]	Sugar beet		*			*	*				*			Netherland
Sharma et al. (2013) [57]	Switchgrass	*	*	*	*		*				*			US
Tan et al. (2012) [58]	Sugarcane and corn	*	*				*				*	*		Philippines
Poudel et al. (2016) [59]	Corn stover and forest residues	*	*		*		*	*			*		*	US
Hombach et al. (2016) [60]	Forest residues, agricultural residues/straw, sawmill waste, and miscanthus		*		*			*			*			Germany
Paulo et al. (2015) [61]	Biomass	*	*		*			*						Portugal
D'amore and Bezzo (2016) [62]	Corn, stover		*			*		*			*			Italy
Woo et al. (2016) [63]	Agricultural residues (rice straw, rice husk, and barley straw), industrial residues, forestry residues, and energy crops	*	*	*				*			*			South Korea
Singh et al. (2008) [64]	Agricultural biomass		*		*		*				*		*	India

Table 1. *Cont.*

Reference	Type of Biomass	Uncertainty	Decision Level		Objective		Technology		Seasonality	Sustainability	Modelling Technique			Case Study
			Strategic	Tactical and Operational	Single	Multiple	Single	Multiple			Mathematical Model	LCA	GIS	
Delivand et al. (2015) [65]	Wheat and crop residue		*				*						*	Italy
Kühmaier et al. (2014) [66]	Wood residue	*	*				*						*	Austria
Balaman (2016) [67]	Wood and manure	*	*			*		*			*			Turkey
Parker et al. (2010) [68]	Agricultural, forest, urban, and energy crop biomass		*		*			*			*		*	US
Singh et al. (2011) [69]	Agricultural residues												*	India
Perpiña et al. (2013) [70]	Residual agricultural and forestry biomass		*										*	Spain
Sharma et al. (2017) [71]	Switchgrass, miscanthus, and corn stover		*										*	US
Lovrak et al. (2020) [72]	Manure and agriculture residue		*						*				*	Croatia
Yılmaz Balaman et al. (2018) [73]	Manure/wood	*	*	*		*		*			*			UK
Durmaz & Bilgen, (2020) [74]	Poultry manure		*	*		*							*	Turkey
Shastri et al. (2011) [75]	AWCB	*	*		*		*						*	Colombia
Balaman, (2016) [67]	Cattle and chicken manure, waste wood		*			*		*	*		*			Turkey
Murphy et al. (2016) [1]	Wood chip and wood pellets, willow, and miscanthus		*		*		*	*			*	*		Ireland
Munasinghe et al. (2019) [76]	Palm tree		*								*	*		Brazil
Ahmadi et al. (2020) [77]	Residues							*				*		Canada

3.1.2. Tactical Decisions

Medium-term decisions which include a multi-period horizon over a few months are called tactical decisions. Production planning in the industry is usually categorised in this level of decision, e.g., determining the amount of products generated in a period. In the context of AWCB supply chains, choosing fleet size for transportation, inventory planning, and control are considered tactical decisions. The planned time period can vary from one day to one month [32,78]. Several studies have focused on planning the supply chain by addressing decision making at both the strategic and tactical levels [22,27,29,39,51]. For example, Ge et al. (2021) [29] proposed a model to determine both the locations, capacities, and conversion technologies of biomass plants (strategic level) as well as biomass flows from resources to different facilities and inventory levels (tactical level).

3.1.3. Operational Decisions

Operational decisions are made for a short period, usually a few days or hours; these include detailed decisions that come from decomposing the tactical decisions described earlier. For instance, in production planning, this refers to scheduling the sequence and starting times for each task or operation. In an AWCB supply chain, scheduling collection operations on a certain day and determining detailed truck routes are usual examples. Most of the studies on AWCBs have focused on strategic and tactical decisions. However, few studies have worked on operational decisions, such as those by Han and Murphy (2012) [1], which solved a scheduling problem for trucks, or Recio et al. (2003) [79], which addressed harvest planning in detail. Indeed, the significant aim is to develop suitable tools for decision-makers to model and assess the chain before implementing it.

3.2. Objective Function

A mathematical model consists of at least one constraint and an objective function. These constraints, formulated as equations, define the problem and are divided into equality and inequality types. The objective function evaluates the solution's quality, aiming for either minimisation or maximisation [80]. Within the AWCB supply chain, the examination of sustainability dimensions in objective functions is approached through two predominant methodologies within optimisation models: (1) the application of a multi-objective model, which concurrently assesses economic, environmental, and/or social impacts through the incorporation of multiple objective functions, and (2) the employment of single-objective models that integrate environmental and/or social impacts as constraints, delineated by specific thresholds or targets.

The data from the literature reveal an apparent trend in the modelling within the AWCB supply chain context. Single-objective models are dominant, accounting for approximately 68% (n = 42) of the studies, while multi-objective models were utilised in 20 papers (about 32%). This distribution could imply that the complexity of multi-objective models, which require the simultaneous optimisation of several conflicting objectives, may be a limitation for their widespread use. On the other hand, the higher prevalence of single-objective models indicates a preference for a more streamlined approach, perhaps due to these models' relative simplicity and the ease of focusing on a singular optimisation criteria, often cost. However, the substantial representation of multi-objective models underscores a significant acknowledgement of the multi-faceted nature of sustainability that includes economic, environmental, and social dimensions.

3.3. Modelling Methodology

This section assesses and examines various modelling techniques applied in the selected papers, emphasising their application within the context of supply chain management. After reviewing chosen studies, the modelling methods employed are organised into three principal groups: mathematical programming, multi-criteria decision making, and GISs.

