Design of resilient supply chains

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Content of this dissertation

LIST OF SCIENTIFIC CONTRIBUTIONS

The following published and submitted scientific contributions are presented within this doctoral dissertation. The articles are sorted following their order of publication. The journal rankings correspond to VHB-JOURQUAL3, published by the German Academic Association for Business Research (VHB).

Contribution A

(Published in Resources; not VHB ranked)

Helbig, C., Bruckler, M., Thorenz, A., & Tuma, A. (2021). *An Overview of Indicator Choice and Normalization in Raw Material Supply Risk Assessments*. Resources, 10(8), 79. https://doi.org/10.3390/resources10080079.

Contribution B

(Published in Computers & Industrial Engineering, ranked **B**)

Bruckler, M., Wietschel, L., Messmann, L., Thorenz, A., & Tuma, A. (2024). *Review of Metrics to Assess Resilience Capacities and Actions for Supply Chain Resilience*. Computers & Industrial Engineering, 192, 110176. https://doi.org/10.1016/j.cie.2024.110176.

Contribution C

(Published in Journal of Industrial Ecology, ranked **A**)

Bruckler, M., Wietschel, L., Sartor, S., Thorenz, A., & Tuma, A. (2025). *Encounter the Unforeseen: Resilient Supply Chain Modeling for a Sustainable Bioeconomy*. Journal of Industrial Ecology, 29(3), 908–923. https://doi.org/10.1111/jiec.70027.

Contribution D

(Under review in Computers & Industrial Engineering, ranked **B**)

Bruckler, M., Wietschel, L., Gahm, C., & Tuma, A. (Under review). *Designing Resilient Large-Scale Supply Chains: the Triangle Between Resilience Actions, Targets, and Economic Leeway*. Available at SSRN 6516881.

1

INTRODUCTION

1.1 MOTIVATION

Recent decades have witnessed fundamental economic transformations, particularly in amplifying international trade and globalization of industrial organization (Gereffi et al., 2005; Meixell & Gargeya, 2005; Ribeiro & Barbosa-Póvoa, 2018). Firms have begun to source raw materials and intermediate products globally (Meixell & Gargeya, 2005) and to enter the emerging global market for final goods, thereby profiting from economies of scale across several areas, which has lowered product prices and intensified market competition (Levitt, 1984). The rising competition has exerted pressure on profit margins, compelling firms to reduce their operational costs by fragmenting and outsourcing production to more cost-efficient countries (Feenstra, 1998; Fujita & Thisse, 2006; D. J. Thomas & Griffin, 1996). This transformation was accelerated by advances in communication and information technologies, expanding logistics networks that provide transportation at lower costs, and the reduction of trade barriers (Fujita & Thisse, 2006; D. J. Thomas & Griffin, 1996). Consequently, the globalization of markets and cost pressure have led to global supply chains typically comprising three types of actors, namely supplier, manufacturer, and customer (D. J. Thomas & Griffin, 1996), that are connected by downstream flows (materials and/or services) and upstream flows (i.e., information) (Beamon, 1998; Christopher, 2009; Oliver & Webber, 1992; D. J. Thomas & Griffin, 1996).

In this regard, 'vertical disintegration' (i.e., outsourcing) enables enterprises to increase cost efficiency (Feenstra, 1998; Fujita & Thisse, 2006; D. J. Thomas & Griffin, 1996) and focus on high-value-added manufacturing and service functions while reducing control over peripheral activities (Gereffi et al., 2005). Under stable, foreseeable conditions, enterprises can thus increase product variety, which allows market share expansion (Tang, 2006a). Despite these benefits, the pursuit of globalization to meet geographically dispersed, customized demand, coupled with the fragmentation of production (i.e., outsourcing), increases the complexity of supply chains (Christopher & Peck, 2004). Inherent complexity arises from the number of connections among different supply chain actors, while dynamic complexity emerges from operational processes (Serdarasan, 2013). As complexity rises, supply chains become increasingly vulnerable to disruptions due to the uncertainties about future developments and potential disasters (Tang, 2006b), which may be caused by natural or man-made events (Katsaliaki et al., 2022; D. Thomas & Helgeson, 2021). In this context, one can distinguish between these two event types.

Man-made events that can affect the functioning of supply chains include (among others) wars and geopolitical conflicts (Katsaliaki et al., 2022). One prominent example is the trade war between the United States (US) and China that began in 2018, when both economies imposed tariffs on their imports (Itakura, 2020). In 2025, the conflict has reignited: China suspends rare-earth exports (MOFCOM, 2025), causing immediate disruptions of global supply chains, especially affecting the European automotive sector (CLEPA, 2025). Many global supply chains depend on critical raw materials whose availability and accessibility are at risk (high probability) of disruption due to factors such as high market concentration (Kannan et al., 2025; Wietschel et al., 2025). Consequently, an escalating geopolitical conflict, such as the US-China trade war, can turn a hypothetical (supply) risk into a real disruption, challenging supply chain resilience (Wietschel et al., 2025).

Natural events such as earthquakes, floods, and extreme weather events can disrupt supply chains with severe economic impairments (Katsaliaki et al., 2022). From 2009 to 2019, direct and indirect economic damage due to climate change-related extreme events (i.e., floods, droughts, storms) has accumulated to an estimated average of over 120 billion USD each year, representing 46% of the total losses caused by all kinds of extreme events (Wang et al., 2025). As climate change continues, economic damage from extreme weather is projected to increase (IPCC, 2022). Additionally, regions where the climate is deteriorating experience economic damages in agriculture, forestry, and energy, which constrain the availability of renewable resources and impair the fulfillment of human necessities (IPCC, 2022). Consequently, cascade effects propagate climate risk and resource supply disruptions triggered by local extreme weather events throughout the entire global supply chains and thereby even affect less-exposed regions such as Europe (IPCC, 2022). Although the relationship between conflicts and climate change-related extremes is statistically weak, it may increasingly influence the duration, severity, and frequency of some conflicts in climate-affected regions in the future (IPCC, 2022; Mach et al., 2019). In conclusion, climate change necessitates both sound mitigation and adaptation actions to enable resilient supply chains against extreme weather-related disruptions and, consequently, to support sustainable global economic development (IPCC, 2022; Sun et al., 2024).

Acknowledging the multifaceted nature of supply chain disruptions stemming from both man-made and nature-based causes, global supply chains face unprecedented challenges and thus require a resilient design. Events like the trade war between China and the US also stress the connection between supply risk associated with raw materials (i.e., probability of disruption (U.S. National Research Council, 2008)) and supply chain resilience, which encompasses the timely and economically efficient preparedness (absorption), response (adaption), and recovery (restoration) from supply chain disruptions (Bruckler et al., 2024; Ribeiro & Barbosa-Póvoa, 2018; Wietschel et al., 2025). To support the design of resilient supply chains in a world characterized by uncertainty and disruptions, this cumulative dissertation (1) addresses challenges regarding the quantitative assessment of supply risk and supply chain resilience, and (2) provides methodological approaches to account for resilience in supply chain design modeling. Consequently, the contributions of this dissertation can be categorized along these two research topics:

(1) *contributions A* and *B* investigate and harmonize existing quantitative supply risk and resilience assessment methods and, thereby, contribute to a more standardized quantification of risks that supply chains are exposed to, and the supply chain resilience as a consequence of vulnerability and recoverability when a risk occurs (Wietschel et al., 2025).
(2) *contributions C and D* focus on the methodological advancement for designing resilient supply chains by utilizing exact and heuristic approaches from Operations Research, advanced by the concept of the resilience curve, and on the assessment of resulting implications.

Section 1.2 summarizes the four contributions of this cumulative dissertation and their research questions, while Section 2 presents the individual contributions in detail. Section 3 discusses the insights from the four contributions comprehensively and provides an outlook on future research pathways.

1.2 Summary of contributions & research goals

This section gives a brief overview of the cumulative *contributions A–D* constituting this dissertation.

Contribution A relates to the research topic of supply risk as one dimension of raw material criticality (Graedel et al., 2012). While the literature has already investigated existing criticality assessment methods and the influence factors on their development and results (Schrijvers et al., 2020), *contribution A* focuses on indicator selection, measurements, and related normalization approaches. As supply risk indicator scores heavily depend on the individual measurement and normalization applied, they vary remarkably across existing assessments, which impedes consistent interpretation (Graedel & Reck, 2016). To analyze the range of existing approaches, *contribution A* identifies, categorizes, and harmonizes existing supply risk indicators, measurements, and normalization approaches until 2020. Therefore, the identified normalization approaches are illustrated for each harmonized indicator category to represent the diversity of resulting indicator scores. Thus, *contribution A* provides a structured overview of the prevalent indicators, measurements, and the variance of existing normalization approaches, which can be used as guidance for the development of future supply risk assessment methods (see research contribution *(RC) A* in Figure 1).

In contrast, *contribution B* relates to supply chain resilience, namely the consequences (i.e., vulnerability) and recoverability from a disruption (Hosseini et al., 2019). Literature reviews have already identified and categorized existing metrics along the resilience curve, which visualizes system performance over time and characterizes resilience by its curve shape (Poulin & Kane, 2021). However, the interplay between resilience metrics and the theoretical foundation, namely the absorptive, adaptive, and restorative capacities that determine the extent of resilience, is less explored. This often-missing link stems from the heterogeneous terminology of resilience capacities. In addition, the relation between metrics and both resilience actions (Behzadi et al., 2020; Sharkey et al., 2021) and capacities (Hosseini et al., 2019) is less investigated. Therefore, *contribution B* harmonizes and categorizes prevalent resilience capacity terms and mathematical formulae that are used with resilience metrics, and proposes actions to improve these capacities. Subsequently, a set of harmonized mathematical formulae is derived to quantitatively describe the characteristics of the resilience curve (i.e., the curve shape). They can be used not only to assess the resilience capacities of an existing curve, but also to assess the improvement effect of resilience actions on these capacities and on characteristics of the resilience curve's shape. Consequently, *contribution B* merges quantitative resilience assessment (resilience metrics) and the theoretical foundation of resilience (resilience capacities, resilience curve characteristics, and resilience actions) (*RC B* in Figure 1).

While *contributions A* and *B* focus on the harmonization of existing quantitative assessment concepts regarding supply risk and supply chain resilience to provide a sound basis of metrics that can be utilized to make informed decisions, *contributions C* and *D* are more methodological in nature and aim to design resilient supply chains by integrating those metrics into decision models and by using them to assess resulting implications.

Contribution C proposes an exact optimization approach for integrating the resilience dimension into a strategic supply chain design model. The approach is exemplified for a climate-vulnerable bioeconomic supply chain: the production of second-generation bioethanol (2G EtOH) from lignocellulosic agricultural residues (i.e., straw) in the European Union (EU) to substitute fossil fuel and first-generation bioethanol from crops. While existing decision models mainly address resilience by focusing on the economic performance of the supply chain under uncertain conditions (i.e., disruptions along the supply chain) and thereby take a producer perspective, *contribution C* incorporates the consumer as an additional stakeholder perspective. Also, less attention has been paid to a comprehensive analysis of the economic, resilience, and environmental implications of resilience actions for biofuel supply chains (Habibi et al., 2023). Therefore, a two-stage approach has been developed, building on the EU 2G EtOH supply chain model introduced by Wietschel et al. (2021): in stage one, economically optimal strategic supply chain decisions are made by two-stage stochastic programming for a set of feedstock (straw) supply scenarios representing the influence of extreme weather events to account for the producer perspective of resilience. In this stage, the model additionally incorporates a resilience metric as a satisfaction objective, ensuring a certain extent of supply security to account for the consumer perspective. Thus, both stakeholder perspectives, namely the producer and the consumer, are addressed. In stage two, an out-of-sample test is conducted to assess the economic, resilience, and environmental implications for unanticipated scenarios, as resilient supply chains need to be prepared for unexpected disruptions (Inan et al., 2024; Reyers et al., 2022). Therefore, a new scenario set is randomly drawn to validate the strategic decisions made in the first stage. The environmental implications are computed by the optimization model across different life cycle assessment categories, similar to Wietschel et al. (2021) and Messmann et al. (2023). A resilience curve assessment is employed by applying related metrics and formulae introduced in *contribution B*. The resilient supply chain designs are benchmarked against a deterministic supply chain design anticipating average supply conditions. In summary, *contribution C* provides an exact approach that utilizes mathematical optimization and a resilience curve metric to design resilient supply chains and, subsequently, evaluates their economic, resilience, and environmental implications (*RC C*).

Contribution D proposes a heuristic approach to designing resilient supply chains. Thereby, it addresses the limitations of the exact optimization approach in *contribution C*, namely the limited time horizon and the number of disruption scenarios. Therefore, a three-stage approach decomposes strategic network and tactical flow decisions. Stage one uses a deterministic supply chain model to retrieve initial strategic network decisions. Stage two optimizes the flows of the initial network for an extensive scenario set to simulate supply disruptions and unveil resilience gaps that shape the resilience curve and its metrics. Stage three aims to reduce these gaps: a matheuristic (combination of local search and flow optimization) uses a resilience curve metric as a decision criterion and a self-adaptive economic lower bound. Therefore, both economic performance and resilience improvement are simultaneously captured. Different local search strategies and self-adaptive economic bounds for flow optimization are combined to yield six matheuristic variants, which are evaluated and compared. As in *contribution C*, the three-stage approach is examined for the 2G EtOH supply chain case in the EU. Consequently, *contribution D* provides a heuristic decomposition-based approach for resilient supply chain design to handle large-scale supply chain problems (i.e., extensive scenario sets and time horizons) and to balance economic performance and resilience simultaneously (*RC D*).

Figure 1 visualizes the contextual relation among the contributions and provides information on the method, scope, RC, and target audience.

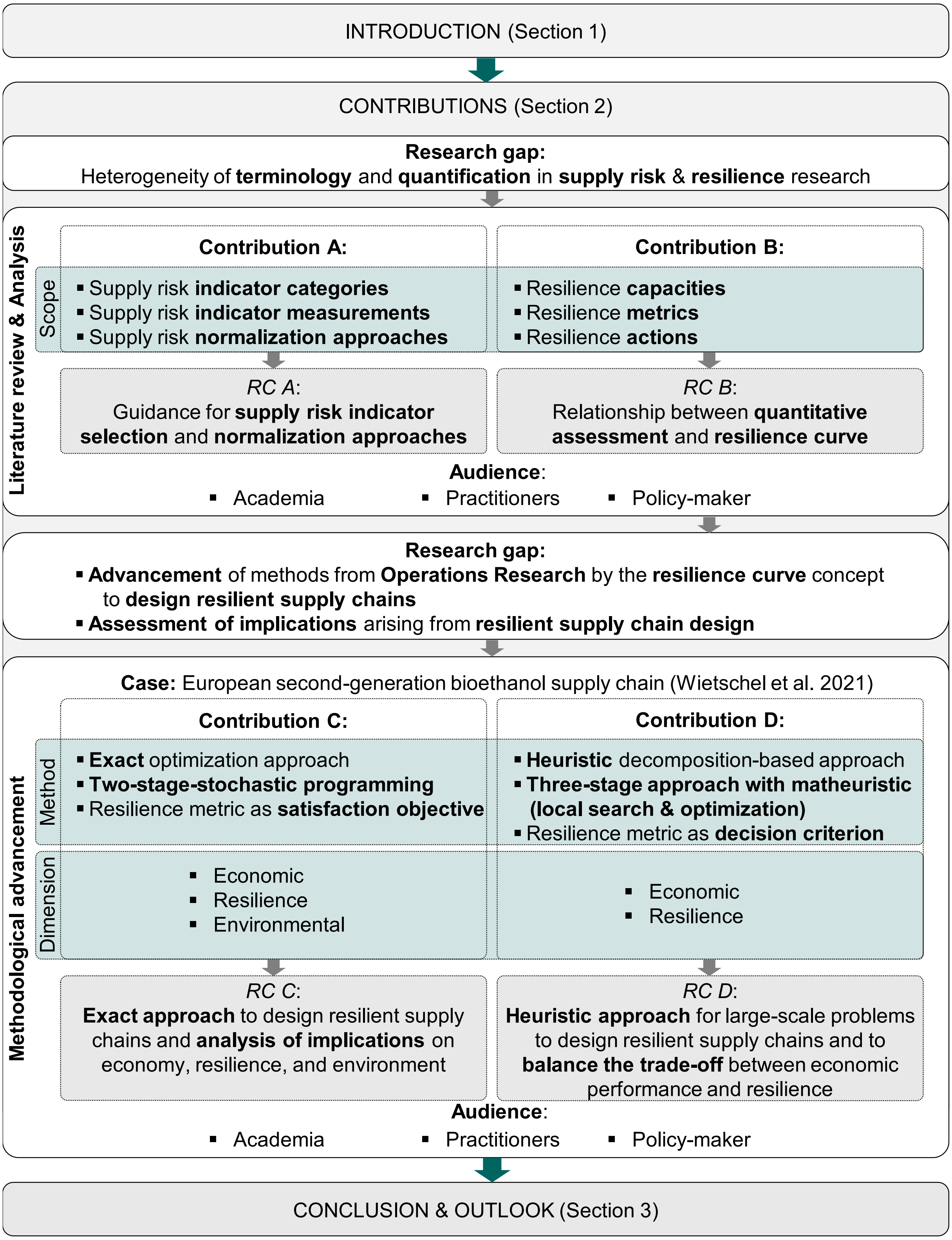

Figure 1: *Overview of the relationship between Contributions A-D.*

2

CONTRIBUTIONS

CONTRIBUTION A

AN OVERVIEW OF INDICATOR CHOICE AND NORMALIZATION IN RAW MATERIAL SUPPLY RISK ASSESSMENTS

Christoph Helbig*, Martin Bruckler, Andrea Thorenz & Axel Tuma
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ABSTRACT

Supply risk assessments are an integral part of raw material criticality assessments frequently used at the country or company level to identify raw materials of concern. However, the indicators used in supply risk assessments to estimate the likelihood of supply disruptions vary substantially. Here we summarize and evaluate the use of supply risk indicators and their normalization to supply risk scores in 88 methods published until 2020. In total, we find 618 individual applications of supply risk criteria with 98 unique criteria belonging to one of ten indicator categories. The most often used categories of supply risk indicators are concentration, scarcity, and political instability. The most frequently used criteria are the country concentration of production, depletion time of reserves, and geopolitical risk. Indicator measurements and normalizations vary substantially between different methods for the same criterion. Our results can be used for future raw material criticality assessments to screen for suitable supply risk indicators and generally accepted indicator normalizations. We also find a further need for stronger empirical evidence of widely used indicators.

1. INTRODUCTION

Raw material criticality Assessments are carried out to identify materials of concern (Schrijvers et al., 2020). Their goals range from risk mitigation to hotspot analysis. The actors can be governments and companies alike. The scope of risk consideration ranges from physical accessibility to reputation damage. Even the material scope can differ from chemical elements to whole supply chains (Helbig et al., 2021). It is good practice to follow four phases for the design and communication of a criticality assessment, consisting of (i) goal and scope definition, (ii) indicator selection and evaluation, (iii) aggregation, (iv) interpretation and communication (Helbig et al., 2021). Most criticality assessments consider indicators in the two dimensions, 'supply risk' (Achzet & Helbig, 2013) and 'vulnerability' (Helbig, Wietschel, et al., 2016). Several different indicator categories are used for both, as identified by Schrijvers et al. (2020). However, there is little evidence for the general significance of individual risk aspects for raw material criticality (Hatayama & Tahara, 2018). Commodity prices are linked to changes in supply risk aspects, but the scale and significance level of this empirical evidence depends strongly on the specific raw material (Mayer & Gleich, 2015).

The present article is an update to an earlier review by Achzet & Helbig (2013). When that review was published, only 15 criticality assessments were available for a systematic review. In the past eight years, raw material criticality assessments have increased substantially in quantity, impact, and scope (Graedel & Reck, 2016). The International Round Table on Materials Criticality (IRTC) held a series of expert workshops and conducted a broad review of various criticality assessments, focusing on risk types, geographical scope, time horizons, and objectives of the methods (Schrijvers et al., 2020). However, their study did not cover the details of each criterion and the normalization and interpretation of each of the supply risk and vulnerability indicators (Schrijvers et al., 2020).

Nevertheless, looking at such information is essential to guide future method developers and users in applying assessments. Such detailed information helps in the second criticality assessment phase, indicator selection and evaluation (Helbig et al., 2021). Therefore, the present review focuses on indicator usage instead of the general goals of the methods or aggregation procedures. We provide an overview of supply risk indicator usage in all relevant criticality assessment schemes.

For this purpose, we distinguish indicator categories, criteria, measurements, and normalizations. Indicator categories are general supply risk aspects considered in assessments and may have multiple evaluation criteria. We identify frequently used indicator categories and, for each category, the most relevant supply risk criteria. The criteria need to be measured and consequently normalized. We want to provide an overview of possible measurements and normalizations. Due to a lack of empirical evidence, we cannot provide a recommendation for best practice on each criterion. Normalization can happen with a continuous formula, stepwise normalization, or point-wise evaluation. For example, Graedel et al. (2012) consider the country concentration of production as a criterion for concentration, measured with the Herfindahl-Hirschman Index (HHI), and apply a logarithmic normalization formula to evaluate this criterion on a shared supply risk score. Using such a procedure transparently and in a reproducible manner helps improve criticality assessments and follows good practice (Helbig et al., 2021). Our review fosters this transparency and reproducibility.

2. METHOD

Our review includes 88 supply risk assessment methods published from 1977 to 2020. The methods are published in peer-reviewed literature, research reports, working papers, books, book sections, or corporate or institutional websites. The previous reviews by Achzet & Helbig (2013) and Schrijvers et al. (2020) contributed to this collection. The list of studies was extended with citation chaining, considering only publications in English or German. The complete list of studies is included in Appendix A 1.

Most of the 88 methods are full criticality or supply risk assessments that follow the four good practice steps in criticality assessment (Helbig et al., 2021). Others are either a collection of indicators, which do not aggregate the results, or methods consisting of only a single supply risk indicator. Supporting Information A additionally lists publications that we did not include in our review because they were reviews, obsolete publications (which have been updated by the same authors or institutions by now), or applications of supply risk assessment methods without any methodological change. All of these exclusions avoid double-counting.

All methods included in the review were reviewed concerning their supply risk indicators. If the method additionally had a vulnerability or economic importance dimension, those indicators were not considered. For each of the 618 indicators used in the various supply risk assessments, we identify the overarching indicator category, the measurement (with minimum and maximum values), and the normalization type (normalization formula, stepwise supply risk levels, point-wise evaluation, or no normalization). The list of all indicators, including the normalization formula, supply risk levels, or evaluation points, can be found in Supporting Information A (S01). Table A 1 shows a glossary for the relevant terms contained in this data sheet.

The review process also included an attempt for harmonization of terminology in supply risk assessments. For reasons of transparency, Supporting Information A (S03) therefore also contains the original criterion name. However, in our review, harmonized criterion names are used. For example, one method may call its indicator ‘producer diversity’, while another calls its indicator ‘company concentration’, and both may be measured with the HHI. Therefore, company concentration is used in this case as the harmonized criterion name for both cases.

Figure A 1: *Overview of supply risk categories identified in the review. Sector width is not proportional to indicator frequency.*

Category names are also harmonized to indicate risk or problem, as shown in Figure A 1. For example, many supply risk assessments consider some form of recycling in their method, but recycling itself is not a problem for supply risk–the contrary is the case. The lack of secondary production increases the dependence on primary production to maintain global material flows and supply chains. Therefore, all categories have received a name indicating that ‘more’ in this indicator equals higher supply risk and criticality, even for those studies that initially assessed supply security or supply chain resilience rather than supply risks.

Table A 1: *Glossary of Supporting Information A*.

Column Name	Explanation
Method	Scientific publication (peer-reviewed, technical report, book, book section, or website) with a novel approach to assess supply risk
Original criterion name	Name of indicator as it appeared in the publication
Criterion harmonized	The overarching term for indicators expressing the same risk
Category harmonized	The overarching term for indicators used to express similar risks
Year	Year of publication
Type	**Assessment:** indicators aggregated to an overall supply risk **Collection of indicators:** indicators assessing supply risk without aggregation **Single indicator:** only one indicator presented
Measurement	Determination approach of an indicator
Unit	Unit of measurement
Norm. type	**Level:** subdivision of indicator values into supply risk levels **Points:** assignment of discrete indicator values or qualitative descriptions of indicator values to a supply risk point **Normalization:** formula to transform indicator values into a supply risk score

3. RESULTS

The review of all 88 supply risk assessments results in a list of 618 individual indicators. These indicators can be grouped into ten indicator categories with a varying number of criterions each. Risks and criterion labeling follow a single Latin letter and a two-digit numerical code, e.g., A01 for country concentration production.

Table A 2: *List of supply risk categories identified in the review. Categories define the leading letter (A–J, X) by order of frequency of their indicators.*

Criterion codes	Category name	Frequency
A01–A18	Concentration	137
B01–B25	Scarcity	93
C01–C09	Political instability	75
D01–D15	Regulations	68
E01–E02	By-product dependence	44
F01–F08	Dependence on primary production	43
G01–G11	Demand growth	32
H01–H03	Lack of substitution options	26
I01	Price volatility	17
J01–J04	Import dependence	16
X01–X53	Other indicators	67

The categories are (A) concentration, (B) scarcity, (C) political instability, (D) regulations, (E) by-product dependence, (F) dependence on primary production, (G) demand growth, (H) lack of substitution options, (I) price volatility, and (J) import dependence. A total of 53 additional indicators did not fit these ten categories and, therefore, have been allocated to the group of other indicators (X). The review results in each of these categories are described in the following subsections one by one. Table A 1 shows the indicator categories and their frequency.

Figure A 2: *Occurrence of indicators by publication year. Only indicators occurring at least three times are shown. Each rhombus represents at least one occurrence.*

Figure A 2 summarizes the use of all criteria used at least three times. It shows almost all criteria are still used nowadays, with the prominent exception of criterion B07, *depletion time reserve base*, which is not used anymore because most data providers have discontinued reserve base data.

For each of the indicator categories, we show a graphical representation of relevant normalizations. To allow a better comparison, the original formulas are rescaled to a common 'normalized supply risk score' between 0 and 100 for all categories.

3.1. CONCENTRATION (A)

The *market concentration* (A) is the most frequently used indicator category, making up 137 of the 618 indicators (22%). The associated indicators can be grouped into a total of 18 harmonized criteria, of which the five most frequently used criteria are *country concentration production* (A01), *company concentration* (A02), *country concentration reserves* (A03), and *country concentration import* (A04). In total, these four criteria are used in 118 of 137 indicators (86%) of the concentration category.

The first appearance of concentration as a supply risk indicator dates back to 1977, when Grebe et al. (1977) considered the number of countries accounting for 40%, 60%, or 80% of the global production or global reserves as a measurement of A01 and A03. These measurements were converted for both indicators into a scale from 1 to 5, indicating the extent of supply risk, whereby the exact transformation routine is not given (Grebe et al., 1977). The so-called Herfindahl-Hirschman Index (HHI) (Herfindahl, 1950; Hirschman, 1980) is a much more frequent concentration measurement for criteria A01 to A04. Some publications proposed a combined indicator composed of the HHI and an indicator from another category as a weighting factor, for example, the political instability category. Another frequently used measurement is the accumulated share gathered from the top countries of production or reserves, as presented in Grebe et al. (1977). Normalization approaches using the HHI measurement for A01 to A04 are presented in Figure A 3. Information about the remaining harmonized criteria can be found in Supporting Information A (S03).

In the case of country concentration production (A01), the logarithmic transformation of the HHI (ranging from 0 to 10,000) into a normalized supply risk scale (ranging from 0 to 100) was applied by Graedel et al. (2012) and other methods (cf. Equation (A.1)).

$$HHI_{normalized} = 17.5 \cdot ln(HHI) - 61.18 \tag{A.1}$$

The values 17.5 and 61.18 in Equation (1) have been set by Graedel et al. (2012) to fit the normalization so that an HHI value of 1,800 results in a normalized score of 70, and an HHI value of 10,000 marks a normalized score of 100. Helbig, Bradshaw, et al. (2016) adopted this approach with other fitting parameters, resulting in a slightly different normalization applied by three other publications.

Nassar et al. (2015) and four other methods do not explicitly mention a normalization procedure for the HHI. We conclude that a simple linear transformation of the HHI into a score from 0 to 100 represents their interpretation of the country concentration best. N. Zhou et al. (2020) also determined normalized scores by scaling the HHI values linearly, but they use the extreme values observed in their data set as thresholds.

Schneider et al. (2014) define a threshold of 1,500 for the HHI. Below this threshold, the normalized supply risk score is 0. Above 1,500, the HHI is normalized by the squared ratio of the HHI value, which is also called a distance-to-target method (Frischknecht et al., 2009). Three other methods applied this parabolic approach. A similar approach is proposed by Pell et al. (2019), but we could not fully reconstruct the normalization approach. We interpret that the HHI values were first scaled from 0 to 1 by the minimum and maximum values of the observed raw material and consequently normalized by the distance-to-target method. Based on the results, the normalization formula of Equation (A.2) was applied.

$$HHI_{normalized} = \left(\frac{HHI - HHI_{min}}{HHI_{max} - HHI_{min}}\right)^2 \cdot 100 \quad \text{(A.2)}$$

The remaining normalization schemes for A01 use various stepwise functions with two (Frondel et al., 2006) to seven levels (Eggert et al., 2000). Except for Habib et al. (2016), the stepwise procedure only has single appearances.

