Computers & Industrial Engineering 193 (2024) 110270

Contents lists available at ScienceDirect

Computers & Industrial Engineering

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

Biomass supply chain network design under uncertainty, risk and resilience: A systematic literature review

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ARTICLE INFO

Keywords:
Biomass supply chain design
Uncertainty
Risk management
Resilient supply chain
Robust optimization
Systematic literature review

ABSTRACT

Biomass supply chain faces numerous challenges, uncertainties and risks. Resilience holds the key for effectively addressing these dynamic challenges and uncertainties and risks inherent in biomass supply chain management. This paper aims to highlight the uncertainty, risk, and resilience, which are significant concepts of biomass supply chain network design, with a systematic literature review. An innovative classification scheme is developed to combine these concepts from an operational research perspective. First, the articles are investigated according to the sources of uncertainty, risk management, resilient network designs, and detailed subcategories. Then, the problem characteristics, modeling uncertainty, and solution methods are analyzed. This systematic literature review serves as a guide for further studies by analyzing uncertainty, risk, and resilience in the biomass supply chain network design, and identifies a list of potential issues for future research directions.

1. Introduction

Energy consumption is constantly increasing worldwide, primarily due to population growth, widespread use of technology, and increased industrialization (Ghaderi et al., 2016; Mottaghi et al., 2022; B. Sharma et al., 2013). Meeting the majority of energy needs from fossil fuels has led to global environmental problems and, has increased concerns about energy security due to the risk of the depletion of fossil resources (Saidur et al., 2011; Zahraee et al., 2020). The growing attention towards meeting the energy needs of future generations and reducing environmental damage has directed scientific research on biomass resources which are considered a promising energy resource due to their environmentally friendly and renewable properties (Awudu & Zhang, 2012; Helal et al., 2023; Yue et al., 2014).

A biomass supply chain (BSC) is an integrated network of suppliers, facilities, and demand points, and also has a dynamic, complex, and large-scale system structure with a number of processes such as land allocation, cultivation, harvesting, storage, energy generation, and distribution (Atashbar et al., 2018; Lo, How, & Leong, et al., 2021). Biomass supply chain network design (BSCND) refers to both long-term strategic decisions such as determining facility location and production technology, as well as product flows, connections, and the interactions of all components. Thus, BSCND is required to manage these interdependent and interconnected processes (De Meyer et al., 2014; Lim et al., 2018).

BSC has several distinctive characteristics that make it a dynamic and complex structure (Atashbar et al., 2018; O. Sun & Fan, 2020). The seasonal availability of biomass feedstock is one of the main characteristics of the BSC. The amount of biomass to be supplied includes uncertainty and depends on the harvest period of the crop, the weather conditions, and the availability of land for replanting. If a single-source BSC is considered, long-term storage of very large quantities of biomass at harvest times is needed so that energy production can continue uninterrupted throughout the year. Supplying and storing large amounts of feedstocks in a limited time require seasonal additional equipment, labor, and storage needs. In addition, this seasonal increase in biomass demands causes an increase in acquisition costs. The fluctuating chemical and physical properties of biomass are other characteristics of BSC (Lim et al., 2018; Shabani et al., 2013). Considering low-density raw materials increases the need for different equipment in the transportation, handling, and storage stages. Finally, the variety of feedstocks and final products require simultaneous management of the differences in all supply chain (SC) stages such as supply location, production technology, and transportation type which increase the complexity of BSC. Different biomass types require customized harvesting and collection planning, handling equipment, and storage types. The variety of feedstocks used in the SC directly creates customized needs in

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https://doi.org/10.1016/j.cie.2024.110270
Received 24 June 2023; Received in revised form 1 May 2024; Accepted 3 June 2024
Available online 6 June 2024

production technologies and plant types. Therefore, these characteristics directly affect the investment and operational costs of the BSC (Rentizelas et al., 2009).

The complexity of a BSC can be correlated with the number of processes in the chain, the number of interactions among its processes, the diversity of business processes, and internal and external entities or drivers (Shabani et al., 2013). In addition to internal factors such as management and planning decisions, uncertainties and market dynamics that may arise at different stages increase the complexity of the SC (Dashtpeyma & Ghodsi, 2021; Helal et al., 2023; Saavedra M et al., 2019; F. Sun et al., 2018). Moreover, the fact that BSCND requires long-term strategic decisions and significant investments increase the importance of uncertain parameters that may arise over time (Awudu & Zhang, 2012).

Uncertainties that are not considered in the BSCND can cause challenges to the flow of the SC and disruptions in operations and production processes (Lo, How, & Leong, et al., 2021; Soren & Shastri, 2021). Deterministic SC designs have recently been found to be more vulnerable to significant operational risks and may have resulted in either suboptimal or infeasible solutions (Awudu & Zhang, 2012; Kamalahmadi & Parast, 2016; Mottaghi et al., 2022). Additionally, uncertainties give rise to the concept of risk, defined as potential losses or adverse effects (Scholz et al., 2012). In today's dynamic business environment, BSC more easily encounters risks that may cause disruptions in the continuity of flow and result in long-term negative impacts on SC performance. The potential risks of BSC can be related to a negative deviation in expected value or any potential loss of a disruption arising from uncertainty (Ho et al., 2015; Hosseini et al., 2019). Recent scientific research on network designs with the capabilities of mitigating vulnerabilities and recovery against disruptions has gathered considerable attention on the concept of SC resilience (Emenike & Falcone, 2020; Helal et al., 2023). In the context of SC network design, resilience refers to the ability to be sensitive to uncertainties, adapt to different conditions, and maintain flow and progress (Aldrighetti et al., 2021; Suryawanshi & Dutta, 2022). Today's rapidly changing business environment causes difficulties in long-term planning by increasing uncertainties and risks of disruption in many elements that determine the functioning of the SC, such as the continuity of raw material and labor supply, ensuring environmental standards and economic targets (Kamalahmadi & Parast, 2016; Shekarian & Mellat Parast, 2021). A resilient network design allows the SC to mitigate the negative effects of disruptions and recover its original functional state, by identifying the proactive or reactive strategy (Emenike & Falcone, 2020; Rajesh, 2020; Tordecilla et al., 2021). For more detailed definitions of uncertainty, risk, and resilience, an interested reader can be referred related books and articles by Scholz et al. (2012), Ivanov (2018), Ho et al. (2015), Ivanov et al. (2017), and Tang (2006).

In the real world, decision-makers face several challenges that cause disruptions in the operation of BSC and reduce profitability. A BSCND requires long-term strategic planning and large investments, with decisions such as facility location, technology, and supplier selection that are very difficult to change and are implemented for many years. Additionally, major fluctuations can be observed over time in many parameters such as supply, demand, and cost, and this may cause losses in the performance of the SC. In both strategic and operational decisions, decision-makers need to resilient network design to adapt BSC to the dynamic business environment. Incorporating different risk mitigation strategies into network design under various types of uncertainty increases BSC resilience by providing the ability to overcome challenges and the capacity to maintain continuous operation.

There is an increasing attention on the concepts of uncertainty, risk, and resilience from both academics and practitioners in the literature, and they have been the focus of numerous recent papers. Despite considerable attention in the literature dedicated to tackling these concerns in BSCND, there remains a deficiency in providing a systematic review paper. Based on the issues mentioned above, this study provides a comprehensive literature review on the field of BSCND from an operational research perspective, integrating the concepts of uncertainty, risk, and resilience. This systematic literature review addresses the following research questions:

(1) Which uncertainties are encountered in the design of BSCND depending on its dynamic and complex structure?
(2) How uncertain parameters are incorporated into the network design process?
(3) Which solution methods are used to tackle uncertainty in BSCND in the literature?
(4) Which risk factors are considered in BSCND and risk measurement techniques applied to incorporate them into the network design?
(5) What is the importance of resilient network design and resilience strategies in BSCND?

This study is organized as follows: Section 2 gives an analysis of related previous literature reviews. Section 3 provides information on systematic research methodology. Sections 4-8 describe the main parts of the literature analysis with a systematic approach and are organized according to the classification scheme. In section 4, the articles are investigated according to the sources of uncertainty. Section 5 presents information about risk factors and risk management approaches used in the BSCND literature. Section 6 describes the importance of resilient network design and gives a review of resilience strategies considered in the BSCND literature. Section 7 focuses on problem characteristics regarding decision levels, sustainability issues, and mathematical modeling formulations in the BSCND literature. Section 8 provides uncertainty modeling approaches and solution methods. Section 9 presents the conclusion and future research directions of this study.

2. Previous literature reviews

This section presents previous review works that have been done on BSCND under uncertainty. In the second decade of the 2000 s, Awudu and Zhang (2012) analyzed articles according to the decision levels, uncertainties, modeling uncertainties, and sustainability concepts. Sharma et al. (2013) presented a detailed review of energy trends, biomass feedstocks, and biofuel processes; they provide a classification of biofuels and feedstocks. Yue et al. (2014) provided a detailed analysis of biofuel generations and modeling structure. Ghaderi et al. (2016) developed a comprehensive main classification scheme for the BSC network models. Sun et al. (2018) classified articles according to the taxonomic literature review for the design and operation of BSC. Sun and Fan (2020) focused on robust BSC literature and wide applications of classic and well-studied optimization models. They analyzed challenges and opportunities in BSC regarding uncertainty and sustainability. Zahraee et al. (2020) presented a systematic review of BSC modeling and optimization, they discussed uncertainty as a factor capable of influencing BSC performance and classified articles according to the uncertain parameters and solution methods. Lo et al. (2021a) reviewed techno-economic evaluation to analyze the feasibility of BSCND. In a very recent review, Helal et al., (2023) conducted a bibliometric review in the field of biomass-to-bioenergy supply chain and presented potential research gaps.

To highlight the contributions of our review, Table 1 presents a brief description of previous related review papers based on the review characteristics, subject area, scope, time horizon number of papers reviewed, comprehensive analysis on uncertainty, risk, and resilience, and journal names published. Review characteristics of the previous reviews are classified as *overview, literature review, and systematic review* based on the taxonomies of Grant and Booth (2009), Kraus et al. (2022), and Schryen and Sperling (2023). As can be seen in Table 1, although various review studies related to BSCND under uncertainty exist in the literature, to the best of our knowledge, there has not been any recent

Table 1
Review characteristics, scope and special features of previous literature reviews.

References	Review Characteristics	Area	Scope	Time Horizon	No. of Articles	Comprehensive Analysis on			Journal
						Sources of Uncertainty	Risk Management	Resilience	
Awudu and Zhang (2012)	Overview	Biofuel SC	problem characteristics; uncertainty; sustainability; modeling	–	–	*			Renewable and Sustainable Energy Reviews
Sharma et al. (2013)	litrerature review	General BSC	problem characteristics; BSC characteristics; network structure; modeling	until 2011	32	*			Renewable and Sustainable Energy Reviews
Yue et al. (2014)	overview	General BSC	BSC characteristics; sustainability modeling	–	–	*	*		Computers and Chemical Engineering
Ghaderi et al. (2016)	systematic review	General BSC	SC characteristics; uncertainty; sustainability; modeling	1997—2016	146	*			Industrial Crops and Products
Sun et al. (2018)	litrerature review	General BSC	SC problem types; problem characteristics; modeling	1989—2017	185				International Journal of Production Research
Sun and Fan (2020)	litrerature review	General BSC	SC problem types; SC characteristics; sustainability; modeling	2009—2019	258				Process Integration and Optimization for Sustainability
Zahraee et al. (2020)	systematic review	General BSC	problem characteristics; sustainability; uncertainty; modelling	1980—2020	300				Biomass and Bioenergy
Lo et al. (2021a)	systematic review	General BSC	SC problem types; problem characteristics; uncertainty	2008—2021	44	*			Renewable and Sustainable Energy Reviews
Helal et al. (2023)	Bibliometric – literature mapping	General BSC	potential research gaps	1992—2022	1711				Energies
This study	systematic review	General BSC	Uncertainty; risk management; resilience; problem characteristics; modeling	2011—2024	138	*	*	*	Computers & Industrial Engineering

review paper that examines the BSC literature under the concepts of uncertainty, risk, and resilience from an operational research perspective, as well as analyzes all uncertainty types and related solution methodologies in detail. The closest review study has been conducted by Awudu and Zhang (2012). This former review study investigates an uncertainty analysis in the BSC, but not all uncertainty types are examined. In addition, this former study covers the papers up to 2012. In the last decade, since there is an increasing number of papers, our paper provides a systematic and up-to-date review and classification of studies on BSCND under uncertainty. In the current survey in this area:

- We propose a comprehensive classification scheme to analyze BSCND under uncertainty, risk and resilience in an integrated manner in terms of design and methodology.
- In this review, the conceptual importance of risk and resilience and the necessity of including uncertainty in BSCND are discussed in detail. The types of uncertainty sources encountered in the BSCND are examined and categorized.
- The relationship between the uncertainty type and the solution methods used is discussed and analyzed numerically.

3. Review methodology

A systematic literature review is conducted to address the research questions defined in the Introduction section. The methodology of this literature review is developed by using the methodologies proposed by Cooper et al. (2018), Tranfield et al. (2003), and Spieske & Birkel (2021). Table 2 describes the flow of the review methodology step by step. These main stages are:

Stage 1- Planning the Review begins with identifying and highlighting the reasons for the need for this review and the research motivations. The review of previous surveys is motivated and presented to accurately address the definitions and relations of the main concepts. And, the scoping study is conducted to limit the subject area for reviewing the relevant literature. The research questions, presented in the introduction, are identified to reveal the purpose of the review and the literature contributions planned to be obtained.