3.3.1. Mathematical Models

Mathematical programming is the most popular approach among different techniques. It consists of decision variables, constraints, and one or multiple objective functions. The principle of mathematical programming is to find the best value for decision variables that optimises the objective function and simultaneously meets all the constraints.

Mathematical modelling helps break down the supply chain into equations, identifying key activities and components as either constraints or objective functions. While it is ideal to create a detailed model covering every aspect, such models can often be too complex to solve effectively. The practical approach is to focus on the most impactful features of the supply chain, ignoring minor details that do not significantly influence the outcomes. This method strikes a balance, ensuring that the model is both realistic and computationally feasible [20,40]. There are different types of mathematical programming used, such as linear programming (LP), nonlinear programming (NLP), mixed-integer linear programming (MILP), and mixed-integer nonlinear programming (MINLP). MILP is the most commonly applied in supply chain modelling [16,81].

Linear Programming (LP)

Linear programming is the simplest model as its components (constraints and objective function) are linear and all decision variables are continuous [78]. Tatsiopoulos and Tolis (2003) [50] used a linear optimisation model to find the optimum location and size for a power plant to convert chopped cotton-plant stalks to electricity and heat through the minimisation of the total cost in the whole supply chain. In another research study, Morrow et al. (2006) [47] applied a programming model to minimise the distribution cost of bioethanol produced from corn and switchgrass. An LP model presented by [48] aimed to minimise the ecological footprint in a biomass supply chain by considering multiple biomass, conversion technologies, and transportation methods from a life cycle viewpoint. Some researchers developed a scenario-based linear programming model to cope with climate and biomass production uncertainty [57,78].

Mixed-Integer Linear Programming (MILP)

Similar to LP models, objective functions and constraints in MILP models are linear, but in MILP models, at least one of the decision variables is an integer. MILP is an effective model for solving the problem that binary or integer variables are essential due to the existence of discrete facts. MILP is applied in the vast majority of AWCB models because of its potential to make decisions among a number of choices of facility location, conversion technology, transportation modes, supplier options, etc. [49]. The review results show that 82% (*n* = 51) of studies have applied MILP models (Figure 5). This preference comes from MILP's ability to model complicated, real-world problems that involve discrete decision-making processes, such as selecting locations for facilities and determining the types of conversion technologies, modes of transportation, and choices of suppliers.

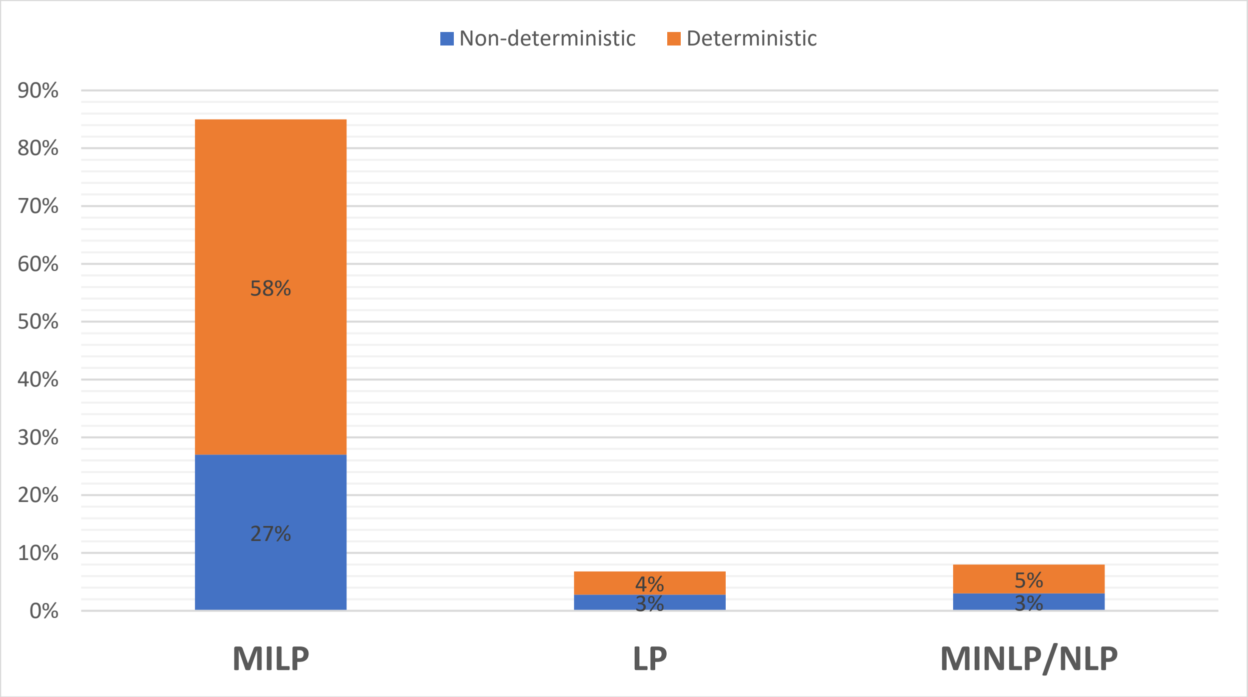

Figure 5. Distribution of three kinds of mathematical models and uncertainty in papers.

Several factors contribute to MILP's widespread adoption in AWCB research. Firstly, the AWCB supply chain is characterised by inherently discrete decisions, such as the yes/no decision to build a facility at a particular location or the choice among a finite set of transportation modes. MILP excels in these environments by allowing for integer variables that model such binary or integer-based decisions precisely. Secondly, the flexibility of MILP to incorporate linear constraints and objective functions aligns well with the linear nature of many cost and operational efficiency calculations within the supply chain, making it a helpful tool for optimising various performance indicators. Additionally, the advanced computational algorithms available for solving MILP problems have become more accessible and efficient, reducing the computational complexity of solving large-scale MILP models. This availability has encouraged scholars to tackle more complex and detailed supply chain models to obtain practical solutions within reasonable time frames by applying the MILP model [40].