For A02, we identified less variety in terms of measurements and normalization schemes. The most frequently used is the method of Schneider et al. (2014) which was already explained for A01. The threshold of 1,500 is once again used, which results in an identical normalization curve. Three other publications applied this approach. Pell et al. (2019) applied the same normalization scheme with extreme values of HHI observed for A02 and the distance-to-target approach. Helbig, Bradshaw, et al. (2016) adopted their normalization formula from A01 for A02 with different key points, leading to a slightly different formula (cf. Equation (A.3)).

$$HHI_{normalized} = 15.81 \cdot ln(HHI) - 45.62 \quad \text{(A.3)}$$

The same formula is also applied in two other publications. Kolotzek et al. (2018) stuck to the key points used by Helbig, Bradshaw et al. (2016) for A01 and applied a logarithmic transformation for A02. The work from Rosenau–Tornow et al. (2009) is the only study involving a level-based normalization on the HHI for A02.

A03 is also dominated by normalizations based on normalization formulas. Habib & Wenzel (2016) and Nassar et al. (2015) applied no transformation. Therefore, we assigned an HHI of 0 to the normalized supply risk score of 0 and an HHI of 10,000 to a score of 100. Helbig et al. (2017) applied the same logarithmic transformation as Helbig, Bradshaw, et al. (2016) for A01. Schneider et al. (2014) also used the distance-to-target method with a HHI threshold of 1,500 as for A01 and A02. Each of the three approaches is applied in one other publication. Pell et al. (2019) proceeded as in A01, A02 scaling the HHI values according to the observed minimum and maximum values for A03 followed by the distance-to-target method. Eggert et al. (2000) also use the same levels as in A01 to assign HHI values to supply risk levels.

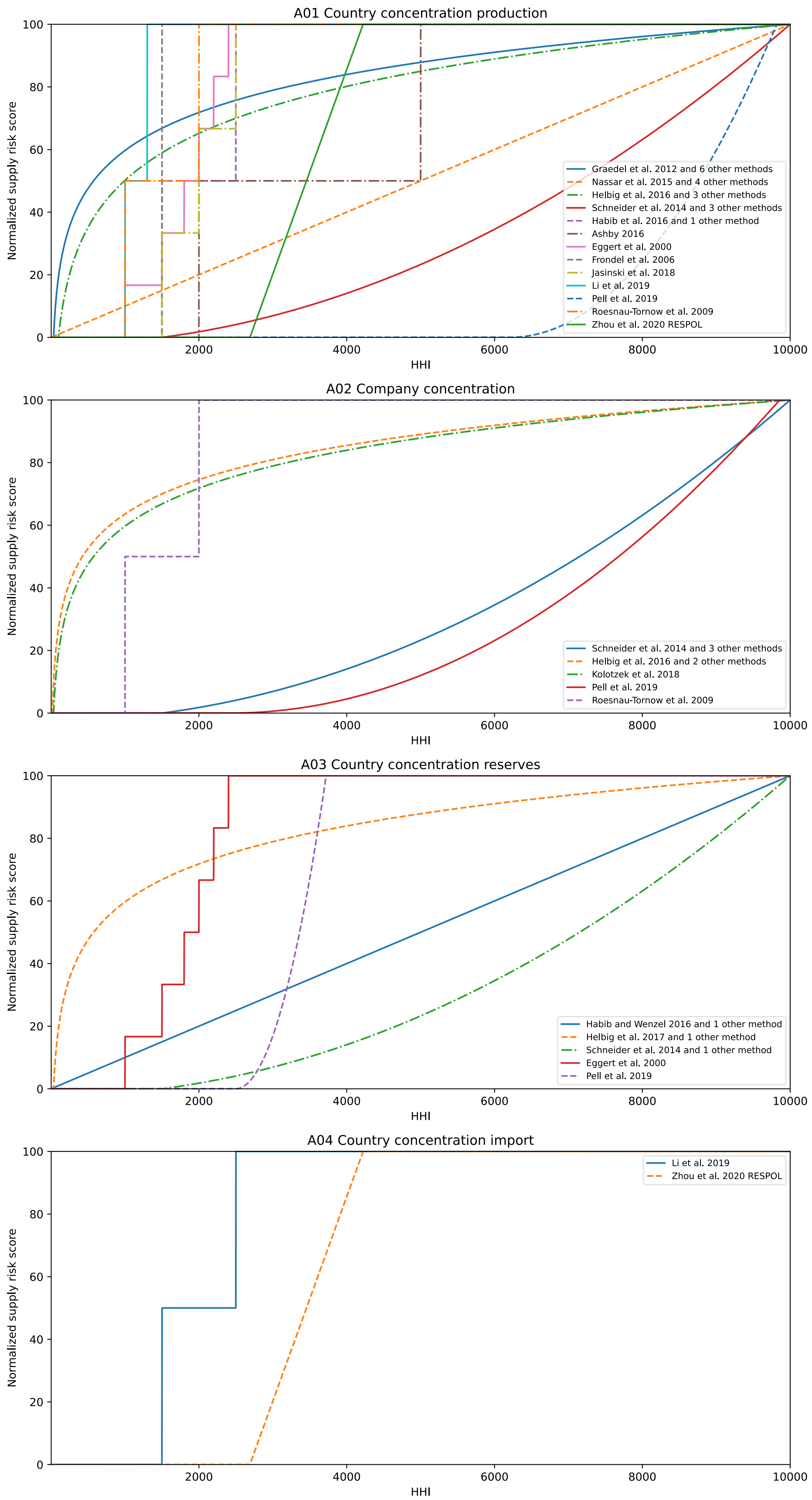

Figure A 3: *Selected normalization schemes of concentration criteria: (A01) country concentration production, (A02) company concentration production, (A03) country concentration reserves, (A04) country concentration import. All four criteria are measured with the Herfindahl-Hirschman Index (HHI).*

For A04, only two different normalization approaches for the HHI are identified. N. Zhou et al. (2020) applied the same curve to A04 as for A01. X. Y. Li et al. (2019) decreased the number of levels from four for A01 to three for A04, using thresholds of HHI 1,500 and 2,500. The limits of the levels applied in this approach are identical to those of Rosenau–Tornow et al. (2009) for A01 and A02.

3.2. Scarcity (B)

The second-most frequently occurring indicator category is scarcity (B), for which we identified 25 different harmonized criteria. The four most common criteria are the *depletion time of reserves* (B01) and *resources* (B02), the *sufficiency of reserves* (B03), and the *crustal content* (B04). Figure A 4 visualizes the normalization approaches for B01, B02, and B04. Information about the remaining harmonized criteria can be found in Supporting Information A (S03).

Both *depletion time of reserves* (B01) and *depletion time of resources* (B02) first appeared in the work of Grebe et al. (1977). The ratio between the available deposits and the current (primary) production rate determines the depletion time. Some authors also use terms like the *static reach* for these criteria. No matter the name, the ratio is typically expressed in years. For B01, the considered deposits are available reserves, meaning the deposits are identified, and extraction is techno-economically viable. Graedel et al. (2012) presented the most frequently used normalization scheme adopted by 11 other methods (cf. Equation (A.4)).

$$\mathrm{DT_{normalized}} = 100 - 0.2 \cdot \mathrm{DT} - 0.008 \cdot \mathrm{DT}^2 \tag{A.4}$$

A parabolic function is used to assign a high depletion time (DT) to low supply risk scores. Three key points are used to determine the shape of the parabola in Equation (A.4): A DT of 0 years leads to a normalized supply risk score of 100, whereas a value of 50 years is assigned to a score of 70, and a DT of 100 years results in a score of 0. Depletion times above 100 years are interpreted with no supply risk by Graedel et al. (2012).

Pell et al. (2019) applied their approach already presented for concentration criteria A01 to A03 by rescaling the inverted DT to a score from 0 to 1 with the observed minimum and maximum values and applying the distance-to-target method. The remaining publications presented for B01 in Figure A 4 developed individual level-based normalization approaches. The number of levels varies from just two, proposed by Behrendt et al. (2007), to five in the work of Grebe et al. (1977).

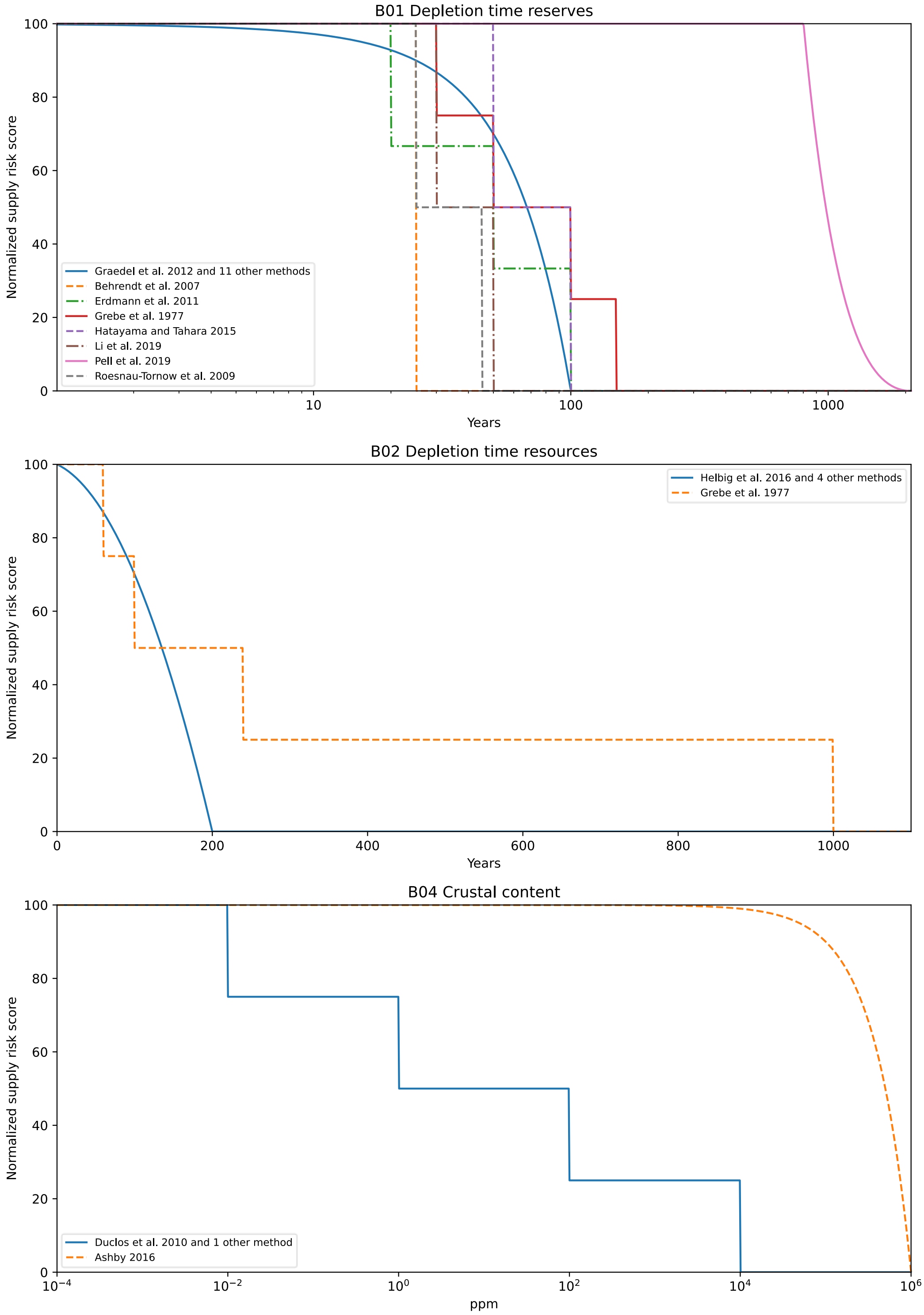

Figure A 4: *Selected normalization schemes of scarcity criteria: (B01) depletion time reserves, (B02) depletion time resources, and (B04) crustal content. Both depletion times are quantified in years, crustal content in parts-per-million (ppm). The criterion B03, the sufficiency of reserves, is not shown due to a lack of evident normalization and measurement in the respective assessments.*

The *depletion time of resources* (B02) shows more consensus in the normalization approach. Resources, in contrast to reserves, also include inferred and sub-economic deposits; therefore, the depletion time of resources is larger than the depletion time of reserves. In most cases, the normalization of B02 is similar to that of B01. Helbig, Bradshaw et al. (2016) proposed a parabolic transformation comparable to the approach of

Graedel et al. (2012) for B01. For the DT of the resources, they suggest different key points by doubling the periods: A DT value of 200 years is considered as causing no supply risk at all, resulting in a supply risk score of 0, and 100 years results in a score of 70. Four other publications followed this approach. The only different normalization approach found was the level-based normalization by Grebe et al. (1977), consisting of five levels. Here, a DT exceeding 1000 years yields a supply risk score of 0. However, this method has never been applied by another study in our review.

For the *crustal content* (B04), the 'abundance in earth's crust' was identified as the main indicator. Two different approaches were found for normalization. Ashby (2016) considers a high supply risk for materials with rare abundance in the earth's crust, but does not propose a specific transformation into a normalized supply risk score. Nevertheless, we want to display Ashby's intention of assigning a high supply risk score to a low abundance (Ashby, 2016). Therefore, we conducted a simple linear transformation considering a value of 10^6 ppm as no supply risk and a value of 0 ppm as a normalized score of 100. An alternative method of normalization was applied by Duclos et al. (2010), and another method subdividing abundance values into five levels of supply risk.

3.3. Political instability (C)

The third most used supply risk category is political instability (C), which is dominated by two harmonized criteria, namely *geopolitical risk* (C01) and *political instability* (C02). These two criteria make up 67 out of 75 cases (89%) for this category. Each of the eight remaining criteria identified is applied only once.

C01 appeared for the first time in the work of Eggert et al. (2000). To evaluate the geopolitical risk, they used the political country risk evaluation of Hermes-/BMWi classification on a scale from 1 to 7. They use this classification three times for indicators in this category, each with a different weighting: the production shares, the export shares, and the reserve shares of the countries, respectively.

In contrast, C02 appeared first in the method of Morley & Eatherley (2008). They classified the percentile rank of the Worldwide Governance Indicator 'Political Stability and Absence of Violence/Terrorism' ($\mathrm{WGI}_{\mathrm{PV}}^{\mathrm{PR}}$) (Kaufmann et al., 2010) of the largest producer into a supply risk score using a three-level normalization function. In addition, the World Bank developed five other Worldwide Governance Indicators, which are updated yearly: 'Government Effectiveness ($\mathrm{WGI}_{\mathrm{GE}}$)', 'Voice and Accountability', 'Control of Corruption', 'Regulatory Quality', and 'Rule of Law' (Kaufmann et al., 2010). They are available as WGI score and WGI percentile rank (Kaufmann et al., 2010).

The classification displays the normalization schemes used for the criteria of political instability according to their measurement: WGI score and WGI percentile rank (cf. Figure A 5). In most cases, the WGI scores or ranks are weighted by production share. Other weighing factors are import shares (Gemechu et al., 2016) or the consideration of the largest producers (Erdmann et al., 2011). The composition of a WGI dimension in combination with the HHI is described in Section 3.1. Other schemes are expressed in Supporting Information A (S03).

The WGI indicators in the default unit usually range from –2.5 to 2.5 (Kaufmann et al., 2010), where a low value indicates bad governance. Consequently, the most frequently used normalization approach for both C01 and C02 is the linear transformation of WGI scores based on a hypothetical lower bound of –2.5 and upper bound of 2.5, as presented in Equation (A.5). After the conversion, values of –2.5 in WGI units and lower yield the highest supply risk score. Twelve other methods have adopted this transformation.

$$WGI_{normalized} = 20 \cdot (2.5 - WGI) \tag{A.5}$$

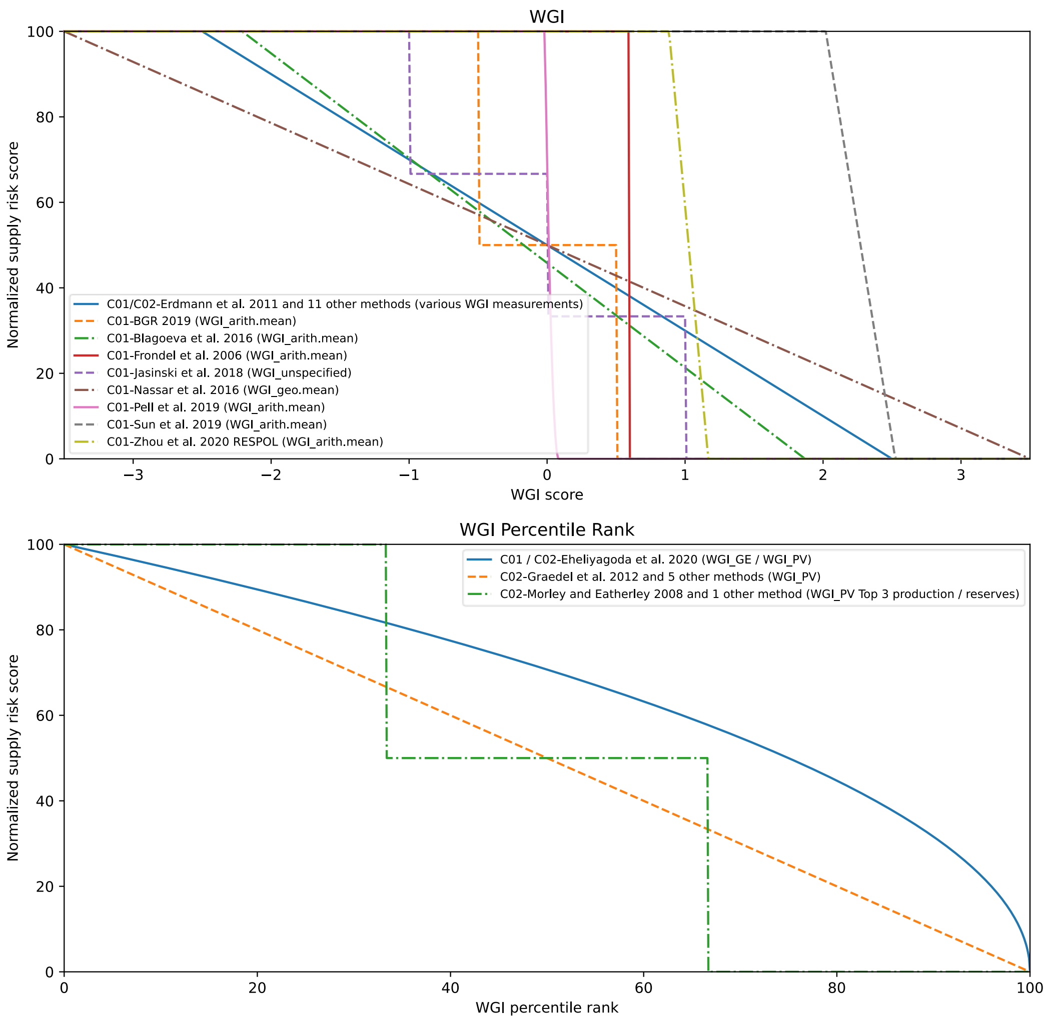

Figure A 5: *Selected normalization schemes of political instability criteria: (C01) Geopolitical risk and (C02) Political instability. Indicators use either the score or the percentile rank of the Worldwide Governance Indicators (WGI).*

Diverging from this are Nassar et al. (2016), who instead assume a range from –3.5 to 3.5 (cf. Figure A 5). Three methods use the observed minimum and maximum WGI scores for normalizing them to supply risk scores: Blagoeva et al. (2016) and N. Zhou et al. (2020) based on the arithmetic mean of all six WGI dimensions, and Nassar et al. (2015) based on the geometric mean of all six WGI dimensions. DERA (2019) and Jasiński et al. (2018) presented a level-based normalization with three and four levels, respectively. In addition to the approach of Erdmann et al. (2011), none of the above-presented methods has been taken up so far. Sun et al. (2019) used the function presented in Equation (A.6) to normalize the weighted arithmetic mean of the WGI-dimensions.

$$WGI_{normalized} = -1.9841 \cdot WGI_{arith.mean} + 5.7001 \quad \text{(A.6)}$$

For the normalization of the percentile rank of the WGI dimensions, four different methods were identified. Graedel et al. (2012) simply inverted the percentile rank (on a scale from 0 to 100) by assigning the highest political stability with the lowest supply risk (cf. Equation (A.7)). This approach was adopted by five other methods, whereas other methods did not take up the remaining approaches for the normalization of WGI percentile ranks.

$$WGI_{normalized} = 100 - WGI^{PR} \quad \text{(A.7)}$$

Eheliyagoda et al. (2020) developed a procedure for both C01 and C02 using Equation (A.8) to invert and rescale the weighted $\mathrm{WGI}_{\mathrm{PV}}^{\mathrm{PR}}$ respectively $\mathrm{WGI}_{\mathrm{GE}}^{\mathrm{PR}}$ (Governance and Effectiveness).

$$WGI_{normalized} = \sqrt{(100 - WGI_{PV/GE}) \cdot 100} \quad \text{(A.8)}$$

3.4. Regulations (D)

The fourth most often mentioned category is regulations (D), used in 68 out of 618 indicators (11%). We identify *policy perception* (D01), *human development* (D02), *trade barriers* (D03), and *environmental performance* (D04) as the most prominent harmonized criteria. In contrast to most other categories, the risk from regulations has emerged more recently in the work of Thomason et al. (2010). They determined the percentage of produced goods expressed in U.S. market shares that a country intends to supply to the U.S. as a measurement of D03. In 2012, Graedel et al. (2012) developed a measure to determine D01 and D02 for the first time.

It is worth mentioning that three dominant measurements of regulations have been developed within the criteria: The Policy Perception Index (PPI) in D01 is provided by the Fraser Institute and captures the influence of policies on mining activities in a country (Yunis & Elmira, 2021). The Human Development Indicator (HDI) in D02 has been developed by the

UNDP and evaluates the living conditions of a country (UNDP, 2020b). The Environmental Performance Index (EPI) in D04 is provided by Yale University and rates the ability of a country to cope with environmental challenges (Wendling et al., 2020). All three measurements are updated annually. The associated normalization schemes are displayed in Figure A 6.

Graedel et al. (2012) weighted the PPI of mining regions by the respective production share. They normalized this measurement by a simple inversion, subtracting the PPI from 100 according to Equation (A.9). The PPI ranges from 0, indicating low policy attractiveness, to 100, displaying high policy attractiveness for mining activities. Ten other methods adopted this approach in the same way.

$$PPI_{normalized} = 100 - PPI \tag{A.9}$$

Bach et al. (2016) applied the distance-to-target method as described in Section 3.1 on the inverted and weighted PPI values using a threshold of 55. Eheliyagoda et al. (2020) applied the same approach for the WGI percentile ranks of D01 and D02 (cf. Equation (A.8)) on the weighted PPI values. Both N. Zhou et al. (2020) and Pell et al. (2019) adopted their previously presented approaches. N. Zhou et al. (2020) applied the normalization based on the minimum and maximum observed values of the PPI, whereas Pell et al. (2019) first applied a rescaling from 0 to 1 according to the minimum and maximum observed values, followed by the distance-to-target approach.

For D02, the HDI weighted by production shares of mining countries was the most often used measurement. The HDI evaluates the three dimensions of life expectancy, educational standard, and standard of living on a scale from 0 to 1 (UNDP, 2020a). Ciacci et al. (2016) rescaled the weighted HDI values as presented in Equation (A.10) by a scaling factor of 100, which was followed by eight other methods.

$$HDI_{normalized} = 100 \cdot HDI \tag{A.10}$$

Eheliyagoda et al. (2020), N. Zhou et al. (2020), as well as Pell et al. (2019), applied their approaches to the HDI as conducted for previous criteria: Eheliyagoda et al. (2020) applied the normalization formula shown in Equation (A.8) on HDI values, N. Zhou et al. (2020) normalized according to the observed minimum and maximum values, Pell et al. (2019) applied their combination of a normalization to a scale from 0 to 1 based on minimum and maximum values, and the distance-to-target method. Schneider et al. (2014) also stuck to their distance-to-target method already performed for A01–A03 with a threshold for the weighted HDI of 0.12. Helbig et al. (2020) applied the formula presented in Equation (A.11) to normalize the weighted HDI values, resulting in a 0 to 100. All of the previously mentioned studies deem high values of the HDI as high supply risk.

$$HDI_{normalized} = 100 \cdot \frac{HDI - 0.352}{0.949 - 0.352} \tag{A.11}$$

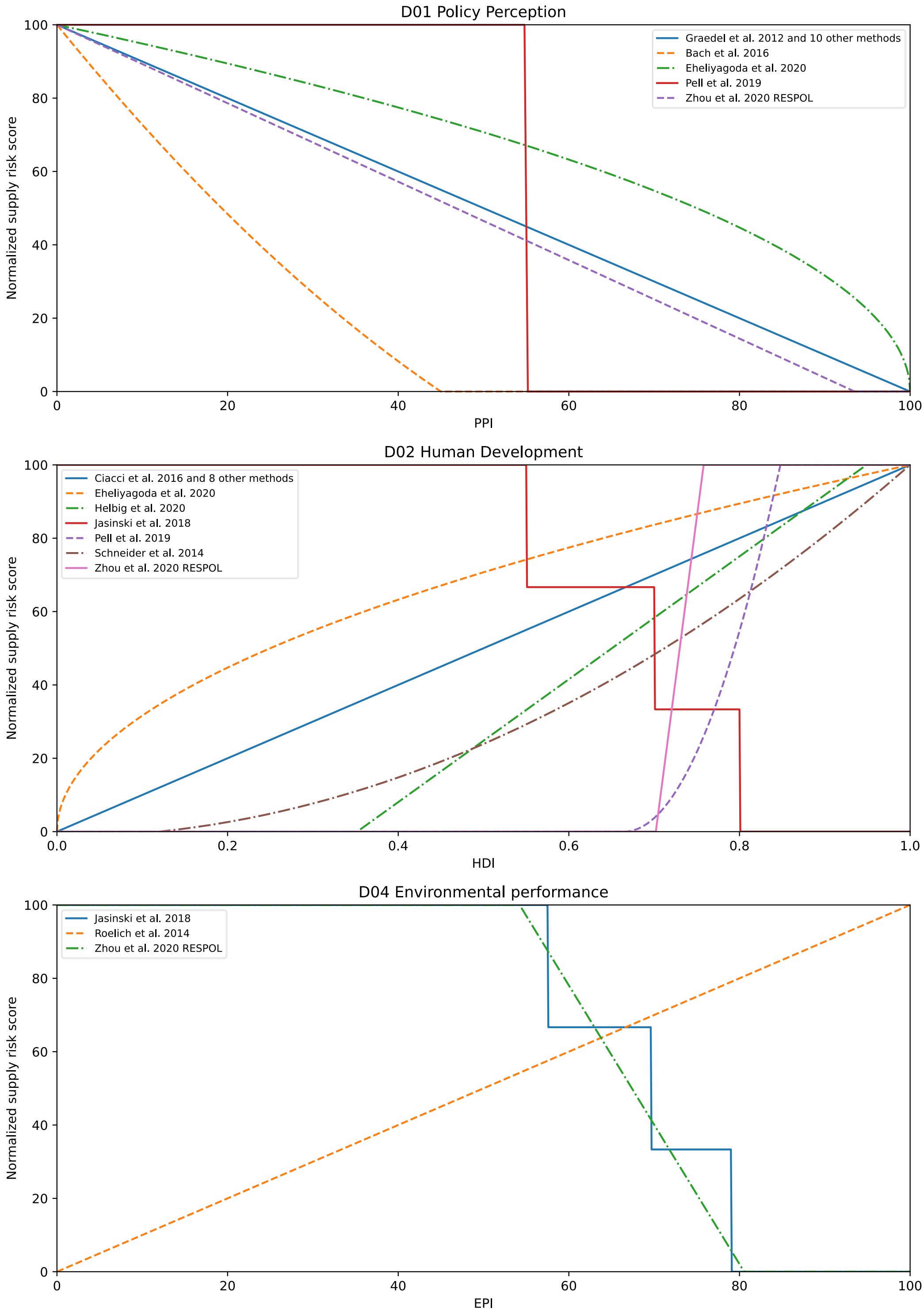

Figure A 6: *Selected normalization schemes of regulations criteria: (D01) policy perception, (D02) human development, and (D04) environmental performance. Policy perception is measured with the Policy Perception Index (PPI), human development with the Human Development Indicator (HDI), and environmental performance with the Environmental Performance Index (EPI).*

An opposite interpretation of the HDI was proposed by Jasiński et al. (2018), resulting in an alternative normalization. They consider countries with low human development as critical because of the high probability of improving social conditions by introducing policies that disrupt mining activities. In other words, high weighted HDI values lead to a low supply risk in their study. Therefore, a stepwise normalization consisting of four levels is conducted.

The discrepancy in the interpretation of indicators continues for D04 with the EPI as a single measurement. Roelich et al. (2014) used the production-weighted EPI as a measurement of D04 for the first time to describe the risk that a country has or introduces environmental policies that might restrict mining activities. Thus, an EPI value of 100 yields a high potential for restrictions in mining activities due to environmental policies. Since an EPI of 100 indicates high supply risk, no further normalization needs to be applied.