Stage 2 – Conducting the Literature Review requires creating a detailed and clearly explained search strategy. A structured and systematic review, beginning with the identification of keywords, inclusion criteria, and exclusion criteria, provides the most efficient method for the literature search and identifying relevant articles (Cooper et al., 2018). The following criteria clarify the literature search strategy:

- International peer-reviewed academic journals are selected.
- Articles must be written in the English language.
- Electronic databases are searched including Scopus, Web of Science, Wiley Online Library, Science Direct, Springer, Taylor, and Francis Online.
- The timeline is determined from 2011 until today.

Table 2
Review methodology.

Stage 1- Planning the Review	
Step 1: Identification of Research Motivation	• Importance of the concept of uncertainty in BSCND • The supply chain characteristics that unique to BSC • The relationship between uncertainty, risk management and resilient supply chain
Step 2: Analyzing the Previous Literature Reviews	• Providing a better understanding of the scope, scheme, and general considerations of BSCND • Analyzing trends and gaps identified in the BSC literature over time and determining issues that have evolved over the time period
Step 3: Developing the Classification Scheme	• Identifying the main parts of the BSCND subject • Describing the main parts of literature analysis depending on the research questions • Developing a flow for review and a categorization to analyze references
Step 4: Determining Research Questions	• Revealing the purpose of the review by integrating the findings obtained from the examination of previous literature studies and the motivation of the study • Determining literature contributions planned to be obtained as a result of the review • Highlighting questions that readers will find answered by the review
Stage 2 – Conducting the Literature Review	
Step 5: Designing the Search Strategy and Selection of studies based on inclusion and exclusion criteria	• Literature Search Strategy; • Published articles in international peer-reviewed journals • Written in the English language • The most prominent electronic databases (Scopus, Web of Science etc.) • Published articles in the period 2011–2022 • Relevant keywords such as biomass, supply chain optimization, uncertainty, biomass supply chain, and supply chain design in titles or keywords • Inclusion Criteria; • Articles focusing on BSC in terms of network design, facility location, transportation planning, supply management and planning, capacity and production technology selection, and inventory planning. • Exclusion Criteria; • Conference papers and commercial publications are excluded • Articles that do not propose a quantitative method on BSCND • Articles that do not consider uncertainty on BSCND
Stage 3 – Analysis and Reporting	
Step 6: Managing References	• Managing the output of literature searches • Analyzing and sorting articles by categories • Tabulation of articles by classification scheme and subheadings
Step 7: Documenting the Review Findings	• Reporting and documenting the process of analyzing articles • Developing numerical data and figural expressions • Recording and concluding the findings of the review

- Three keyword categories are defined. “Biomass, bioenergy, biofuels, and biogas” are in the first category. “Supply chain, network design, and supply chain optimization” are in the second category. “Uncertainty, risk management, resiliency, resilient design” are in the third keyword category. Different keyword combinations selected using all three categories are applied to titles, abstracts, and keywords.
- *Inclusion Criteria;* Articles focusing on BSC in terms of network design, facility location, transportation planning, supply management and planning, capacity and production technology selection, and inventory planning.
- *Exclusion Criteria*; Conference papers and commercial publications, articles that do not propose a quantitative method on BSCND, and articles that do not consider uncertainty on BSCND are excluded.

Based on this research methodology, 138 articles related to the BSCND under uncertainty consideration are collected. Fig. 1a presents an illustration of the numerical distribution of reviewed articles according to the years between 2011 and 2024. And, Fig. 1b lists the journals in which the reviewed articles were published and shows their numerical distributions.

Stage 3 – Analysis and Reporting is the final stage of the review methodology. This stage includes the analysis of the output of the literature search. A classification scheme, presented in Fig. 2, is derived based on both the benefits of reviewing previous surveys (Hoo et al., (2020), Atashbar et al. (2018), and Sun et al. (2018)) and the characteristics of the selected articles in the literature search. The proposed classification scheme presents the categorization of the BSCND and, identifies the flow and main parts of the analysis and reporting stage of this literature review. The results of these analyses are interpreted and discussed to answer research questions.

4. Uncertainty in biomass supply chain network design

Uncertainty is one of the main challenges in BSC and can occur in almost all stages and functions depending on different conditions (Helal et al., 2023; Mottaghi et al., 2022). Long-term resource problems, instability in economic conditions, technological developments, and changes in policies and regulations in bioenergy generation are among the main uncertain factors that affect performance in BSC. The inclusion of unexpected events in the design and planning process, depending on the SC’s environment and conditions, will give results closer to the real-life performance of BSC. Bairamzadeh et al. (2018) presented a taxonomy of uncertainty types including randomness, epistemic and deep uncertainty depending on available information on uncertain parameters. Randomness stems from the random (chance) nature of the input parameters and random events in usual activities (Tofighi et al., 2016). In the randomness assumption, sufficient and reliable historical data are available, which are necessary to reveal the probability distributions of uncertain parameters in the system. Stochastic programming (SP) or robust scenario-based SP can be proposed for the randomness that can be calculated through probability distributions with available historical data. In the epistemic assumption, the available historical data is not sufficient or reliable about uncertain parameters in the system (Pishvaee & Torabi, 2010). That is, it is related to a lack of data on inputs of the system. Possibilistic programming or robust possibilistic programming can be proposed for epistemic uncertainties. Deep uncertainty can be defined as the lack of available information about time, severity, and location to assess the probability of non-repetitive extreme events (Shavazipour et al., 2020). Deep uncertainty partially has a more serious impact on the system. In deep uncertainty, robust optimization approaches and narrative scenarios can be applied to imagine the “worst-case” scenario (Bairamzadeh et al., 2018; Klibi et al., 2010).

In this study, uncertainties frequently encountered in the BSCND are categorized as biomass-related, selling prices of by-product and final product, demand of the final product, cost/market, process-related, transportation and logistics uncertainties, and environmental impact.

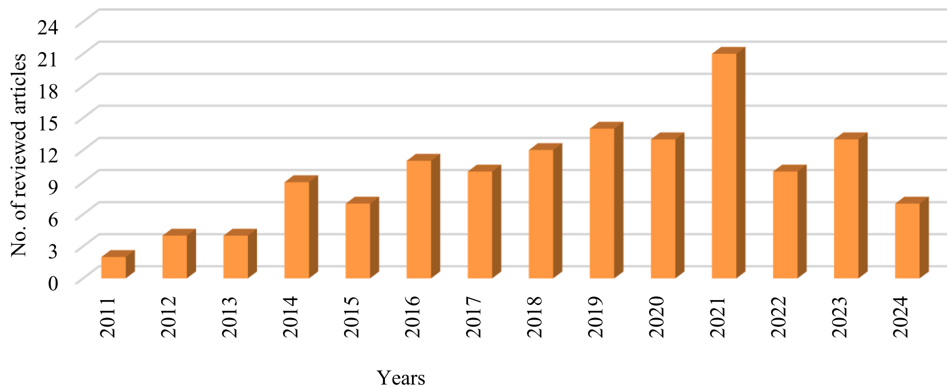

Fig. 1a. Numerical distribution of reviewed articles according to years between 2011 and 2024.

Table 3 shows a detailed analysis of uncertain parameters. Fig. 3a presents the illustration of the numerical distributions of reviewed articles according to the uncertainty sources and years.

4.1. Biomass-related uncertainties

A wide variety of biomass types are used in bioenergy production. In Fig. 4a and 4b, biomass resources are categorized according to feedstock type into four main groups: waste, forest/forest residues, energy crops, and algae (Sharma et al., 2013; Zahraee et al., 2020). As can be seen in Fig. 3b, biomass-related uncertainties are the most considered uncertainty factor in BSCND. Depending on feedstock type, the amount of available biomass or biomass yield can often change between periods due to variations in weather conditions (temperature, rainfall, etc.) (Huang et al., 2014). Land limitation, forest fire incidents, plant diseases, farmers' planting decisions, and participation are other common factors that cause supply uncertainty (O'Neill et al., 2022). The amount of available biomass affects production and harvest planning decisions. Uncertainty in biomass supply can result in bottlenecks and disruptions in SC's flow. Therefore, biomass supply uncertainties must be considered to determine decisions such as capacity and the amount of land to be cultivated.

Another source of uncertainty in BSCND is biomass quality. Biomass quality refers to biomass composition (content specifications) such as moisture/ash content, energy density, and higher heating value (Castillo-Villar et al., 2017). The main factors affecting biomass quality are the climate/storage and soil conditions, the handling method and the logging technique, and the harvesting season. Depending on the type of biomass, physical and chemical properties can differ. Even, since woody biomasses are heterogeneous materials, there may be differences in the biomass quality of different parts of a tree (Shabani & Sowlati, 2016b). Biomass quality is a determining and important factor in conversion rates, production efficiency, and fuel quality in the bioenergy production process from biomass. Probability distributions are mostly used to model biomass-related uncertainties by analyzing historical biomass availability data.

4.2. Market conditions–uncertainties of prices and cost

In an uncertain market environment, prices and uncertainty in costs are generally considered BSC parameters that affect each other (Lo et al., 2021). Considering the BSC issue globally, it is worth mentioning the fluctuations in exchange rates. Different currency revenues and costs must be converted to a single reference currency. Especially in low-income countries, exchange rates vary depending on the value of the dollar, and their fluctuations need to be estimated over the planning horizon (Razm et al., 2019). Another important factor causing uncertainty in BSC is related to government incentives and policies. Frequent fluctuations in the energy market cause unexpected results in BSC performance in the long run, which are different from those planned. Given the competition in the energy sector, the long-term failure of incentives and pricing policies for the production and use of bioenergy, frequently changing policies and economic conditions cause uncertainty in the economic parameters of the BSC (Sharma et al., 2020). Since BSCND is planned for the long term, it is very likely that operating costs, raw material costs, government grants, or interest rates will change in this process. Thus, these changes in many cost parameters cause deviations in planned BSC performance and are reflected in the final product selling price. Long-term planning, considering the uncertainties in market conditions and competitive environments, reduces unexpected losses in BSC performance.

4.3. Uncertain demand for the final product

Concerning final product prices, demand may decrease or increase over time due to changes in market conditions or seasonal reasons. Supportive government policies and incentives are among the driving forces that increase demand in BSC, since bioenergy generation is relatively more costly (C. Gao, 2022; Gilani & Sahebi, 2021). The uncertain demand is that the amount and timing of changes in demand are unknown. Accepting the demand as constant in the long term can cause unexpected economic losses in the BSCND (Delkhosh & Sadjadi, 2020). Demand uncertainty in BSC planning will affect strategic and tactical decisions such as capacity, investment cost decisions, periodic production planning, raw material procurement, and inventory planning. The number of articles that consider demand uncertainty is quite high.

4.4. Process-Related uncertainties

In addition to these uncertain parameters, disruptions or unplanned situations that affect the productivity of the production process may occur. Over time, capacity increase or technological developments may be needed. In this study, the uncertainties related to the production and operation process are called process-related uncertainties. Process-related uncertainties usually refer to uncertainties such as production yields, technology change, and interruptions/breakdowns. Li and Hu (2014) considered uncertainties in technological advancement that highly affect conversion rates and production. Marufuzzaman et al. (2014) also studied the impact of technology development uncertainty on SC's performance. Yue and You (2016) considered technology evolution as strategic uncertainty. They defined technology evolution as the deviation of actual process conversion efficiency from the designated value, which may originate from design or implementation errors. Hu et al. (2017) quantified the uncertainty and sensitivity impact of the biomass-ethanol conversion rate on ethanol production costs and optimal BSC configuration. Bairamzadeh et al. (2018) studied on improvements of conversion technologies through time and proposed robust scenario-based SP. Zhao and You (2019) addressed uncertain