Different objectives are considered in AWCB models although the vast majority of MILP models have taken into account economic aspects. Akgul et al. (2011) [44] applied MILP for the designing of an AWCB, considering the minimisation of the total cost of the considered supply chain. The result determined both the optimal location and size of a biorefinery to produce bioethanol as well as the biomass production amount and the quantity of transportation mode and this was applied for a case study in Northern Italy. Leão et al. (2011) [45] proposed a methodology to optimise a biodiesel supply chain through a MILP model, minimising investment, transportation, processing, and operation costs. The applicability of the model was illustrated by a case study in Brazil. A MILP model was presented by [46] to maximise the net profit to design production planning and locate biorefinery and pre-treatment hub facilities. The model is capable of selecting the optimal layouts by considering the certain location structure (centralised and/or distributed), type of biomass, and conversion plants at the same time. Woo et al. (2016) [63] proposed a novel MILP model framework for the optimisation of the hydrogen supply chain from agricultural residues, industrial residues, and forestry residues to estimate and meet the hydrogen demand of South Korea in 2040. In this model, decision variables such as the sites and scales of the facilities, the amount of biomass, hydrogen, and transportation flows are determined through the minimisation of the total annual cost.

Some works have focused on optimising economic and environmental aspects simultaneously as the objective functions in MILP models. You and Wang (2011) [49] designed a network supply chain to convert corn stover, energy crops, and wood residues to liquid fuel by applying multi-objective and multi-period MILP models. They considered total cost as an economic objective and the life cycle of GHG emissions to be the optimal one for the environment. Ivanov et al. (2022) [21] developed a bi-objective MILP model to minimise the total cost and greenhouse gas emissions for supply chains to produce biodiesel in Bulgaria. However, few studies have addressed all three criteria of sustainability in their MILP models [39,40,43,49].

Nonlinear Programming (NLP)/Mixed-Integer Nonlinear Programming (MINLP)

NLP models are another category of mathematical models in which one or more constraints or objective functions are nonlinear. If there are integer variables in the model, it would be MINLP. NLP provides a more accurate optimisation tool for complex supply chains, demand forecasting, and inventory management involving nonlinear cost structures or constraints. A few papers have suggested NLP models consist of MINLP and NLP models. Since NLP models are complicated to solve, most scholars prefer to apply LP models. Most of the NLP models in the literature review have a single objective [40,42,55,59,69,82]. Some researchers have addressed the environmental and economic objectives in their NLP models [16,83]. Čuček et al. (2012) [38] developed a MINLP model to optimise biomass to the energy supply chain by considering three objective functions. The model maximises the economic objective and minimises social and environmental footprints.

3.3.2. Geographic Information System (GIS)

A Geographic Information System (GIS) is widely acknowledged as an effective methodology that enables the characterisation and analysis of geographical data related to biomass locations, supply chains, and the identification of suitable facility locations [7].

Emphasising the advantages of a GIS, particularly its ability to analyse spatial relationships, is essential. This capability is crucial for accurately evaluating transportation logistics, feedstock accessibility, and customer connectivity. The strategic positioning of facilities significantly influences transportation costs in the AWCB supply chain. Thus, employing a practical methodology for optimisation is imperative. A GIS offers a robust solution, enabling the identification of optimal facility locations within a specific region by considering various data, including available land, proximity to farms, and road infrastructure. This approach ensures a comprehensive assessment of critical factors, enhancing supply chain efficiency and decision making [68]. It has been utilised in the dairy industry to allocate processing plants, such as AD, optimally [84]. There have been several studies that have used GISs to gain an optimal location for different facilities in a biomass supply chain [28,85–89]. Furthermore, a GIS can be combined with other modelling techniques; Durmaz and Bilgen (2020) [74] combined a GIS with multi-criteria assessment to identify appropriate sites for the construction of biomass facilities. In another work, Sharma et al. (2017) [71] integrated a GIS with Multi-Criteria Evaluation (MSE) to find a suitable capacity and location to build a plant in the US to produce biofuel from switchgrass, miscanthus, and corn stover. Durmaz and Bilgen (2020) [74] first used a GIS to find potential candidate locations for a biogas plant, then applied multi-criteria decision making to narrow down the candidates and finally optimised a mathematical model to obtain an optimal location for the biogas plant. Lovrak et al. (2020) [72] applied a GIS with Mixed-Integer Linear Programming (MILP) to determine appropriate locations and sizes of biorefineries to maximise profit. The spatial information used in their work included biomass resources, current and prospective facility sites, and a transportation system. Wu et al. (2021) [28] integrated MILP and a GIS to present a supply chain model for straw at a strategic level to minimise the total cost by finding the optimal number and size of centralised storage locations and conversion plants.

Furthermore, GIS has been used as a powerful tool to evaluate the spatial distribution of biomass in recent years, and it helps maximise biorefinery production [70]. Singh et al. (2008) [82] used a GIS to assess the accessibility of biomass and identify potential areas. They integrated it with a mathematical model for the collection of agricultural residue in the lands. Lourinho and Brito (2015) [90] developed a GIS-based method to calculate the availability of agroforestry residues to generate electricity through combustion technologies in Portugal. The total potential of energy production from agricultural and forest residues was assessed in Uganda by Okello et al. (2013) [91] through GIS. Lovrak et al. (2020) [72] evaluated the capacity of producing biogas from crop residue through a GIS-based method that integrates a GIS and statistics. They also considered the seasonality factor and its impact on the variation in biogas production. The approach was examined in a real study in Croatia.