In contrast, N. Zhou et al. (2020) and Jasiński et al. (2018) oppositely interpreted the EPI. According to their normalization approaches, a higher EPI value leads to lower supply risk scores. They are less vulnerable to incidents and related supply failures because of their environmental standards (Jasiński et al., 2018). While N. Zhou et al. (2020) applied the same method as previously used for A by scaling the weighted EPI according to the minimum and maximum values observed, Jasiński et al. (2018) used a four-level normalization applied for D02 with slightly different limits.

3.5. By-product dependence (E)

The fifth most often occurring category is by-product dependence (E), used in 44 out of 618 indicators (7%). We have found one dominant criterion giving the same name as the category *by-product dependence* (E01), which first appeared in the work of Grebe et al. (1977). A qualitative approach was used to assign the observed raw materials to a supply risk score ranging from 1 to 5. More information about the classification can be found in Supporting Information A (S03). However, the most commonly used measurement for E01 is companionality, developed by Nassar et al. (2015), and the companion metal fraction (CMF), which is the percentage share of a raw material produced as a by-product. Companionality (CP) evaluates the contribution of raw material to the profitability of a mine in contrast to other raw materials sourced from the same mine for all sourcing locations. The CP values are usually rescaled by a factor of 100, as shown in Equation (A.12), to result in a supply risk score from 0 for no risk by independent raw materials to 100 for high supply risk posed by full dependence of raw materials on other mined materials.

$$CP_i = \frac{\sum_j \left(\left(100 \cdot \left(1 - min\left(\frac{Revenue_{ij}}{Cost\ of\ sales_j}, 1 \right) \right) \right) \cdot Sales\ volume_{ij} \right)}{Sales\ volume_i} \tag{A.12}$$

The normalization schemes of CMF are displayed in Figure A 7. Same as for CP, the most common approach is a multiplication by 100 to create a supply risk score ranging from 0, indicating a raw material is not produced as a by-product, to 100, meaning a raw material is entirely made as a by-product. This method is used by Graedel et al. (2012), followed by six other methods. Schneider et al. (2014) applied the same distance-to-target approach for the categories above using a threshold of 0.2. BGS (2015) and Jasiński et al. (2018) proposed a stepwise three-level and four-level normalization. Other methods have not adopted either approach.

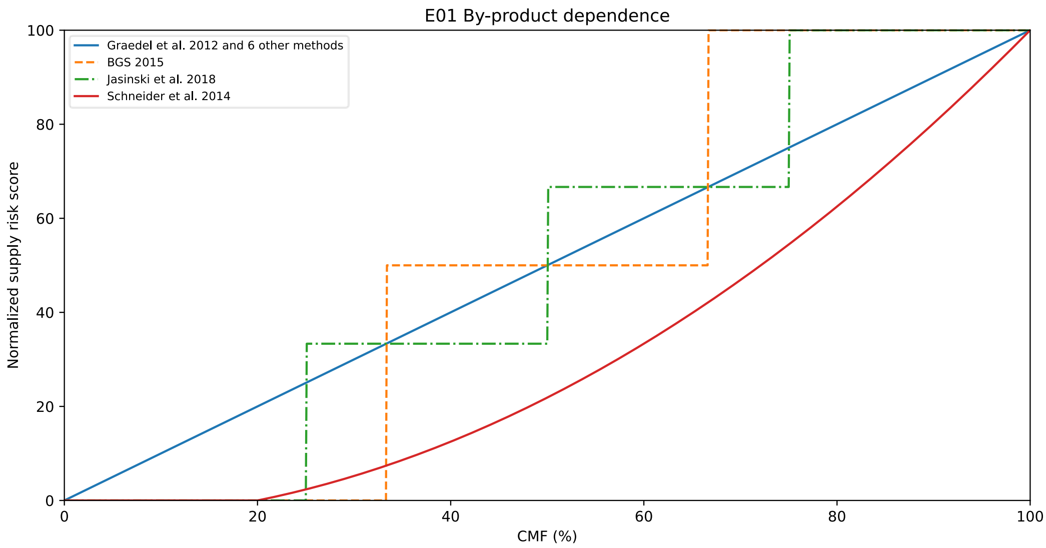

Figure A 7: *Normalization schemes for the by-product dependence criterion (E01) relying on the Companion Metal Fraction (CMF), given in percentages.*

3.6. Dependence on primary production (F)

The sixth supply risk indicator category is the dependence on primary production. This terminology inverts the typically used original category name of recycling or recyclability. The inversion reflects that it is precisely the lack of recycling that increases the supply risk. The two most often used criteria in this category are the *end-of-life recycling rate* (F01) and the *recycled content ratio* (F02). The UNEP report on recycling of metals a decade ago has given a good overview of the terminology on metal cycles, including differentiation between old scrap and new scrap, and the importance of collection rates, remelting yields, and growing material demands for the measurements of recycling in global cycles (Graedel et al., 2011). The report is still often used as the data source for various supply risk assessments.

The argument for why dependence on primary production and thus a lack of secondary production, i.e., recycling, causes higher supply risk is the following: secondary raw materials are a raw material source independent of the primary production route, in particular mining; it is available without geological exploration, with its availability depending predominantly on past material use, and it is known locally in the countries of utilization. Therefore, the availability of secondary raw materials makes shortages of primary raw materials and high market concentrations less likely.

In general, there are two schools of thought on how recycling should be measured as a criterion for dependence on primary production: either method uses the end-of-life recycling rate (EoLRR) as the measurement, or they use the recycling content ratio (RCR). Figure A 8 shows the normalization schemes applied in these two measurements.

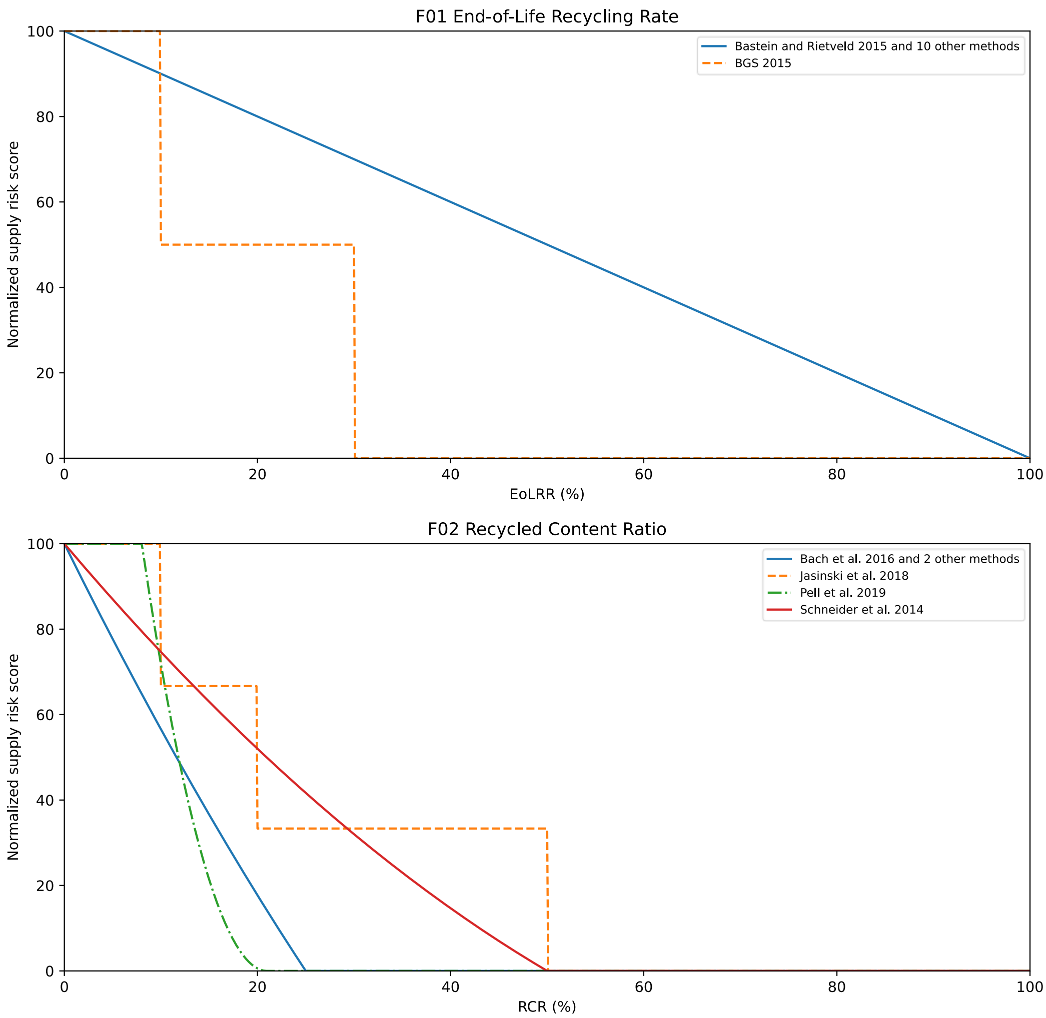

Figure A 8: *Selected normalization schemes for criteria for dependence on primary production: (F01) end-of-life recycling rate and (F02) recycled content ratio. Both End-of-Life Recycling Rate (EoLRR) and Recycled Content Ratio (RCR) are given in percentages.*

The EoLRR measures the share of end-of-life wastes collected and recycled so that the material can enter a new fabrication or manufacturing stage. Since there will always be waste flows that are not collected and thermodynamic limits to remelting yields, this EoLRR will always be smaller than 100%. The predominant normalization formula applied to the EoLRR is the naïve approach to linearly rescale the values of 0% to 100% to scores of 100 to 0 points.

In contrast, the RCR measures the share of recycled content in fabricated or manufactured goods. Since these goods can only consist of primary or secondary materials, this ratio will also be between 0% and 100%. However, because raw material markets have been growing for most materials over the past decades, the RCR will often be lower than the EoLRR. Therefore, methods already attribute no supply risk scores for any RCR over 50%.

Both EoLRR and RCR have their flaws as measurements for primary production dependence. For the EoLRR, there may be high recycling rates at end-of-life; however, these are irrelevant if the supply risks are emerging from rapidly growing future technology demand. As the EoLRR considers only recycling from old scrap, which is only formed after the use phase, there is a natural time lag between demand growth and growth of end-of-life wastes. For the RCR measurement, the ratio of recycled content may be high in a fabricated product. Still, if this all came from new scrap recycling, recycling before the use phase does not alter the primary material demand. One should be cautious that high prompt scrap formation rates with high recycling rates for prompt scrap might artificially increase the RCR without providing any risk-reducing alternative raw material source.

3.7. DEMAND GROWTH (G)

The seventh supply risk category is that of expected demand growth, in particular from future technologies. The most common approach is to relate the expected additional demand in the future to current production volumes. Angerer et al. (2009) first utilized this approach, which is a study that has been excluded from our dataset because it has been updated by Marscheider-Weidemann et al. (2016).

This approach to calculate the future technology demand as a ratio between additional demand growth and current production typically needs a base year (for current production) and a reference year (for future technology demand). For example, Angerer et al. (2009) originally calculated the raw material demand for various future technologies for 2030 and used 2006 as the base year. Using the ratio rather than, e.g., the quantity or value of future technology demand also allows comparing different raw materials produced in orders of varying magnitude. Not the absolute amount of material production is problematic, but rather the required relative demand growth. Since base years and reference years differ between supply risk assessments naturally, depending on their publication date and goal and scope of the evaluations, normalizations can only be compared based on the annualized additional demand growth, given in percentages (cf. Figure A 9).

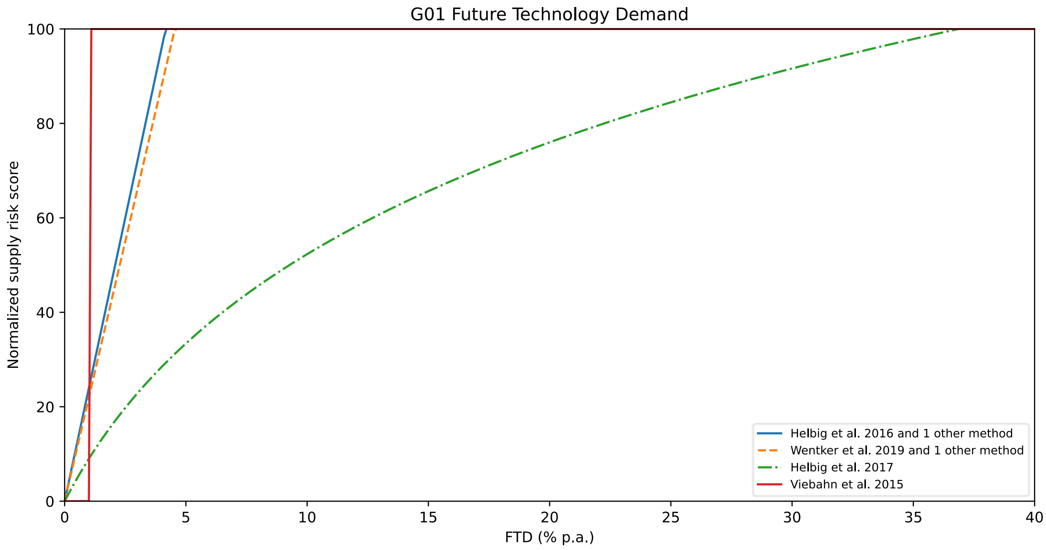

Figure A 9: *Normalization schemes for the future technology demand criterion (G01). Underlying measurements are annualized in Future Technology Demand (FTD) growth per year (% p.a.).*

3.8. Lack of substitution options (H)

The eighth indicator category for supply risk is that of lack of substitution options. A lack of viable substitutes for a material or product creates a dependency in the supply chains, reducing the system's resilience. In 22 out of 26 cases (84 %), the substitutability of raw material is used as a criterion in this category. Substitutability can happen on a material, component, assembly, or conceptual level as described by Habib & Wenzel (2016) at the example of wind turbines. In particular, for high-tech applications, the substitution of materials is often limited, as developed by Nassar (2015) for platinum-group metals. The most prominent evaluation of substitutability for a large set of raw materials has been published by Graedel, Harper, Nassar, & Reck (2015), who set out to identify the main applications of each element, identify possible substitute materials in each of these applications, and then evaluate the performance of that substitute. As a result of the heterogeneity of applications, these are difficult to quantify. Therefore, experts' judgment on a multi-point scale is used to conclude the substitutability score, and application shares are afterwards used to calculate a weighted average of the scores (Graedel, Harper, Nassar, & Reck, 2015). Graedel, Harper, Nassar, & Reck (2015) were not the first and not the only ones to use such an approach for evaluating the lack of substitution options. The first to use the lack of substitution options as an indicator for supply risk was again Grebe et al. (1977), however, only with the straightforward classification of raw materials with 'no substitution', 'hardly any substitution', and 'substitution', and no differentiation of application shares. The European Commission (2010) and Erdmann et al. (2011) also applied this concept of a weighted average of expert assessment for the main applications of the raw material. A shift from substitutability to substitution has been used for the later updates of the EU Critical Raw Materials list (Blengini et al., 2017b). While this may sound like quibbling, the difference is substantial, as substitution only considers proven and readily available substitutes. Consequently, the supply risk scores of many raw materials in the EU criticality study increased due to this change (European Commission, 2014, 2017).

The normalization scheme for lack of substitution options is trivial: typically, a linear scale is used, with no further rescaling. Therefore, no figure is shown for this indicator category.

3.9. PRICE VOLATILITY (I)

The ninth indicator category for supply risk is price volatility. It was impossible to identify different criteria for this category, so all 17 cases are assigned to the same criterion, I01. In detail, the measurements vary between the price volatility, the variation coefficient, and the relative price change within a specific period. All methods use a stepwise normalization of price volatility measurements to supply risk scores. Most studies use four-level to five-level normalization functions in which higher price volatility leads to higher supply risks. The only exception is the method by Eggert et al. (2000), who use a seven-level decreasing normalization function. The authors were among the early supply risk assessments, and they did not explain why they evaluated low price volatility with high supply risk. Figure A 10 shows the different level choices of the four methods. Other methods' schemes are shown in Supporting Information A (S03).

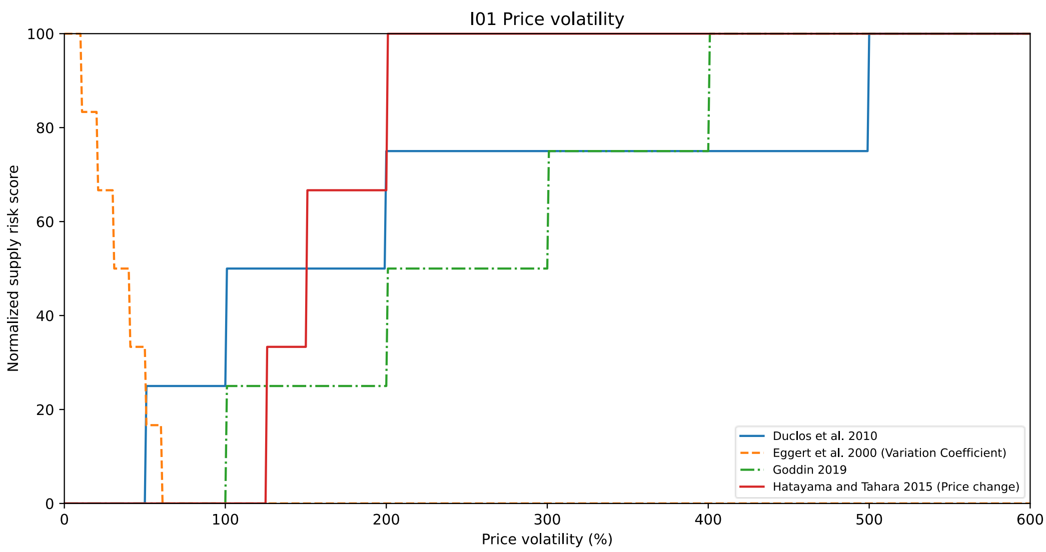

Figure A 10: *Normalization schemes for the price volatility criterion (I01). Price volatility is either used directly, in percentage, or calculated as variation coefficient or price change, also in percentages.*

According to economic theory, the interpretation of the criterion price volatility is ambiguous, because a price increase should result from a supply-demand gap, not the reason. It is also questionable if one can anticipate future supply risks by the analysis of historical price development. Therefore, it is not surprising that this indicator category has only been used in very selected supply risk assessments and has not been used consecutively by a series of methods.

3.10. Import dependency (J)

The tenth indicator category for supply risks is import dependency. This indicator category is specifically designed for a national perspective. This category is measured with the *net import reliance* criterion in eight out of 16 cases (50%) (J01). The net import reliance (NIR) is calculated as the ratio between net imports and apparent consumption, as shown in Equation (A.13).

$$NIR = \frac{Net\ imports}{Apparent\ consumption} = \frac{Imports - Exports}{Domestic\ Production + Imports - Exports} \tag{A.13}$$

The rationale behind using this indicator for supply risk assessments is to identify materials for which the upstream supply chain is out of the hands of domestic policy and trade. If a country has to rely on foreign exploration, extraction, or processing, it can consider its continuous operation, or the access to the materials, as less reliable. Therefore, higher net import reliance is considered with higher supply risks.

Most methods, starting with Goe & Gaustad (2014), use the simple linear normalization approach where no net imports result in no supply risk, and 100% NIR results in a supply risk score of 100. Only S. Li et al. (2019) define the steps at 40% and 70% NIR as thresholds for their three-level normalization function. Figure A 11 shows the normalization functions for J01. Other criteria are shown in Supporting Information A (S03).

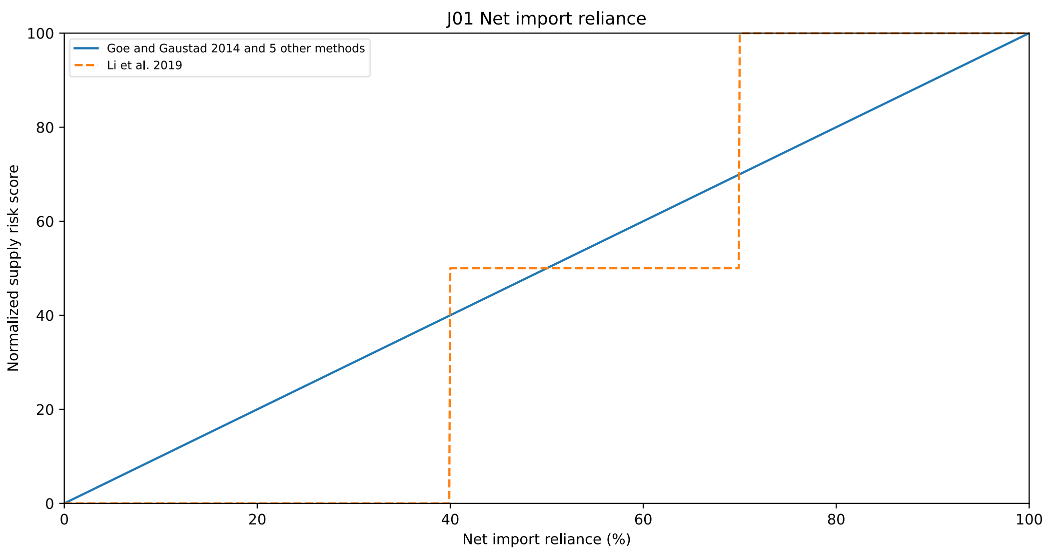

Figure A 11: *Normalization schemes for the net import reliance criterion (J01), which is measured in per cent.*

3.11. Other indicators

Our review found an additional 67 cases of indicator uses that could not be grouped into indicator categories. Therefore, these ‘other’ indicators are a collection of 53 widely differing criteria, none of them used more than four times in total. Those that are at least used twice are the *current market balance* (X01), *stock keeping* (X02), *purchasing potential* (X03), *supply adequacy* (X04), *natural disasters* (X05), *economic importance* (X06), the *Sector Competition Index* (X07), the *economy of storage and transport* (X08), *storage complexity* (X09), *investment potential* (X10), *material cost impact* (X11), and *material dependency* (X12).

If one wants to find patterns in this loose collection of indicators, three areas of interest may occur: stocks and storage patterns, price and cost aspects, as well as total demand and market size. However, due to the high variation in indicator application and measurements and a lack of repeated implementation in supply risk assessments, we will refrain from discussing these indicators in detail. All individual indicators are listed with their respective measurement and normalization scheme in Supporting Information A (S03).

4. Discussion and conclusion

The variety in supply risk indicator usage is impressive. It is understandable because of the different goals and scopes of studies in our review. For example, omitting physical scarcity as a risk factor makes sense when the assessment is focused on short-term risks. Likewise, companies will be much less concerned about import dependence than nations. Therefore, even after another ‘five years of criticality assessments’, the harmonization that Graedel and Reck asked for has not taken place (Graedel & Reck, 2016). However, many other Graedel and Reck’s ‘desirable aspects’ are covered nowadays by the methods in this review.

The material scope often includes various chemical elements, biotic raw materials and minerals (Bach et al., 2018; European Commission, 2020). The risk factors also include geology (scarcity, by–product dependence), regulations, and geopolitics (political instability, import dependence). For example, even cultural aspects are used, such as the ‘conformity of ideological values’ by Nassar et al. (2020). The substitutability or the lack thereof, the dependence on primary production, and the by-product dependence are three of the ten indicator categories. However, these categories often rely on previous assessments like Graedel et al. (2011), Graedel, Harper, Nassar, & Reck (2015), or Nassar et al. (2015). In contrast to the studies reviewed by Achzet & Helbig (2013), most of the methods in this review are now published in peer-reviewed journals, not as technical reports. Similar to the European Commission or the United States, some governmental reports undertake the split path of publishing the technical report and a peer-reviewed methodological paper in parallel (Blengini et al., 2017a; Nassar et al., 2020).

However, the periodical update that Graedel & Reck (2016) also asked for is a rare feature. Many studies are carried out by researchers at universities or other academic institutes without permanent funding for such updates. The EU and US criticality lists, updated every three to four years, are exceptions (European Commission, 2020; Nassar & Fortier, 2021).

The transparency of some methods is hampered by the non-disclosure of data (Malinauskienė et al., 2018; Pfleger et al., 2015; Schneider et al., 2014; Y. Zhou et al., 2019, 2020). While we understand the importance of confidentiality, particularly for company reports, from a scientific perspective, this reduces the transparency and accessibility of corporate supply risk assessment reports (Apple, 2019; Duclos et al., 2010). Some other methods used sophisticated intermediate scores, thresholds, and renormalizations up to the point that results turned out to be irreproducible or the quantitative results simply contradict the textual explanations (Althaf & Babbitt, 2020; Blagoeva et al., 2016; Nassar et al., 2020; Pell et al., 2019).

Some methods such as N. Zhou et al. (2020), Pell et al. (2019), and Bach, Finogenova, et al. (2017) use normalizations based on the specific material scope, for example setting the bounds by looking at the minimum and maximum observed measurement, leading to a distortion of the supply risk score since the score is dependent on the raw materials selected for the assessment. In other words, the supply risk score of the observed raw materials varies depending on the investigated raw materials. The integration of individual bounds depending on the values in the normalization function leads to different supply risk scores for the same indicator value. Therefore, results between studies are not comparable, and the overall results are weakened. Adjusting indicator calculation or normalization schemes may be viable for specific purposes of custom methods. However, in these cases, full transparency and reproducibility are even more important.

The supply risk assessments in the review still often do not adequately report data uncertainties and sensitivity to methodological choices. Only very few authors undertake the effort of doing Monte Carlo simulations or other error propagation methods (Gemechu et al., 2016; Graedel et al., 2012; Helbig, Bradshaw, et al., 2016; Helbig et al., 2018). Variations of indicator choices and normalizations, which have been discussed by Erdmann & Graedel (2011), are also rare.

Concluding, we want to highlight two efforts by individual researchers and one general recommendation which, in our view, would improve future supply risk assessments. Firstly, the effort from Mayer & Gleich (2015) (and in many other publications from this working group) to link commonly used supply risk indicators with price variations, as the theoretical result of supply shortages through multiple regression analysis, is a practical approach. One of their results was that impacts of supply risk aspects vary between chemical elements and, therefore, no universal indicator set will be found. Secondly, Hatayama & Tahara (2018) established a list of supply disruption events, which, if continued, extended to global coverage, and further evaluated could be an excellent basis for event studies. Such event studies could be used to statistically assess the likelihood of supply disruptions at various levels of supply risk indicators. For example, this would eventually allow identifying a non-linear normalization formula instead of naïve approaches or single threshold values. However, normalization formula and thresholds are still better than the semiquantitative approach of point-wise or step-wise normalizations used in many assessments. Supply risk indicators can be measured and should be interpreted quantitatively.

We strongly recommend updating some of the data sources commonly used in supply risk assessments. While the USGS provides annual updates to production and reserves data, and while the various political and regulatory indices are also updated annually, the data sources for by-product dependence, dependence on primary production, and lack of substitution options are, by now, up to a decade old. Given increasing efforts to implement a circular economy, ongoing technological development, and rapid material extraction growth, the values of these data sources are at risk of becoming outdated.

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Contribution B

Review of Metrics to Assess Resilience Capacities and Actions for Supply Chain Resilience

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Abstract

Efficiency and profitability are the main drivers of globalization and have led to long and complex supply chains. Recent disturbances, such as COVID-19 or the Suez Canal obstruction, caused severe supply disruptions and thereby unveiled the vulnerability of global trade. Resilient supply chains are characterized by the capacity to absorb, adapt to, and restore from disruptions. Building upon the established concept of the 'resilience curve', this article explores the interplay between resilience capacities, metrics, and actions in the state-of-the-art literature. We first analyze and harmonize the terminology used to describe capacities as well as metrics for quantifying resilience. This results in a set of 17 resilience metrics that describe all characteristics of the resilience curve and can be used as a tool to assess the resilience of a supply chain. Subsequently, we propose how these metrics can be applied to quantify the effect of resilience actions. Finally, we analyze which actions are proposed in the literature and classify those actions according to their relation to traditional supply chain planning tasks. Practitioners, such as supply chain decision-makers, can implement these actions to strengthen the absorptive, adaptive, and restorative capacities and are provided with mathematical formulations to quantify the strengthening effect of actions. Academic research can, inter alia, integrate the metrics into multi-criteria optimization models for decision-making and explore the interplay between economic efficiency, environmental sustainability, and resilience.

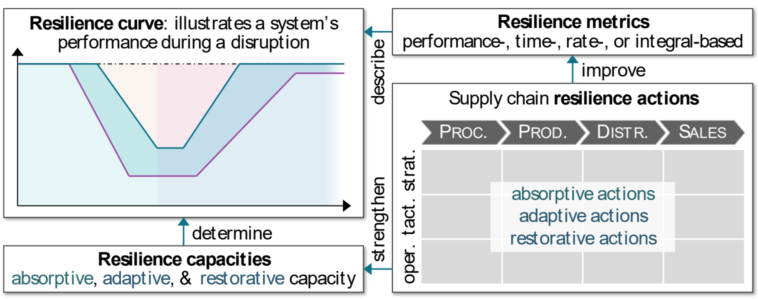

Figure B 1: *Graphical abstract. Relationship between resilience capacities, resilience curve, resilience metrics, and resilience actions.*

1. INTRODUCTION

Supply chains provide products and services to customers and society, and to be competitive, the product or service must be provided cost-efficiently and fast. Companies thus strive to increase their economic performance by increasing revenues (e.g., expansion of product variety), reducing costs (e.g., reduction of the number of suppliers, just-in-time production), and reducing assets (e.g., outsourcing of less profitable divisions), which has led to long and complex global supply chains (Tang, 2006). However, economic efficiency under normal circumstances can come with high costs and even lead to uncompetitive supply chains in case of unexpected disruptions and changing market environments (Lee, 2004). In light of pandemics, politically unstable regions, vulnerable trade routes, and consequences of climate change, the topic of supply chain disruptions is more discussed than in previous decades. For example, the COVID-19 pandemic demonstrated how shortages due to local production stops can propagate through highly specialized, efficient, and global supply chains, leading to disrupted systems and networks (Pujawan & Bah, 2022). Similarly, the obstruction of the Suez Canal by the *Ever Given* in March 2021 blocked 12% of the daily global trade for six days and caused a total economic loss of between $6 and $10 billion, illustrating the vulnerability of global supply chains (Russon, 2021).