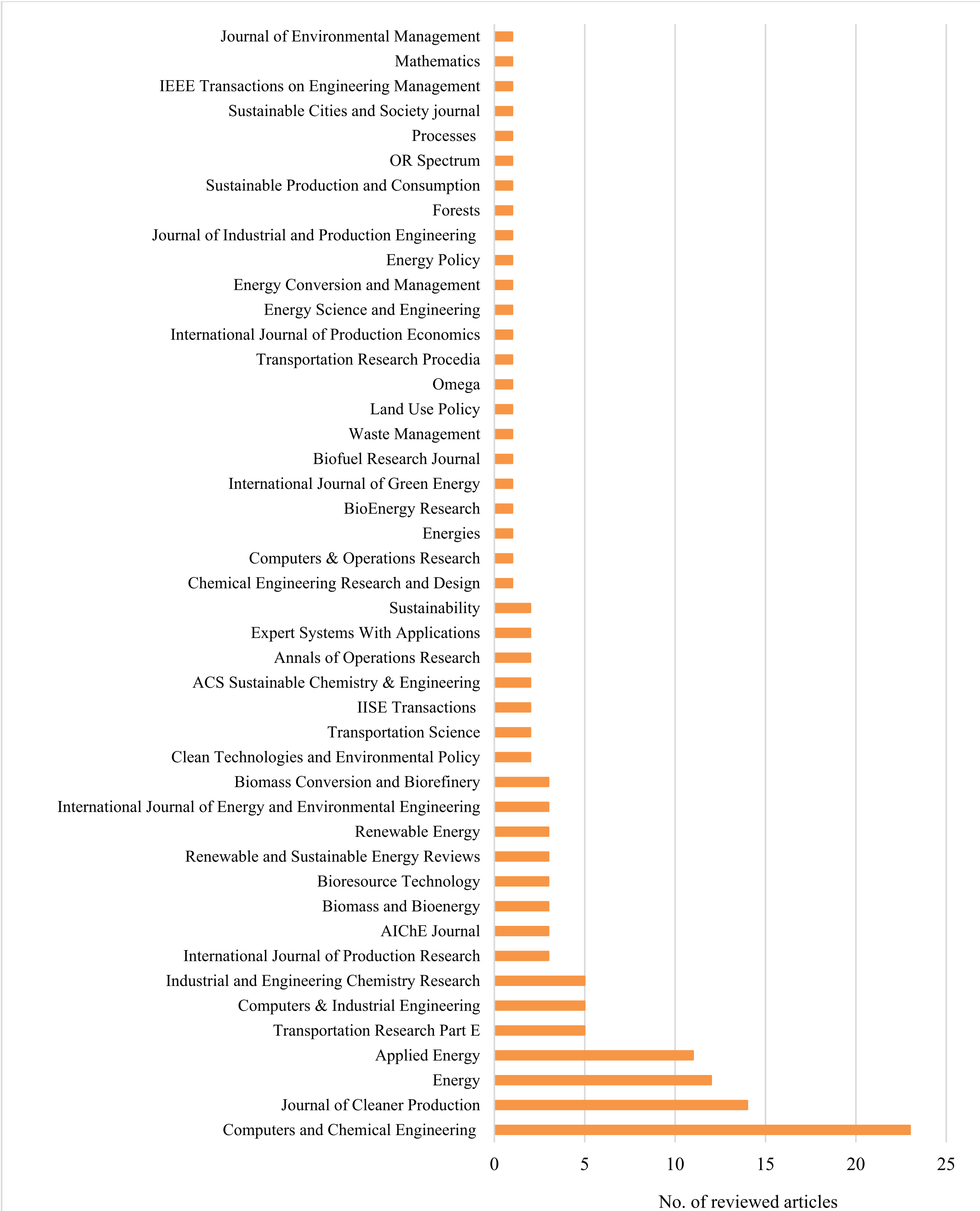

Fig. 1b. Numerical distribution of reviewed articles according to journals.

disruptions in the design and operations of resilient supply chains. Nugroho et al. (2022) recommended utilizing an agent-based simulation–optimization model to evaluate methanol synthesis pathways under uncertainties of the efficiency of the conversion processes.

4.5. *Transportation and logistics-related uncertainties*

The logistics process is one of the most significant and vital components of SC planning. Ren et al. (2016) considered transportation capacities as an uncertain parameter and proposed a bi-objective interval mixed integer programming model. They used interval numbers to

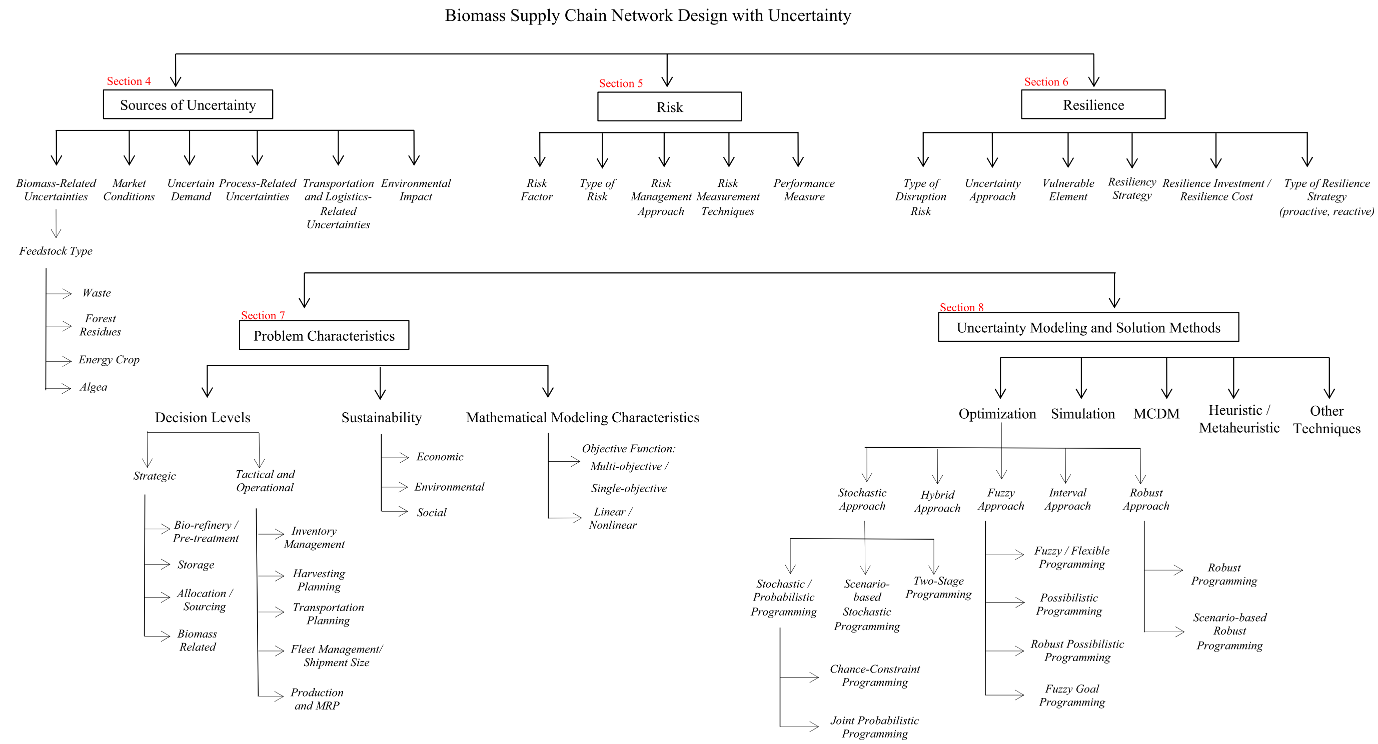

Fig. 2. Classification Scheme.

represent the uncertainties factors. Hu et al. (2017) studied on logistics loss rate which has a direct impact on the number of centralized storage and preprocessing facilities, in BSC optimization. They conducted Monte Carlo methods to quantify the uncertainty impact on optimal BSC configuration.

4.6. *Environmental impact*

Compared to fossil sources, the significant potential for reducing environmental pollution is one of the main reasons that make biomass resources popular. In the BSC, consideration of environmental impact along with the concept of sustainability has been widely considered in recent years. Although biomass is relatively costly compared to fossil fuels, its acceptance as an environmentally friendly energy source plays an important role in its preference. Environmental impacts depending on the production volume, transportation distance, or any other SC stages can be considered undesirable uncertainties. Bairamzadeh et al. (2016) used fuzzy numbers to model uncertainty related to the environmental impacts of biomass production, transportation, and conversion of biomass to bioethanol processes. Rezaei et al. (2020) developed a scenario-based robust optimization model under environmental uncertainty. The environmental impacts of all processes, obtained by Eco-indicator 99 method, must not exceed the stated upper bound. Ko et al. (2022) suggested a multi-objective SP for sustainable biomass transportation, and they identified the impact level of model selection on the transportation mode with uncertain environmental transportation cost factors.

Fig. 3c shows the relationship between the uncertainty types and the corresponding solution approaches that are used to address uncertainty. With the set of diagrams given in Fig. 3c, a summary of the used methods for the solution of the uncertainty types is given below. Stochastic models are the most used for uncertainties in general and especially for uncertainties related to biomass. Robust models are used in a similar number in all uncertainty types, that is, it can be inferred that robust models are used to address all types of uncertainty. Although fuzzy models are applied for all types of uncertainty, it is seen that fuzzy models are used commonly to address biomass-related and demand uncertainties. Only two articles used the interval model in this review study and treat biomass-related, demand, and transportation/logistics-related uncertainties. The simulation is the widely used method to address biomass-related, price, cost, and process-related uncertainties.

5. Risk management in biomass supply chain network design

The traditional definition of risk refers to potential losses or adverse effects of potential disruptions and hazards (Scholz et al., 2012). In terms of the SC, risk can be defined as the potential losses in objectives, caused by uncertain variations of parameters (Snyder et al., 2016). Depending on the impact, severity, and frequency of the hazardous event, potential losses and disruptions have a significant impact on SC performance (Hosseini et al., 2019). According to the classification presented by Tang (2006), considered risks in a SC can be defined into two groups: operational risks and disruption risks. Inherent uncertainties in the BSC data, such as supply availability and customer demand, are defined as operational risks. On the other hand, disruption risks refer to disruptive events caused by natural and man-made disasters such as earthquakes, hurricanes, floods, terrorist attacks, and financial crises (Goh et al., 2007; Kleindorfer & Saad, 2005). In addition to the complex and competitive business environment, uncertainties such as weather-related disasters and currency fluctuations that may have a negative impact on SC's performance and continuity increase the importance of risk management (Hamdi et al., 2018; Shekarian & Mellat Parast, 2021). Different from the traditional SC, BSC has several distinctive risks such as seasonal biomass availability, fluctuations in biomass quality, and geographical distributions of feedstock. Risk management strategies are applied to BSCND to mitigate possible losses in SC performance and to ensure continuity. According to the decision maker's behavior and willingness to take a risk, risk management can be classified in two ways; risk-averse decision-making (RA) and risk-neutral decision-making (RN) (Khezerlou et al., 2021; B. P. Sharma et al., 2020). First, risk-averse decision-making seeks to minimize risks while simultaneously improving returns (or SC's performance). That is,

Table 3
Classification of articles according to uncertain parameters and main categories.

	Uncertainty									
References	**Biomass Related**	**Selling Prices of By-Product and Final Product**	**Demand for the Final Product**	**Cost /market**	**Process Related**	**Trans. / log.**	**EI**	**Biomass Type**	**Solution Approach**	**Sustainability**
Kim et al. (2011)	BS	*	*	CC, OC, TC, FC	*			FR	S	E
Dal-Mas et al. (2011)		*		FC				EC	S	E
Chen & Fan (2012)	BS		*					W, FR	S	E
Gebreslassie et al. (2012)	BS		*					W, FR, EC	S	E
Giarola et al. (2012)				FC, Cac				W, EC	S	E, ENV
Kostin et al. (2012)			*					EC	S	E
Foo et al. (2013)	BS							W	S	ENV
Awudu & Zhang (2013)		*	*					EC	S, Sim	E
Giarola et al. (2013)				FC, Cac				W, EC	S	E, ENV
Osmani & Zhang (2013)	BS	*	*	FC				W, EC	S	E
Yilmaz Balaman & Selim (2014)	BS							W, EC	F	E, ENV
Marufuzzaman et al. (2014)	BS				*			W	S	E, ENV
Tong et al. (2014)	BS	*	*	FC, OC, CC, GI				W, FR, EC	S	E
Huang et al. (2014)	BS							W, FR	S	E
Osmani & Zhang (2014)	BS	*	*	FC				W, FR	S	E, ENV
Nguyen et al. (2014)	BS							W	GIS, Sim	ENV
Shabani et al. (2014)	BS							FR	S	E
Li & Hu (2014)	BS	*			*			W	S	E
Azadeh et al. (2014)		*	*					W, FR, EC	S	E
Gonela, Zhang, Osmani, et al. (2015)	BS	*	*					W, EC	S	E, ENV, SC
Yeh et al. (2015)	BS		*	FC, OC				FR	S	E
Yilmaz Balaman & Selim (2015)	BS							W	F	E
Gonela, Zhang, & Osmani (2015)	BS	*	*					FR	S	E
Sharifzadeh et al. (2015)	BS		*					EC	I	E
Ren et al. (2015)	BS		*	FC, TC, PC				EC	S	E
Serrano et al. (2015)	BS							A	R, GIS, MCDM	E
Mohseni et al. (2016)	BS		*	TC, CC, PC				EC	S	E
Santibañez-Aguilar, Guillen-Gosálbez, et al. (2016)	BS	*	*					EC	S	E
Azadeh & Vafa Arani (2016)	BS	*						EC	S, Sim	E
Bairamzadeh et al. (2016)		*	*			*	*	W	F	E, ENV, SC
Shabani & Sowlati (2016a)	BQ, BS							FR	H	E
Yue & You (2016)	BS		*		*			W	H	E
Ren et al. (2016)	BS		*			*		EC	I	ENV
Shabani & Sowlati, (2016b)	BQ, BS	*		FC				FR	S, Sim	E
Santibañez-Aguilar, Morales-Rodriguez, et al. (2016)				FC				FR, EC	S, Sim	E, ENV
Poudel et al. (2016)	BS							W, FR	S, H/M	E
Yılmaz Balaman and Selim (2016)			*	*				W, EC	F	E,SC
Hu et al. (2017)	BS			TC	*	*		EC	S, Sim, GIS	E
Ranisau et al. (2017)	BS							W	S	E
Gao and You (2017)	BS		*					W, FR, EC	S	E, ENV
Mirkouei et al. (2017)	BQ, BS							FR	S, H/M	E, ENV
Zhang and Jiang (2017)		*						W	R	E, ENV, SC
Osmani and Zhang (2017)	BS	*	*					W, FR, EC	S	E, ENV, SC
Babazadeh et al. (2017)	BS		*					W, EC	F	E, ENV
Quddus et al. (2017)	BS							W, FR, EC	S, H/M	E, ENV
Castillo-Villar, Eksioglu, and Taherkhorsandi (2017)	BQ							EC	S	E
Cobuloglu and Büyüktahtakın (2017)	BS			FC				W, EC	S	E, ENV
Ghaderi, Moini, and Pishvaee (2018)	BS		*					EC	F	E, ENV, SC