3.3.3. Multi-Criteria Decision Making (MCDM)

MCDM just provides a methodology to decrease the difficulty of decision making with several conflicting objectives or attributes. This method has long appealed to decision-makers, offering a valuable approach to assessing and supporting decisions. It effectively addresses the complex challenges of uncertainty, conflicting criteria, diverse data types or information, and multiple interests and viewpoints [92]. MCDM can be classified into two groups: Multi-Attribute Decision Making (MADM), which works with alternatives, and Multi-Objective Decision Making (MODM), which suggests indefinite scenarios. Mathematical models apply MODM as they have objectives like maximising profit and results in an optimal scenario; however, MADM approaches are applied to find the best alternative among some alternatives [93,94]. Analytical Hierarchy Process (AHP), elimination and choice expressing reality (ELECTRE), and preference ranking methods use to improve evaluations are classified as methods of MADM [94].

MCDM can be applied as a type of integrated sustainability assessment in BSCs. On the other hand, MODM considers multiple objectives simultaneously in a mathematical model. These objectives might conflict with each other; these objectives in AWCB models can be combinations of two or more objectives [83]. In some works, two different economic objectives used in mathematical models for BSC models (Mas et al., 2010) [95] addressed Opportunity Value (OV) and Value-at-Risk (VaR) as economic objectives to optimise BSCs for producing bioethanol in Northern Italy. Gebreslassie et al. (2012) [96] proposed a multi-objective stochastic MILP model to design a biofuel supply chain by considering the expected annual cost and the financial risk as two economic objectives. Another combination of different objectives can be of economic and environmental objectives [43,97]. Wang et al. (2013) [83] investigated a mixed-integer nonlinear programming (MINLP) model to optimise biorefinery design with regard to economic and environmental criteria. An example of integrating economic and social objectives is the work that was done by [67] Balaman and Selim (2016). Cambero and Sowlati (2016) and Roni et al. (2017) [43,97] combined environmental, economic, and social objectives.

One of the advantages of MCDM that makes it a powerful tool is its capability to integrate with other techniques to create more flexible multiple methods. Furthermore, it is a valuable method that allows decision-makers and stakeholders to communicate with process planning (Malczewski & Rinner, 2015) [98]. In this context, MCDM can be integrated with GISs to develop new alternatives for considering social and environmental criteria to have better planning and management [70]. Many works focus on this application. Singh et al. (2011) and Perpiña et al. (2013) [69,70] proposed the MCDM–GIS approach to identify the proper locations to construct biomass facilities in Spain. First, the main criteria were identified and weighted based on Saati's analytic hierarchy process (AHP) method, which is one of the MCDM methods. The criteria are classified into environmental, economic, and social criteria. Their results showed that the most appropriate regions for establishing biomass facilities are placed near residential areas. The sensitivity analysis demonstrated that the most important factors in deciding on energy plans are biomass types, demand transportation costs, etc. A spatial MCDM model was presented to find suitable areas for wood storage in Australia by [66]. After identifying the suitable assessment criteria, fuzzy AHP techniques were applied by considering the stakeholder preferences, which consist of both academics as well as operational managers. Delivand et al. (2015) [65] applied the AHP–GIS method to identify the best locations for power plant locations to produce bioelectricity from wheat and agricultural residue in Italy. Figure 6 shows the percentages of the methodologies used in the literature review. Also, the numbers of papers that applied different mathematical modelling, methodologies, decision levels, and objective functions are displayed in Figure 7.

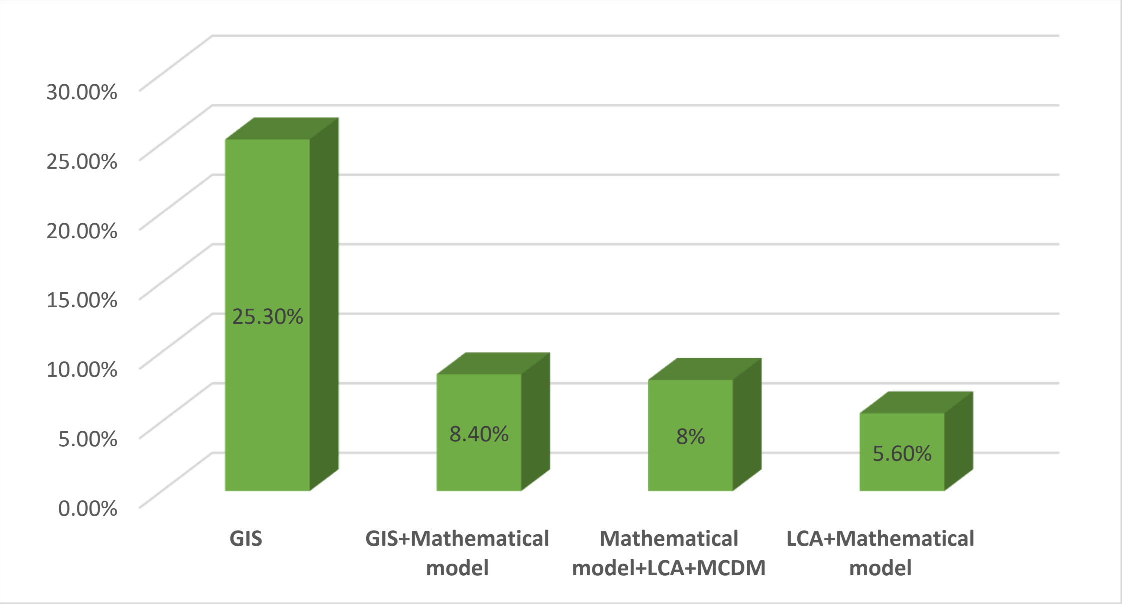

Figure 6. Distribution of different modelling methodologies in publications.