Those two prominent examples demonstrate that a wide variety of causes can compromise the performance of a supply chain. Bruneau et al. (2003) initially presented a conceptual framework for studying a system's resilience by mapping a performance degradation after a disruption over time, which later resulted in the so-called 'resilience curve'. *Resilience metrics* formally describe the curve and are thereby an indicator for the resilience of a system that faces a disruption (Poulin & Kane, 2021). How good or bad a supply chain copes with a disruption depends on its *resilience capacities*, i.e., its capabilities to absorb the disturbance, adapt to the changed conditions, or restore the status quo ante (Biringer et al., 2013; S. Hosseini et al., 2019; Vugrin et al., 2011). *Resilience actions* are precautionary, anticipatory steps that decision-makers can proactively take to strengthen the absorptive (e.g., physical protection of plant), adaptive (e.g., rerouting), and restorative (e.g., repair team) capacities and thereby to improve the resilience metrics (Carvalho et al., 2012; S. Hosseini et al., 2019; H. Sun et al., 2022).

Several literature reviews on supply chain resilience (SCR) have investigated definitions, quantification methods, and resilience actions. Among existing definitions of SCR, there is little consensus regarding terminologies and the various aspects that 'resilience' may comprise (Y. Han et al., 2020; Hohenstein et al., 2015; Kamalahmadi & Parast, 2016; Poulin & Kane, 2021; Ribeiro & Barbosa-Póvoa, 2018).

To fill this gap, some reviews have synthesized existing definitions (e.g., Kamalahmadi & Parast, 2016) or proposed frameworks to analyze existing and standardize new definitions (e.g., Ribeiro & Barbosa-Póvoa, 2018).

Other reviews have focused on existing quantitative SCR assessment methods and their relation to qualitative, theoretical resilience concepts. Y. Han et al. (2020) synthesized the literature on performance metrics of resilience, identified *readiness*, *response*, and *recovery* as the three main resilience capacities, and presented a framework to link capacities to metrics. S. Hosseini et al. (2019) reviewed operations research (OR) models incorporating resilience metrics and categorized actions (i.e., proactive or reactive decisions) to increase SCR according to the absorptive, adaptive, and restorative capacities. Both studies identified a lack of resilience metrics that are developed based on capacities (Y. Han et al., 2020; S. Hosseini et al., 2019). Ribeiro & Barbosa-Póvoa (2018) reviewed quantitative SCR models and concluded that many studies examine drivers of resilience (e.g., connectivity of edges within a network, or robustness of a supply chain) without quantifying resilience per se. Similarly, Sharkey et al. (2021) investigated the relationship between network optimization and resilience theory in articles on physical or cyber-physical systems by classifying networks according to four resilience aspects (robustness, rebound, adaptability, and extensibility). They found that most models focus on the optimization of system robustness and rebound, while the aspects of adaptability and extensibility are rarely represented. As a first attempt to close the gap between quantitative approaches and concepts of resilience theory, Poulin & Kane (2021) addressed previous findings on heterogeneous metrics and terminologies. They introduced a standardized taxonomy and categorized existing metrics according to the characteristics of the resilience curve they describe (Poulin & Kane, 2021).

Other reviews have focused on quantitative methods that aim to increase SCR by actions. Hohenstein et al. (2015) and Behzadi et al. (2020) analyzed existing quantitative methods and categorized actions separately, and Snyder et al. (2016) categorized methods from OR and management science according to their aim (e.g., assessment of disruption effects on supply chains, modeling of decisions on sourcing strategy) and found that most models consider only a single resilience action.

Although the existing reviews contribute to a better understanding of existing SCR definitions and the interrelations between resilience capacities and resilience metrics, as well as between resilience actions and resilience metrics, the following research gaps still exist:

Gap 1: The terminology for resilience capacities is heterogeneous and needs clarification and consolidation. In contrast to existing reviews, we aim to provide an overview of various existing terms and analyze which of the aforementioned capacities established in resilience theory (i.e., absorptive, adaptive, restorative capacity) is addressed.

Gap 2: The relation between the concept of the resilience curve, resilience capacities, and existing quantitative metrics needs to be analyzed. To extend the work of Poulin & Kane (2021), we use their proposed taxonomy to reformulate the heterogeneous mathematical formulation of the various metrics employed in the literature, locate them along the resilience curve, and analyze the differences in the mathematical formulation. Finally, we propose a set of metrics with a unified terminology and synthesized mathematical formulations, with which all characteristics of the resilience curve can be described quantitatively. In addition, we integrate the resilience capacities into the resilience curve to draw the relationship between resilience capacities, resilience metrics, and the resilience curve.

Gap 3: The benefit of resilience actions needs to be quantifiable (Behzadi et al., 2020). We conceptually present how the set of metrics (cf. gap 2) can be used to quantify the positive effect of resilience actions on each characteristic of the resilience curve.

Gap 4: The relation between resilience actions, traditional supply chain planning tasks, and their effect on resilience is underrepresented in SCR literature. Sharkey et al. (2021) state that the contribution of resilience actions to the improvement of the overall resilience of a system is insufficiently investigated. Studies have already classified existing resilience actions according to their type (e.g., Hohenstein et al., 2015), time-horizon (e.g., Ribeiro & Barbosa-Póvoa, 2018), or which capacities they strengthen (e.g., S. Hosseini et al., 2019). However, understanding the interplay between traditional supply chain planning tasks, resilience actions, and the capacities strengthened by these actions is essential for estimating the effect of planning decisions on SCR. Our work categorizes identified resilience actions according to their time-horizon and type of planning task and draws the link to the capacities that are strengthened. Against this background, we investigate the following research questions:

- *RQ1:* Which terminology does resilience literature use to describe *resilience capacities* (*gap 1*)?
- *RQ2*: Which general mathematical formulations of *resilience metrics* can be derived from literature to describe the resilience curve and to assess the *resilience capacities* (*gap 2*)? How can the effect of *resilience actions* be quantified with these metrics (*gap 3*)?
- *RQ3*: Which *resilience actions* for strengthening the SCR are proposed in the literature, and how can they be classified (*gap 4*)?

To answer RQ1 and RQ2, we review articles on SCR as well as articles on systems and networks other than supply chains. This is attributed to the rapid development of the field of resilience research, which is why including systems and networks ensures that the state-of-the-art of system resilience theory and resilience quantification is captured. Finally, RQ3 is answered based on the reviewed supply chain literature specifically.

This work adds to the existing literature by investigating the relations between *resilience capacities*, *resilience metrics*, and *resilience actions.* It further contributes to a standardized terminology and, consequently, a common qualitative and quantitative understanding of resilience in the supply chain context based on the concept of the resilience curve. To the best of our knowledge, our work is the first that derives a literature-based set of generalized metrics for assessing the benefit of resilience actions on each characteristic of the resilience curve. This set is proposed as a basis for decision-making to strengthen the resilience of supply chains. Section 2 presents the method to identify, review, and analyze the relevant literature. Section 3 answers the research questions: Section 3.1 analyzes the existing types of *performance, i.e*., the benchmark value against which the resilience of a system is measured. Section 3.2 analyzes how resilience capacities are understood in the literature and which terms are used. Section 3.3 analyzes existing metrics, their relation to the resilience curve and the capacities, and how they can be used to assess resilience actions. In Section 3.4, the resilience actions proposed in the supply chain literature are classified into an extended version of the traditional supply chain planning matrix by Fleischmann et al. (2008). Finally, Section 4 discusses the limitations of our work and provides an outlook on how our findings can be used by both academia for future research and supply chain decision-makers.

2. METHOD

Figure B 2 visualizes the research procedure to identify resilience capacities, metrics, and actions from existing literature. Since we focus on articles that explicitly provide a resilience metric, keywords referring to *metrics* and *resilience* are included in a title search. Many quantitative SCR articles have developed optimization models containing metrics as objective functions or constraints to design or improve resilient systems. Consequently, the title search also includes two keywords referring to optimization to cover these articles in our analysis. Furthermore, the applied search string is tailored to detect metrics in the context of systems and networks, and supply chains in particular. Since existing research on resilience theory mainly focuses on systems, with supply chains being one prominent example (S. Hosseini et al., 2016; Poulin & Kane, 2021; Quitana et al., 2020), we extend the search to the literature on resilient systems in general, aiming to transfer insights (e.g., metrics) to supply chains specifically. The terms *system*, *network*, *supply network*, and *supply chain* are therefore searched in title, abstract, and keywords. The terms *capacity* and *actions* are intentionally not included in the search string since existing literature may refer to these concepts with a plethora of different terms. The search for peer-reviewed articles was conducted in August 2023 in the 'Web of Science' database, which was chosen due to its multidisciplinary scope and frequent use within quantitative resilience reviews. We are aware that the applied search string might not identify all articles on resilience optimization models that might be applied in individual OR case studies. However, the search string adequately covers our primary goal to include a broad set of existing metrics that are sufficient to quantify all resilience curve characteristics and the effect of resilience actions. The application of a broader search string, including synonyms of *resilience* (e.g., *disruption* or *risk*) or the keywords *metric* or *optimization* in the topic search, would lead to an unmanageable number of results.

In total, 1,653 articles were identified and subsequently screened based on their title, abstract, and keywords. In this step, 1,159 articles were excluded when they (1) focus on psychology, livelihood, or human, animal, social, or ecological systems, (2) do not present resilience metrics or a resilience objective function, or (3) cannot be linked to the resilience curve. Consequently, 494 articles were identified as eligible for the full-text analysis as they present a resilience metric in the context of supply chains, systems, or networks and can be linked to the resilience curve or resilience capacities.

After the full-text analysis, 323 articles were excluded when (1) the proposed resilience metric cannot be expressed quantitatively, (2) the resilience metric cannot be linked with the resilience curve, (3) the mathematical formulation of the resilience metric is missing, or (4) the article presents a review of resilience metrics, resulting in 171 relevant articles. Lastly, we conducted a backward search with (previously excluded) SCR reviews and the identified SCR articles, which yielded 49 additional articles. In total, 220 relevant articles (see Appendix B 1) were analyzed in depth. If possible, three main pieces of information were extracted from these articles: (1) the terminology applied to describe resilience capacities, (2) the resilience metric and its mathematical formulation, and (3) the resilience actions proposed to strengthen the resilience capacities of supply chains.

Section 3.2 assigns the identified terms to describe resilience aspects to the corresponding capacities. Section 3.3 analyzes and consolidates the resilience metrics. First, we identify the mathematical formulations of 395 metrics in the investigated literature. Second, these metrics are reformulated using the taxonomy of Poulin & Kane (2021) to express the mathematical formulations in a standardized language (e.g., $p(t)$ is the performance at any time t).

Third, the standardized metrics are mapped to the characteristics of the resilience curve they describe. Fourth, we analyze the variants of the mathematical formulations for each characteristic and ultimately synthesize them into 17 unified metrics. Finally, in Section 3.4, the identified resilience actions are assigned to existing supply chain planning tasks and categorized according to the planning horizon and the resilience capacity that is strengthened. All identified actions are located in an extended version of the traditional supply chain planning matrix introduced by Fleischmann et al. (2008).

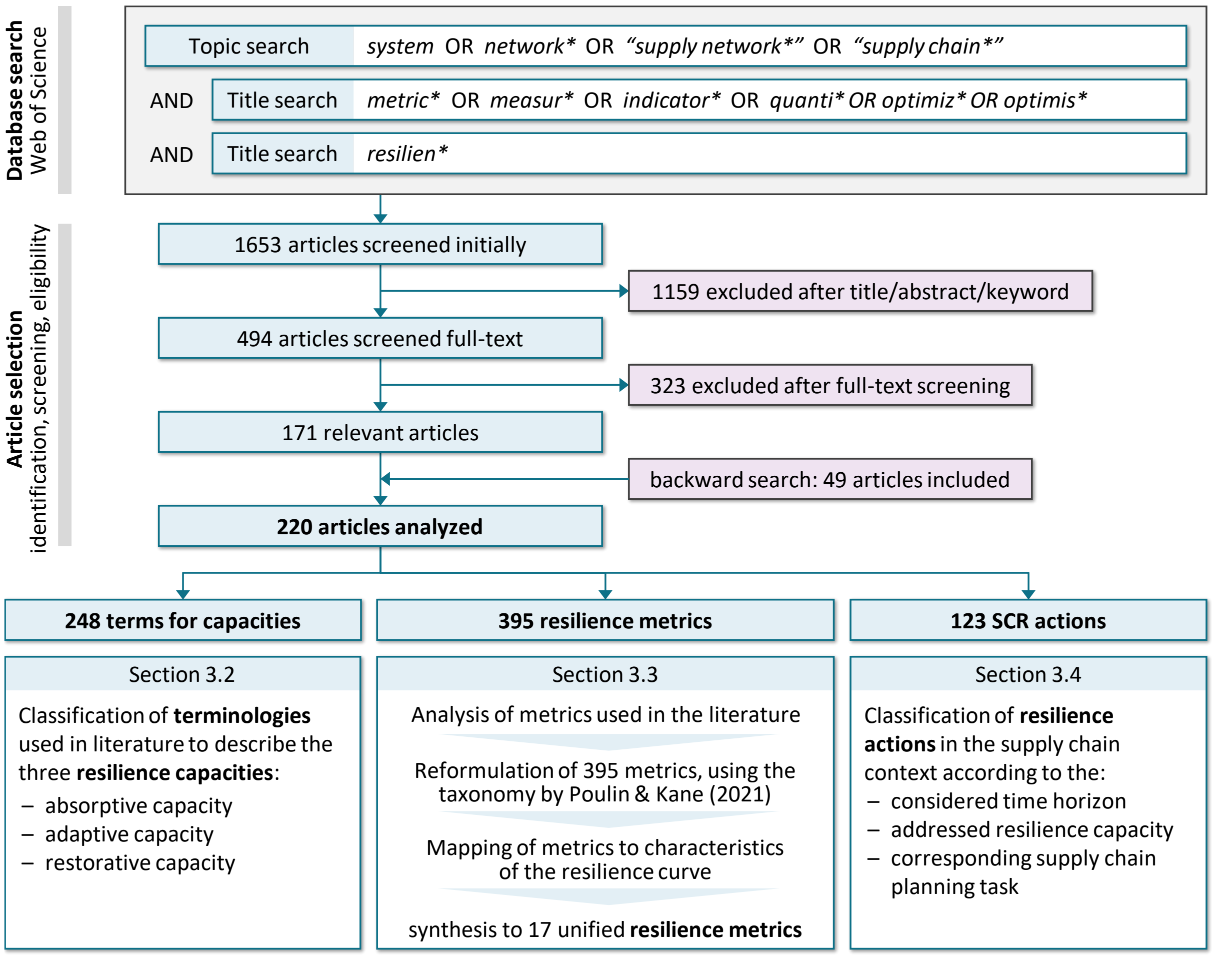

Figure B 2: *Literature search and review methodology.*

3. Results

Section 3 analyzes the identified terminologies for capacities, metrics, and actions. It discusses different types of system performances (Section 3.1), analyzes and harmonizes terms used to describe resilience capacities and maps them to the resilience curve (Section 3.2), compiles a set of 17 metrics to quantify all characteristics of the resilience curve and the benefit of resilience actions (Section 3.3), and reviews resilience actions and classifies them into an extended supply chain planning matrix (Section 3.4).

3.1 TYPES OF PERFORMANCE

A wide variety of causes can disrupt the performance of supply chains. Observing *performance* over time allows for illustrating the resilience curve of disrupted systems, which builds the foundation for resilience considerations in various studies. Since there is no unambiguous measure of a system's performance, this section examines how 'performance' is interpreted in the literature: It either refers to the *productivity* of a system (economic performance $p_e(t)$, physical output $p_o(t)$), to the *quality* ($p_q(t)$), or to *availability* criteria (availability/number of components $p_n(t)$) (Poulin & Kane, 2021).

The majority (174 of 220) of the reviewed articles present resilience metrics based on output performance. In the context of supply chains specifically, this can refer to the percentage of fulfilled demand (Ojha et al., 2018; Ribeiro & Barbosa-Póvoa, 2022; Sawik, 2017; Schmitt & Singh, 2012; Zavala et al., 2019), the number of products shipped from the manufacturer to the customer (Fattahi et al., 2017; Rajesh, 2016), the number of products not delivered from supplier to the manufacturer (Torabi et al., 2015), or the production capacity (Vugrin et al., 2011). Most of the remaining studies refer to the output performance in terms of the loss in system functionality (e.g., Francis & Bekera, 2014; Ghosh & De, 2022; Henry & Ramirez-Marquez, 2012; Sun et al., 2022). Only 52 of 220 studies present resilience metrics based on economic, quality, or availability criteria. Economic criteria determine the system's performance in 30 studies, especially in the context of SCR. Here, most of the presented metrics are based on the increase in costs associated with a disruption and/or recovery (e.g., Anderson et al., 2018; Arab et al., 2016; Belhadi et al., 2021; Carvalho et al., 2012; Fattahi et al., 2020; Hishamuddin et al., 2013; Maheshwari et al., 2017; Mari et al., 2014; Shahbazi et al., 2021; Smith et al., 2020; Vugrin et al., 2011; H. Zhang et al., 2018, 2019), or to the overall profit or lost profit (e.g., Bao et al., 2019; Behzadi et al., 2020; Shang et al., 2022; W. J. Tan et al., 2020). Ribeiro & Barbosa-Póvoa (2022) propose the cash flow-based expected net present value as part of their resilience metric. 16 studies describe the performance through quality parameters $p_q(t)$ such as the lead time (Carvalho et al., 2012; Spiegler et al., 2012), the ratio of products delivered on-date, the ratio of shipments arriving with no damage (Rajesh, 2016), the reliability of infrastructure (Aghababaei et al., 2021; Bruneau et al., 2003), or individual performance indices (e.g., Y. Bai et al., 2022; Zarghami & Zwikael, 2022). Ten studies refer to the performance based on the availability of components $p_n(t)$ by evaluating the number of failed edges or nodes in power systems (Ouyang et al., 2012; Panteli et al., 2017; Yarveisy et al., 2020; H. Zhang et al., 2018), the number of employed workers (Di Tommaso et al., 2023), or the number of facilities affected by a stockout within a supply chain (Rajesh, 2016).

3.2 Resilience capacities

How a system maintains its performance in case of a disruption depends on the system's *resilience capacities*. Most conceptual resilience literature differentiates between *absorptive*, *adaptive*, and *restorative capacity* (Biringer et al., 2013; S. Hosseini et al., 2019; Vugrin et al., 2011), with some literature separately including a *withstanding capacity* (Ouyang et al., 2012; Shin et al., 2018; Umunnakwe et al., 2021). *Absorptive capacity* is the extent of a system's ability to resist or absorb external impacts and refers to the system's vulnerability (Biringer et al., 2013; Vugrin et al., 2011). A*daptive capacity* is a system's ability to reorganize itself to offset disruptions (Biringer et al., 2013; Vugrin et al., 2011), and *restorative capacity* describes a system's repair efficiency and effectiveness (Biringer et al., 2013; Vugrin et al., 2011); both refer to a system's recoverability. In this chapter, we investigate the terms used in literature to refer to the characteristic of the resilience curve that is addressed by a metric. Consequently, the evaluated terms are assigned to the related resilience capacity. Our procedure aims to categorize heterogeneous terminology on resilience capacities. We thereby contribute to a better understanding of the relation between resilience metrics and absorptive, adaptive, and restorative capacity, as pointed out by Y. Han et al. (2020). In some works, it is noticeable that the terms *capacity* and *capability* have been used interchangeably, with a majority of studies using the term *capacity*. This work only uses *capacity* but understands the two terms as synonyms. In total, 248 terms (81 unique terms) relating to the absorptive, adaptive, or restorative capacity were identified in the literature and are analyzed in detail in the following (cf. Table B 1).

95 of the 220 investigated studies refer to the *absorptive capacity*. Absorptive capacity has the highest impact on a system's performance from the beginning of the disruptive event until the performance is compromised the most (cf. Figure B 3). The term 'absorptive capacity' itself has been used by ten studies (Aghabegloo et al., 2023; Cheng et al., 2020; Francis & Bekera, 2014; Jinyi et al., 2020; Ouyang et al., 2012; Vugrin et al., 2011; Y. Yang et al., 2018; Yarveisy et al., 2020; Zhao et al., 2016, 2017). Eleven studies use the term 'robustness' when referring to absorptive capacity (Ahmadi et al., 2022; Amirioun et al., 2019; Beyza & Yusta, 2021; Cimellaro et al., 2010; Dong et al., 2022; Fang & Zio, 2019; Goldbeck et al., 2019; Y. Li & Zobel, 2020; Reed et al., 2009; Tao et al., 2022; Yao et al., 2023; Z. Zhang et al., 2023). For example, Fang & Zio (2019) propose a resilience metric to quantify the robustness of a system as the functionality right after the disruption. Nine studies use the term 'vulnerability' (Alguacil et al., 2014; Amirioun et al., 2019; Fang et al., 2015; Ghorbani-Renani et al., 2020; Kim & Yeo, 2016; Mari et al., 2014; Niu et al., 2023; Ojha et al., 2018; Z. Zhang et al., 2023) to describe resilience metrics which, e.g., assess the event impact in terms of the immediate performance decline (Amirioun et al., 2019). Six studies use the term 'absorption' (Najarian & Lim, 2019;

Roach et al., 2018; Tran et al., 2017; Valenzuela et al., 2018; Veit et al., 2023) for metrics that evaluate, e.g., how well the performance of a system can be retained during a disruption (Najarian & Lim, 2019). Five studies refer to 'responsiveness' to describe the immediate reaction to a disruption (Ahmadian et al., 2020; Ayala-Cabrera et al., 2019; Rajesh, 2016; Schmitt & Singh, 2012). Three studies use the term 'resistance', which is used similarly to 'robustness' (Amirioun et al., 2019; H. Li et al., 2023; H. Zhang et al., 2018). Only three studies use the term 'absorptive capability' (Nan et al., 2016; Nan & Sansavini, 2017; X. Wang et al., 2022), underlining the dominance of the term 'capacity' in quantitative resilience literature. However, some works use terms like 'recovery speed' (Y. Li & Zobel, 2020; Z. Liu & Wang, 2021; Schmitt & Singh, 2012) or 'rapidity' (Huang & Pang, 2014; Ren et al., 2017; X. Wang et al., 2022), which do not explicitly refer to absorptive capacity. Those works aim at quantifying resilience on an aggregated level without differentiation between resilience capacities. In this case, we separated the applied metrics into the components that describe the characteristics of the resilience curve that refer to absorptive capacity (see Section 3.3). For example, the duration of performance degradation from the start of disruption to the minimum performance describes the absorptive capacity of the system as part of a metric that quantifies the total duration of disruption (e.g., Ren et al., 2017). The remaining identified terms are closely related to absorptive capacity and either refer to the aspect of robustness (i.e., 'redundancy and robustness', 'resistant capacity', 'resistance ability', 'withstanding capacity', 'withstanding capability') or absorption (i.e., 'response', 'mitigation', 'mitigation ability', 'sustainability'). 78 studies do not use a term related to the absorptive capacity, although we conclude that they present a corresponding metric.

The *adaptive capacity* and *restorative capacity* jointly correspond to a system's recoverability (S. Hosseini et al., 2019) after a shock and thus affect the performance from its lowest point to the end of recovery. The *adaptive capacity* is mentioned in eleven studies, of which the majority directly refer to the resilience curve and the differentiation between the three resilience capacities. The majority of studies use the term '*adaptive capacity'* (Aghabegloo et al., 2023; Francis & Bekera, 2014; Gotangco et al., 2016; Vugrin et al., 2011; Yarveisy et al., 2020; Zhao et al., 2016, 2017). These studies aim to assess the extent to which a system can increase its performance to a new equilibrium as a reaction to a disruption. Alternative terms are 'adaptive capability' (C. Chen et al., 2021; Nan & Sansavini, 2017) and 'adaptation' (Najarian & Lim, 2019, 2020), appearing in two studies each, and 'adaptability' (Ojha et al., 2018). The term 'redundancy' is used by two studies to evaluate the extent of performance recovery by using alternative routes within a redundant road network (Aghababaei et al., 2021) or the duration until the redundancy of a network is used for performance recovery of a communication network (Appasani et al., 2022). 33 studies refer with their metrics to *restorative capacity*. Most of them use the term 'restoration' (Alizadeh et al., 2022; Arab et al., 2016;

Baroud et al., 2014; Cavdaroglu et al., 2013; Fang & Sansavini, 2017b, 2019; Heath et al., 2016; Henry & Ramirez-Marquez, 2012; Matisziw et al., 2010; Ni et al., 2018; Niu et al., 2023; Nurre et al., 2012; Nurre & Sharkey, 2018; Pant et al., 2014; Sang et al., 2021; Y. Tan et al., 2018, 2019; Ulusan & Ergun, 2018; Z. Yang & Marti, 2022), followed by the term 'restorative capacity' (Aghabegloo et al., 2023; Cheng et al., 2020; Ouyang et al., 2012; Vugrin et al., 2011; Y. Yang et al., 2018; Yarveisy et al., 2020). The majority of these studies present metrics to assess the extent of performance restored from disruptions by repair activities (e.g., Baroud et al., 2014; Henry & Ramirez-Marquez, 2012; Ouyang et al., 2012; Pant et al., 2014; Yarveisy et al., 2020). Similar terms like 'restorative capability' (Nan & Sansavini, 2017), 'restoration ability' (Khayatzadeh et al., 2022), and 'restoration capability' (C. Chen et al., 2021) appear in single studies. Two studies each refer to the terms 'restoration efficiency' to assess the effectiveness (Amirioun et al., 2019; H. Zhang et al., 2018) and 'restoration economy' to evaluate the costs (H. Zhang et al., 2018, 2019) of restoration.

108 studies use terminology that cannot be mapped unambiguously to one of the three capacities. The most common ambiguous term is 'recovery', appearing in 36 studies (e.g., R. Li et al., 2017), followed by 'recovery ability' in ten studies (Galbusera et al., 2016; Hao et al., 2023; Jinyi et al., 2020; H. Li et al., 2023; Nan et al., 2016; Podesta et al., 2021; W. J. Tan et al., 2020; Tao et al., 2022; J. W. Wang et al., 2010; Zhao et al., 2016) indicating that most of these studies do not build their resilience metrics on the theoretical concept of three distinct capacities. Instead, they differ in the ability of a system to absorb and recover from a disruption (e.g., Galbusera et al., 2016) without clearly indicating if the adaptive or restorative capacity has affected the recovery. In eight studies, the term 'responsiveness' is used to describe the speed and extent of performance recovery attributable to the system's restorative and adaptive capacities (Fattahi et al., 2017; Ribeiro & Barbosa-Póvoa, 2022; Schmitt & Singh, 2012; Watson et al., 2022; H. Zhang et al., 2018). The term 'rapidity' and 'recovery rapidity' is used in eight and four studies and refers to the speed (Goldbeck et al., 2019; Mao et al., 2021; Najarian & Lim, 2020; Ren et al., 2017; Q. Zhang et al., 2020; L. Zhou & Chen, 2020), the slope of the performance curve (Arjomandi-Nezhad et al., 2021; Cimellaro et al., 2010; Reed et al., 2009), or the ability/inability to recover within a proper time (Arjomandi-Nezhad et al., 2021; Bruneau et al., 2003; Fang & Zio, 2019; Huang & Pang, 2014), which could either be attributed to adaptive or restorative capacity. The terms 'recovery capability', 'recovery capacity', 'recovery effort', and 'recoverability' are also used to describe metrics focusing on the extent of performance recovery and do not explicitly refer to adaptive or restorative capacity. 29 studies use individual terms to describe their resilience metrics.

However, 90 studies present resilience metrics, which, according to our understanding, assess adaptive or restorative capacity without using any terminology besides ‘resilience’.