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Table 3 (*continued*)

	Uncertainty									
References	**Biomass Related**	**Selling Prices of By-Product and Final Product**	**Demand for the Final Product**	**Cost /market**	**Process Related**	**Trans. / log.**	**EI**	**Biomass Type**	**Solution Approach**	**Sustainability**
Ghelichi, Saidi-Mehrabad, and Pishvaee (2018)	BS		*					EC	S	E, ENV
Bairamzadeh, Saidi-Mehrabad, and Pishvaee (2018)	BS		*		*			W	H	E
Xie and Huang (2018)			*					FR	S	E
Asadi et al. (2018)			*					A	S, H/M	E, ENV
Nguyen and Chen (2018)	BS							EC	S	E
Lopez-Dıaz et al. (2018)	*	*	*	FC				EC	S, Sim	E, ENV
Ahmed and Sarkar (2018)	BS		*					W	F	E, ENV
Fattahi and Govindan (2018)	BS							W, FR	S	E, ENV, SC
Quddus et al. (2018)	BS							W, FR	S	E
Üster and Memisoglu (2018)	BS							EC	S	E
Sy et al. (2018)			*					A	R	E, ENV
Yılmaz Balaman et al. (2018)		*	*				*	W, EC, FR	F	E, ENV
Zhao and You (2019)			*		*			EC	R, H/M	E
Khishtandar (2019)	BS	*	*					W	H, H/M, Sim	E
Babazadeh, Ghaderi, and Pishvaee (2019)	BS	*	*	FC, PC, TC, Ccap, FxC				W, EC	F	E
Arabi et al., (2019b)		*						A	S	E, ENV
Arabi et al., (2019a)	BS							A	F	E
Soren and Shastri (2019)	BS							W	S	E
Abriyantoro et al. (2019)	BS, BQ		*					W, FR	S	E
Razm et al. (2019)			*	ExR				W, FR, EC	S	E
Babazadeh (2019)	BS		*	TC, FC, FxC, OC				W, EC	F	E
Gao, Qu, and Yang (2019)	BS	*	*					W	S, Sim	E, SC
Gonela et al. (2019)	BS				*			W, EC, FR	S	E, ENV, SC
Heidari, Yazdanparast, and Jabbarzadeh (2019)	BS							W	F	E, ENV, SC
Alizadeh et al. (2019)	BS			CaC				W, FR	H, Sim	E, ENV
Kesharwani et al. (2019)	BS	*						W	S	E, ENV
Delkhosh and Sadjadi (2020)			*					A	R, MCDM	E, ENV
Saghaei, Ghaderi, and Soleimani (2020)	BS, BQ		*					FR	S, H/M	E
Díaz-Trujillo, Fuentes-Cortés, and Nápoles-Rivera (2020)	BS		*					W	S	E, ENV
Sharifi et al. (2020)			*	TC, PC, IC, CC				EC	H	E, SC
Rezaei et al. (2020)	BS		*	PC, IC, TC		*	*	EC	R	E, ENV
Mohseni and Pishvaee (2020)			*					W	R, Sim	E
Mousavi Ahranjani et al. (2020)	BS	*	*	OC, FC, IC, PC, TC				W	H	E, ENV
Saghaei et al. (2020)	BS, BQ		*					FR	S	E, ENV
Gilani, Sahebi, and Oliveira (2020)	BS	*	*					EC	F	E, ENV, SC
Habib et al. (2020)			*	FC			*	W	F	E, ENV, SC
Sharma et al. (2020)	BS							EC	S	E
Ngan et al. (2020)	BS, BQ	*	*					EC	S, Sim, MCDM	E, ENV
Guericke et al. (2020)		*	*					FR	S	E
Razm et al. (2021)	BS	*	*	TC, FC, PC, OC, IC				W, FR	R, MCDM, GIS	E, SC
Zuniga Vazquez et al. (2021)	BS							EC	S	E, ENV, SC
Samani and Hosseini-Motlagh (2021)			*	TC, OC, CC			*	W	F, DEA	E, ENV
Tey et al. (2021)			*	CC, PC	*			W	F	E, ENV, SC
Baghizadeh, Zimon, and Jum'a (2021)	BS		*		*			FR	H	E, ENV, SC
Gilani and Sahebi (2021)		*	*					EC	F	E, ENV, SC
Karimi, Ekşioğlu, and Carbajales-Dale (2021)	BQ							FR	S, H/M	E, ENV

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Table 3 (*continued*)

References	Uncertainty						EI	Biomass Type	Solution Approach	Sustainability
	Biomass Related	Selling Prices of By-Product and Final Product	Demand for the Final Product	Cost /market	Process Related	Trans. / log.				
Sadeghi Ahangar, Sadati, and Rabbani (2021)	BS							W	F	E, ENV, SC
Lo et al. (2021b)	BS, BQ	*		FC, TC				W	Sim	E, ENV
Sajid (2021)	BS, BQ	*	*	OC, FC, TC		*		W	DBN	E
Liu and Yuan (2021)	BS		*					–	R	E
Fattahi, Govindan, and Farhadkhani (2021)	BS							W, FR	S	E, ENV, SC
Gumte et al. (2021)	BS	*	*					W, FR, EC	R	E, ENV
Khezerlou, Vahdani, and Yazdani (2021)	BS		*					W, FR	H/M	E
Allman et al. (2021)	BS							W	S	E
Aghalari et al. (2021)	BS, BQ							W, FR	S, H/M	E
Aranguren, Castillo-villar, and Aboytes-ojeda (2021)	BS, BQ							EC	S, H/M	E, ENV
Nur et al. (2021)	BS, BQ							W, EC	S, H/M	E, ENV
Memişoğlu and Üster (2021)	BS							EC	S	E
Soren and Shastri (2021)	BS							W	S	E
Elaradi, Zanjani, and Nourelfath (2022)			*					FR	S, Sim	E
Arangurren and Castillo-Villar (2022)	BS, BQ							EC	S, H/M	E, ENV
Reyes-Barquet et al. (2022)	BS, BQ							EC	S, MCDM, H/M	E, ENV
Ko et al. (2022)	BS		*	TC			*	FR	S	E, ENV, SC
Lee, Sun, and Li (2022)		*	*					W, EC	S	E, ENV
Guo et al. (2022)	BS							W	S	E
Salehi et al. (2022)			*					W	R, MCDM, H/M	E, ENV, SC
Aboytes-Ojeda, Castillo-Villar, and Cardona-Valdés (2022)	BS, BQ							EC	S	E
O'Neill et al. (2022)	BS							EC	S	E, ENV
Nugroho, Zhu, and Heavey (2022)			*		*			W	Sim	E, ENV
Ahmadvand and Sowlati (2022)	BS	*	*					W	R	E
Umar et al. (2023)			*				*	A	F, H/M	E, ENV
Theozzo and Teles dos Santos (2023)	BS	*						FR	R	E
Ghozatfar and Yaghoubi (2023)	BS							W	O	E, ENV
Ahmadvand and Sowlati (2023)	BS			*				FR	R	E, ENV
Mondal et al. (2023)	BS		*	FC, FxC, OC, IC, TC			*	W	H	E, ENV, SC
Chen and Liu (2023)							*	W	R	E, ENV, SC
Kalhor et al. (2023)			*					EC	S	E, ENV
Samani et al. (2023)				*	*			W	H	E
Zarrinpoor and Khani (2023)	BS		*	FxC, IC, OC			*	EC	F, MCDM	E, ENV, SC
Gilani et al. (2023)	BS							W, EC	R	E, ENV
Lima et al., (2023)			*					EC	S	E
Piqueiro et al. (2023)	BS							FR	S, Sim	E
Xie, Tian and Wu (2023)	BS			FC				EC, A	S	E
Piedra-Jimenez et al. (2024)	BS		*	FC, PC				FR	R	E
Huang et al. (2024)	BS							EC, FR	S	E, ENV
Sadeghi Darvazeh et al. (2024)	BS			FC				FR	R	E
Wang et al. (2024)	BS		*					W	S, GIS, MCDM	E
Shirazaki et al. (2024)							*	A	R	E, ENV
Ransikarbum and Pitakaso (2024)	BS		*					FR	S, MCDM	E, ENV, SC
Zarrinpoor (2024)	BS	*	*	TC, PC, FC, FxC, IC	*			W	F	E, ENV, SC

BS: Biomass Supply, BQ: Biomass Quality, FC: Feedstock Related Cost, CaC: Carbon Cost, IC: Inventory Holding Cost, FxC: Fixed Installation Cost, TC: Transportation Related Costs, OC: Operation Related Cost, CCap: Capacity Expansion Cost, PC: Production Related Cost, CC: Capital Cost, GI: Government Incentive, ExR: Exchange Rates, W: Waste, FR: Forest Resources/Residues, EC: Energy Crop, A: Algea, S: Stochastic, I: Interval Approach, H: Hybrid, H/M: Heuristic/Metaheuristic, F: Fuzzy, R: Robust, Sim: Simulation, O: Other Techniques, E: Economic, ENV: Environmental, SC: Social.

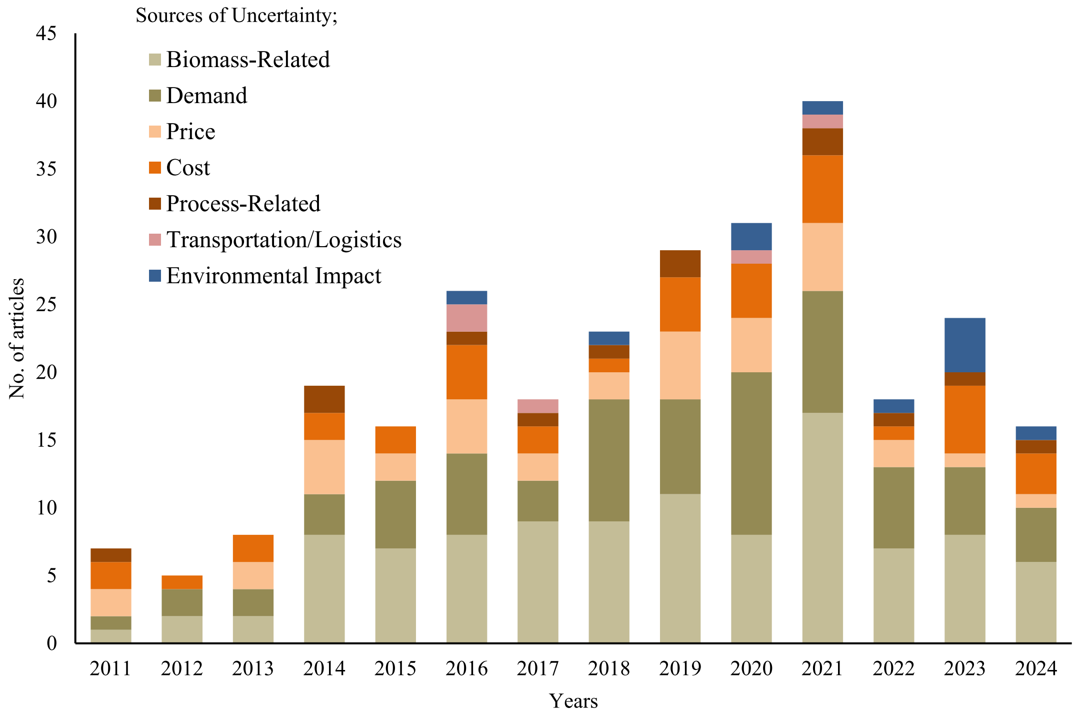

Fig. 3a. The illustration of the numerical distributions of the reviewed articles according to the uncertainty sources and years.

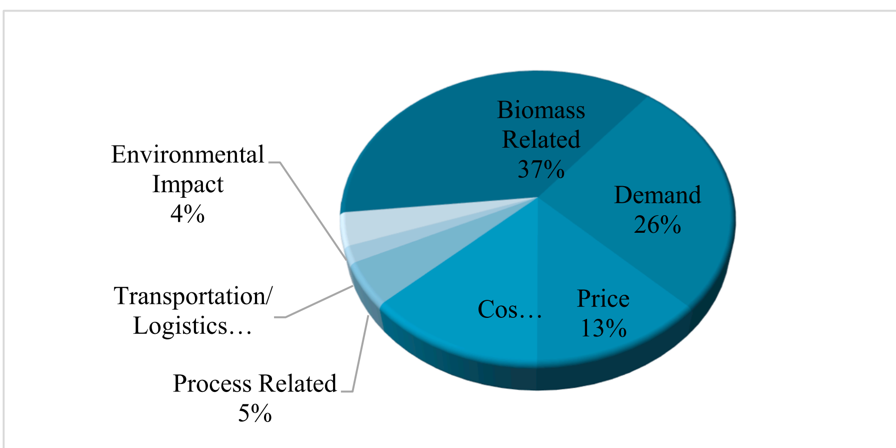

Fig. 3b. A pie chart showing the percentage distribution of reviewed articles according to uncertainty sources.

the decision-maker prefers smaller returns with smaller risks, rather than taking large and unknown risks. Second, risk-neutral decision-making considers maximizing potential returns rather than minimizing risks (Hamdi et al., 2018). In Table 4, articles are classified according to their risk management approach, risk measurement techniques, and related performance measures. Most of these articles are related to the uncertainties in the supply of biomass and the changes in the cost parameters accordingly. Interruptions in feedstock supply and financial losses are the most discussed risk factors. Some articles compare the impact of risk factors on performance measures by applying both risk-averse and risk-neutral approaches. Different risk measurement techniques are applied by decision-makers to quantify SC's risks. The most widely used ones are the variance of the objective function from its expected value, absolute deviation, standard deviation, conditional value at risk (CVaR), and semi-deviation from a predetermined target. Almost all the articles analyzed the differences in economic performance measures depending on the risk factors. According to Table 4, only four articles on BSCND evaluated risk management from an environmental perspective and used environmental impact as a performance measure.