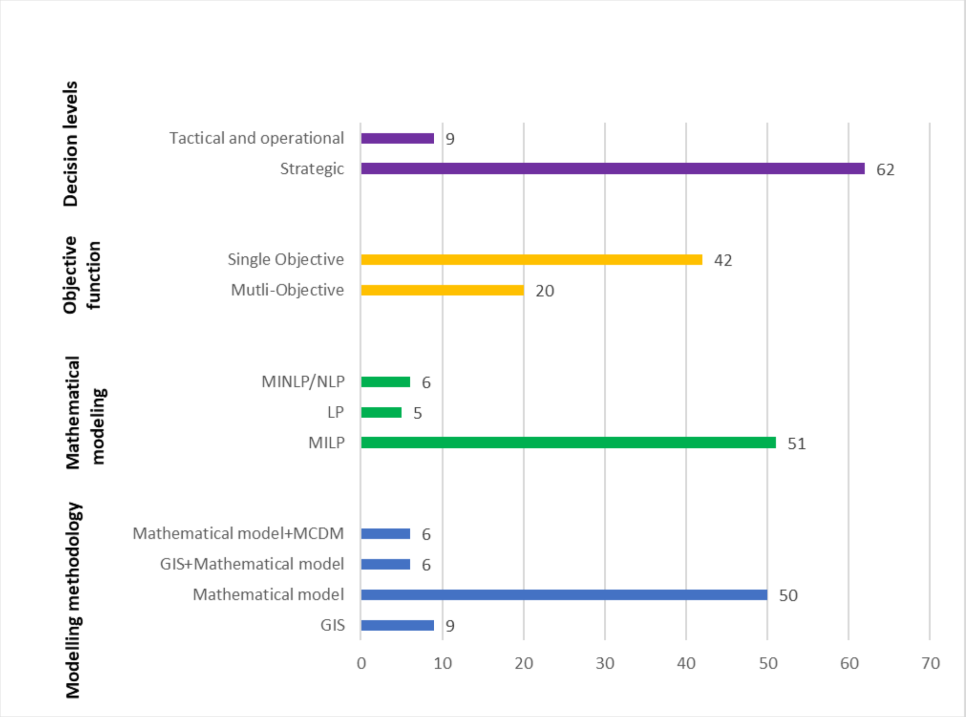

Figure 7. Categories of AWCB supply chain papers according to literature reviewed ($n = 71$).

3.4. Sustainability

The anticipation of oil depletion, alongside worries about energy security and global warming, is a primary factor motivating the endorsement of bioenergy by governmental bodies in developed nations. Although it is technically feasible to completely replace fossil fuels with bioenergy, sustainability constraints are likely to limit their global market share at a low percentage over the long term [99]. Sustainability entails meeting the present needs of humanity without concern about the ability of future generations to meet their own needs [100,101]. Sustainability needs to be assessed via three concepts: economic, environmental, and social aspects. The sustainable AWCB supply chain involves managing the AWCB stream through an integrated value chain, which includes a biorefinery that converts biomass waste into valuable bioproducts. This process aims to maximise economic and social benefits while minimising environmental burdens [102,103].

3.4.1. Economic Aspects

Producing bioproducts may boost the economy—for instance, by attracting investors, making attractive biomass resources that are currently unused, increasing farmers' incomes, and improving related businesses such as producing farming equipment [104].

The economic aspect is the most popular objective in AWCB supply chain modelling. Most researchers have considered minimising the overall cost as their objective [18,29,43,44]. Ge et al. (2021) [29] minimised the overall cost of cellulosic biofuel supply chain through the project time (20 years) to obtain optimal supply chain decisions.

However, maximising total profit and the net present value are other popular economic objectives in models [17,23,26,31,37,74,105]. For instance, Esmaeili et al. (2020) [26] proposed two models to maximise the profit of the corn and corn stover supply chain to produce bioethanol in North Dakota.

The frequency of economic objectives in the reviewed literature highlights the significance of the economic aspect, with 82% ($n = 58$) of papers prioritising this aspect in their research. Moreover, 9% ($n = 7$) of the papers integrated economic objectives with social or environmental considerations, indicating a growing recognition of the connection of these factors in AWCB supply chain management. This observation highlights the need for comprehensive and integrated approaches to address sustainability challenges effectively.

3.4.2. Environmental Aspects

The environmental aspects of sustainability seek to minimise environmental impacts. The most significant environmental burdens of the AWCB supply chain consist of greenhouse gas (GHG) emissions, which affect soil and water resources [58]. Some reports show that energy production through biomass is carbon-neutral because it almost takes in as much CO_2 as it emits. For example, around 1.6 tonnes of CO_2 are avoided per MWh of bioenergy produced from biomass. In another example, manure can be valorised to biogas through anaerobic digestion or fermentation, and it consists of a high amount of methane. The IPCC (Intergovernmental Panel on Climate Change) claimed that methane is around 21 times as efficient as CO_2 to trap heat in the atmosphere. Therefore, reducing 1 tonne of methane has the same positive effect as reducing 21 tonnes of CO_2. Therefore, some research studies considered environmental aspects in their modelling, such as a work by [21], which proposed a MILP model for a bioenergy supply chain from biomass that considers economic and environmental objectives. The authors evaluated the environmental burden of GHG emissions through the whole process. Some of the studies applied the Life Cycle Assessment (LCA) method to assess the corresponding environmental impacts of converting biomass to bioenergy [106,107].