Table B 1: *Heterogeneity in the terminology in the observed literature. The table links the used terms with associated resilience capacities (absorptive, adaptive, and restorative; Vugrin et al., 2011). A complete list of the reviewed articles is provided in Appendix B 1.*

Term		**Articles**
Absorptive capacity		
‘robustness’	11	(Ahmadi et al., 2022; Amirioun et al., 2019; Cimellaro et al., 2010; Dong et al., 2022; Fang & Zio, 2019; Goldbeck et al., 2019; Y. Li & Zobel, 2020; Reed et al., 2009; Tao et al., 2022; Yao et al., 2023; Z. Zhang et al., 2023)
‘absorptive capacity’	10	(Aghabegloo et al., 2023; Cheng et al., 2020; Francis & Bekera, 2014; Jinyi et al., 2020; Ouyang et al., 2012; Vugrin et al., 2011; Y. Yang et al., 2018; Yarveisy et al., 2020; Zhao et al., 2016, 2017)
‘vulnerability’	9	(Alguacil et al., 2014; Amirioun et al., 2019; Fang et al., 2015; Ghorbani-Renani et al., 2020; Kim & Yeo, 2016; Mari et al., 2014; Niu et al., 2023; Ojha et al., 2018; Z. Zhang et al., 2023)
‘absorption’	6	(Najarian & Lim, 2019, 2020; Roach et al., 2018; Tran et al., 2017; Valenzuela et al., 2018; Veit et al., 2023)
‘responsiveness’	4	(Ayala-Cabrera et al., 2019; Q. Han et al., 2023; Rajesh, 2016; Schmitt & Singh, 2012)
’resistance’	3	(Amirioun et al., 2019; H. Li et al., 2023; H. Zhang et al., 2018)
‘absorptive capability’	3	(Nan et al., 2016; Nan & Sansavini, 2017; X. Wang et al., 2022)
‘recovery speed’	3	(Y. Li & Zobel, 2020; Z. Liu & Wang, 2021; Schmitt & Singh, 2012)
‘sustainability’	3	(Anderson et al., 2018; Cimellaro et al., 2015; C. Zhang et al., 2022)
’rapidity’	3	(Huang & Pang, 2014; Ren et al., 2017; X. Wang et al., 2022)
‘redundancy’; ‘robustness’	2	(Ayyub, 2014; Didier et al., 2018)
‘resistant capacity’	2	(Ouyang et al., 2012; Y. Yang et al., 2018)
‘response’	2	(Ahmadian et al., 2020; Z. Zhang et al., 2023)
‘mitigation’	2	(X. Liu et al., 2021; Lücker & Seifert, 2017)
‘resistance ability’	2	(W. J. Tan et al., 2020; Tao et al., 2022)
‘withstanding capacity’	2	(Fan et al., 2023; Marasco et al., 2022)
‘withstanding capability’	2	(Kwasinski, 2016; Tofani et al., 2018)
‘mitigation ability’	2	(Abdin et al., 2019; Gabrielli et al., 2022)
+ 24 other terms	1	
Adaptive capacity		
‘adaptive capacity’	7	(Aghabegloo et al., 2023; Francis & Bekera, 2014; Gotangco et al., 2016; Vugrin et al., 2011; Yarveisy et al., 2020; Zhao et al., 2016, 2017)
‘adaptive capability’	2	(C. Chen et al., 2021; Nan & Sansavini, 2017)
‘adaptation’	2	(Najarian & Lim, 2019, 2020)
‘redundancy’	2	(Aghababaei et al., 2021; Appasani et al., 2022)
‘adaptability’	1	(Ojha et al., 2018)
Restorative capacity		
‘restoration’	20	(Alizadeh et al., 2022; Arab et al., 2016; Baroud et al., 2014; Cavdaroglu et al., 2013; Fang & Sansavini, 2017a, 2019; Heath et al., 2016; Henry & Ramirez-Marquez, 2012; Matisziw et al., 2010; Ni et al., 2018; Niu et al., 2023; Nurre et al., 2012; Nurre & Sharkey, 2018; Pant et al., 2014; Sang et al., 2021; Sharkey et al., 2015; Y. Tan et al., 2018, 2019; Ulusan & Ergun, 2018; Z. Yang & Marti, 2022)
‘restorative capacity’	6	(Aghabegloo et al., 2023; Cheng et al., 2020; Ouyang et al., 2012; Vugrin et al., 2011; Y. Yang et al., 2018; Yarveisy et al., 2020)
‘restoration efficiency’	2	(Amirioun et al., 2019; H. Zhang et al., 2018)
‘restoration economics’	2	(H. Zhang et al., 2018, 2019)
+ 4 other terms	1	

Adaptive or restorative capacity (allocation ambiguous)		
'recovery'	36	(Abdelmalak et al., 2023; Ahmadi et al., 2021, 2022; Ahmadian et al., 2020; G. Bai et al., 2021; Bao et al., 2019; Beyza & Yusta, 2021; Burton et al., 2017; Carvalho et al., 2022; Di Tommaso et al., 2023; Dui et al., 2023; Fattahi et al., 2020; Hishamuddin et al., 2013; Y. Hosseini et al., 2023; Kwasinski, 2016; Kyriakidis et al., 2018; M. Li et al., 2019; R. Li et al., 2017; X. Liu et al., 2021; Mishra et al., 2022; Munoz & Dunbar, 2015; Najarian & Lim, 2019; Reed et al., 2009; Roach et al., 2018; Senkel et al., 2021; Smith et al., 2020; Spiegler et al., 2012; Tofani et al., 2021; Tran et al., 2017; Veit et al., 2023; J. Zhang et al., 2022; J. Zhang, Li, et al., 2023; J. Zhang, Ren, et al., 2023; M. Zhang et al., 2022; Z. Zhang et al., 2023; Zhao & You, 2019)
'recovery ability'	10	(Galbusera et al., 2016; Hao et al., 2023; Jinyi et al., 2020; H. Li et al., 2023; Nan et al., 2016; Podesta et al., 2021; W. J. Tan et al., 2020; Tao et al., 2022; J. W. Wang et al., 2010; Zhao et al., 2016)
'responsiveness'	8	(Fattahi et al., 2017; Q. Han et al., 2023; Rajesh, 2016; Ribeiro & Barbosa-Póvoa, 2022; Schmitt & Singh, 2012; Watson et al., 2022; H. Zhang et al., 2018, 2019)
'rapidity'	8	(Bruneau et al., 2003; Cimellaro et al., 2010; Goldbeck et al., 2019; Huang & Pang, 2014; Reed et al., 2009; Ren et al., 2017; Q. Zhang et al., 2020; L. Zhou & Chen, 2020)
'recovery capability'	7	(Baroud et al., 2014; L. Chen & Miller-Hooks, 2012; Fang & Sansavini, 2017b; Q. Han et al., 2023; Miller-Hooks et al., 2012; Nan & Sansavini, 2017; X. Wang et al., 2022)
'recovery capacity'	6	(Fan et al., 2023; Marasco et al., 2022; Song et al., 2022; Yu & Baroud, 2019; Zhao et al., 2016, 2017)
'recovery rapidity'	4	(Arjomandi-Nezhad et al., 2021; Fang & Zio, 2019; Mao et al., 2021; Najarian & Lim, 2020)
'recoverability'	3	(Fang et al., 2016; Francis & Bekera, 2014; Ghorbani-Renani et al., 2020)
'recovery effort'	2	(Chan & Schofer, 2016; Das, 2020)
+ 29 other terms	1	

3.3 Resilience metrics

Resilience metrics describe the resilience curve and can be used to assess the system's capacities to absorb, adapt, or restore in case of a disruption. In the literature, we identify 395 metrics. As already apparent from the terminology used to describe these metrics (see Section 3.2), many studies combine different aspects of the resilience curve into one single metric, which we break down into its components for comparability. This procedure results in 523 metrics analyzed in this review (see Supporting Information B (B)). We apply a consistent taxonomy (cf. Appendix B 2) on these metrics to reformulate the mathematical formulations for a comparative analysis. Finally, they are categorized according to the characteristic elements of the resilience curve they describe and to the related capacity. Thus, we complement and extend the set of resilience metrics introduced by Poulin & Kane (2021). The resulting set of 17 resilience metrics describes all characteristics of the resilience curve. It represents the state of the art of quantifying resilience (i.e., the absorptive, adaptive, and restorative capacities) of systems and networks, specifically supply chains.

After describing the resilience curve in Figure B 3, this section analyses the 17 metrics in detail and proposes mathematical formulations to assess the improvement of these metrics by resilience actions.

Figure B 3 displays the idealized performance of a system in case of a disruption, commonly referred to as the *resilience curve*. The performance is generically denoted with $p(t)$ and each characteristic point in time is based on the literature: The observation period starts at t_0 (e.g., Fang & Zio, 2019; Q. Han et al., 2023; Losada et al., 2012; Ouyang et al., 2012; Poulin & Kane, 2021; Spiegler et al., 2012; Touzinsky et al., 2018; Veit et al., 2023), the actual hazard at t_{h0} (e.g., Abdin et al., 2019; Amirioun et al., 2019; Anderson et al., 2018; Poulin & Kane, 2021; Y. Yang et al., 2018), and the disruption at t_e (e.g., Fattahi et al., 2020; R. Li et al., 2017; Munoz & Dunbar, 2015; Vugrin et al., 2011). The hazard then ends at t_{h1} (Senkel et al., 2021; Y. Yang et al., 2018; H. Zhang et al., 2018), the performance stops to degrade at t_d (e.g., Ayyub, 2014; Shen et al., 2023; Valenzuela et al., 2018; Zavala et al., 2019; J. Zhang, Ren, et al., 2023), the recovery starts at t_s (e.g., Nan & Sansavini, 2017; Panteli et al., 2017; Poudel et al., 2020; H. Zhang et al., 2019) and ends at t_f (e.g., Das, 2020; Marasco et al., 2022; Omer et al., 2009; Sun et al., 2022). t_c marks the end of the observation period (e.g., Blagojević et al., 2022; Cimellaro et al., 2010; Nozhati, 2021; Tran et al., 2017). Our work introduces the metrics *absorb duration*, *failure ratio*, *cumulative absorptive performance*, and *cumulative absorptive impact* in addition to the resilience metrics *depth of impact*, *residual performance*, *critical threshold, residual capacity*, *failure rate*, and *resistive duration* (defined by Poulin & Kane, 2021), which can be applied for assessing its absorptive capacity. We further introduce the metrics *cumulative recovery performance*, *cumulative recovery impact*, *endure duration*, and the r*ecovery duration* in addition to the *recovery rate*, *recovery ratio*, and *restored performance* (defined by Poulin & Kane, 2021), which can be used to determine adaptive and restorative capacity.

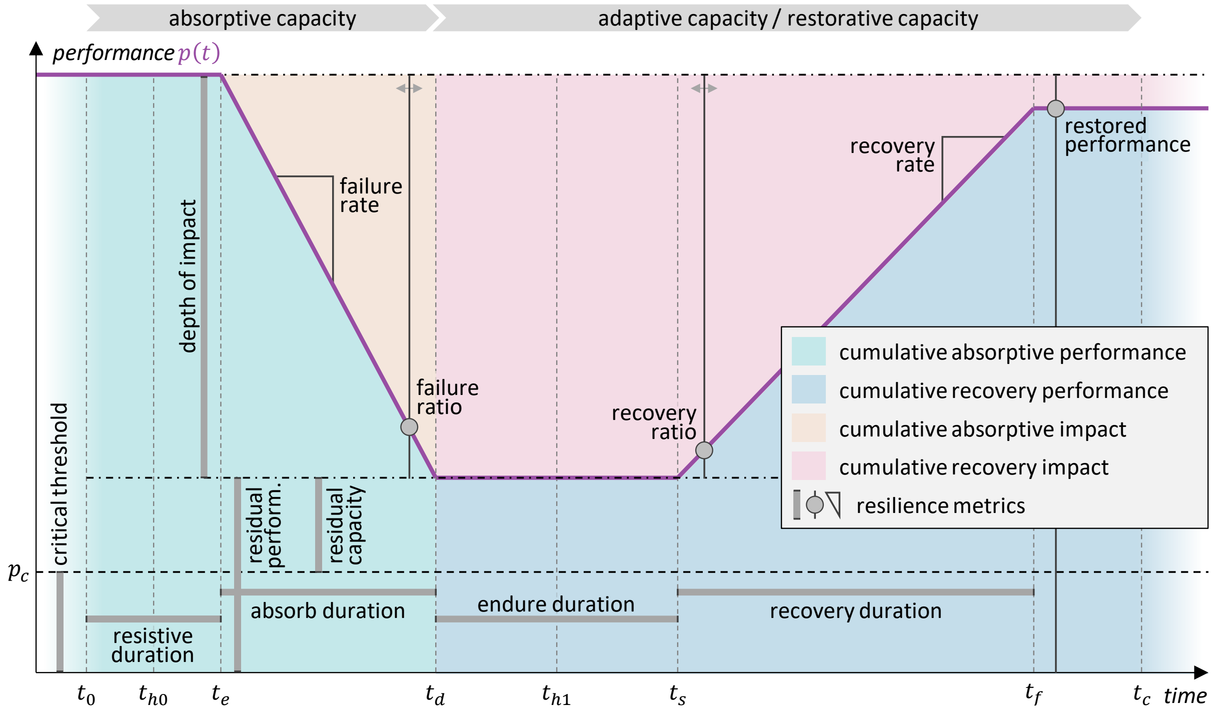

Figure B 3: *General resilience curve with resilience metrics identified in the reviewed literature or as summarized by Poulin & Kane (2021). Nomenclature:* $\boldsymbol{p_c}$ *critical threshold |* $\boldsymbol{t_0}$ *beginning of control interval |* $\boldsymbol{t_{h0}}$ *exposure to hazard |* $\boldsymbol{t_e}$ *initial system disruption |* $\boldsymbol{t_d}$ *end of performance degradation |* $\boldsymbol{t_s}$ *begin of system recovery |* $\boldsymbol{t_f}$ *completion of system recovery |* $\boldsymbol{t_{h1}}$ *end of exposure to hazard |* $\boldsymbol{t_c}$ *end of control interval (see Appendix B 2).*

lists all 17 resilience metrics, separated into metrics affecting the absorptive, adaptive, and restorative capacity, and whether the metric is performance-, time-, rate-, or integral-based. It includes the generic formulation for quantifying each metric (column a). further recommends how these metrics can be applied to assess the positive effect of resilience actions (column b) compared to a system without explicit resilience considerations. Except for three relative metrics, the remaining formulations are not normalized to receive absolute values. However, as identified in some studies, normalization can be useful in the case of comparative studies. Figure B 4 displays the performance increase resulting from improved *resilience capacities* by *resilience actions* for systems facing a disruption. The magnitude of the performance increase can be calculated for each metric using the calculation rule of , column b.

Resistive duration (metric 1a in) was identified in five studies as the duration from the beginning of the hazardous event, which is chosen as the start of the observation period ($t_0 = t_{h0}$) to the start of performance disruption (t_e) (Amirioun et al., 2019; Anderson et al., 2018; X. Wang et al., 2022; J. Zhang et al., 2022) A single study proposes a normalization by the extreme event duration (t_{h0} to t_d) as part of a resistance metric to assess the absorptive capacity (Kwasinski, 2016). A *resilience action* could lead to a delayed start of performance disruption, which could be quantified as the difference between *resistive duration with* implemented resilience actions and *without* (metric 1b). *Absorb duration* (2a) was defined in our study as the duration from t_e to the end of performance degradation (t_d) in line with five studies (Abdelmalak et al., 2023; Malek et al., 2023; Ren et al., 2017; Roach et al., 2018; X. Wang et al., 2022). The remaining 17 studies refer to the *absorb duration* by assessing the total disruption phase from t_e to t_f (e.g., Losada et al., 2012; W. J. Tan et al., 2020) and thus do not differ between the three capacities. For these studies, we focus our analysis on the component of the metric representing the *absorb duration* (i.e., t_e to t_d). Six studies propose to normalize this metric, either against the duration of the hazardous event (Senkel et al., 2021), the observation period (Didier et al., 2018), or the disruption duration (Q. Han et al., 2023; Jinyi et al., 2020; Veit et al., 2023). A *resilience action* could lead to, e.g., a delayed drop in performance, and could be quantified analogously to the *resistive duration* (2b).

Depth of impact (3a) was identified in 28 studies and is measured as the difference between the undisrupted performance ($p(t_0)$) and the performance after the end of performance degradation ($p(t_d)$) (e.g., Ahmadian et al., 2020; Shang et al., 2022). Eleven of these studies propose a normalization by dividing by $p(t_0)$ (e.g., Amirioun et al., 2019; Fang et al., 2015). A resilience action mitigates the impact of the disruption on the maximum performance loss. The performance gap with and without adequate resilience action can quantify this benefit (3b).

The resilience metrics of *critical threshold* and *residual capacity* are only provided in the framework by Poulin & Kane (2021). *Critical threshold* (4a) defines the minimum level of performance required to prevent a system collapse (Poulin & Kane, 2021). A resilience action could lower this threshold and thus decrease the system's vulnerability (4b). *Residual capacity* (5a) is the distance between the *critical threshold* and the performance at its lowest point $p(t_d)$ (Poulin & Kane, 2021). *Residual performance* (6a) is defined in our work according to the majority of studies (14 out of 25) as the distance between $p(t_d)$ and zero performance (e.g., Cimellaro et al., 2010; Nan & Sansavini, 2017; Badr et al., 2023). Ten of 25 studies normalize the *residual performance* against $p(t_0)$ (e.g., Goldbeck et al., 2019). Both *residual capacity* and *residual performance* can be increased by lowering the critical threshold or reducing the depth of impact by a suitable resilience action (5b, 6b).

Failure ratio (7a) is defined in our work as the percentage of performance that, at any time t, has not degraded yet. This is in line with five studies (Azimian et al., 2021; Carvalho et al., 2012; Z. Liu & Wang, 2021; Rajesh, 2016; Schmitt & Singh, 2012), mainly from the supply chain context, which formulate this metric as the current performance during a disruption $p(t)$ normalized by the hypothetical undisrupted performance $p(t_0)$. In contrast, three studies refer to the performance already degraded until time t (Haeri et al., 2020; Hosseini-Motlagh et al., 2020; Zahiri et al., 2017). When this ratio is measured during the *endure* or *recovery duration* instead of the *absorb duration*, it is called the *recovery ratio* (14a; see below). *Failure rate* (8a) is defined as the slope of the performance curve, i.e., the ratio of the total performance loss and the *absorb duration* as identified in six studies (Abdelmalak et al., 2023; Di Tommaso et al., 2023; Nan et al., 2016; Nan & Sansavini, 2017; Panteli et al., 2017; X. Wang et al., 2022). Similar to the *failure ratio*, a higher absorptive capacity due to a resilience action could lead to a shallower slope and, thus, a more controlled, less severe performance degradation. The resulting improvement could be quantified as the difference between the respective metric with and without a resilience action (7b, 8b).

Cumulative absorptive performance is the most common metric identified for measuring absorptive capacity. It represents the area under the performance curve as the time integral of the system's performance until t_d (9a) as identified in 10 studies (e.g., Ayyub, 2014; Cheng et al., 2020; X. Liu et al., 2021; Tao et al., 2022). Another, only rarely employed variant is to calculate the integral between the beginning of the hazard (t_{h0}) and t_e (Anderson et al., 2018) or t_d (Abdin et al., 2019) to assess the ability of a system to completely resist a disruption without performance loss. Most studies propose to normalize the integral of the disrupted against the undisrupted performance. Conversely, *cumulative absorptive impact* represents the time-integrated *performance loss*. It is measured as the area over the resilience curve until t_d (Amirioun et al., 2019; Chan & Schofer, 2016; Nan et al., 2016; Nan & Sansavini, 2017; Shen et al., 2023). Analogously to the *disruption duration* as a proposed metric of Poulin & Kane (2021), 71 studies refer to the area above or under the resilience curve and quantify resilience by a single value comprising the absorptive, adaptive, and restorative capacity. Thus, these studies do not refer exclusively to the characteristics of the resilience curve attributed to the absorptive capacity. Their metrics capture the area under the performance curve either during the observation period (from t_0 to t_c) (e.g., Cimellaro et al., 2015; Ghorbani-Renani et al., 2020; Kalinowski et al., 2015; Ouyang et al., 2012; Spiegler et al., 2012; Veit et al., 2023) or the disruption phase (from t_e to t_f) (e.g., Cubillo & Martínez-Codina, 2019; Hong et al., 2021; Panteli et al., 2017; Vugrin et al., 2011; Yao et al., 2023). Especially, studies in the optimization context often do not differentiate between resilience capacities but apply area-based metrics as objective functions (e.g., Nozhati, 2021) or just use them to evaluate the resilience of a network (e.g., Lau et al., 2018). When an implemented resilience action has a positive effect on the resilience curve's trajectory (e.g., a longer *resistive duration*, a smaller *failure rate*, or a smaller *depth of impact*), the area below the performance curve increases accordingly. As illustrated in Figure B 4, we propose to measure this *cumulative absorptive improvement* as the difference between the time-integrated performances with and without resilience actions between t_0 and t_d or t_{dr}, depending on which of the two curves reaches the point of lowest performance last (9b, 10b). A selection of cases where the lowest performance is reached earlier, with the resilience action not in place, is displayed in Appendix B 3.

Endure duration (11a) covers the disrupted phase from t_d to t_s, as identified in three studies (Malek et al., 2023; Panteli et al., 2017; Ren et al., 2017), only two studies propose a duration from the end of the hazard (t_{h1}) to t_s (H. Zhang et al., 2018, 2019). As for the *absorb duration*, eleven studies propose the total disruption phase (from t_e to t_f) as resilience metric (e.g., Losada et al., 2012; Paseka et al., 2018), which includes the *endure duration* without explicitly referring to its characteristic of the resilience curve or its relation to the capacities. A resilience action could shorten the endure phase by a prolonged *absorb duration* or by an earlier start of recovery activities (11b). *The endure duration* is followed by the *recovery duration* (12a) from t_s to t_f which is in line with 16 studies (e.g., Carvalho et al., 2022; Goldbeck et al., 2019; Munoz & Dunbar, 2015; Pant et al., 2014). Another 16 studies measure it from t_d to t_f or t_c, either assuming that recovery operations start immediately ($t_d = t_s$, no *endure duration*) (e.g., Francis & Bekera, 2014; Veit et al., 2023) or do not precisely differentiate between *endure* and *recovery duration* (e.g., Ahmadi et al., 2021; Burton et al., 2017; Chan & Schofer, 2016). Simultaneously to the *absorb* and *endure duration*, the *recovery duration* is identified as part of the disruption duration (e.g., Badr et al., 2023; Belhadi et al., 2021). Like for the *endure duration*, a resilience action could have the effect of a shortened *recovery duration* (12b).

Restored performance (13a) and the *recovery ratio* (14a) describe the percentage of performance after full recovery relative to the undisrupted performance $p(t_0)$. *Restored performance* is identified in 27 studies (e.g., Miller-Hooks et al., 2012; Podesta et al., 2021; Zavala et al., 2019) as the metric of the performance after full recovery at t_f. The metric is often used as objective function of models optimizing the SCR (e.g., Dixit et al., 2016; Ribeiro & Barbosa-Póvoa, 2022). Few studies either quantify the extent of recovered performance ($p(t_f) - p(t_d)$ or $p(t_f) - p(t_s)$) .(e.g., Q. Han et al., 2023; Jinyi et al., 2020; Zavala et al., 2019; H. Zhang et al., 2018), or the deviation of $p(t_f)$ from $p(t_0)$ (H. Li et al., 2023; Z. Zhang et al., 2023). The *recovery ratio* is applied in five studies (e.g., Carvalho et al., 2012; Schmitt & Singh, 2012) as the metric of recovered performance relative to the undisrupted performance generically for any time t. As already identified for the *failure ratio*, three studies quantify the performance not recovered yet as the difference between the performance at any time $p(t)$ and $p(t_0)$ (Haeri et al., 2020; Hosseini-Motlagh et al., 2020; Zahiri et al., 2017) during the *endure* and *recovery duration*, whereas one study additionally normalized this expression by $p(t_0)$ (Gotangco et al., 2016). Two studies quantify the actual performance restored ($p(t) - p(t_s)$) relative to the performance lost ($p(t_0) - p(t_s)$) (Baroud et al., 2014; Henry & Ramirez-Marquez, 2012), which we adopted for our set of mathematical formulations (14a). The effect of a resilience action can be quantified analogously to the *failure ratio* (13b, 14b; see 7b).

Recovery rate (15a), analogously to *failure rate* (8a), is defined as the slope of the performance curve during the *recovery duration* and appears in seven studies as proposed in our work (e.g., Kwasinski, 2016; Reed et al., 2009). A resilience action that leads to a steeper slope thus strengthens the restorative and/or adaptive capacities of the system (15b).

Similar to *cumulative absorptive performance* during the *resistive* and *absorb duration*, the most common metric to quantify the recoverability is *cumulative recovery performance*, which is identified in 106 studies. 43 of these studies refer to the area under the curve during the complete observation or disruption period, as already discussed for *cumulative absorptive performance*, and consequently do not propose metrics exclusively assessing the adaptive or restorative capacity. In contrast, 21 studies explicitly correspond to the area under the performance curve from t_d to t_c which is adopted in our formulation (16a) (e.g., Alizadeh et al., 2022; Cavdaroglu et al., 2013; Iloglu & Albert, 2020; Shang et al., 2022) or from t_d to t_f as in 26 studies (e.g., Arjomandi-Nezhad et al., 2021; Ayyub, 2014; Lei et al., 2019). Most of the studies propose a normalization against the area under the undisrupted performance curve. Eight studies subtract the performance at the end of degradation ($p(t_d)$) to only consider the recovered part of the area under the performance curve (e.g., Mishra et al., 2022; Sharkey et al., 2015). Only a few studies refer to the performance integral from t_d to t_s (e.g., Poudel et al., 2020) or from t_s to t_f as in ten studies (e.g., Cheng et al., 2020). Conversely, *cumulative recovery impact* is–similar to *cumulative absorptive impact*–defined as the integral of the performance lost. The most common formulation is the area above the curve during disruption (from t_e to t_f) (e.g., Ghosh & De, 2022) or observation period (t_0 to t_c) (e.g., Huang & Pang, 2014). 13 studies (e.g., Bao et al., 2019; Bruneau et al., 2003; Fang & Sansavini, 2019; Kyriakidis et al., 2018) measure it from t_d to t_f, while four studies integrate from t_d until a defined level of recovery (t_c) (Burton et al., 2017; Munoz & Dunbar, 2015; Y. Tan et al., 2018, 2019), which we choose as the most appropriate formula in our work (17a) to additionally consider the performance loss until the end of the observation period when the performance does not return to the initial state. Only four studies integrate from t_s to t_f (Goldbeck et al., 2019; Y. Hosseini et al., 2023; Nan et al., 2016; Nan & Sansavini, 2017). Thirteen studies propose a normalization against the undisrupted performance curve (e.g., Amirioun et al., 2019; Uday & Marais, 2014) or the duration of *endure* and/or *recovery duration* (e.g., Hong et al., 2021; X. Wang et al., 2022). Two studies quantify the area above the curve from t_s until any time t (e.g., G. Bai et al., 2021; Dui et al., 2023) following the idea of the *recovery ratio*. An exemplary resilience action could increase the overall *cumulative recovery performance* and reduce the *cumulative recovery impact* (e.g., through a shorter *endure phase*, a shorter *recovery phase*, a higher *recovery ratio*, a faster *recovery rate*, or a higher *restored performance*).

This effect can be quantified analogously to *cumulative absorptive performance* as *cumulative recovery improvement* (16b, 17b; see 9b, 10b), starting at the point (t_d or t_{dr}) at which the latter two end. Heath et al. (2016) propose to assess the benefit of network restoration according to the area between the resilience curve with and without the implementation of a resilience action as proposed in this work.