6. Resilient biomass supply chain network design

An effective SC design must have the capability of overcoming all the challenges and the capacity to maintain continuous functioning (Emenike & Falcone, 2020; Rajesh, 2020; Tordecilla et al., 2021). From this viewpoint, the concepts of flexibility and resilience are of significance in BSCND in recent years. Resilient BSCND should have the ability to recover from disruptions and then return to its original state quickly, and effectively (Behzadi et al., 2020). As mentioned in Section 5, compared to operational risks, disruptive risks are uncertainties with greater impacts that will interrupt the flow and functioning of the SC. That is, the disruption risks, although less frequent, have greater severity and longer duration. The potential loss or adverse impact of the uncertain events and the vulnerability of the SC should also be considered.

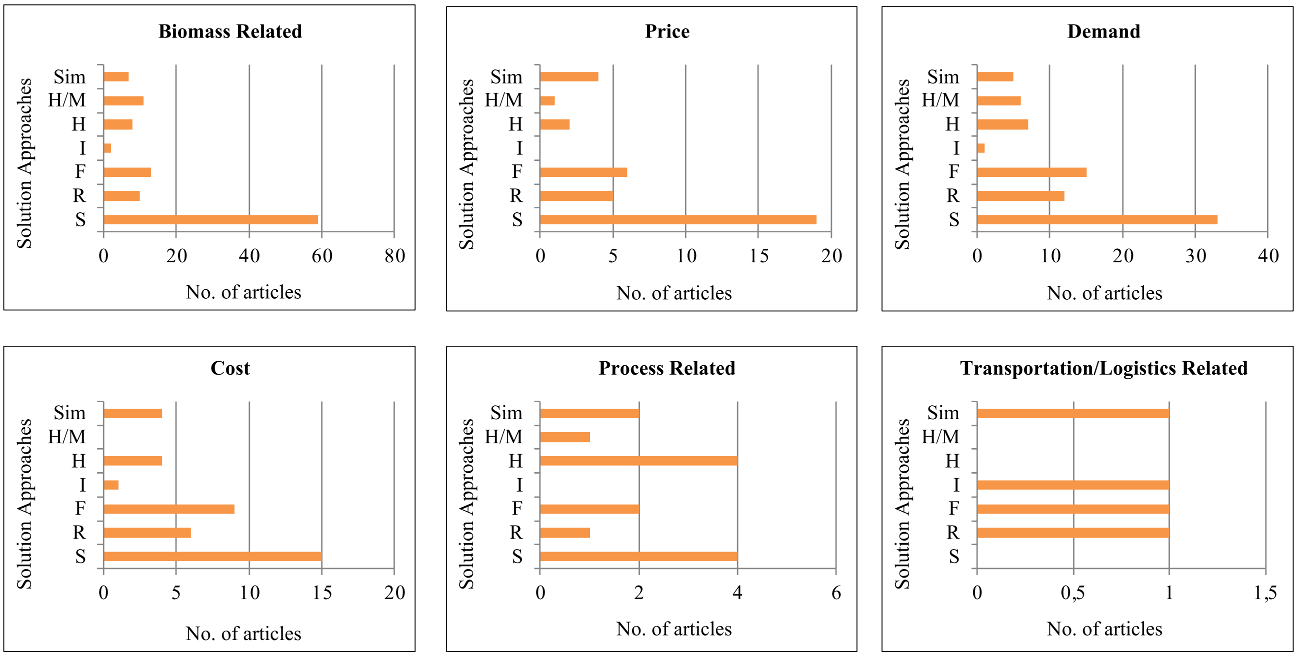

Fig. 3c. Numerical relationships between the source of uncertainty (biomass-related, price, demand, cost, process-related, and transportation) and solution approaches used in articles (Sim: Simulation, H/M: Heuristics and Metaheuristics, H: Hybrid, I: Interval, F: Fuzzy, R: Robust, S: Stochastic).

Biomass Type

Waste	Agricultual Waste (corn stover, wheat straw, rice straw etc.) Organic Waste (municipial solid waste, waste water, animal fat etc.)
Forest Resources / Forest Residues	wood chips, wood, sawdust, logging residues, thinnings, shavings, lumber mill residues, pine pulpwood, wood powder etc..
Energy Crop / Agricultural - Food Based	Corn, wheat, sugarcane, palm oil, switchgrass, miscanthus etc.
Algea-Microalgea	

Fig. 4a. Classification of biomass resources according to feedstock types.

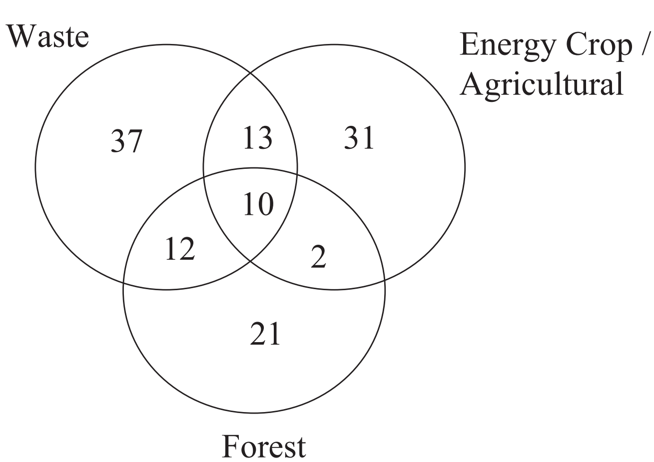

Fig. 4b. A Venn diagram showing the numerical distribution of reviewed articles according to biomass sources.

The vulnerable element of the SC is a sensitive and open component (e.g., supplier, facility, etc.) to potential loss and against disruptive risks (Ivanov, 2018). To enhance SC resiliency, the concept of vulnerability is complementary and a key point to applying an appropriate resilience strategy (Hosseini et al., 2019).

Incorporating resilience into a SC through various strategies has been a popular issue in the literature in recent years (Shekarian & Mellat Parast, 2021; Suryawanshi & Dutta, 2022). In both strategic and operational decisions, decision-makers need to apply and manage different risk mitigation strategies under various uncertainty types (Lotfi et al., 2021). In recent articles, proactive and reactive mitigation strategies against disruptions are applied to design a resilient BSCND. Proactive strategies consider preventive actions to protect the SC before disruptions without recovery actions (e.g. fortification of facilities and pre-positioned inventory). On the other hand, the reactive strategies consider recovery plans to return the SC to its original state when disruptive events occur (e.g., operational reassignment and backup assignment of another reliable facility) (Behzadi et al., 2020). The existing modeling efforts on resilient BSCND include resilience strategies to enhance robustness against disruptions. In Table 5, articles that consider resilient network design and resilience strategies are analyzed. Although BSCND needs large-scale investments and should be well

Table 4
Classification of articles according to risk management approach.

References	Risk Factor	Type of Risk (operational / disruption)	Risk Management Approach	Risk Measurement Techniques	Performance Measure
Dal-Mas et al. (2011)	F	Op	RN / RA	CVaR	NPV
Kostin et al. (2012)	F	Op	RN / RA	VaR	NPV
Gebreslassie, Yao, and You (2012)	F	Op	RN / RA	CVaR – downside risk	Cost
Giarola, Bezzo, and Shah (2013)	F	Op	RN / RA	expected Downside Risk – VaR	NPV
Shabani et al. (2014)	S	Op	RN	variability index and downside risk	Expected Profit
Azadeh, Vafa Arani, and Dashti (2014)	S	Op – Dis	RA	Variance for OF	Profit
Serrano et al. (2015)	S	Op	RN / RA	mean – standard deviation	Cost
Shabani and Sowlati (2016b)	S, F	Op	NS	mean – standard deviation	Profit
Azadeh and Vafa Arani (2016)	S	Dis	RN / RA	Variance for OF	Profit
Santibañez-Aguilar, Guillen-Gosálbez, et al. (2016)	F	Op	NS	NS	Profit
Fattahi and Govindan (2018)	Fc	Dis	RA	NS	NS
Ghaderi, Moini, and Pishvaee (2018)	S, D	Op	RA	Absolute deviation of OF	Cost, EI
Üster and Memisoglu (2018)	S	Op	RN / RA	NS	Cost
Babazadeh (2019)	S, D, F	Op	RA	Absolute deviation of OF	Cost
Babazadeh et al. (2017)	S, D, F, E	Op	RA	Absolute deviation of OF	Cost, EI
Saghaei, Ghaderi, and Soleimani (2020)	F	Dis	NS	Downside Risk	NPV
Habib et al. (2020)	D, F, EI	Op	RA	deviation of expected value	Cost, EI
Delkhosh and Sadjadi (2020)	D	Op	RA	Standard deviation	Cost
Sharifi et al. (2020)	Fc, D	Dis	RA	NS	NS
Sharma et al. (2020)	F	Op	RN / RA	CVaR – VaR	Cost
Díaz-Trujillo, Fuentes-Cortés, and Nápoles-Rivera (2020)	S, D	Op	NS	CVaR	Profit, EI
Mousavi Ahranjani et al. (2020)	S, D, F	Op – Dis	RA	deviation of expected value	Cost
Ngan et al. (2020)	S, F, E, Tec	Op	NS	Variance for NPV and PP	NPV, PP
Sajid (2021)	S, Tr, L, F	Oo – Dis	NS	DBN	Cost
Nur et al. (2021)	S	Op	RN / RA	NS	NS
Fattahi, Govindan, and Farhadkhani (2021)	E	Op	RA	semi-deviation	Cost, EI
Lo et al. (2021b)	F	Op	NS	mean – standard deviation	NPV
Khezerlou, Vahdani, and Yazdani (2021)	Fc, D	Op – Dis	RN / RA	semi deviation – CVaR	Cost
Aboytes-Ojeda, Castillo-Villar, and Cardona-Valdés (2022)	S	Op	RA	CVaR	Cost
Ghozatfar and Yaghoubi (2023)	S	Op	RA	CVaR	Cost
Samani et al. (2023)	S	Oo – Dis	RA	CVaR	Cost
Huang et al. (2024)	S	Op	RN / RA	Robust optimization	Profit
Wang et al. (2024)	S, D	Op	RA	Risk tolerance	Cost

S: Supply, F: Financial, D: Demand, Fc: Facility, E: Environmental, Tec: Technology, L: Labour, Op: Operational, Dis: Disruption, EI: Environmental Impact, PP: Payback Period, DBN: Dynamic Bayesian Network, OF: Objective Function, NS: Not Specified.

Table 5
Classification of articles according to resilience strategy.

References	Type of Disruption Risk	Uncertainty Approach	Vulnerable Element of the BSC	Resiliency Strategy	Resilience Investment/ Resilience Cost	Type of Resilience Strategy
Zhao and You (2019)	NS	Robust	F	Redundancy Additional Capacity Recovery Schedule	Extra Production Capacity Cost	P – R
Soren and Shastri (2019)	Drought	Scenario based-Stochastic	S	Backup Supplier Fortification of Facilities	Procurement Cost Penalty, Unmet Demand Penalty	P – R
Sharifi et al. (2020)	NS	Scenario based-Stochastic	F – S	Coverage radius Backup Supplier Additional Capacity Node Complexity Flow Complexity	Unmet Demand Penalty	P – R
Mousavi Ahranjani et al. (2020)	Drought	Scenario based-Stochastic	S	Prepositioned Inventory Fortification of Facility Location	Operational Cost Variation	P
Soren and Shastri (2021)	Drought	Scenario based-Stochastic	S	Backup Supplier Fortification of Facilities	Procurement Cost Penalty, Unmet Demand Penalty	P – R
Khezerlou, Vahdani, and Yazdani (2021)	NS	risk-averse optimization, transitional probabilities, and spatial statistics models	F- S – CL	Fortification of Facility Location Backup Assignment Strengthening Connectivity	Unmet Demand Penalty, Inventory Cost, Transportation Cost	P – R
Salehi et al. (2022)	NS	Robust	F	Time limit of disruption Additional capacity	Resiliency measure (the ratio of production capacity during and after disruption)	P – R

NS: Not Specified, S: Supplier, F: Facility, CL: Connection Links P: Proactive, R: Reactive.

managed to maintain its functionality for many years, only a few articles incorporate resilient BSCND and resilience strategies. The resilience strategies implemented in the articles are listed below:

- *Additional Capacity* is an increase in production, labor, or throughput as a capacity expansion to compensate for the lost capacities of facilities in disruptions (Sharifi et al., 2020; Zhao & You, 2019).
- *Redundancy* in total production volume is proactive planning as an extra production capacity or building extra facilities to improve the SC's resiliency against disruptions (Zhao & You, 2019).
- *Recovery Schedule* enables planning the time until the SC returns to its normal level of performance after a disruption and minimizes the time delay in consequence of disruptions (Zhao & You, 2019).
- *Backup Supplier* is considered an emergency source, providing additional feedstocks when primary suppliers are affected by disruptions (Sharifi et al., 2020; Soren & Shastri, 2019, 2021).
- Coverage radius decreases transportation between facilities and demand zones and prevents unmet demands (Sharifi et al., 2020).
- *Node complexity* reduces the total number of nodes in the SC to minimize network complexity (Sharifi et al., 2020).
- *Flow complexity* reduces the total number of links in the SC to minimize network complexity (Sharifi et al., 2020).
- *Strengthening Connectivity* improves the connecting links in the SC network that need to be strengthened post-disaster (Khezerlou et al., 2021).
- *Backup Assignment* is the assignment of customer demand to another available facility when the primary facility is disrupted (Khezerlou et al., 2021).
- *Fortification of Facility Location* is the identifying potential facility locations in the SC, taking into account the possibilities of the certain disruptive events (e.g. earthquake, drought) of the locations (Khezerlou et al., 2021; Soren & Shastri, 2019, 2021).