3.4.3. Social Aspects

Sustainability is not limited to economic and environmental factors, and it includes social criteria such as job creation, poverty, social acceptability, etc. An AWCB supply chain can decrease poverty by creating jobs and enhancing the income of local people. It can also improve the quality of life by providing easy access to biofuel and energy. Furthermore, it forms practical equity among individuals [108]. Despite the importance of social impacts, only one paper (about 1%) of the studies incorporated both economic and social objectives. And only six papers (8%) considered three sustainability factors simultaneously, as shown in Figure 8 [38–40,43,49,109]. The objective functions regarding the social aspect could be maximising job creation, the total service level, etc. Using a different methodology, Panepinto and Genon (2012) [110] conducted an analysis of external costs to determine the social cost of biorefinery.

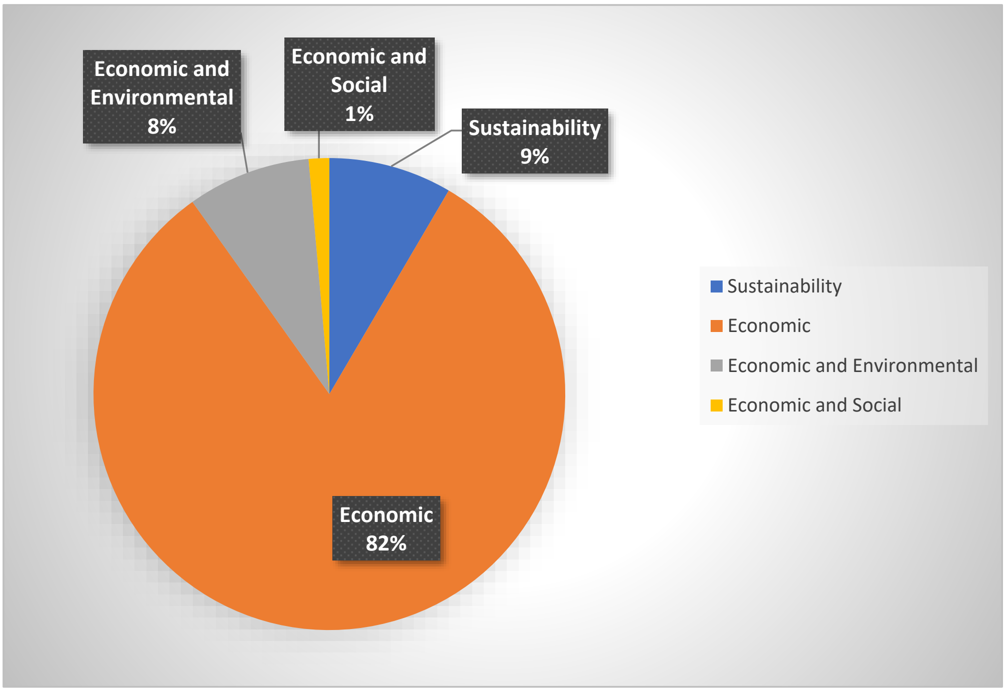

Figure 8. Percentages of three sustainability aspects in reviewed papers.

The minimal focus on social factors alongside economic ones may point to the complexity of quantifying social impacts and integrating them into objective functions. This represents a significant gap in the literature, revealing an opportunity for future research to develop comprehensive models that consider the social dimension of sustainability more robustly.

3.5. Uncertainty in AWCB Supply Chain

Uncertainty is described as the absence of data or lack of a certain level of belief in the data about the current or upcoming situation of a structure [111]. The source of uncertainty may originate from measurement faults, which are sometimes unavoidable and can be controlled by additional experiments or by applying advanced technology to obtain more accurate data [112,113]. Uncertainty can be caused by variability in the unpredictability of future incidents because of their physical and chemical characteristics, which may be reduced by utilising improved prediction techniques and/or employing professional experts. It may also originate from the absence of valid historical data or lack of reliability in historical information, such as a shortage of data on demand. With respect to time, uncertainty might be the consequence of short-time changes, such as daily processing changes, variation in orders, and machine failure, or long-term changes—for example, fluctuating feedstock/product prices, seasonal supply/demand changes, and technology changes. Thus, uncertainty can be considered in supply chains at all levels of decision making, i.e., strategic, tactical, and operational.

In an AWCB supply chain, uncertainty can be the result of several sources, such as the variability of climate conditions; seasonality, inherent natural characteristics, geographical distribution, and high volume of raw material; transport and delivery network; supplier contracts; and international and national rules or regulations [22,78,114,115]. Different parameters considered as uncertain factors in AWCBs are illustrated in Table 2.

Table 2. Uncertain parameters used in literature works.