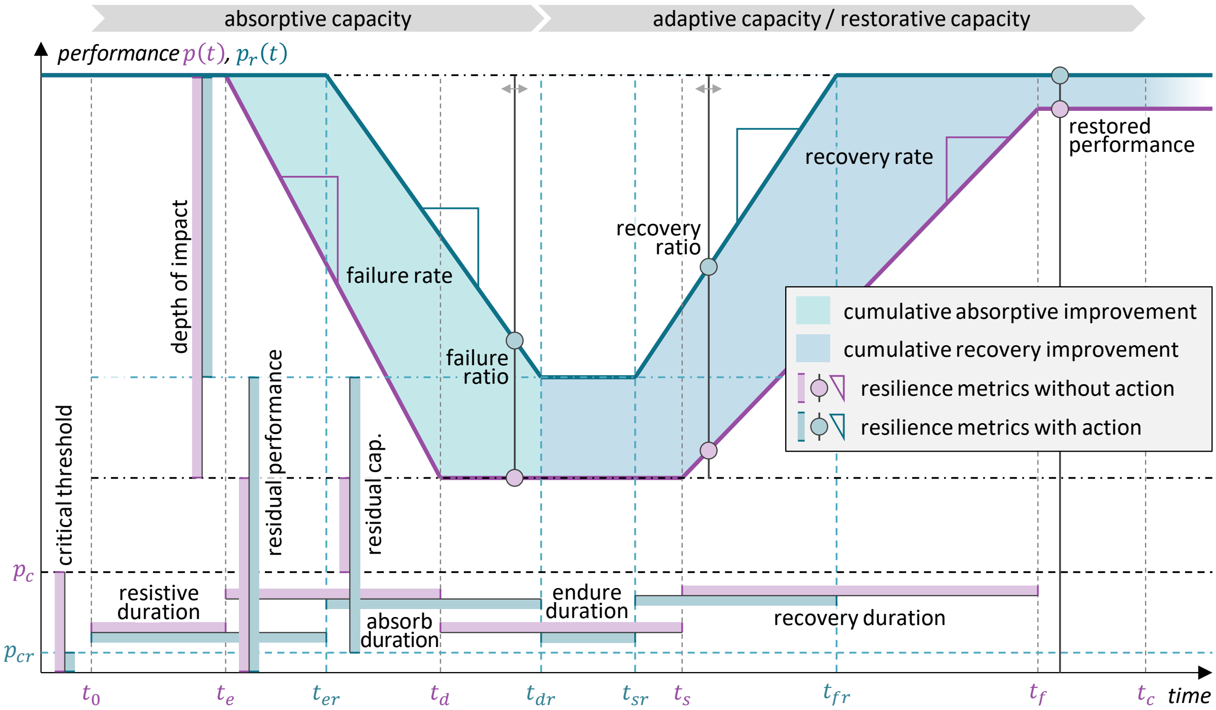

Figure B 4: *Application of resilience metrics to determine the effect of resilience decisions on performance. Mathematical formulations for the computation of the positive effect of resilience decisions can be found in , column b. Nomenclature:* $\boldsymbol{p_{cr}}$ *lower critical threshold |* $\boldsymbol{t_{er}}$ *delayed initial system disruption |* $\boldsymbol{t_{dr}}$ *delayed end of performance degradation |* $\boldsymbol{t_{sr}}$ *earlier begin of system recovery |* $\boldsymbol{t_{fr}}$ *earlier completion of system recovery (cf. Figure B 3 and Appendix B 2).*

Table B 2: *Overview of resilience metrics, their localization along the resilience curve, their quantification (column a), and how they quantify the positive effect of resilience decisions (b).*

	Resilience metric	Articles	Capacity	Type	(a) Quantification	(b) Positive effect of resilience decisions
(1)	$resistive\ duration$	1	absorptive	time-based	$t_e - t_0$	$(t_{er} - t_0) - (t_e - t_0) = t_{er} - t_e$
(2)	$absorb\ duration$	8	absorptive	time-based	$t_d - t_e$	$(t_{dr} - t_{er}) - (t_d - t_e)$
(3)	$depth\ of\ impact$	10	absorptive	performance-based	$p(t_d) - p(t_0)$	$\left(p_r(t_{dr}) - p_r(t_0)\right) - \left(p(t_d) - p(t_0)\right)$
(4)	$critical\ threshold$	1	absorptive	performance-based	p_c	$-(p_{cr} - p_c)$
(5)	$residual\ capacity$	1	absorptive	performance-based	$p(t_d) - p_c$	$(p_r(t_{dr}) - p_{cr}) - (p(t_d) - p_c)$
(6)	$residual\ performance$	11	absorptive	performance-based	$p(t_d)$	$p_r(t_{dr}) - p(t_d)$
(7)	$failure\ ratio$	5	absorptive	performance-based	$\frac{p(t) - p(t_d)}{p(t_0) - p(t_d)}$	$\frac{p_r(t) - p_r(t_{dr})}{p_r(t_0) - p_r(t_{dr})} - \frac{p(t) - p(t_d)}{p(t_0) - p(t_d)}$
(8)	$failure\ rate$	2	absorptive	rate	$\frac{p(t_d) - p(t_e)}{t_d - t_e}$	$\frac{p_r(t_{dr}) - p_r(t_{er})}{t_{dr} - t_{er}} - \frac{p(t_d) - p(t_e)}{t_d - t_e}$
(9)	$cumulative\ absorptive\ performance$	20	absorptive	time integral	$\int_{t_0}^{t_d} p(t)\, dt$	$\int_{t_0}^{max(t_d,t_{dr})} \left(p_r(t) - p(t)\right) dt$
(10)	$cumulative\ absorptive\ impact$	14	absorptive	time integral	$\int_{t_0}^{t_d} \left(p(t) - p(t_0)\right) dt$	$\int_{t_0}^{max(t_d,t_{dr})} \left[\left(p_r(t) - p_r(t_0)\right) - \left(p(t) - p(t_0)\right)\right] dt$
(11)	$endure\ duration$	14	adapt. / restor.	time-based	$t_s - t_d$	$-\left((t_{sr} - t_{dr}) - (t_s - t_d)\right)$
(12)	$recovery\ duration$	22	adapt. / restor.	time-based	$t_f - t_s$	$-\left((t_{fr} - t_{sr}) - (t_f - t_s)\right)$
(13)	$restored\ performance$	13	adapt. / restor.	performance-based	$\frac{p(t_f)}{p(t_0)}$	$\frac{p_r(t_{fr})}{p_r(t_0)} - \frac{p(t_f)}{p(t_0)}$
(14)	$recovery\ ratio$	7	adapt. / restor.	performance-based	$\frac{p(t) - p(t_s)}{p(t_0) - p(t_s)}$	$\frac{p_r(t) - p_r(t_{sr})}{p_r(t_0) - p_r(t_{sr})} - \frac{p(t) - p(t_s)}{p(t_0) - p(t_s)}$
(15)	$recovery\ rate$	5	adapt. / restor.	rate	$\frac{p(t_f) - p(t_s)}{t_f - t_s}$	$\frac{p_r(t_{fr}) - p_r(t_{sr})}{t_{fr} - t_{sr}} - \frac{p(t_f) - p(t_s)}{t_f - t_s}$
(16)	$cumulative\ recovery\ performance$	32	adapt. / restor.	time integral	$\int_{t_d}^{t_c} p(t)\, dt$	$\int_{max(t_d,t_{dr})}^{t_c} \left(p_r(t) - p(t)\right) dt$
(17)	$cumulative\ recovery\ impact$	22	adapt. / restor.	time integral	$\int_{t_d}^{t_c} \left(p(t) - p(t_0)\right) dt$	$\int_{max(t_d,t_{dr})}^{t_c} \left[\left(p_r(t) - p_r(t_0)\right) - \left(p(t) - p(t_0)\right)\right] dt$

3.4 Resilience actions

This section reviews the resilience actions identified in the observed literature on SCR in particular. *Resilience actions* are precautionary, anticipatory actions that decision-makers can implement proactively to strengthen the system's absorptive, adaptive, and restorative capacities to cope with disruptions and improve resilience, as visualized in Figure B 4. The observed literature does not apply a consistent terminology for resilience actions, wherefore different studies refer to *management controls* (e.g., Pettit et al., 2010), *resilience* or *mitigation measures* (e.g., C. Chen et al., 2021; L. Chen et al., 2020; Lücker & Seifert, 2017), and *resilience* or *mitigation strategies* (e.g., Carvalho et al., 2012). In quantitative models for SCR planning, the resilience actions are the 'objects of decision', i.e., it needs to be decided which set of different actions is to be implemented, at what time, and to what extent. The type of action varies according to the capacity to be strengthened, the planning horizon (strategic, tactical, operational), the potential disruption, and the industry. Actions take a central role in quantitative decision models (Behzadi et al., 2020; Ribeiro & Barbosa-Póvoa, 2018), which is why an overview and classification of identified actions is given in the following.

Figure B 5 gives an overview of the analyzed systems and the type and frequency of the investigated disruptions. Supply chains are, with 29 studies, most frequently subject to resilience considerations, followed by electric power systems, communities, and production sites. Generic disruptions without further specification and meteorologically caused disruptions (e.g., storms, tornadoes, blizzards, and drought) are most frequently assumed, followed by geophysical-caused disruptions (e.g., earthquakes) and generic supply disruptions. A few studies assume anthropogenic disruptions, such as cyber and terrorist attacks. While studies on multi-echelon supply chains mostly consider generic supply, transportation, or distribution disruptions without further description of causality, studies on electric power systems and communities primarily assume natural disasters (especially meteorological and geophysical).

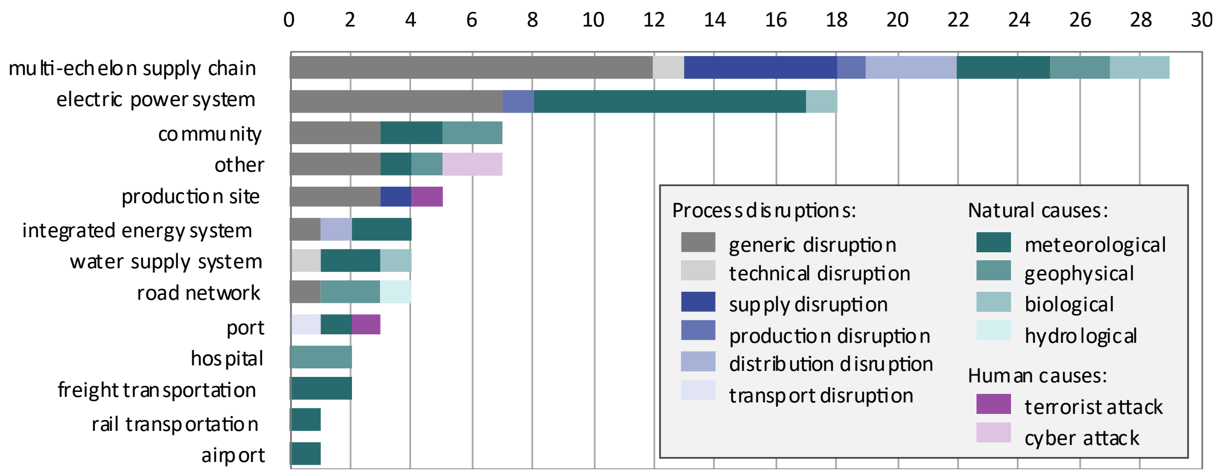

Figure B 5: *Frequency of analyzed systems in the identified literature with the assumed type of disruptions.*

The supply chain planning matrix is a model for structuring the planning tasks that underlie supply chain decision-making (Fleischmann et al., 2008). It hierarchizes the individual decisions in supply chain management by their *planning horizon* into the strategic, tactical, and operational decision levels (Fleischmann et al., 2008). It further subdivides the planning tasks by the *supply chain processes* of procurement, production, distribution, and sales. Figure B 6 gives an overview of all identified resilience actions classified by an extended supply chain planning matrix (Fleischmann et al., 2008) that additionally clusters into absorptive, adaptive, and restorative actions alongside the two regular dimensions. Since some resilience actions cannot be matched with the four existing SC processes, it introduces *supporting actions* as an additional process. To indicate the focus of current research, the figure further shows the number of studies in which a resilience action was mentioned. We identified 63 actions on the strategic level, 44 on the tactical level, and 16 on the operational level. While most actions are identified in the *procurement*, only a few are found for *sales*.

Very few studies classify their proposed resilience actions by resilience capacity, horizon, or process. S. Hosseini et al. (2019) are the only study to classify SCR actions by their hierarchical decision level. To address this literature gap, this work classifies the actions based on the context of the studies they originate from and matches them to the planning tasks and horizons of the original supply chain planning matrix introduced by Fleischmann et al. (2008).

Actions associated with large investments and long-term planning horizons are classified on the *strategic level*, and most identified actions on the strategic level strengthen absorptive capacity. The strategic procurement strengthens absorptive capacity through supplier segregation (rejection of high-risk suppliers) and multiple sourcing (S. Hosseini et al., 2019). *Storage planning* for raw material and intermediates, storage location, and capacity is suggested by various literature as actions for increasing the absorptive capacity (Ribeiro & Barbosa-Póvoa, 2018). Adaptive capacity is enhanced by the identification of potential backup suppliers, by strategic cooperations with backup suppliers that are used in case of primary supplier disruption (S. Hosseini et al., 2019), and by sharing information that contributes to the recovery process with cooperating supply chain partners (Belhadi et al., 2021). A resilience action of strategic production planning is *location planning* that contributes to absorptive capacity by spatially distributed facilities and warehouses (Fang & Zio, 2019; Senkel et al., 2021). *Production system planning* increases absorptive capacity through resilience-oriented planning of production capacities, which mainly includes the planning of redundant production capacities (Ribeiro & Barbosa-Póvoa, 2018; W. J. Tan et al., 2020). Another action is the physical protection of assets (Vugrin et al., 2011). To strengthen adaptive capacity, backup facilities and technologies can be implemented, which are only activated in the event of disturbances (W. J. Tan et al., 2020). Strategic distribution planning increases absorptive capacity by implementing redundant transportation links (Ribeiro & Barbosa-Póvoa, 2018) and resilience-oriented warehouse location planning (Fattahi et al., 2017; Schmitt & Singh, 2012). A supporting action with a strategic character that increases absorptive capacity is the implementation of big data analytics for the early identification of disruptions (Rajesh, 2016). To strengthen adaptive capacity, financial resources can be kept available for urgently required system modifications (Vugrin et al., 2011).

On *tactical level*, procurement strengthens the absorptive capacity through resilience-oriented inventory policies (Spiegler et al., 2012). Qualifying staff can prevent potentially hazardous behavior (Sun et al., 2022) and improve staff's ability to analyze and interpret information on critical system components (Belhadi et al., 2021). Adaptive capacity is strengthened by flexibly adapting inventory policies in the event of disruptions, e.g., by placing orders at backup suppliers (Torabi et al., 2015). Restorative capacity is strengthened by introducing a qualified repair team (C. Chen et al., 2021; Sun et al., 2022; Vugrin et al., 2011). Tactical production planning increases resilience by outsourcing production capacities (Ribeiro & Barbosa-Póvoa, 2018) and proactive maintenance (Sun et al., 2022). Adaptive capacity is strengthened by backup resources such as machinery and personnel (Behzadi et al., 2020; Vugrin et al., 2011). Tactical distribution planning improves absorptive capacity by increasing final product inventories (Ojha et al., 2018) and by proactive maintenance of lifelines (Belhadi et al., 2021). Adaptive capacity is strengthened by keeping backup transportation modes available in case of primary mode disruptions (S. Hosseini et al., 2019). Reallocating final product inventories in case of disruptions increases the adaptive capacity (Fattahi et al., 2017; Zavala et al., 2019). Tactical sales improves adaptive capacity by prioritizing customers (Fattahi et al., 2017). The regular monitoring of critical system components is a supporting action that increases the absorptive capacity (Datta et al., 2007). To strengthen the restorative capacity, resilience management can implement a monitoring system that detects failures and tracks down disruptions efficiently (Vugrin et al., 2011).

		PROCUREMENT	PRODUCTION	DISTRIBUTION	SALES	SUPPORTING ACTIONS
strategic (63)	*Absorptive capacity*	**supplier selection** multiple sourcing 6 supplier segregation 4 **storage planning** storage location 6 storage capacity 5	**location planning** production location 6 **production system** prod. capacity planning 7 physical protection 3	**distribution system** warehouse location 5 warehouse capacity 4 redundant transp. link 1		big data analytics 2
	Adaptive capacity	**supplier selection** backup supplier 3 **cooperation** backup cap. of supplier 2 information sharing 1	**location planning** backup cap. (facilities) 5 **production system** backup technology 2			financial resources for system modifications 1
tactical (44)	*Absorptive capacity*	**mat. requirem. planning** inventory policy 8 **personnel planning** qualification 2	**production planning** outsourcing prod. cap. 1 proactive maintenance 1 technological update 1	**distribution planning** inventory policy 8 proactive maintenance 1		monitoring 3
	Adaptive capacity	**mat. requirem. planning** inventory policy 2	**capacity planning** backup cap. planning 4	**distribution planning** inventory reallocation 2 backup transport mode 5	**mid-term sales planning** customer prioritization 1	
	Restorative capacity	**staff planning** qualified repair team 3				monitoring 2
operational (16)	*Adaptive capacity*	**ordering materials** usage of backup cap. 2 order management 2 input mat. substitution 2	**machine scheduling** usage of backup cap. 2 prod. rescheduling 2	**transport planning** rerouting 1	**short-term sales plan.** service level adaptation 1 price adaptation 1 customer prioritization 1 product substitution 1	
	Restorative capacity					supp. disrupted suppl. 1

Figure B 6: *Supply chain planning matrix based on Fleischmann et al. (2008), extended by absorptive, adaptive, and restorative resilience actions, and structured by hierarchical decision-level and supply chain process. The number indicates in how many studies the respective measures were found (please find the full table with references in Supporting Information B (C)).*

On the *operational decision level*, no actions for improving absorptive capacity were identified. Adaptive capacity is determined by the actual realizable quantities of backup suppliers (Torabi et al., 2015; Zhao et al., 2017), the agile adaptation of order management (C. Chen et al., 2021; Hishamuddin et al., 2013), and the ability to flexibly substitute input materials (Vugrin et al., 2011). The adaptive capacity of the production is strengthened by the efficient integration of backup production capacities and flexible production rescheduling (Hishamuddin et al., 2013). Distribution planning improves the adaptive capacity by flexible routing abilities (Carvalho et al., 2012). In sales, adjusting prices and flexibly adjusting the pursued service level (e.g., not serving the entire demand) simultaneously increase the supply chain's adaptive capacity (S. Hosseini et al., 2019). Customer prioritization (Fattahi et al., 2017) and the ability to temporarily deliver a product substitute (Carvalho et al., 2022) also improve adaptive capacity. Torabi et al. (2015) suggest supporting disrupted suppliers in their recovery efforts to ensure continuous supply, which we ascribe to the supporting actions that increase restorative capacity.

4. Discussion and conclusion

Hardly predictable disturbances can affect the functionality of systems and impair their performance. Depending on how well a system can absorb, adapt to, or restore from a disruption, the performance decline and recovery will turn out differently. Building upon Poulin & Kane (2021), who set the basis for assessing infrastructure resilience by a consistent set of metrics that describe the resilience curve, our work covers the interplay between the curve, capacities, metrics, and actions in a supply chain context, as illustrated in the graphical abstract (cf. Figure B 1). First, we extract 395 metrics from the investigated literature, and second, harmonize them by the terminology of Poulin & Kane (2021). We then map the standardized metrics to the characteristics of the resilience curve and eventually synthesize them into 17 unified metrics with respective mathematical formulations (i.e., 1a–17a). This set represents the state-of-the-art of quantifying resilience based on the concept of the resilience curve and the absorptive, adaptive, and restorative capacities of systems and networks generally and supply chains specifically. Based on the identified set of metrics, we propose a set of mathematical formulations for those metrics to assess the effect of resilience actions (i.e., 1b–17b).

The applicability is given in science and practice: Research, for example, could apply the set of standardized mathematical formulations (i.e., 1a–17a) in ex-post analyses to compare, e.g., how different systems have coped in the face of disruption and what resilience capacities the system possessed in each case. Companies could apply the metrics for assessing the resilience of their supply chain by simulating hypothetical disruption scenarios to approximate their resilience curve and gain insights into their absorptive, adaptive, and restorative capacities. As an example, an OEM interested in assessing its absorptive capacity could investigate the performance (e.g., in terms of produced units) in the face of a real historical or simulated hypothetical disruption. The resulting curve could then be characterized by the metrics relating to the absorptive capacity (e.g., resistive duration, absorptive duration, depth of impact, failure rate) to draw conclusions on the state of resilience or to deduce if additional actions are required to build up resilience capacities.

Decision-makers aiming to increase resilience (of a system in general, a supply chain, or a specific process) could apply the metrics (i.e., 1b–17b) to compare the efficiency of different potential resilience actions in cost-benefit assessments. These metrics could further be integrated into optimization models to decide on the optimal combination of actions aiming at maximizing economic or resilience objectives. For instance, Iris & Lam (2019) studied the case of berth and quay crane planning in vessel loading by using the concept of *recoverable robustness* to optimally balance the absorption of uncertainties through buffers and the recoverability through efficient rescheduling in case of disruptions. Our concept could be applied in such assessments to quantify the benefit of integrated optimization approaches compared to less elaborate resilience planning approaches.

Furthermore, we classified anticipatory resilience actions identified in literature into the traditional supply chain planning matrix according to their time horizon, similar to S. Hosseini et al. (2019), and the supply chain stage. In addition, we identified supporting actions for strengthening resilience capacities, extending the traditional supply chain planning tasks. The resulting Figure B 6 gives practitioners and researchers an overview of actions, organized by planning task, time horizon (i.e., short-term, mid-term, long-term), and affected resilience capacity.

Naturally, the conclusions drawn from our results are subject to certain limitations. While applying the proposed metrics works in a synthetic and academic setting, real-life cause-effect chains are often difficult to trace and interpret. Therefore, the applicability of practical case studies and potential adjustments needs further investigation. Consequently, the trajectory of the resilience curve (Figure B 3) and the effect of resilience actions on it (Figure B 4) are only illustrated exemplarily. To show the abundance of possible trajectories, Appendix B 3 presents three alternative examples of how actions could affect the resilience curves and their metrics. The concept of the resilience curve, the proposed set of metrics, and the understanding of 'resilience' in our study are only one attempt to assess resilience in a supply chain context. Without adjustments, it is not universally applicable to other resilience contexts, such as urban or food system resilience. In addition, we only consider metrics that can be located along the resilience curve and exclude formulations that do not fit the resilience curve concept, e.g., metrics that quantify the volatility of performance during recovery (Tran et al., 2017).

As illustrated in Appendix B 3, resilience actions do not necessarily positively impact all metrics simultaneously. For example, the positive effect of a shorter *endure duration* and an earlier start of recovery could come, in turn, with a decreased *recovery rate* (cf. Appendix B 3, case IV). Consequently, we advise decision-makers to select resilience metrics according to the supply chain process they want to improve. For instance, in critical infrastructure (e.g., electric grids, hospitals), the time-integrated performance may be less relevant than the ability to ensure a minimum performance level, for which magnitude-based metrics may be more meaningful. It also bears mentioning that the presented resilience metrics are interdependent, meaning that a change in one metric will automatically lead to a change in at least one other metric (e.g., between duration-based and integral-based metrics). Generally, we deem time-integral–based resilience metrics like the *cumulative absorptive performance* preferable, as they convey the most information. However, they require a high level of available data to be precise and meaningful. Time-based (e.g., *endure duration*) or performance-based metrics (e.g., *depth of impact*) may be preferable when performance data is only available for certain points in time or when single characteristics of the curve are to be assessed.

The underlying data to describe the resilience curve can either be empirical (real-life data of disruption and following recovery) or be estimated based on simulated disruption scenarios and predictions of the resulting reactions (Poulin & Kane, 2021). While ex-post analyses can yield relevant insights on past events, conclusions for future system performances are limited since disruptions can occur in a wide variety of different and hardly predictable ways. The decision as to which resilience actions should be implemented requires a prediction of disruption scenarios and an approximation of the resulting change in performance. It must be emphasized that an exact determination of a system's resilience is hardly possible due to uncertainties in predicting the nature, scope, and timing of eventual disruptions. The precision of resilience considerations depends on various factors, such as the accuracy of prediction on how an action affects the system or whether a disruption occurs as predicted.

Building upon our findings, future research could focus on the following aspects: (1) application of the proposed metrics and their mathematical formulations in real case studies for a better understanding of resilience curve characteristics and related capacities, (2) application of the metrics to select and assess the effect of actions to strengthen capacities, (3) integration of the proposed metrics as resilience objectives in multi-criteria optimization models to weight the benefit of resilience actions against economic or environmental objectives (e.g., minimizing costs) or by integrating them as constraints. If research introduces new metrics, they should be categorized according to the presented characteristics of the resilience curve and related capacities.

The uncertainty of future disruptions remains the main challenge. Therefore, future studies could assess the effect of actions on the resilience curve by the proposed metrics for various scenarios weighted by their probability of occurrence as a measure of risk. To bring the concepts of 'resilience' and 'risk and uncertainty' together, future studies could also examine the existing literature specifically on risk and uncertainty in the context of resilience. The overview of SCR actions gives an idea about possible resilience-enhancing measures and how actions could be classified in future studies. This study's search string was not pivotally designed to identify resilience actions, wherefore future research could explicitly review feasible actions to be applied to strengthen the absorptive, adaptive, and restorative capacities of supply chains.

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CONTRIBUTION C

ENCOUNTER THE UNFORESEEN: RESILIENT SUPPLY CHAIN MODELING FOR A SUSTAINABLE BIOECONOMY

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ABSTRACT

Bioeconomic supply chains (BioSC) processing biogenic resources and substituting fossil-based products are prone to weather-induced feedstock supply disruptions, which likely increase in severity and frequency due to climate change. To attain supply security of biobased products that contribute to sustainable development, BioSC should be equipped with a certain level of ‘resilience’ against unexpected feedstock fluctuations. Existing bioeconomic supply chain models usually capture producer resilience to maximize profitability for anticipated feedstock scenarios. Consumer supply security for unanticipated events has drawn less attention. To encounter the unforeseen and both producer and consumer perspectives, we present a two-step approach: (1) resilient planning of a European BioSC producing bioethanol as a petrol substitute from straw for both producer and consumer perspectives; a novel step (2) assesses the ‘actual’ resilience for unanticipated, random feedstock scenarios and economic and environmental implications. While a producer-resilient supply chain has lower bioethanol production capacity and already high straw storage capacities to maximize profitability under feedstock fluctuations, supply security degrades. In contrast, consumer-resilient supply chains have higher production and storage capacities to maintain supply security. Although this network redundancy comes with higher environmental impacts from facility construction and supply chain operation (production, transport), the environmental benefit of substituting petrol exceeds those burdens in most environmental life cycle assessment categories. Consequently, consumer resilience can be congruent with environmental sustainability and should be supported by policymakers to strengthen European bioeconomy and guide producers toward consumer-resilient supply chains. This article met the requirements for a gold-gold JIE data openness badge described at http://jie.click/badges.

1. Introduction

The bioeconomy endeavors to satisfy humans' hunger for materials and energy through renewable biological resources and is a central sector of the global economy and of key importance for leading society toward a sustainable pathway (El-Chichakli et al., 2016). Depending on its realization, bioeconomic value chains enable a positive contribution to multiple stakeholders, from the economy to the environment and society (Messmann et al., 2023; Wietschel et al., 2021). However, recent global supply disruptions insinuate ever-increasing vulnerabilities of efficiency-trimmed supply chains (SC) (Bruckler et al., 2024; Carvalho et al., 2012; Golan et al., 2020; Sheffi & Rice, 2005; Tang, 2006). Bioeconomic SC (BioSC) are particularly vulnerable to disruptions: even in the optimistic 1.5°C global warming scenario, temperature extremes, heavy precipitation, and droughts will occur more frequently and intensely (IPCC, 2022), increasing the likelihood of weather-induced resource shortfalls (Lesk et al., 2016) and making BioSC more susceptible than fossil and mineral resource-based SC (Habibi et al., 2023). Increasing BioSC resilience, which paves the way for a more sustainable future, is therefore of great interest to society as a whole. The field of industrial ecology, traditionally focused on reducing environmental impacts through technology, identified the urgent need to equip sustainable development with resilience considerations to protect the path to sustainability from the impacts of climate change (Chester, 2020; Dijkema et al., 2015; Elmqvist et al., 2019; Kendall & Spang, 2020; Meerow & Newell, 2015; Yang et al., 2020).

The term 'resilience' could be translated to 'rebound' from a disturbance and is popular in several fields, such as psychology, livelihood, social, economic, engineering, or ecological systems. Engineering resilience is a reactive concept that targets stability around an equilibrium state and investigates a system's capacity to absorb and recover from disturbances (Holling, 1996). Supply chain resilience (SCR) is based on this school of thought and is usually defined by a combination of preparedness for a disturbance and the ability to respond, recover, and maintain a positive equilibrium state within reasonable costs and time (Ribeiro & Barbosa-Póvoa, 2018). These abilities are known as absorptive, adaptive, and restorative capacities (Vugrin et al., 2011). SCR research has already developed quantitative methods to evaluate the effects of high-impact, low-probability disruptions: the so-called resilience curve maps a system's performance over time and, thereby, illustrates its degradation and recovery in case of disruptions (Bruneau et al., 2003), depending on the available absorptive, adaptive, and restorative capacities (Bruckler et al., 2024). Resilience metrics assess characteristics of the curve, such as the *depth of impact* (extent of performance decline) or the *recovery rate* (slope of performance recovery) (Poulin & Kane, 2021). BioSC, such as biofuel production, can be termed resilient when absorptive, adaptive, and restorative capacities ensure an efficient response, adaption, and recovery of the network from disruptions (e.g., feedstock shortfall) to meet the system's objectives (e.g., profitability from a producer perspective) and the consumer needs (e.g., demand coverage) (Habibi et al., 2023). Deliberate actions can strengthen those capacities, improve resilience metrics, and, consequently, improve overall SCR (Bruckler et al., 2024). These precautionary actions can already be considered in strategic planning to increase resilience towards supply disruptions.

BioSC depend on low-density and low-cost feedstock, which is spatially spread, resulting in non-linear feedstock transportation costs (Lauven et al., 2018; Wietschel et al., 2021; Wright & Brown, 2007). Consequently, these SC require context-specific models and actions to improve resilience, which have already been addressed in the literature.

Existing approaches that explicitly consider resilience actions in BioSC modeling include resilience-oriented biorefinery (BR) location and capacity planning (e.g., Bai et al., 2015), feedstock storages or collection centers (e.g., Fattahi et al., 2021; Liu et al., 2017; Mousavi Ahranjani et al., 2020; Saghaei et al., 2020; Yazdanparast et al., 2022), pretreatment facilities (e.g., Khezerlou et al., 2021; Maheshwari et al., 2017; Osmani & Zhang, 2013, 2017), or multiple feedstock types (e.g., Fattahi et al., 2021; Huang & Pang, 2014; Khezerlou et al., 2021; Mousavi Ahranjani et al., 2018, 2020; Osmani & Zhang, 2013, 2017). Some of these articles incorporate environmental or social objectives or constraints alongside the predominant economic perspective and examine the implications of different dimensions on the SC design (e.g., Mousavi Ahranjani et al., 2020; Salehi et al., 2022).