Zhao and You (2019) studied resilient supply chain optimization, including a quantitative measure of resilience. The time delay between disruptions and recovery was also considered in their model. Soren and Shastri (2019) proposed a resiliency model optimizing the location of pre-processing depots and biorefinery by including the disruptions at the farms. Mousavi Ahranjani et al. (2020) studied resilient bioethanol SC under operational and disruption risks. Sharifi et al. (2020) presented several resiliency measures in the model to enhance the resiliency of the network and resist any disruption. Khezerlou et al. (2021) proposed an optimization model for designing a resilient and reliable biomass-to-biofuel SC network. Soren and Shastri (2021) compared the resiliency model with a base model which ignores the disruption in biomass availability. The resiliency and base models were compared by using the respective optimal solutions to operate the system when disruption was manifested. Salehi et al. (2022) designed a resilient and sustainable BSCND by an optimization method based on the demand uncertainty and the disruption in the biorefinery. They determined the relation between resiliency and sustainability by specifying the critical resilience

Mathematical Modelling

Objective Function	Linear / Non-linear (interval /quadratic)	References	Share (%)	
SO	LP	Awudu and Zhang 2013, Azadeh et al. 2014, Cobuloglu and Buyuktahtakın 2017 (MIP), Ren et al. 2015	4.4%	64.4 %
	MILP	Foo et al. 2013, Razım et al. 2019, Quddus et al. 2018, Quddus et al. 2017, Poudel et al. 2016, Gonela et al. 2015b, Sharifzadeh et al. 2015, Nur et al. 2021, Kim et al. 2011, Dal-Mas et al. 2011, Chen and Fan 2012, Kostin et al. 2012, Osmani & Zhang 2013, Marufuzzaman et al. 2014, Tong et al. 2014, Huang et al. 2014, Osmani and Zhang 2014, Shabani et al. 2014, Li and Hu 2014, Gonela et al. 2015, Yeh et al. 2015, Yue and You 2016, Shabani and Sowlati 2016a, Mohseni et al. 2016, Azadeh and Vafa Arani 2016, Hu et al. 2017, Ranisau et al. 2017, Mirkouei et al. 2017, Ghelichi et al. 2018, Bairamzadeh et al. 2018, Xie and Huang 2018, Nguyen and Chen 2018, Ahmed and Sarkar 2018, Babazadeh et al. 2019, Arabi et al. 2019b, Soren and Shastri 2019, Razm et al. 2020, Mohseni and Pishvaee 2020, Mousavi Ahranjani et al. 2020, Soren and Shastri 2021, Allman et al. 2021, Aghalari et al. 2021, Sharma et al. 2020, Fattahi et al. 2021, Liu and Yuan 2021	50 %	
	ILP	Serrano et al. 2015	1.1 %	
	NLP	Ngan et al. 2020	1.1 %	
	INLP	Üstel and Memişoğlu 2018	1.1 %	
	MINLP	Shabani and Sowlati 2016b, Khishtandar 2019, Saghaei et al. 2020a, Babazadeh 2019, Abriyantoro et al. 2019, Khezerlou et al. 2021	6.6 %	
MO	MILP	Gebreslassie et al. 2012, Giarola et al. 2012, Giarola et al. 2013, Y. Balaman and Selim 2015, Ren et al. 2016, Santibanez-Aguilar et al. 2016, Santibañez-Aguilar et al. 2016b, Bairamzadeh et al. 2016, Zhang and Jiang 2017, Osmani and Zhang 2017, Babazadeh et al. 2017, Ghaderi et al. 2018, Lopez-Dıaz et al. 2018, Zhao and You 2019, Delkhosh and Sadjadi 2020, Sharifi et al. 2020, Fattahi and Govindan 2018, Gilani et al. 2020, Habib et al. 2020, Gumte et al. 2021	22.2 %	27.7 %
	MILFP	Gao and You 2017	1.1 %	
	MINLP	Asadi et al. 2018, Díaz-Trujillo et al. 2020, Saghaei et al. 2020b,	3.3 %	
	MIQP	Arabi et al. 2019	1.1 %	

Fig. 5. Classification of articles according to mathematical modeling (LP: Linear Programming Model, MILP: Mixed Integer Linear Programming Model, ILP: Integer Linear Programming Model, NLP: Non-Linear Programming, INLP: Integer Non-linear Programming Model, MINLP: Mixed Integer Non-linear Programming Model, MILFP: Mixed Integer Linear Fractional Programming Model, MINLP: Mixed Integer Non-linear Programming Model, MIQP: Mixed-Integer Quadratic Programming Model).

factors and sustainability indicators of the BSC.

7. Problem characteristics

In this section, we focus on problem characteristics in terms of mathematical programming formulations, sustainability, and decision levels in BSCND literature. Almost all articles used mathematical programming to formulate the BSCND. Fig. 5 shows the detailed classification of the articles according to mathematical models. In this study, articles are analyzed as single-objective (SO) and multi-objective (MO). Many of the articles are modeled as economic-effective SO programming. MO programming simultaneously optimizes all objectives with the Pareto-optimality approach. Most of the multi-objective models are formulated according to economic and environmental objective functions. Regarding sustainability, economic considerations, and profitability are mostly addressed in BSCND. Environmental sustainability is another important issue addressed in BSC. Particularly, minimizing GHG emissions and resource use are the most common issues. Social sustainability is generally the least considered issue. In social sustainability, goals that will increase social welfare are considered. There are a few articles incorporating social goals into the mathematical model. The criterion for job creation is the most considered social sustainability in BSCND. The analysis of the articles according to the sustainability dimensions is given in Table 3.

7.1. Decision levels

Like a typical SC, BSC decision levels are also classified as strategic, tactical, and operational levels. Fig. 6a shows decision level classification and the main important decisions with the subtitles of each group (Atashbar et al., 2018; Ghaderi et al., 2016; Sharma et al., 2013).

Strategic decisions take into account long-term, at least one-year decisions that require large financial investments (Yue et al., 2014). According to this review, facility location is one of the most important strategic decisions that constitute the network structure in BSCND. The determining of facility capacity and selection of production technology is also significant for BSCND. However, these decisions cannot be made in a short time, even removing the existing technology and adopting new technology may take enough time to disrupt the flow of the SC. Also, the production technology differs depending on the type of biomass used (Awudu & Zhang, 2012). Technology change is a strategic decision that cannot be changed frequently, as it may cause raw material problems (Li & Hu, 2016). At the same time, capacity expansion is an economically critical decision that will incur extra costs. Biomass-related decisions are strategic decisions that directly affect the designing and planning of the SC (Lo, How, & Leong, et al., 2021). The selection of biomass type to be used in production is related to and binding decisions regarding production technology, production capacity, and warehouse capacity. In addition to these, almost all BSCND involve sourcing and allocation decisions regarding the network structure to be established between supply points and facilities. These decisions determine which facility will receive service from which supply point and, and how much feedstock will be transported between these nodes.

BSC is usually planned by dividing into multi-period periods, either seasonal or monthly, depending on biomass harvest periods, production planning, or material requirement planning (Yue et al., 2014). Seasonal biomass harvesting amount, monthly production or material requirement planning, the amount of biomass to be stored, the number of products to be transported/shipment size in a certain period, and transportation planning as the number and capacity of vehicles are the common tactical decisions (Mottaghi et al., 2022). And, operational decisions consider short-term, daily, or hourly plans such as daily production scheduling, and start times of operations. BSCND is mostly related to long-term plans with large capital investments, most of the previous works consider long-term investment and production plans. The planning horizon is considered mostly annual, seasonal, or monthly. Articles including monthly or seasonal plans are considered as tactical and operational decision levels in this study.

Table 6 and Fig. 6b present the decision levels analysis of the articles. The most common strategic decisions are those facilities and biomass-related. Determining the facility locations for the establishment, biomass selection to be used as feedstock, technological investments,

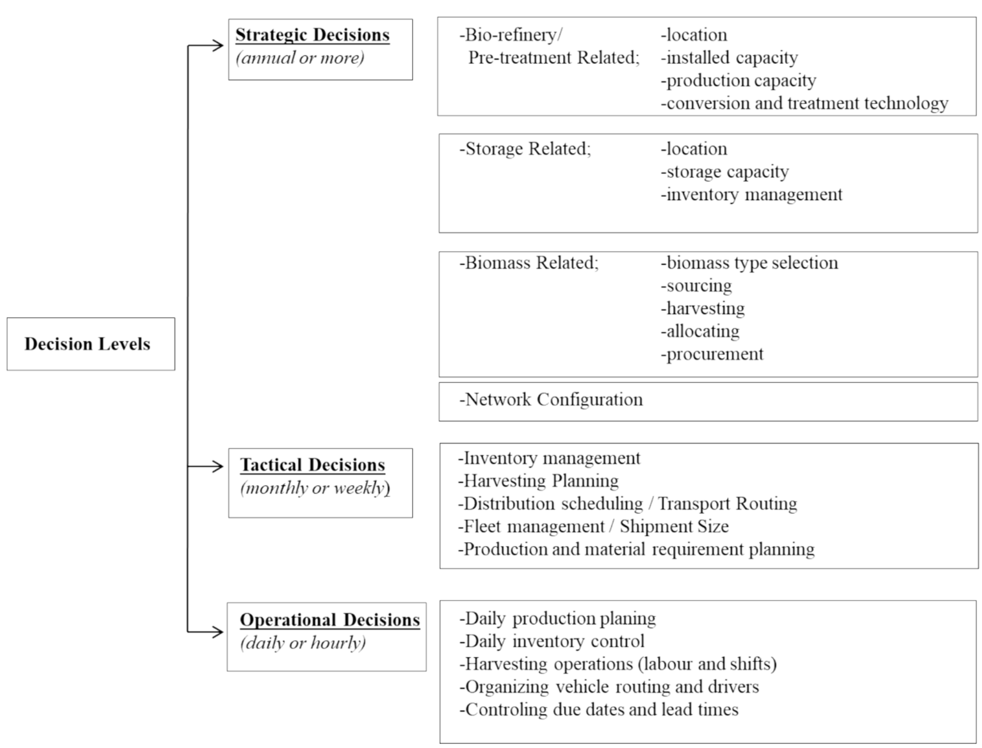

Fig. 6a. Classification of decision levels and main decisions.

Table 6
Classification of articles according to decision levels.

References	Strategic Decisions				Tactical and Operational Decisions				
	Network Configuration				Inventory Management	Harvesting Planning	Transportation Planning		Production Planning
	Bio-refinery / Pre-treatment	Storage	Allocation	Multi-feedstock			Fleet Management	Shipment Size	
Kim et al. (2011)	FL, Cap		*	*				*	*
Dal-Mas et al. (2011)	FL, Cap						*	*	*
Chen & Fan (2012)	FL, Cap		*	*				*	*
Gebreslassie et al. (2012)	FL, Cap, Tec			*	*			*	*
Giarola et al. (2012)	FL, Tec			*				*	*
Kostin et al. (2012)	FL, Cap, Tec	*	*		*		*	*	*
Foo et al. (2013)	FL		*						
Awudu & Zhang (2013)					*			*	*
Giarola et al. (2013)	Tec, Cap			*				*	*
Osmani & Zhang (2013)	FL		*	*		*		*	*
Yilmaz Balaman & Selim (2014)	FL, Cap	*	*	*	*			*	*
Marufuzzaman et al. (2014)	FL		*				*	*	*
Tong et al. (2014)	FL, Cap, Tec		*	*				*	*
Huang et al. (2014)	FL	*		*	*	*		*	*
Osmani & Zhang (2014)	FL, Cap, Tec			*	*			*	*
Shabani et al. (2014)				*	*			*	*
Li & Hu (2014)	FL, Cap		*					*	
Azadeh et al. (2014)	FL, Tec, Cap			*	*			*	*
Gonela, Zhang, Osmani, et al. (2015)	FL, Cap		*	*		*		*	*
Yeh et al. (2015)	FL, Cap		*			*			*
Yilmaz Balaman & Selim (2015)	FL, Cap		*	*				*	*
Mohseni et al. (2016)	FL, Cap							*	*
Gonela, Zhang, & Osmani (2015)	FL		*	*			*	*	*
Sharifzadeh et al. (2015)	FL, Cap		*				*	*	
Ren et al. (2015)									
Serrano et al. (2015)	FL		*	*					
Santibañez-Aguilar, Guillen-Gosálbez, et al. (2016)	FL, Cap, Tec			*				*	*
Azadeh & Vafa Arani (2016)	FL, Tec		*		*			*	*
Bairamzadeh, Pishvaee, and Saidi-Mehrabad (2016)	FL, Cap, Tec		*	*	*	*		*	*
Shabani and Sowlati (2016b)				*	*			*	*
Yue & You (2016)	FL, Cap, Tec				*			*	*
Ren, An, Liang, Dong, Gao, Geng, et al. (2016)	FL, Tec			*				*	
Shabani & Sowlati (2016b)				*	*				*
Santibañez-Aguilar, Morales-Rodriguez, et al. (2016)	Tec	*		*				*	*
Poudel et al. (2016)	FL, Cap			*	*		*	*	
Yılmaz Balaman and Selim (2016)	FL, Cap	*			*			*	*
Hu et al. (2017)	FL, Cap		*					*	*
Ranisau et al. (2017)	FL							*	*
Gao and You (2017)	FL, Cap, Tec			*	*		*	*	*
Mirkouei et al. (2017)								*	*
Zhang and Jiang (2017)	FL, Cap		*					*	
Osmani and Zhang (2017)	FL, Cap, Tec		*	*		*		*	*
Babazadeh et al. (2017)	FL, Cap	*	*	*					
Quddus et al. (2017)		*		*	*			*	
Castillo-Villar, Eksioglu, and Taherkhorsandi (2017)	FL, Cap							*	
Cobuloglu and Büyüktahtakın (2017)			*	*		*			*
Ghaderi, Moini, and Pishvaee (2018)	FL, Cap	*	*		*	*		*	*