Uncertain Parameter	**Reference**
Availability of biomass	Cundiff et al. (1997) [78], Kim et al. (2011b) [37], Nilsson (2000) [36], Fattahi and Govindan (2018) [34], Abriyantoro et al. (2019) [32]
Demand	Kim et al. (2011b) [37], Abriyantoro et al. (2019) [32], Razm et al. (2019) [53]
Cost parameters	Cobuloglu and Büyüktahtakın (2017) [33], Fattahi and Govindan (2018), Abriyantoro et al. (2019) [32], Razm et al. (2019) [53]
Critical technical factors	Razm et al. (2019) [53]
Technology evolution	Razm et al. (2019) [53]
Selling price	Kim et al. (2011b) [37], Abriyantoro et al. (2019) [32]
Number of harvesting workdays	Sharma et al. (2013) [57], Nilsson (2000) [36], Razm et al. (2019) [53]
The consumed transportation fuel	Razm et al. (2019) [53]
The used fuel	Razm et al. (2019) [53]
The used electricity	Razm et al. (2019) [53]
The quantities of seed, fertiliser, pesticides, and herbicides	Razm et al. (2019) [53]
The used human labour	Nilsson (2000) [35], Razm et al. (2019) [53]
Velocity of the vehicle	Razm et al. (2019) [53]
Yield of crop	Nilsson (1999) [35], Cobuloglu and Büyüktahtakın (2017) [33], Razm et al. (2019) [53]
Rainfall value	Nilsson (1999) [35]
Moisture and ash contents	Nilsson (1999) [35], Castillo-Villar et al. (2017) [23], Abriyantoro et al. (2019) [32], Aboytes-Ojeda et al. (2020) [30]
Capacity of facilities	Fattahi and Govindan (2018) [34]

Techniques to Deal with Uncertainty

There are several techniques to deal with uncertainty. The most commonly used methods are scenario-based approaches, stochastic optimisation, robust optimisation, fuzzy programming, simulation, and the probabilistic approach [116]. Uncertainty in the biomass supply chain was reviewed by [117]. Stochastic programming is relatively difficult as it is not possible to ensure the feasibility of constraints for all insights into stochastic parameters [16]. An easier approach were applied in several works, considering anticipated amounts for the random variables. Another simple method is to produce different scenarios, find a solution for each of them, and merge these separate solutions using some heuristic rules. Generating scenarios can be demanding and can be carried out by employing prediction approaches, historical data, decisions, and professional opinions [118,119]. The scenario-based method considers a wide-ranging what-if analysis that assesses the results based on various scenarios of random variables. A group of the optimum solutions obtained from this approach can be applied to have the expected value and standard deviation of the objective function and decision variables. However, it might not be the optimum value for some uncertain factors, or a better total optimal answer may exist. A further issue with this technique is that the probability of incidence of each scenario affects the optimal result; however, it is not possible to determine with certainty [120]. Cundiff et al. (1997) [78] developed a scenario-based model to deal with uncertainty in biomass production and find the optimal size of facilities. Sharma et al. (2013) [57] applied a scenario-based multi-period approach to determine the optimal configuration for a biomass supply chain by considering variability in weather conditions. Another scenario-based MILP model was proposed by [37] to determine the location and size of supply chain facilities along with the best amount of biomass flow under demand uncertainty.

When there is a large number of scenarios, simulation methods can be a suitable tool that can assess various scenarios and provide a solution that can be used in real-world conditions. This method also provides "What-if" analysis, is capable of considering different factors of variability in a problem, and has been developed widely in the industry. An AWCB supply chain is complicated to model with all uncertain parameters in mathematical programming. Therefore, simulation optimisation can be a solution to this problem by combining the simulation and optimisation approaches [71]. A simulation model called the Straw HAndling Model (SHAM) was presented by Nilsson (1999) [35] to develop a delivery system for biofuel and straw under uncertain weather, geographical, and straw characteristic factors in Sweden. Straw has been known as an important biomass resource for producing bioenergy in this country. Different climate conditions, rainfall rates, humidity levels, wind speeds, moisture contents, straw yields, and transportation distances influence the delivery cost. The simulation shows that transportation and straw yield have the most impact on the total cost of the system. Moreover, the optimisation of strategic decisions such as the storage location, number of balers, and transportation vehicles can significantly reduce costs (Nilsson, 2000) [35].

In stochastic programming, the assumption is that stochastic variables follow probability distributions or densities. Stochastic programming was described in detail by [119] Birge and Louveaux (2011). Variables are categorised into the first- and second-stage variables, which are made before and after the recognition of stochastic parameters, respectively In the initial step, the optimal solution is derived along with a set of rules guiding recourse decisions. These decisions are then applied in the second step to address each stochastic variable. Cobuloglu and Büyüktahtakın (2017) [33] proposed a two-stage stochastic MIP model to maximise the economic and environmental aspects of producing biofuel. Biomass yield and price were considered stochastic parameters that evaluated by utilising real case studies. Castillo-Villar et al. (2017) [23] optimised the bioethanol supply chain through a two-stage stochastic model under uncertainty of moisture content.

Fattahi and Govindan (2018) [34] proposed a multi-stage stochastic model to combine strategic and tactical decisions to plan a biofuel supply chain network by considering disruption risk, biomass seasonality, and uncertainty in facilities' capacity. They also studied both the environmental and social aspects as well as economic and life-threatening issues. Table 3 demonstrates the studies that considered different methods of uncertainty and uncertainty parameters.

Table 3. Studies in the literature review considered different types of uncertainty.