Besides the integration of resilience actions, literature on BioSC planning has considered resilience by models intended to optimize or at least maintain economic efficiency in case of parameter uncertainty. In this context, strategic planning encompasses uncertainty of feedstock availability (e.g., Mousavi Ahranjani et al., 2020; Soren & Shastri, 2019), demand (e.g., Kalhor et al., 2023), operational availability (e.g., Huang & Pang, 2014; Khezerlou et al., 2021), or joint uncertainties of multiple parameters (e.g., Liu et al., 2017; Mousavi Ahranjani et al., 2020; Osmani & Zhang, 2013; Saghaei et al., 2020). The dominant method to consider uncertainty in BioSC is stochastic programming with objective functions minimizing costs or maximizing profit (Habibi et al., 2023). To reduce complexity, uncertainty is typically represented by finite random scenarios with given probabilities (Habibi et al., 2023). Few articles consider realistic scenarios drawn from probability distributions based on historical data (Bairamzadeh et al., 2018; Mousavi Ahranjani et al., 2018).

Resilience is rarely considered within BioSC by integrating resilience objectives, constraints, or metrics. Zhao & You (2019) optimize the area under the resilience curve for the performance measure of available BR capacity in a bi-objective two-stage robust model. They additionally use Pareto curves to analyze trade-offs between resilience and economic performance for two small-scale cases (transportation network and biofuel SC). Salehi et al. (2022) incorporate resilience and sustainability factors into a joint objective function of a robust optimization model, assuming demand and operational uncertainty. Resilience is achieved by penalizing the use of old technology and critical nodes and flows along the SC. They apply the same metric as Zhao & You (2019) as a constraint to assess the resilience, also for the performance measure of available BR capacity.

Based on the existing scientific literature, the following research gaps are identified:

- *Resilience operationalization:* To design resilient BioSC, most models follow economic objectives under uncertainty through fictive, randomly chosen scenarios, including explicit decisions on resilience actions, whereas most works exclusively focus on 'operational resilience' from the producer perspective. However, multiple stakeholders might be affected by disruptions and countervailing resilience actions (Grafton et al., 2019), requiring an inclusive assessment of the different affected perspectives to avoid unwanted problem shifting (Elmqvist et al., 2019). Approaches of explicit resilience objectives or metrics integrated into models to address different stakeholders, such as the consumer (ensuring supply security), are barely investigated.
- *Resilience against the unforeseen:* Existing models rely on anticipated scenarios for which resilience is determined as an a priori assessment. However, resilience is not necessarily improved against unknown future events (Inan et al., 2024). This 'actual' SCR against unforeseen, not anticipated scenarios has not yet gained much attention (Bruckler et al., 2024).
- *Implications of incorporating resilience:* Less attention has been paid to jointly investigating the effect of resilience considerations in SC modeling on resilience, economic, and environmental performance (Habibi et al., 2023).

Against this background, this article investigates the following research questions:

- *RQ1:* How can resilience in terms of supply security (consumer perspective) be considered in quantitative models for the strategic planning of BioSC?
- *RQ2:* How can the 'actual' resilience regarding unanticipated events be assessed?
- *RQ3:* Which effect do these resilience considerations in SC modeling have on the economic and environmental performance of a second-generation bioethanol (2G EtOH) SC?

This article presents a real-data experiment design to model and assess resilient SCs for 2G EtOH production in the European Union (EU), considering feedstock supply uncertainty due to extreme events. Therefore, Section 2.3 presents a new two-step approach: In step 1 (strategic planning), a bi-criteria two-stage stochastic linear programming decides on the combination of actions to optimize economic profit under feedstock uncertainty (producer perspective) and to meet a resilience satisfaction goal to ensure 'supply security' (consumer perspective). Therefore, we select a set of realistic feedstock scenarios from historical feedstock data. In contrast to existing approaches that are based exclusively on a priori optimization, a subsequent simulation (step 2) is used to validate these strategic decisions from the resilient model for a new set of randomly drawn scenarios, which the model did not yet anticipate. This enables the analysis of economic and environmental implications (Section 3.2) of resilience considerations in SC modeling and to assess the ‘actual’ SCR (Section 3.3) for unforeseen scenarios. Thereby, our article contributes to the required shift in research that a resilient system needs to deal with unknown developments for a sustainable future (Reyers et al., 2022). Although our approach is tailored for BioSC, this work contributes to a general understanding of how the resilience curve, its metrics, and SC modeling can be combined to increase resilience and which implications can come along with resilient SC planning.

2 METHOD

2.1 PROBLEM DESCRIPTION & AIM

This article builds upon the model of a large-scale 2G EtOH production network introduced by Wietschel et al. (2021) as an advanced real-case model for the EU. In their work, a mixed integer linear programming model (MILP) is used to determine 2G EtOH SC configurations as trade-off solutions according to different objectives: an economic objective function maximizing the profit and several life cycle assessment (LCA) based environmental objective functions maximizing benefits of the network design and operation. The SC configurations are designed within 91 nomenclature des unités territoriales statistiques (NUTS 1) regions of the EU28 and comprise the following decisions (Figure C 1): feedstock harvesting (cereal straw) and transport to the BR, BR location and production capacity, and 2G EtOH production and distribution to either substitute petrol or first-generation (1G) EtOH. However, their model considers average feedstock availability, which may limit the validity of the results (Wietschel et al., 2021). While their approach shows a potential course toward a more sustainable future, additionally considering the resilience of different affected stakeholders would strengthen the system’s capacity to adhere to the pathway, especially in light of the increasing frequency and intensity of climate change-induced weather extremes (IPCC, 2022). Consequently, we aim for an approach that combines tools (metrics) and concepts (resilience curve) of resilience research with SC modeling to (1) strengthen the resilience of vulnerable BioSC and (2) analyze their 'actual' resilience, economic, and environmental performance regarding not anticipated scenarios. Therefore, we adapt the model of Wietschel et al. (2021) by considering resilience within the model formulation and decisions to enable coping with feedstock disruptions. In contrast to the original model, where economic and environmental objective functions are (Pareto) optimized, our model is solely optimized economically, while a resilience satisfaction goal is introduced (see Section 2.2), and the environmental performance is co-calculated for several LCA end/midpoints.

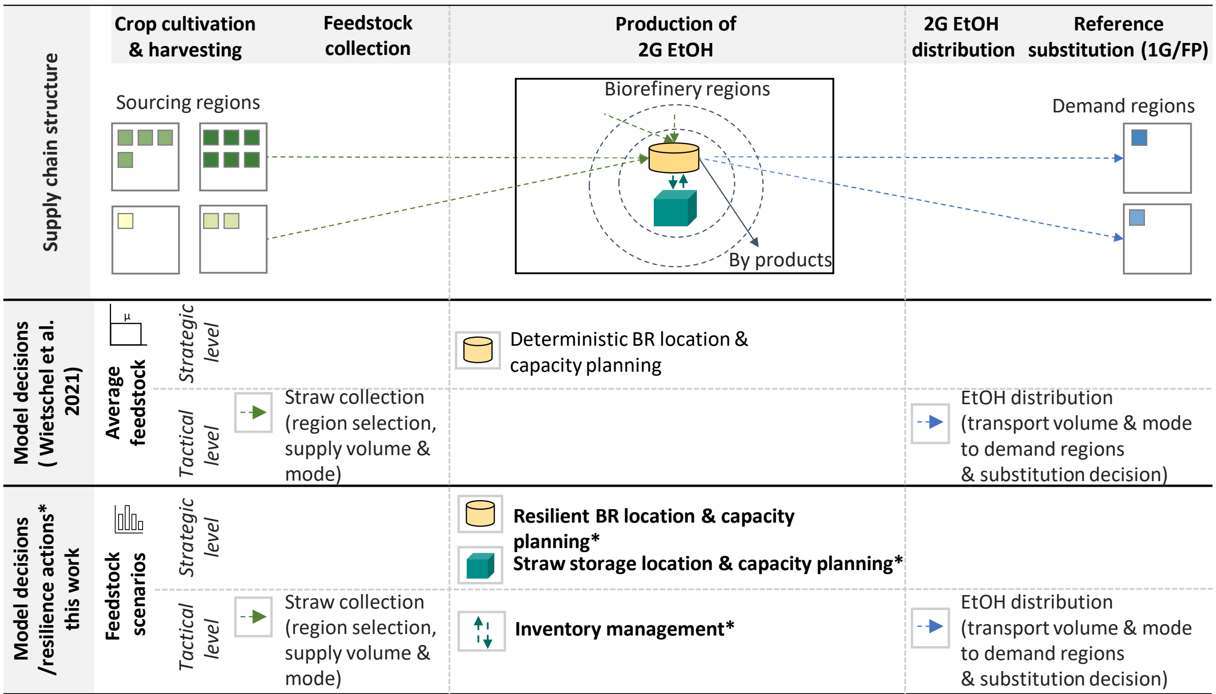


Figure C 1: *Overview of network structure, model decisions of Wietschel et al. (2021), and model decisions/resilience actions of the developed model. Decisions made by Wietschel et al. (2021) include the amount and transport mode (truck, train, or tractor) of straw from a sourcing region or the BR region itself to the BR, the location and production capacity level of the BR, the amount and transport mode of 2G EtOH from the BR region to the demand region, as well as the substituted product (fossil petrol or 1G EtOH). Model decisions marked with * are considered as resilience actions that are integrated into our model to strengthen resilience. These decisions include the selection of location and production capacity level of BR to be resilient against feedstock fluctuations, the decision on locations and capacities of straw storage that can be constructed at the BR, and the straw flows in and out of the storage. Please see Supporting Information C1 for the mathematical formulation of the proposed model, which includes parameters, objective function, and constraints (own figure based on Wietschel et al. (2021)).*

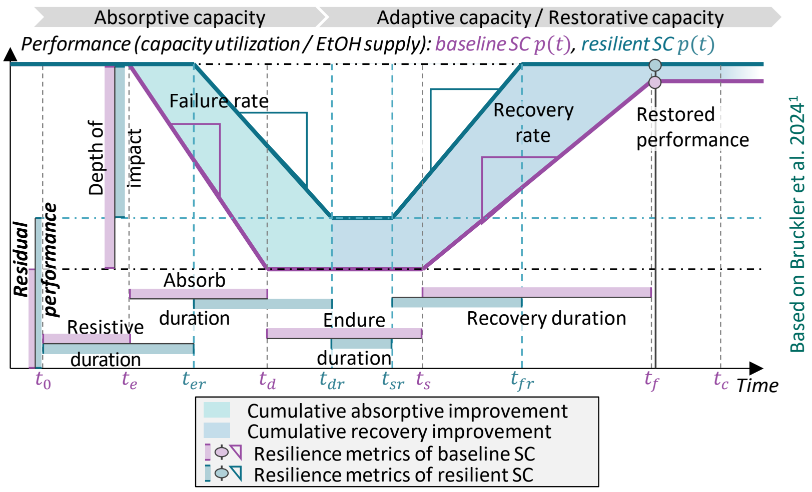
2.2 Resilience consideration and assessment

Unlike existing articles, we differentiate between the producer and consumer resilience of a BioSC. From a producer perspective, the performance measure is the BR capacity utilization: a resilient production maintains high capacity utilization by absorption, adaptation, or restoration from a disruption, which aligns with existing models (e.g., Salehi et al., 2022; Zhao & You, 2019). Regarding the stakeholder 'consumer', we define performance as EtOH supply to cover a demand (supply security): a fully resilient EtOH SC maintains a constant supply to fulfill demand at any time and disruption scenario equal to the covered demand in case of average feedstock availability.

To operationalize resilience, the deterministic MILP of Wietschel et al. (2021) is transformed to explicitly consider the consumer: a satisfaction objective (constraint) enforces a minimum residual performance in demand coverage in each period and feedstock scenario as a first resilience consideration. To cover the producer perspective, the model is turned into a time-discrete, two-stage stochastic linear programming model considering feedstock supply uncertainty. Consequently, the proposed model decides on BR locations and capacities at the strategic level under consideration of feedstock disruption scenarios, which can be considered a second resilience consideration for the improvement of absorptive capacity (Bruckler et al., 2024; Sharkey et al., 2021), since the network design already reflects the supply uncertainty of each individual region. The resulting network design intends to reduce impacts on EtOH production and supply volumes, which is analyzed in Section 3.3.

Besides the model formulation, resilience can be influenced by explicit actions that decision-makers proactively choose to improve absorptive, adaptive, and/or restorative capacities (Bruckler et al., 2024). The underlying model incorporates actions at the strategic and tactical planning levels (Figure C 1). Research on BR network planning considers different types of storage to hedge feedstock uncertainty (Fattahi et al., 2021; Liu et al., 2017; Mousavi Ahranjani et al., 2020; Saghaei et al., 2020; Yazdanparast et al., 2022). Therefore, as a third resilience consideration, our model makes strategic decisions on feedstock storage locations at BR sites and capacities as explicit, strategic resilience action aiming at improving absorptive capacity by absorbing feedstock shortages through inventory (Bruckler et al., 2024). In addition, our model decides on inventory management (storage in-/ outflow) as a tactical resilience action.

Finally, the effect of the proposed resilience considerations is assessed by the resilience curve, which results from mapping the performance measures (capacity utilization = producer resilience; EtOH supply = consumer resilience) over time. Metrics from Bruckler et al. (2024) quantify the effect of resilience actions, the ‘resilience gain’, on the curve’s characteristics that improve absorptive, adaptive, and restorative capacities and, thereby, overall SCR. This article applies only metrics computable with the available data (Figure C 2) to assess how the resilience considerations affect the resulting networks compared to a deterministic baseline supply chain (BSC), which is planned without resilience considerations and based on average feedstock availability similar to Wietschel et al. (2021).



Resilience metric	Description
Resistive duration	*Duration until performance decline*
Absorb duration	*Duration of performance decline*
Depth of impact	*Extent of performance decline*
Residual performance	*Remaining performance*
Failure rate	*Slope of performance decline*
Cum. absorptive improvement	*Area between curves during absorb duration*
Endure duration	*Duration of disrupted performance before recovery*
Recovery duration	*Duration of recovery*
Restored performance	*Performance after recovery*
Recovery rate	*Slope of recovery*
Cum. recovery improvement	*Area between curves during endure & recovery duration*

Figure C 2: *Assessment of resilience. The resilience curve enables the visualization of the performance of different SC configurations from two different perspectives: producer perspective = BR capacity utilization; consumer perspective =EtOH supply to the demand region. In this work, we aim to compare the resilient SC configuration (determined by the resilient model in this work) with a baseline SC (determined by the deterministic baseline model similar to Wietschel et al. (2021)) in the case of feedstock disruption scenarios. Therefore, the proposed resilience metrics are used to quantify the effect of resilience consideration in SC modeling regarding several curve characteristics. For example, the residual performance quantifies the difference between the remaining performance (BR capacity or EtOH supply) after the disruption of the resilient SC and the remaining performance of the baseline SC. This difference represents the positive effect of resilience considerations (by two-stage stochastic modeling, resilience satisfaction objective, and the explicit resilience action of feedstock storages). (own figure based on Bruckler et al. (2024)).*

2.3 EXPERIMENT DESIGN

This work's experiment design aims at the methodological inclusion of resilience in the strategic planning of BioSC and the investigation of its interplay with economic and environmental performance for unforeseen scenarios. Therefore, the regional scope is limited to NUTS1 regions of Romania (RO), Hungary (HU), and Bulgaria (BG), which were identified as promising for 2G EtOH production due to relatively low BR construction and operation costs and high-feedstock availability (Wietschel et al., 2019, 2021). A timeframe of 16 quarters (4 years) is chosen as a suitable compromise between accurate temporal resolution and computational efficiency to account for seasonal supply patterns and inventory holding costs.

Figure C 3 visualizes the proposed two-step approach: in *step 1, strategic SC decisions* based on selected, representative feedstock scenarios from real historical data are drawn. Therefore, *two-stage stochastic programming* determines the capacity levels of biorefinery production and straw storage as well as their locations. *Step 2* then *simulates* *tactical decisions* on storage in- and outflows, feedstock sourcing, and EtOH supply based on scenarios randomly drawn from historical feedstock distributions and thus assesses the performance *for unforeseen scenarios*. The results from the resilient model are benchmarked to the strategic decisions of a baseline model for these scenarios to calculate the 'resilience gain'.

- *Step 1:* the *baseline model* is formulated as a deterministic MILP assuming average supply (baseline scenario) in each region, similar to the assumptions made by Wietschel et al. (2021), and is solved only once to determine the strategic decisions (BR/storage locations and capacities) of a reference network named baseline SC (*BSC*). Furthermore, the 2G EtOH supply volume to each demand region is calculated to serve as *benchmark EtOH demand fulfillment* in the resilient model (*2G EtOH supply (baseline)* in Figure C 3). The *resilient model* is implemented as a two-stage stochastic model: the first-stage ('here-and-now') decisions (Li & Grossmann, 2021) involve location and capacity planning for BR and storage facilities. The second-stage ('wait-and-see') decisions depend on the first-stage decisions and are determined for each scenario realization (Li & Grossmann, 2021). They comprise decisions on feedstock, and EtOH flows and storage in- /outflows. The objective function is the expected net present value for the realization of the 25 selected scenarios with their respective (joint) probability, which results from five discrete feedstock supply scenarios in years two and four (Supporting Information C1, Sections 1.4 and 4.1). In addition, the resilience satisfaction objective ensures a certain level of minimum EtOH demand fulfillment (*residual performance*) for each demand region. It is solved for 11 different *residual performances* between 0% and 100% (represented by ρ^{min} in Figure C 3) of the *benchmark EtOH demand fulfillment* in the baseline. This results in 11 different SC configurations determined by the first-stage decisions with the ascending impact of the resilience satisfaction objective (resilient SC0–SC10).
- *Step 2:* each resulting SC configuration of step 1 is fixed (strategic decisions of BSC; first-stage decisions of the resilient model forming resilient SC0–SC10), and their performance is simulated for the new 25 randomly generated feedstock scenarios (Supporting Information C1). Therefore, an economic optimization of the flows across these scenarios takes tactical decisions: tactical resilience actions (rerouting feedstock collection, storage in- /outflows) and decisions on EtOH supply to demand regions.

Finally, an ex-post analysis assesses the economic (expected net present value) and environmental performance regarding three LCA endpoints of ReCiPe 2016 (Huijbregts et al., 2017) and most contributing midpoints (Figure S2 of Supporting Information C1) of the resulting SC configurations. Additionally, the effect of resilience considerations in SC modeling is evaluated based on the resilience curve for two different performance measures (BR capacity utilization and EtOH demand fulfillment) to investigate both the producer and consumer resilience as conceptually explained in Section 2.2.

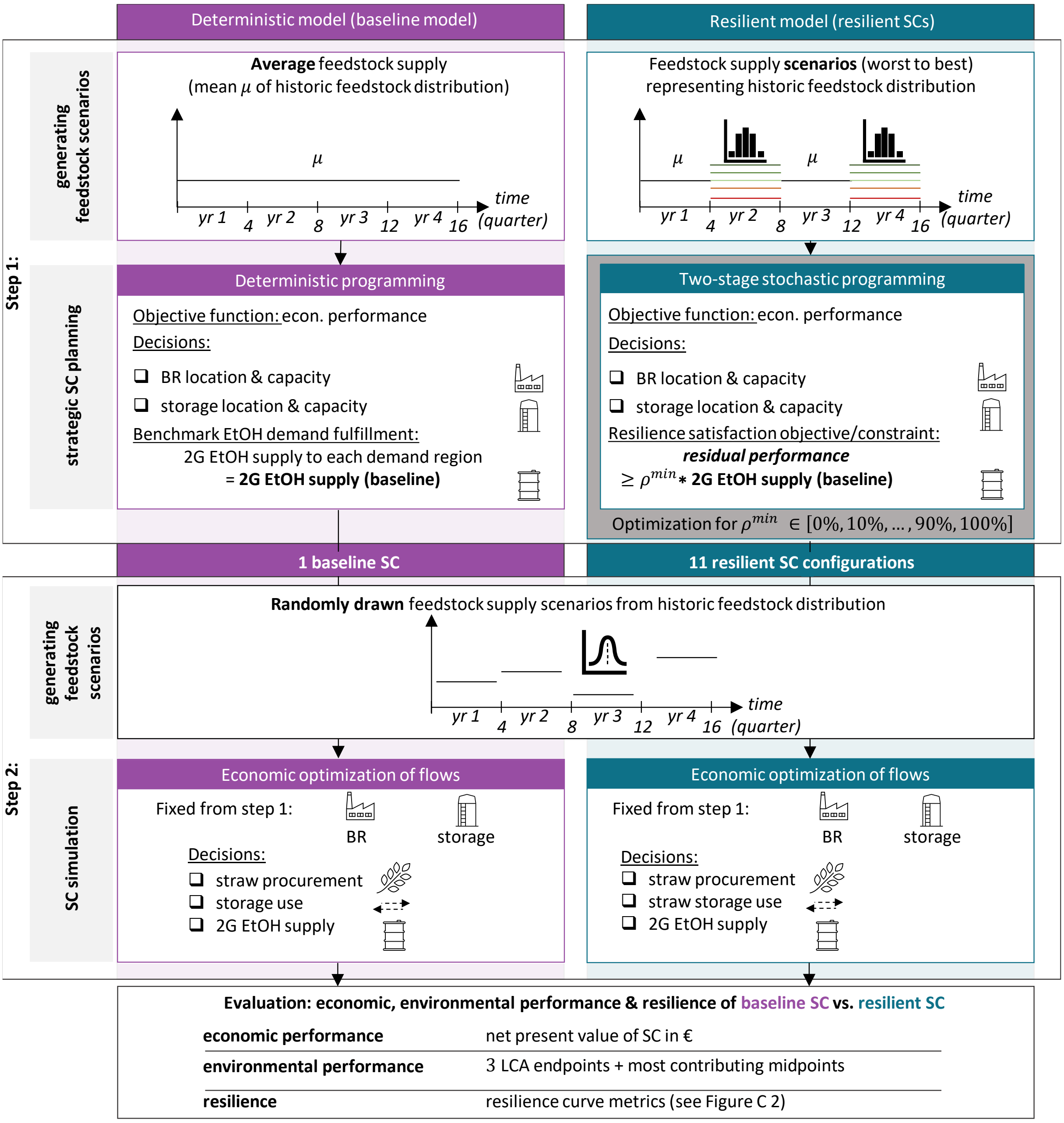


Figure C 3: *Two-step experiment design for strategic supply chain planning (step 1) and simulation of performance for not anticipated scenarios (step 2); feedstock scenarios (step 1): regional historical feedstock volumes are determined based on the approach of (Thorenz et al., 2018) using crop production data between 1987 and 2021 (eurostat, 2024). The feedstock volumes are then trend-adjusted and clustered for each region into five discrete feedstock scenarios (worst to best). Finally, 25 feedstock scenarios are built for the 4–year time horizon: scenario 1–5: years 2 and 4; average feedstock availability: years 1 and 3 (to avoid overlap of effects from consecutive scenarios) (see Supporting Information C1 (1.4 & 4.1) for further explanations on scenario generation and probabilities). For the baseline model, mean historical feedstock volumes in each region were assumed to be available (baseline scenario); feedstock scenarios (step 2): to validate the SC designs of step 1, 25 regionally correlated feedstock scenarios are randomly generated (Supporting Information C1 (4.2)).*

3 RESULTS

In the following, the results of the strategic planning (step 1) and the SC simulation for not anticipated scenarios (step 2) are visualized (see Figure C 4) and described.

3.1 STRATEGIC SUPPLY CHAIN PLANNING

- ❖ *Baseline model, step 1:* the BSC has a total BR capacity of 781.3 kt 2G EtOH/quarter without straw storage since it is not economically viable. The largest BR is built in RO3 (187.5 kt), followed by HU2 and HU3 (150 kt each), RO4 (100 kt), and BG3 and RO2 (87.5 kt each). A comparatively small BR is built in HU1 (18.8 kt). The EtOH produced is finally distributed to high-profit demand regions (i.e., Austria (AT1, AT2), Finland (FI1, FI2), and Sweden (SE2)).
- ❖ *Resilient model, step 1:* considering the stochasticity of feedstock supply and the ascending levels of the resilience satisfaction objective *residual performance* (0%–100% of the benchmark performance)*,* 11 SC configurations (SC0 to SC10) are identified. Since for SC0 the constraint *residual performance* is set to 0% (not binding), the model solely maximizes the economic objective. Compared to BSC, the total capacity reduces to 756.3 kt due to a smaller BR in RO3, RO4, and HU3. Even though the total capacity decreases, a new BR is constructed in RO1. The capacity reduction ensures higher utilization rates even in adverse feedstock supply scenarios, but also results in lower total EtOH production volumes. In contrast to BSC, a total of 128 kt straw storage is built in RO3, HU1, and HU3 to cushion fluctuating supply. These strategic decisions remain robust until the resilience constraint enforces a minimum *residual performance* of 60%, resulting in an identical network of SC0 to SC6. A *residual performance* of at least 70% (SC7) further increases the storage capacity in HU1 to a total of 133.5 kt. For a *residual performance* of 80% (SC8), the BR capacity of RO4 increases, totaling a capacity of 769 kt. For further accentuating *residual performance* to 90% (SC9), the resulting network is characterized by a capacity increase in RO1 to 775 kt. To ensure a *residual performance* equal to the benchmark performance in the baseline scenario (100%), the total BR capacity of SC10 increases to 787.5 kt while the storage capacity remains unchanged.

3.2 Economic & environmental implications

- *Economic performance and resilience of the SC simulation, step 2:* under optimization of the economic objective, the performance of BSC and SC0–SC10 are simulated for the new set of 25 random feedstock scenarios per region and year drawn from the correlated normal distribution. Regarding economic performance, the expected net present value of SC0–SC7 is 1.58% higher than that of the BSC (4.09 E08 €) due to higher average utilization rates of BR capacities (99.42% vs. 98.77% for BSC). Consequently, producer resilience and profitability seem complementary, as higher capacity utilization rates were identified as economically efficient. However, the average quarterly EtOH production volume of 752 kt EtOH is lower due to the smaller total BR capacity of 756.3 kt, resulting in a lower mean covered demand of 96.24% compared to the baseline supply, which indicates lower consumer resilience (more details in Section 3.3). For SC8–10, the economic performance remains better than for the BSC, but the advantage slightly declines from +1.58% (SC8) to +1.17% (SC10). At the same time, the average produced EtOH volume significantly increases from 764 kt (SC8) to 783 kt EtOH (SC10), and demand coverage rises from 97.84% (SC8) to 100% (SC10). The economic benefit of SC0–SC10 compared to BSC is even more apparent in single low feedstock availability scenarios, resulting in above-average performance of up to 4.8% (SC0) and 4.5% (SC10), proving the robustness of the proposed SC configurations, especially against severe events. In contrast, for high-feedstock availability scenarios, the performance is mainly below average, but except for few scenarios, SC10 is preferable compared to BSC. A scenario-wise analysis for each of the 25 scenarios is conducted in Supporting Information C1 (5.2).
- *Environmental performance of the SC simulation, step 2:* the environmental performance is represented by three LCA endpoints and the context-specific most important mid-points (global warming (M1), fine particulate matter formation (M5), terrestrial acidification (M7), human non-carcinogenic toxicity (M14), and land use (M15)). Figure C 4 groups them according to their correlation to economic performance and resilience.
  - Group 1: all endpoints and the midpoints M1, M5, and M7 positively correlate with consumer resilience (maintaining high EtOH demand fulfillment) and negatively correlate with profitability. Two clusters of SC configurations with similar performance were detected. Cluster 1 (SC0–SC7) performs up to 2.3% worse than BSC for these categories, mainly due to the comparatively lower EtOH production. Like the economic performance, the environmental performance in severe scenarios is mainly higher than the average results, but still worse compared to BSC. For high-feedstock scenarios, the performance is even below average, with

up to 2.9% worse (regarding E3). It increases with higher resilience satisfaction due to higher total EtOH production volumes substituting fossil petrol. In cluster 2 (SC8–SC9), the performance is almost equal to or better than that of BSC, while SC10 shows, on average, up to 2.1% (M5) and, in severe scenarios, up to 2.6% (M5) better performance.

- Group 2 (M14 and M15) shows an inverse behavior: with increasing demand fulfillment (resilience satisfaction), the environmental performance degrades. On the other hand, those categories positively correlated with the economic objective and negatively with consumer resilience. Cluster 1 has up to 3.3% (M14) higher performance and higher average capacity utilization rates because of a smaller total BR capacity. However, the environmental performance of SC0 in low feedstock scenarios is mainly below average, with up to only 2.4% (M15) due to less EtOH production of BSC compared to high feedstock availability scenarios. With increasing residual performance from 80% to 90% and the resulting higher BR capacities, cluster 2 converges to the performance of BSC from 1.4 % (SC8) to 0.5% (SC9) for M14. However, capacity utilization rates remain high as the main objective is still the economic dimension. SC10 performs 1.4% regarding M14 and 1.7% regarding M15 worse than BSC, and even worse in low feedstock scenarios, as maintaining EtOH supply high leads to more land use required for SC operations compared to BSC providing less EtOH.