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Table 6 (*continued*)

References	Strategic Decisions				Tactical and Operational Decisions				
	Network Configuration				Inventory Management	Harvesting Planning	Transportation Planning		
	Bio-refinery / Pre-treatment	Storage	Allocation	Multi-feedstock			Fleet Management	Shipment Size	Production Planning
Ghelichi, Saidi-Mehrabad, and Pishvaee (2018)	FL	*	*		*	*	*	*	*
Bairamzadeh, Saidi-Mehrabad, and Pishvaee (2018)	FL, Cap, Tec			*	*	*		*	*
Xie and Huang (2018)	FL, Cap							*	*
Asadi et al. (2018)	FL		*		*		*	*	
Nguyen and Chen (2018)					*			*	*
Lopez-Dıaz et al. (2018)	FL		*	*				*	*
Ahmed and Sarkar (2018)							*	*	
Fattahi and Govindan (2018)	FL, Cap	*		*	*		*	*	*
Quddus et al. (2018)	FL, Cap			*	*		*	*	*
Üster and Memisoglu (2018)	FL, Cap		*					*	
Yılmaz Balaman et al. (2018)	FL, Cap, Tec							*	*
Zhao and You (2019)	FL, Cap							*	*
Khishtandar (2019)	FL		*	*			*	*	
Babazadeh, Ghaderi, and Pishvaee (2019)	FL, Cap		*	*				*	*
Arabi et al., (2019b)	FL, Tec				*			*	
Arabi, Yaghoubi, and Tajik (2019a)	FL				*			*	
Soren and Shastri (2019)	FL, Cap	*			*			*	*
Abriyantoro et al. (2019)					*		*		*
Razm et al. (2019)	FL, Cap		*	*				*	*
Babazadeh (2019)	FL, Cap		*	*				*	*
Gao, Qu, and Yang (2019)	FL, Cap, Tec			*	*			*	*
Gonela et al. (2019)	FL, Cap			*	*			*	*
Heidari, Yazdanparast, and Jabbarzadeh (2019)	FL, Cap, Tec								
Alizadeh et al. (2019)	FL, Cap	*		*	*		*	*	*
Kesharwani et al. (2019)	FL, Cap								
Delkhosh and Sadjadi (2020)					*			*	*
Saghaei, Ghaderi, and Soleimani (2020)	FL	*	*	*	*			*	*
Díaz-Trujillo, Fuentes-Cortés, and Nápoles-Rivera (2020)	FL, Tec			*				*	*
Sharifi et al. (2020)	FL, Cap		*	*	*			*	*
Rezaei et al. (2020)	FL, Cap		*	*	*	*		*	*
Mohseni and Pishvaee (2020)	FL, Cap							*	*
Mousavi Ahranjani et al. (2020)	FL, Tec			*	*	*		*	*
Saghaei et al. (2020)	FL	*	*	*	*	*		*	*
Gilani, Sahebi, and Oliveira (2020)	FL, Cap, Tec				*	*	*	*	*
Habib et al. (2020)	FL, Cap, Tec	*	*		*			*	*
Sharma et al. (2020)	FL, Cap		*		*	*		*	
Guericke et al. (2020)	FL				*				
Razm et al. (2021)	FL, Cap, Tec		*	*	*				*
Zuniga Vazquez et al. (2021)	FL, Cap							*	
Samani and Hosseini-Motlagh (2021)	FL, Cap		*		*			*	*
Tey et al. (2021)									*
Baghizadeh, Zimon, and Jum'a (2021)			*		*	*	*	*	
Gilani and Sahebi (2021)	FL, Cap, Tec				*			*	*
Karimi, Ekşioğlu, and Carbajales-Dale (2021)			*						
Sadeghi Ahangar, Sadati, and Rabbani (2021)	FL						*	*	*
Liu and Yuan (2021)	Cap, Tec								*

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Table 6 (*continued*)

References	Strategic Decisions				Tactical and Operational Decisions				
	Network Configuration				Inventory Management	Harvesting Planning	Transportation Planning		
	Bio-refinery / Pre-treatment	Storage	Allocation	Multi-feedstock			Fleet Management	Shipment Size	Production Planning
Fattahi, Govindan, and Farhadkhani (2021)	FL, Cap, Tec	*		*	*			*	*
Gumte et al. (2021)	FL			*	*			*	*
Khezerlou, Vahdani, and Yazdani (2021)		*		*	*	*		*	*
Aranguren, Castillo-villar, and Aboytes-ojeda (2021)		*	*						
Nur et al. (2021)	FL, Cap	*		*	*		*	*	*
Memişoğlu and Üster (2021)	FL, Cap				*			*	
Soren and Shastri (2021)	FL, Cap	*		*	*			*	*
Elaradi, Zanjani, and Nourelfath (2022)	FL,Cap, Tec				*			*	*
Arangurren and Castillo-Villar (2022)		*					*	*	
Reyes-Barquet et al. (2022)	Tec							*	*
Ko et al. (2022)							*		
Lee, Sun, and Li (2022)	FL		*		*		*	*	
Guo et al. (2022)	FL, Cap							*	
Salehi et al. (2022)	FL, Cap, Tec	*	*	*	*	*		*	*
Aboytes-Ojeda, Castillo-Villar, and Cardona-Valdés (2022)	FL, Tec							*	*
O'Neill et al. (2022)	Tec	*			*	*		*	*
Ahmadvand and Sowlati (2022)		*			*			*	
Theozzo and Teles dos Santos (2023)	FL		*		*	*		*	
Mondal et al. (2023)	FL				*			*	*
Chen and Liu (2023)	FL, Tec	*	*		*			*	*
Kalhor et al. (2023)	FL, Cap				*			*	*
Samani et al. (2023)	FL, Cap, Tec		*		*			*	
Zarrinpoor and Khani (2023)	FL							*	
Gilani et al. (2023)	FL		*			*		*	*
Lima et al., (2023)	FL, Cap, Tec	*				*	*	*	*
Piqueiro et al. (2023)						*		*	*
Piedra-Jimenez et al. (2024)	FL, Cap, Tec					*		*	*
Huang et al. (2024)									
Sadeghi Darvazeh et al. (2024)	FL, Cap	*	*		*			*	*
Wang et al. (2024)	FL, Cap							*	*
Ransikarbum and Pitakaso (2024)	FL, Cap							*	*
Zarrinpoor (2024)	FL, Cap	*	*		*		*	*	*

FL: Facility Location, Cap: Capacity, Tec: Technology.

determining the capacity of the facility, and network configuration are the most handled strategic decisions. More than half of the reviewed articles involve a facility capacity decision, also approximately one-third of articles consider the production technology decision. In a certain period, flow rate between SC nodes, transportation amount, and shipment size are among the main tactical decisions. Many articles also have decisions on production planning and the required biomass amount to meet a certain demand for a month or season. However, relatively little work is done in harvest planning and inventory management.

8. Uncertainty modeling and solution methods

SP, fuzzy programming, and robust optimization are popular analytic tools to handle uncertain parameters. This section is related to the main features and fundamentals of the solution techniques used to handle uncertainty in BSCND literature, for the more interested readers, Sahinidis (2004) can be referred. The analysis of the articles according to the solution approaches is given in Table 3. Fig. 7a presents a pie chart showing the percentage distribution of reviewed articles according to the uncertainty modeling approach. SP is the most popular mathematical programming method used under uncertainty, based on the probability distribution of uncertain parameters. Most of the articles reviewed in this study use the stochastic approach. Two-stage SP is a widely applied method (Arabi et al., 2019b; Gao & You, 2017; Ranisau et al., 2017).

Fuzzy programming is also used to deal with the uncertainty in BSC modeling and is based on fuzzy sets theory (Pishvaee et al., 2012). Fuzzy programming enables the incorporation of uncertainty into the mathematical model with membership functions that can include personal judgments when there is not enough information about the uncertain parameters (R. Wang et al., 2015). According to types of uncertainty, fuzzy mathematical programming is classified into three categories. In flexible programming, both fuzzy goals and fuzzy constraints are incorporated into optimization models as fuzzy membership functions.

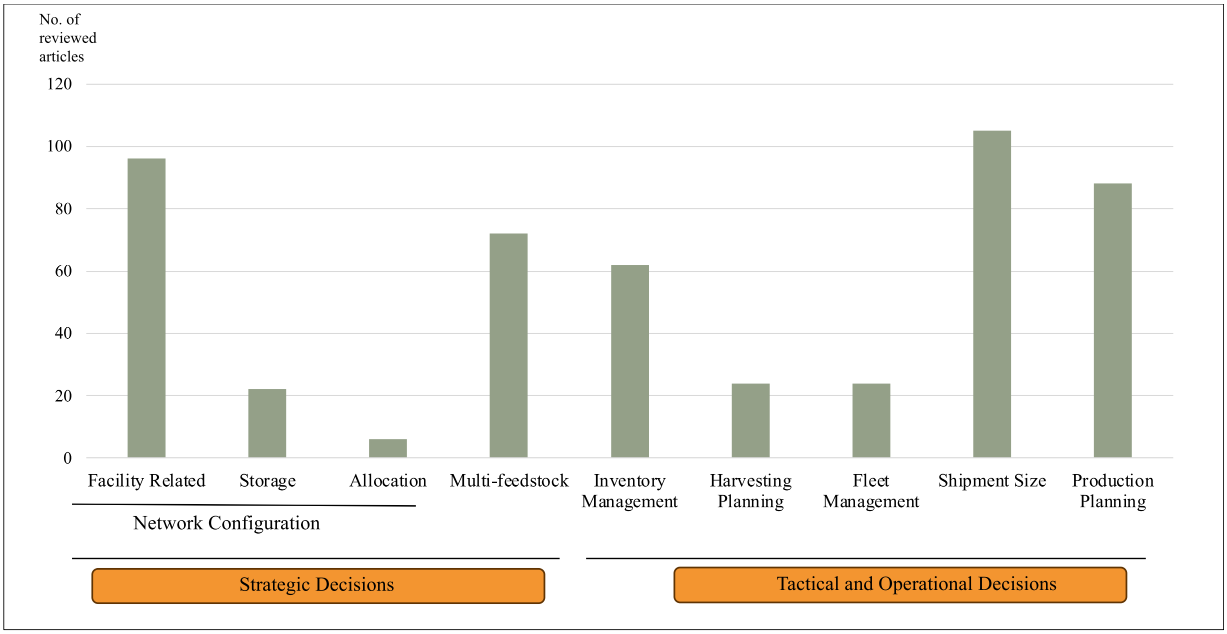

Fig. 6b. Numerical distribution of the reviewed articles according to decision levels.

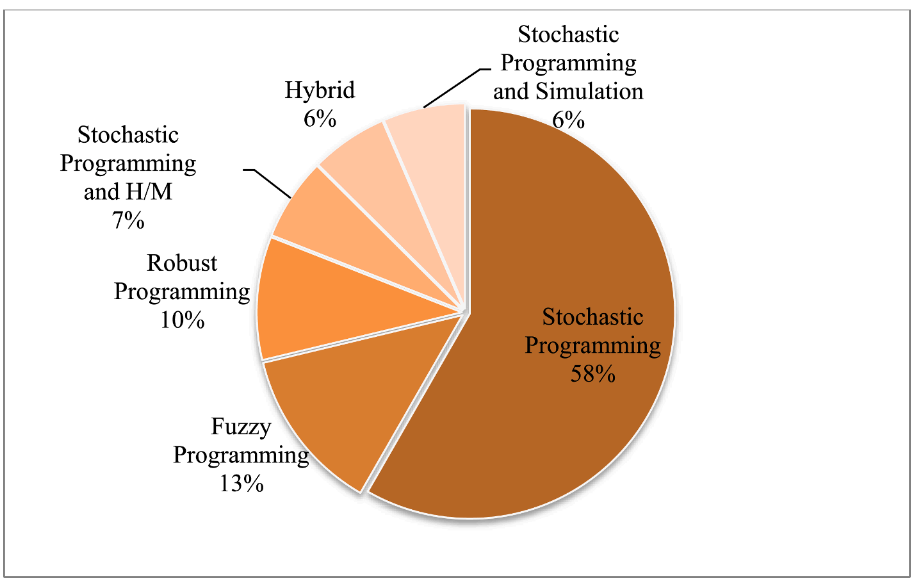

Fig. 7a. A pie chart showing the percentage distribution of reviewed articles according to the uncertainty modeling approaches.