Uncertainty Method	Uncertainty Parameter	Level of Decision	Case Study	Reference
Scenario-based/MILP	Biomass availability, biofuel demand, price	Strategic	US	Kim et al. (2011b) [37]
Scenario-based/LP	Production levels of biomass	Strategic	US	Cundiff et al. (1997) [78]
Scenario-based/LP	Number of harvesting workdays	Strategic Tactical Operational	US	Sharma et al. (2013) [57]
Simulation	Average straw harvest, average combining to baling time, field area, fraction of the land area with harvestable straw, transport work between the stores and heating plant, number of days	Strategic	Sweden	Nilsson (2000) [36]
Simulation	Weather, stack size, type of crop, moisture content, straw yield, wind speed	Strategic	Sweden	Nilsson (1999) [35]
Two-stage stochastic model and L-shaped algorithm	Biomass price, yield of biomass	Strategic Operational	US	Cobuloglu and Büyüktahtakın (2017) [33]
Two-stage stochastic model	Moisture and ash contents	Strategic	US	Castillo-Villar et al. (2017) [23]
Multi-stage stochastic model/fuzzy	Facilities' capacity, disruption risk, biomass supply, cost	Strategic tactical	Iran	Fattahi and Govindan (2018) [34]
Stochastic model	Delays in biomass delivery, biomass moisture content, cement demand	Strategic Tactical Operational		Abriyantoro et al. (2019) [32]
Two-stage stochastic model	Moisture content, ash content	Strategic	US	Aboytes-Ojeda et al. (2020) [30]
The interval linear programming	Costs, prices, the consumed transportation fuel, demand, the used fuel, the used electricity, the quantity of seed, fertiliser, pesticide, and herbicide, the used human labour, the velocity of the vehicle, yield of grain	Strategic		Razm et al. (2019) [53]
Stochastic and fuzzy	Demand	Strategic Tactical	Thailand	Duc et al. (2021) [27]
Two-stage stochastic model	Weather, moisture, and ash		US	Aranguren et al.(2021) [24]
Two-stage stochastic model	Biomass supply	Strategic	Iran	Fattahi et al. (2021) [22]
Two-stage stochastic model	Collectible corn stover removal and farmer participation rates	Strategic Tactical	US	Guo et al. (2022) [121]

4. Main Findings and Future Opportunities

The world is facing a sustainability crisis due to the combined challenges of depleting fossil resources and increasing environmental pressures through waste generation [7]. AWCBs, as a type of biomass, are readily available and can be valorised for energy generation in a useful manner, which otherwise leads to environmental pollution and causes health problems [7–9]. Although it is important to overcome obstacles and uncertainties to have a developed and sustainable market, supply chain network design can play a key role.

This study reviewed the literature that focused on AWCB supply chain network design and optimisation. The papers were classified and analysed based on their modelling methodologies, sustainability, decision levels, uncertainty, and region of the studies to investigate research gaps. With regards to this study, the majority of the papers used a mathematical model as their approach. Three types of mathematical programming, LP, MILP, and NP, were applied, although MILP was more widely used than the other methods. The preference for MILP can be attributed to several factors, with one key reason being the complexity and difficulty associated with solving NP models. NP models, while powerful, often present substantial challenges due to their complex solution landscapes, making them less accessible for certain types of problems. Conversely, LP models, though simpler and more straightforward to solve, are sometimes criticised for their inability to accurately represent the complexities of real-world scenarios as they require linear relationships among variables, which is a significant limitation.

In the context of objective functions, just a few papers (about 28%) applied mathematical models with multi-objective functions. The insights from these findings indicate a potential gap in the literature, pointing to the need for further research and the development of multi-objective models that can capture and balance the complex interplay between the various sustainability dimensions. This balance is crucial to the comprehensive understanding and optimisation of the AWCB supply chain, ensuring that the solutions developed are not only economically viable but also environmentally sound and socially responsible.

On the other hand, the relatively few studies ($n = 9$) on tactical and operational models might indicate a gap in research on the ground-level application of strategies, which includes the day-to-day or short-term decisions required to manage and optimise current operations effectively. Tactical and operational decisions are crucial for the practical implementation of strategy and can significantly impact the responsiveness and agility of a system. The difference in numbers could also reflect the complexity of modelling tactical and operational decisions, or it might highlight an academic and practical preference for engaging with the broader strategic questions that set the direction for a field or an industry. However, this distribution underscores the need for a more balanced approach that encompasses both the visionary planning of strategic models and the practical, immediate concerns of tactical and operational models, ensuring a comprehensive view of the field that spans from conceptualisation to real-world application.

Furthermore, sustainability can play a key role in the AWCB supply chain; it needs to consider three concepts: economic, environmental, and social aspects [102,103]. This research has shown that only 9% ($n = 6$) of the studies considered all aspects of sustainability, and most of them only focused on economic objectives, leading to decisions that are not sustainable in the long term and may place excessive pressure on the environment.

The absence of social sustainability considerations in the reviewed studies stems from the complexities of quantifying such factors. This gap underscores the importance of including social impact assessments in future AWCB supply chain research. However, developing quantitative methods to analyse social aspects is challenging and requires more focused attention in upcoming studies.

Moreover, multi-stage solution methodology has been used recently as an efficient method to solve AWCB problems. However, only a few works have applied it, but it is expected to be seen in more future work. In addition, incentives and regulations can play an important role in developing biomass supply chains and producing bioproducts.

5. Conclusions

This review has highlighted the critical role of advanced supply chain network design in leveraging agricultural waste for sustainable energy production. Our extensive consideration of current literature reveals a predominance of Mixed-Integer Linear Programming (MILP) in modelling efforts, preferred for its ability to model complex systems. Despite this, the literature currently lacks a broad application of multi-objective models that adequately address the linked economic, environmental, and social dimensions of sustainability.

Significant gaps were identified in the areas of tactical and operational decision making—key for the day-to-day efficiency and implementation of strategic goals within AWCB supply chains. Moreover, sustainability considerations are often narrowly focused on economic outcomes, with insufficient attention to environmental integrity and social equity.

As the demand for sustainable bioenergy solutions intensifies, future research must evolve to include holistic sustainability assessments and multi-objective models that balance all three sustainability factors. This advancement is essential not only for academic enrichment but also for driving global efforts towards sustainable energy goals. Thus, fostering a broader, more integrated approach to AWCB supply chain management will be key to meeting both current and future sustainability challenges.

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