Possibilistic programming includes ambiguous coefficients of objective functions and constraints and does not handle fuzzy goals and constraints (Inuiguchi & Ramík, 2000). Two articles present a possibilistic programming model to design a second-generation biodiesel SC network with the uncertainty of input data. Since there is not enough historical data, Babazadeh et al. (2017) utilized experts' opinions to construct the possibility distribution of uncertain parameters, and Babazadeh et al. (2019) proposed a credibility measure-based model. Robust possibilistic programming treats ambiguous coefficients (the lack of knowledge on model parameters) and also vagueness about decision maker's knowledge. Bairamzadeh et al. (2016) developed a multi-objective robust possibilistic programming, Ghaderi et al. (2018) proposed a multi-objective robust possibilistic programming model for the design of a sustainable bioethanol SC network under epistemic uncertainty.

Robust optimization is addressed when an uncertain parameter takes a value as cluster-based, rather than probabilistic (Mohseni & Pishvaee, 2020). Robust optimization provides a guaranteed (worst-case) value that does not depend on the possible realizations of the uncertain parameter. That is, the solution of the robust optimization should be feasible for all possible values of uncertain parameters in its uncertainty set (Mulvey et al., 1995; Park, 2015). Delkhosh and Sadjadi (2020) focused on the application of scenario-based robust optimization for the design of BSC with the uncertainty of final product demand.

Interval mathematical programming includes lower and upper bounds of uncertain parameters and is used in cases where either probability distributions or membership functions of the uncertain parameters are not known by decision-makers. Ren et al. (2015) developed interval linear programming, they regarded the price of the resources, the yield of grain, and the market demands as interval numbers instead of constants. Ren et al. (2016) developed a bi-objective interval MILP and, they used interval numbers by specifying their lower and upper limits to represent the uncertainties factors.

Hybrid modeling approach is emerged to handle complicated problems which mostly include more than one type of uncertainty. Hybrid approaches aim to improve modeling capabilities and increase the effectiveness of problem design by using multiple methods in one model (Gu & Kunc, 2019; R. Wang et al., 2015). Table 7 presents the solution approaches of hybrid models. Khishtandar (2019) proposed a hybrid fuzzy chance-constrained programming model to handle multiple uncertainties expressed as fuzzy relationships and probability distributions in constraints and objective function. Sharifi et al. (2020) developed a novel hybrid stochastic fuzzy-robust approach with different types of uncertainty to design a second-generation biofuel SC network. Shabani and Sowlati (2016a) presented a hybrid, multi-stage, stochastic programming-robust optimization model to simultaneously include uncertainty in biomass quality and biomass availability. Yue and You (2016) integrated SP and robust optimization approaches to reflect the decision maker's different levels of conservativeness toward strategic and operational uncertainties.

The complexity and real-world structure of a SC design can make its network model difficult to solve with numerous inputs, decision variables, and constraints. Heuristics/metaheuristic algorithms are useful and preferred to solve complex problems which are in the class of NP-hard problems within a reasonably short time. Heuristic and *meta*-heuristic algorithms are approximate optimization methods (Ghaderi et al., 2016; Meyer et al., 2014).

Simulation modeling provides to analyze the behavior of the system concerning the uncertainties and variabilities. Monte Carlo Simulation is applied to generate multiple scenarios using possible values of uncertain parameters with its probability distribution (Kim et al., 2011). Awudu and Zhang (2013) studied demand and price uncertainties. Nguyen et al. (2014) used Monte Carlo simulation to estimate the spatial uncertainty in the feedstock logistics. Shabani and Sowlati (2016b) proposed a combination of Monte Carlo Simulation and an optimization model for the forest BSC with uncertainty in biomass quality, availability, cost, and price.

In BSCND, Multi-criteria decision-making (MCDM) is mostly used by combining Geographic Information Systems (GIS) based information (data collection, spatial analysis, etc.). MCDM and GIS analysis are also usually used as input for the next method, that is, they are found in two or more phase solution approaches as a supportive tool that provides data to the next method or that arranges the current data to be used in the next method by eliminating with some criteria (Gital Durmaz & Bilgen, 2020).

Fig. 7b shows the distribution of solution methods that have been proposed to handle uncertainty over the years. At the same time, between 2011 and 2014, the SP technique is the only preferred method for BSC modeling under uncertainty. Despite the development and use of other techniques (robust programming, fuzzy programming, etc.), SP is still the most used technique for considering uncertainty. This situation may be associated with the type of uncertainties often encountered in BSCND. As mentioned earlier in Section 4, the most common types of uncertainty, such as biomass supply and demand, are stochastic uncertainties, which are usually made use of probability distributions.

Table 7
Solution approaches of hybrid model.

References	Hybrid Optimization
Shabani and Sowlati (2016b)	Stochastic programming-robust optimization
Yue and You (2016)	Stochastic programming-robust optimization
Bairamzadeh, Saidi-Mehrabad, and Pishvaee (2018)	Robust scenario-based stochastic programming
Khishtandar (2019)	Fuzzy-stochastic chance-constrained programming
Alizadeh et al. (2019)	Stochastic programming-robust optimization
Sharifi et al. (2020)	Hybrid stochastic fuzzy-robust approach
Mousavi Ahranjani et al. (2020)	Robust stochastic-possibilistic programming
Baghizadeh, Zimon, and Jum (2021)	Hybrid Robust Possibilistic Programming
Mondal et al. (2023)	Fuzzy-random robust flexible programming
Samani et al. (2023)	Robust stochastic-possibilistic programming

9. Conclusion and future research directions

This study aims to present a systematic literature review of articles on uncertainty, risk, and resilience in BSCND. In our study, the solution approaches against uncertain conditions, management insights, and decision levels are analyzed from an operational research perspective. The main findings drawn from the review are as follows: (1) The amount of biomass supply is found to be the most encountered type of uncertainty in BSCND; (2) Seasonality is the most common cause of uncertainty in biomass supply, relative to other common factors such as land limitation, forest fire incidents, plant disease; (3) Changes in market conditions, which can emerge as uncertainty in pricing policies and cost parameters, cause deviations in planned BSC performance; (4) Since BSCND is planned for the long term, considering uncertainties in economic parameters provides BSC competitive advantages; (5) Including demand uncertainty in BSC planning will affect the strategic and tactical decisions such as capacity, production planning, and investments; (6) In BSC, disruptions or unplanned situations that affect the productivity of the production process, called process uncertainties, may arise over time. BSCND can need to be planned with the requirements of capacity increase or technological developments; (7) Transportation and logistics-related uncertainties such as logistics loss rate and transportation capacities have a direct impact on optimal BSC configuration; (8) Although biomass has been accepted as an environmentally friendly energy source compared to fossil fuels, BSC has undesirable uncertainties in environmental impacts depending on the production volume, transportation distance, or any other SC stages; (9) While BSC has several distinctive risks such as seasonal biomass availability, fluctuations in biomass quality, and geographical distributions of feedstock, less than one-third of the articles consider risks and potential losses due to uncertainties; (10) Most of these articles are related to the uncertainties in the biomass supply and economic parameter; (11) Almost all the articles, studies on risk management, analyzed the differences in economic performance measures depending on the risk factors. Only four articles use environmental impact as a performance measure to evaluate risk management; (12) Resilient BSCND research is still in its infancy with a few papers available to date. (13) Almost all the articles have considered strategic decisions level in BSCND; (14) The most common strategic decisions are those facilities and biomass-related; (15) Transportation amount and production planning are among the main tactical decisions; (16) Relatively little work is done in harvest planning and inventory management; (17) This review indicates that biomass diversity has an important impact on BSC characteristics. The vast majority of the articles reviewed used agricultural waste and forest residues as feedstock resources; (18) Economic sustainability is mostly addressed, while social sustainability is generally the least considered issue in BSCND; (19) The criterion for job creation is the most considered social sustainability in BSCND; (20) Many of the articles are modeled as economic-effective single-objective; (21) Most of the multi-objective models are formulated according to economic and environmental objective functions; (22) Most of the articles use the stochastic approach which incorporates uncertainty into the BSC modeling considering the probability distribution of uncertain inputs; (23) The most common type of uncertainties are biomass supply, and demand, uncertainties in BSCND.

As a result of this study, several future research directions are specified to direct further studies and to reveal the gaps in the literature as follows:

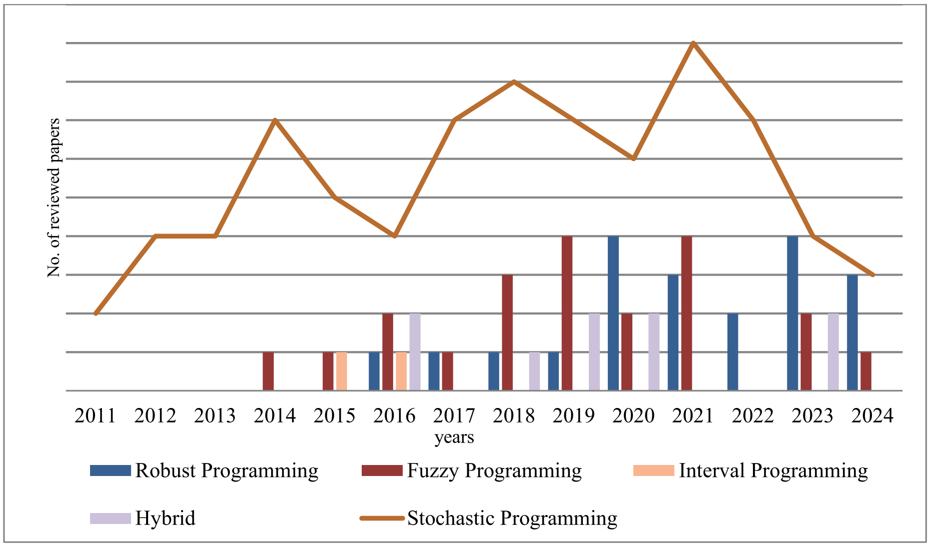

Fig. 7b. The illustration of numerical distribution of the uncertainty modeling approaches of the reviewed articles according to years.

- Biomass will continue to be popular in the future as it is renewable and environmentally friendly. However, the environmental impacts that may arise due to any stage of the BSC should not be ignored. Undesirable environmental uncertainties in BSCND should be considered more in future studies.
- Risk management models should gain more attention in BSCND to mitigate possible losses in SC performance and to ensure continuity. With the complex and competitive business environment of the BSC, economic uncertainties such as currency fluctuations, changes in pricing and incentive policies will also be important for risk management in the future.
- The considerable negative impact of uncertainties and risks within biomass supply chain management on the performance of supply chain members highlights the necessity for ongoing advancements in the field of biomass supply chain management.
- Since BSC is subject to risks and disruptions due to its complex network, there is a need to develop resilient models, to use several resilience strategies in the models. More attention should be paid to the integration of resilient and robust strategies on BSCND.
- In most of the studies, economic performance criteria are considered. The economic sustainability of the SC is prioritized. However, considering the current global considerations such as global warming and employment creation, it is expected that such a long-term and large-scale system design will take into account sustainability in every aspect. While the number of articles dealing with environmental sustainability is relatively higher, there is a gap in the literature regarding social sustainability modeling in BSCND.
- In general, the issue of biomass-based energy production is seen among the remarkable and promising fields. Especially the use of waste feedstocks is highly addressed in BSCND. However, there are limited studies on algae-based energy production. More work is needed on its characteristics, advantages, limitations, and specific uncertain conditions to better understand and develop the algae-based SC.
- SP is a highly advanced technique for uncertainty in BSC. However, there is a need to develop other techniques to model uncertainty in BSC design. Using multi-stage stochastic programming or robust programming techniques depending on the type of uncertainty to be addressed will fill the gap in the literature. In particular, the interval programming technique needs to be used and developed to address uncertainty in BSC.
- The real-world structure of BSCND can make the problem complex and difficult to solve within a reasonably short time. Therefore, using a mathematical programming-based heuristic (mat-heuristics) and SP techniques together can be recommended in future research directions.
- As mentioned in the uncertainty section, there are many types of uncertainty depending on the dynamic nature of the BSC and its raw material/end product type. Due to the large scale and complex nature of the BSC, more than one type of uncertainty should be handled at the same time. Therefore, hybrid approaches that are capable of handling different types of uncertainty into one model can be foreseen to be studied more in the future.
- The use of machine learning techniques with SP and robust programming is another area that is worth investigating.

CRediT authorship contribution statement

Yesim Gital: Conceptualization, Formal analysis, Investigation, Methodology, Visualization, Writing – original draft, Writing – review & editing. **Bilge Bilgen:** Conceptualization, Investigation, Methodology, Supervision, Validation, Writing – review & editing.

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.

Data availability

All articles reviewed in this literature review can be accessed at https://doi.org/10.17632/db4bjzypgw.1.

Acknowledgments

The authors are extremely grateful to the Editor and anonymous referees for their insightful remarks that have significantly helped in revising the manuscript.

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