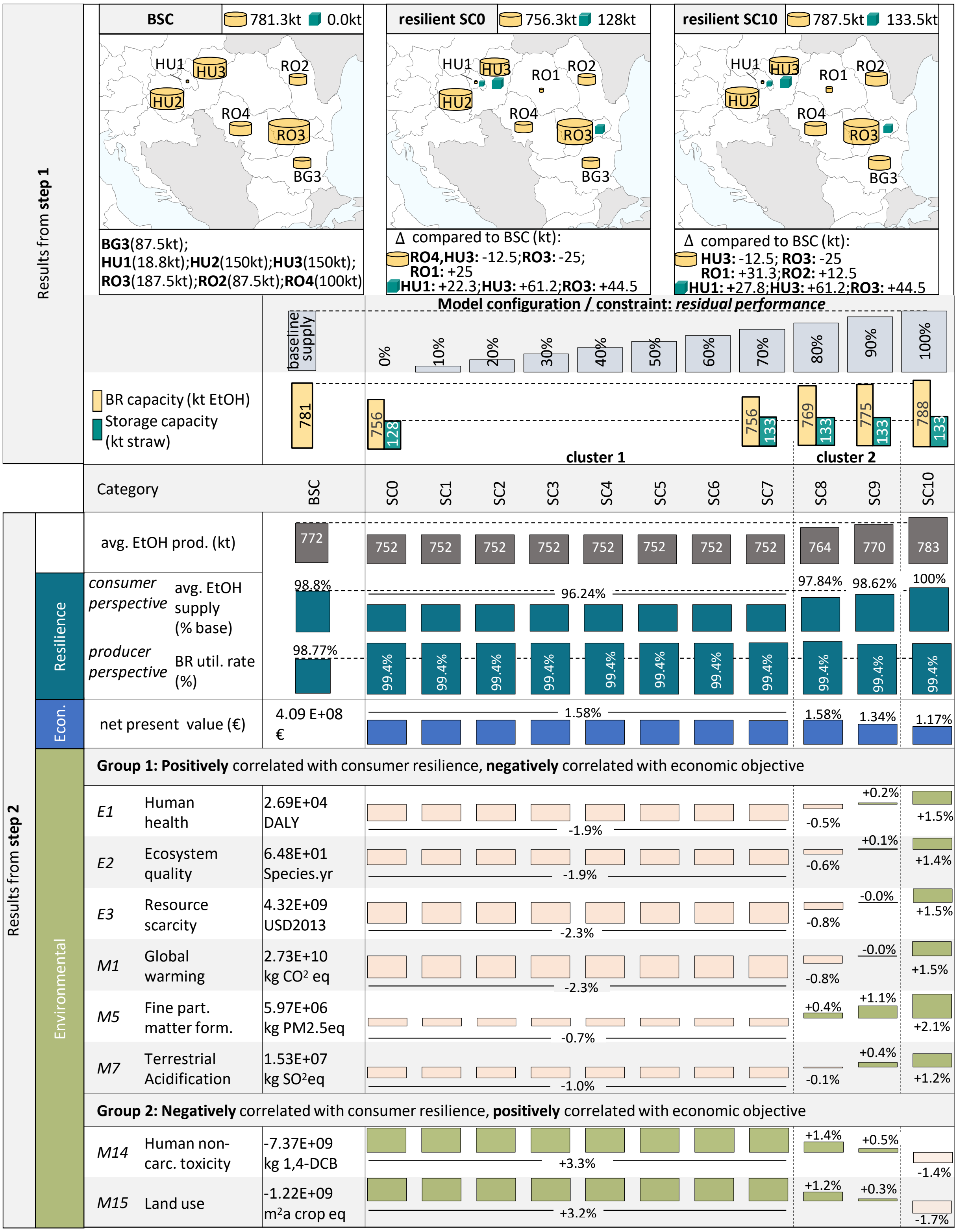


Figure C 4: *SC configurations from step 1 (BR and storage locations and capacities) & economic/environmental performance in step 2 represented as absolute objective value of BSC and percentage increase/decline when choosing a resilient SC (SC0-SC10). Two groups of relations between environmental performance and economic performance /resilience are identified. While the environmental performance regarding LCA categories E1-E3 and M1, M5, M7 (group 1) rises with increasing consumer resilience and decreasing economic performance, group 2 (M14, M15) decreases with rising consumer resilience and decreasing economic performance. Please see Supporting Information C1 (5.1) for the selection process of the LCA categories analyzed within the results. Underlying data for Figure C 4 are available in 'Figure data 2' of Supporting Information C2.*

3.3 Evaluation of consumer and producer resilience

To assess the 'actual' producer and consumer resilience for unanticipated scenarios, the resilience curves of the performance measures of *average BR capacity utilization* and *average EtOH demand fulfillment* (EtOH supply) are analyzed.

Figure C 5 shows the curves for consumer and producer resilience for three representative network configurations: BSC represents the network without resilience considerations, SC0 represents planning under uncertainty without a binding resilience constraint (0%), and SC10 represents planning under uncertainty with a strong resilience constraint (100%).

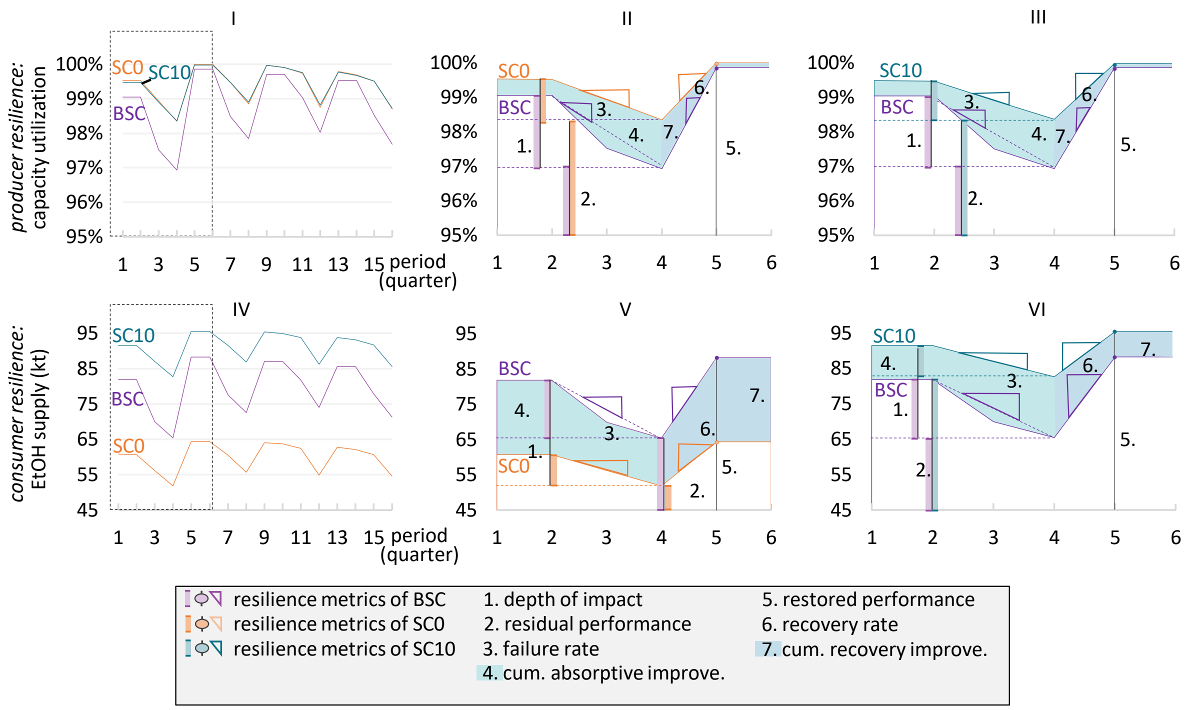


Figure C 5: *Resilience curves & metrics from producer perspective (average BR capacity utilization; producer resilience) and consumer perspective (average EtOH demand fulfillment/EtOH supply of/to NUTS1 region FI1, since the supply disruption only affects this region; consumer resilience): (I) curve for average capacity utilization for complete time horizon (period 1-16) for BSC, SC0 & SC10; (II) curve for average BR capacity utilization for period 1-6 showing resilience benefit of SC0 compared to BSC; (III) curve for average BR capacity utilization for period 1-6 showing resilience benefit of SC10; (IV) curve for average EtOH supply to FI1 for complete time horizon (period 1-16); (V) curve for average EtOH supply to FI1 for period 1-6 showing lack of resilience of SC0 compared to BSC; (VI) resilience for average EtOH supply to FI1 for period 1-6 showing resilience benefit of SC10. Underlying data for Figure C 5 are available in 'Figure data 3' of Supporting Information C2.*

For evaluating the 'resilience gain', the timeframe around the lowest *residual performance* (period 1–6) is selected. The curves of SC0 and SC10 are then separately compared for both performance types to the curve of BSC (II, III, V, VI), and the metrics for quantifying the resilience gain are calculated (Table C 1).

Since the metrics *resistive*, *absorb*, *endure*, and *recovery duration* are unaffected by the proposed resilience considerations, the remaining seven metrics presented in Figure C 2 are evaluated.

- **Producer resilience**: investigating the curves of SC0 and SC10, most metrics indicate a positive effect of integrating resilience into strategic SC modeling. When selecting SC0 instead of BSC, the absorptive capacity increases, which is indicated by the improved metrics *depth of impact* by 0.94%, *residual performance* by 1.42%, *failure rate* by 0.47%, and *cumulative absorptive improvement* by 2.86%. Figure C 5 shows a smaller and less steep performance decline and a higher residual performance for SC0 than for BSC. SC10 shows a slightly higher positive effect on the metrics *depth of impact* (0.99% higher than BSC) and *failure rate* improvement to 0.50% compared to BSC, while *residual performance* is about the same for both SC0 and SC10. However, *cumulative absorptive improvement*, which aggregates the effect of the aforementioned metrics, is lower for SC10 than for SC0, wherefore SC0 is slightly preferable for improving the absorptive capacity from the producer perspective. Since the performance decline of SC0 and SC10 is lower than that of the BSC, less performance must be regained. Therefore, the metrics of *restored performance* and *recovery rate* are lower compared to BSC, leading to negative values. In contrast, the *cumulative recovery improvement* of SC0 (0.92%) and SC10 (0.89%) is higher than for BSC. Compared to SC0, SC10 is slightly preferable when aiming at the improved *restored performance* (+0.02%), but not regarding the *recovery rate* (–0.03%). SC0 is preferable again for maintaining BR capacity utilization high during recovery duration, with a slightly higher *cumulative recovery improvement* (0.03%). Analyzing the resilience metrics, SC0 and SC10 show very similar producer resilience.
- **Consumer resilience:** the difference between SC0 and SC10 becomes apparent from the consumer perspective. SC0 (V) performs worse than BSC in terms of *residual performance* (–13.53 kt) and *cumulative absorptive improvement* (–52.01 kt during the resistive and absorb duration) because of the smaller total BR capacity installed. However, due to a significantly lower production volume, the *depth of impact* (7.62 kt) and *failure rate* (3.81 kt) of SC0 are lower, whereas SC0 performs better in these metrics than BSC. Nevertheless, SC10 (VI.) is preferable for improving the absorptive and adaptive/restorative capacity indicated by almost every single metric (besides *restored performance*). This is especially true for the metrics *residual performance* (+30.83 kt) and *cumulative absorptive/recovery improvement* (+92.33 kt / +62.02 kt), which mainly characterize how well the level of demand coverage is maintained during the observation period.

Table C 1: *Effect of integrating resilience into SC modeling (SC0 and SC10) on metrics compared to BSC. Please refer to Bruckler et al. (2024) for the calculations of the effect on each metric; 'No difference' indicates no effect on a metric when choosing SC0 or SC10 instead of BSC.*

			Producer resilience			Consumer resilience		
	Resilience metrics	**Description**	**Δ(BSC-SC0)**	**Δ(BSC-SC10)**	**Δ(SC0-SC10)**	**Δ(BSC-SC0)**	**Δ(BSC-SC10)**	**Δ(SC0-SC10)**
Effect on absorptive capacity	Resistive duration	duration until performance decline	No difference					
	Absorb duration	duration of performance decline	No difference					
	Depth of impact	extent of performance decline	0.94%	0.99%	0.06%	7.62 kt	7.70 kt	0.08 kt
	Residual performance	remaining performance	1.42%	1.43%	0.01%	-13.53 kt	17.30 kt	30.83 kt
	Failure rate	slope of performance decline	0.47%	0.50%	0.03%	3.81 kt	3.85 kt	0.04 kt
	Cum. absorptive improve.	area between curves during absorb duration	2.86%	2.78%	-0.08%	-52.01 kt	40.32 kt	92.33 kt
Effect on adaptive/restorative capacity	Endure duration	duration of disrupted performance before recovery	No difference					
	Recovery duration	duration of recovery	No difference					
	Restored performance	performance after recovery	-0.35%	-0.32%	0.02%	-0.019%	-0.035%	-0.016%
	Recovery rate	slope of recovery	-1.27%	-1.31%	-0.03%	-10.36 kt	-10.12 kt	0.25 kt
	Cum. recovery improve.	area between curves during endure & recovery duration	0.92%	0.89%	-0.03%	-42.61 kt	19.41 kt	62.02 kt

3.4 Performance under increasing disruption severity

This chapter investigates the effect of increasing disruption severity in light of climate change-related extreme weather events (IPCC, 2022; Lesk et al., 2016) on the economic and environmental performance regarding global warming potential (GWP) of BSC, SC0, and SC10 (Figure C 6). To reflect event severity for the randomly drawn feedstock scenarios, the extreme events are assumed to occur in years 2 and 4 and reduce the supply by a factor from 0% to 80%.

The environmental and economic performance decreases with rising disruption severity. In the economic dimension, SC0 consistently performs best. At a severity level of 60% (rather unrealistically high severity), the economic performance of SC0, SC10, and BSC turns negative. Around that point (50–60%), the relative economic advantageousness of SC0 and SC10 compared to BSC peaks. For even higher severity, all configurations show further decreasing economic performance, while the relative economic advantage of SC0 and SC10 still remains, but decreases again as this extreme level of low feedstock availability has not been anticipated in the planning step. The relative economic advantage of SC10 is especially decreasing as the investment in resilience actions weighs relatively high compared to the low economic revenue from EtOH production for high severity. The GWP benefit is more robust against increasing severity than the economic performance and consistently stays positive for each severity scenario and SC configuration. SC10 has the highest average GWP benefit, and its advantage, compared to the BSC, peaks at 3.9% for 60% severity before it decreases again. Similarly, the relative GWP disadvantage of SC0 compared to BSC decreases with increasing severity, and from 60% severity onwards, SC0 has a higher GWP benefit than BSC due to available resilience actions like feedstock storage that cover shortages. Figure C 6 further unveils a high correlation between the average EtOH production volumes of SC0 and SC10 and the GWP benefit. Figure S4 of Supporting Information C1 (5.3) describes the performance of land use for increasing severity.

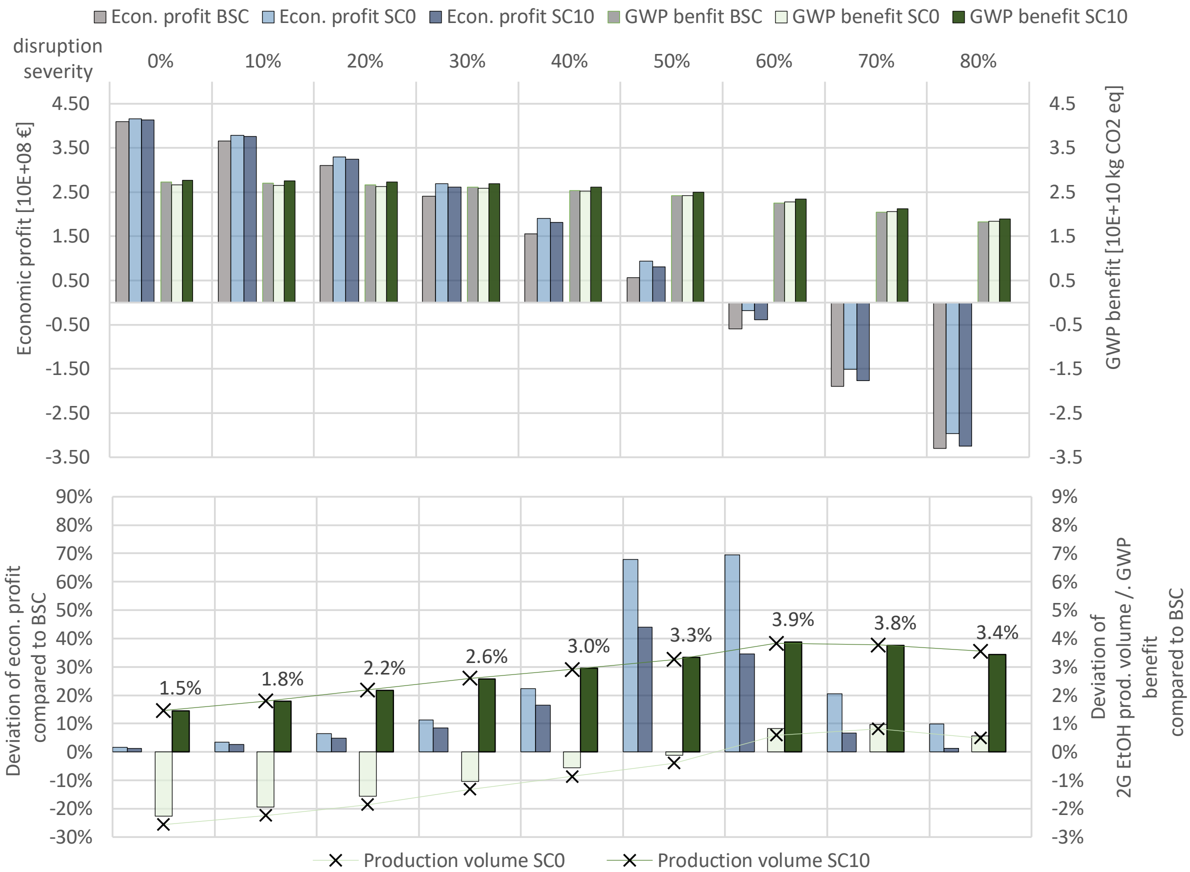


Figure C 6: *Economic and environmental performance regarding GWP (M1) for increasing disruption severity. The diagram at the top visualizes the absolute economic profit (blue) and GWP benefit (green) for increasing severity for the configurations SC0, SC10, and BSC (grey). The diagram at the bottom displays the relative deviation (benefit or drawback) of SC0 and SC10 compared to BSC regarding economic profit (blue) and GWP benefit (green), as well as the deviation of the EtOH production volume (green lines) compared to BSC. Underlying data for Figure C 6 are available in 'Figure data 4' of Supporting Information C2.*

4 Discussion and conclusion

This article presents a two-step experiment design that integrates resilience considerations into the strategic planning of BioSC. The principal idea behind the experiment design is the anticipation of future feedstock disruptions already within strategic SC design. We, therefore, propose a stochastic MILP that optimizes the economic dimension, adheres to resilience constraints, and co-calculates the environmental dimension.

Step 1 takes strategic SC decisions on scenarios that represent the historical supply variance. Using representative scenarios that typify realistic future developments instead of randomly drawn scenarios from probability distributions is a common approach in SC decision-making (Maier et al. 2016). To account for the unknown future, step 2 simulates the performance of the resulting networks by drawing equally weighted random feedstock scenarios. We thereby validate the strategic SC decisions from step 1, which pursues the necessary shift towards the assessment of the 'actual' resilience to unforeseen events called for in the literature (Bruckler et al., 2024; Inan et al., 2024; Reyers et al., 2022).

The feedstock scenarios used in this work reflect realistic supply fluctuations in promising bioeconomy regions such as Eastern Europe to investigate the ramifications of fluctuations in the BioSC performance. Our results indicate that scenario-based stochastic modeling that considers feedstock uncertainty and integrates deliberate resilience actions, such as feedstock storages, strengthens producer resilience. However, consumer resilience is not inherent, as it is not necessarily profitable for the producer. This requires an explicit consideration of resilience metrics within the model constraints, such as a minimum *residual performance* in EtOH demand coverage, to steer BioSC planning toward consumer resilience. The positive effect of explicitly incorporating consumer resilience in the supply chain planning is proven by the simulation of unforeseen supply fluctuations in step 2: with very high consumer resilience requirements (e.g., due to contracted supply rates), the resulting SC10 achieves a higher EtOH supply security (consumer resilience), higher economic benefit and higher environmental benefits for several impact categories (e.g., GWP) compared to the deterministic baseline SC (BSC). This observation is especially pronounced in severe disruption scenarios. Compared to SC0, the resilience curve of SC10 shows a higher *residual performance* and related metrics like *cumulative absorptive/recovery improvement*. Planning without the binding consumer resilience constraint (SC0) results in slightly higher economic benefit for the producer compared to SC10 and BSC, and a noticeably lower EtOH supply security for the consumers. For practitioners such as SC planners, our results demonstrate the necessity of considering consumer resilience in SC modeling to fulfill the system objective (economic profitability) and customer needs simultaneously as the requirements for resilient BioSC.

Although the expected objective values and resilience metrics of the different SC configurations differ only slightly in the aggregated results, the scenario-wise analysis unveiled more pronounced economic and environmental benefits of resilient SC, especially for low feedstock supply scenarios. Eventually, the performance of different SC configurations is simulated for increasing disruption severity to investigate the impacts of ongoing climate change with increasing frequency and intensity of weather extremes. Similar to Pizzol (2015), we confirm an increasing outperformance of resiliently planned networks over vulnerable networks in terms of GWP for growing disruption severity. However, we observe a nonlinear behavior of the economic and environmental (GWP) benefit of the resilient SC compared to the BSC, as the relative advantage peaks at 60% severity.

The bigger picture of considering resilience in BioSC modeling unveils heterogeneous patterns for different environmental categories, resilience, and the economic dimension. Consumer resilience is congruent with environmental goals of group 1, where considerable benefits (e.g., regarding global warming) can be realized by producing second-generation bioethanol to substitute petrol. In line with Pizzol (2015), this phenomenon particularly applies to BioSC when environmentally beneficial alternatives substitute fossil-based products. Policymakers can conclude from our study that strengthening the consumer resilience of BioSC increases environmental benefits regarding several LCA categories and serves the goal of sustainable development. Therefore, incentivizing consumer-resilient SC planning contributes to a successful European Bioeconomy. Conversely, resilience conflicts with environmental categories like land use (group 2), where the product performs worse than its reference. Due to the multiplicity of goals for sustainable development, it is not possible to equally satisfy all objectives simultaneously. Especially, policymaking may be confronted with remaining conflicts between desirable aspects, which necessitates a transparent discussion of such limitations (European Commission, 2018).

A limitation of our approach is the small number of 25 different scenarios in the strategic SC planning. However, Shapiro & Philpott (2007) note that a high number of scenarios does not necessarily result in a solution closer to the 'actual' optimum of the real problem. Since the exact prediction of future supply is impossible, we decided to base the strategic planning on explicitly chosen scenarios representing the historical range of feedstock availability in each region. Although some assumptions, such as the constant feedstock availability within a year (seasonality is considered by seasonal inventory holding costs at the farmer), the pattern of average feedstock availability in years 1 and 3 and explicit feedstock scenarios in years 2 and

4 are arbitrarily chosen to represent two isolated extreme years that do not interfere, the viability of our approach is proven by step 2.

The presented approach is specifically elaborated for the 2G bioethanol production in the EU, which limits drawing more general conclusions. Nevertheless, for SC planners, the approach can serve as a methodological blueprint for other BioSC using straw or feedstock with similar properties, as biorefineries could also produce other green chemicals like methanol to substitute fossil-based products. Also, for a completely different SC, the integration of resilience constraints or objectives to strengthen consumer resilience might be possible and desirable to increase supply security. Conclusions about the environmental performance cannot be transferred to other SC, as this depends heavily on the product under consideration. A possible extension would be an integration of different metrics to improve specific characteristics of the resilience curve according to the decision-maker's preference. As this work has not considered resilience metrics as maximizing the objective function, multi-criteria approaches optimizing economic, environmental, and/or resilience aspects would provide deeper insights into relevant trade-offs for decision- and policy-making. Our research approach sets a basis for future research to derive a more standardized methodology for various application cases to prepare for the unforeseen in resilient planning.

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CONTRIBUTION D

DESIGNING RESILIENT LARGE-SCALE SUPPLY CHAINS: THE TRIANGLE BETWEEN RESILIENCE ACTIONS, TARGETS, AND ECONOMIC LEEWAY

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ABSTRACT

At present, the uncertain supply of resources is a major concern of decision-makers when designing supply chains. Since improving supply chain resilience through actions like installing storages is associated with higher costs, a trade-off between resilience and economic performance must be found. Most existing approaches for designing resilient supply chains focus on optimizing economic performance under different sources of uncertainty. However, only few approaches explicitly incorporate a resilience dimension into their objective systems. Therefore, we propose a three-stage decomposition-based approach: The first stage economically optimizes the initial strategic supply chain design. The second stage uses simulative scenario-based flow optimization to assess resilience gaps. The third stage uses a matheuristic to optimize both criteria (economic performance and resilience) and compute desirable trade-off solutions.

We evaluate our approach for the large-scale problem of advanced (second-generation) bioethanol supply chain, which is vulnerable to climate change and related extreme weather events affecting the feedstock supply (i.e., straw). The combination of different local search strategies for implementing resilience actions with different self-adaptive economic lower bounds and resilience targets allows decision-makers to regulate the trade-off between resilience and economic performance. The two resilience actions (reallocation of production capacities and storage installation) reveal different characteristics in improving resilience, which can be visualized by resilience curves and metrics. Thereby, long-term or high-impact disruptions are best addressed by focusing on resilience actions, avoiding disruptions (e.g., reallocating production capacities). Short-term small or moderate disruption scenarios should be handled by resilience actions that strengthen production facilities (e.g., additional storage).

1. INTRODUCTION

The frequency and intensity of extreme weather events and compound weather extremes rose in the last decades (IPCC, 2022), with severe implications for the provision of resources essential for a functioning society. In 2016, for example, a compound of an abnormally warm autumn with wet spring conditions led to severe agricultural yield losses of up to 45 % in central Europe, which disruption forecasting systems have entirely failed to anticipate (Ben-Ari et al., 2018). In 2021, Taiwan unexpectedly suffered a major drought due to the absence of typhoons, which typically account for about 70 percent of total rainfall (Narvaez et al., 2022; Unabiz, 2021). Consequently, significant water shortages severely impacted agricultural production and Taiwan's most important industry, the semiconductor production (Narvaez et al., 2022). More than 80 % of the global supply of high-performance semiconductors is produced in Taiwan, wherefore this disruption rippled through the global high-tech industry (World Economic Forum, 2024). While these cases show the relevance of supply disruptions for companies and society, most academic work on supply chain (SC) risk management focuses on demand uncertainty, and yet only a few works on supply uncertainty (Govindan et al., 2017; Tang, 2006). Rising geopolitical tensions and intensifying weather extremes, however, elevate the pressure on the supply of resources and basic materials, wherefore actions and strategies for ensuring SC resilience are increasingly gaining interest (Bruckler et al., 2025).

Resilience in the context of SCs can be described by its performance over time in the face of disruptive events (Cheng et al., 2022; Ivanov, 2024; C. Zhou et al., 2025). It can be visualized by resilience curves and quantified by resilience metrics, numerically describing the curve's shape (Bruneau et al., 2003; Poulin & Kane, 2021; Sheffi & Rice, 2005). Depending on the perspective, the performance of a SC can be interpreted very differently: for example, a customer aims at supply security while a producer focuses on maintaining facility capacity utilization (Bruckler et al., 2024, 2025; Poulin & Kane, 2021). The extent of resilience depends on the availability of absorptive capacity (i.e., the ability to absorb impacts on the performance), adaptive capacity (i.e., the ability to align the SC network elements to new conditions for recovering performance), and restorative capacity (i.e., the ability to recover the original structure and performance) to counteract negative impacts from extreme events (Biringer et al., 2013; Vugrin et al., 2011). In the context of SC, resilience actions are strategies that can be applied along with traditional SC planning tasks to improve resilience (capacities), which can be visualized by an improved curve shape and metrics (Bruckler et al., 2024). Depending on the individual preference of the decision-maker on which resilience characteristics should be improved (e.g., less deep disruptions, shorter disruption duration, less overall performance loss), different resilience actions are required. However, fewer articles have evaluated the characteristic effect of different resilience actions on the resilience curve (Bruckler et al., 2024).

The major challenge for determining and improving resilience is the uncertainty of future development (Reyers et al., 2022). In the early 2000s Sabri and Beamon (2000) had already identified uncertainty as one of the most important aspects to be considered in SC management. While an extensive conceptual literature on SC resilience against exogenous events already exists, methodological approaches on resilient SC network design have focused on the development of robust or stochastic models considering the inherent uncertainty of demand and facility perturbations rather than the uncertainty of supply due to possible disruptive events (Govindan et al., 2017). Additionally, most existing resilient SC design models consider a single period instead of a multi-period time-horizon, meaning that long-lasting disruptions are not covered, and mainly focus on the economic efficiency or profitability under uncertainty while disregarding explicit resilience objectives such as the consumer perspective (Govindan et al., 2017; Heckmann et al., 2015). For example, Bruckler et al. (2025) contribute to this research on disruption-related uncertainty by considering a small set of representative supply disruption scenarios in strategic SC design for the case of biofuel to increase resilience regarding unexpected scenarios that may result from extreme weather events. The authors additionally take the consumer perspective into consideration by requiring a certain level of demand fulfillment as resilience satisfaction objective related to the resilience curve concept (Bruckler et al., 2025). Other approaches, like stochastic models, that consider a high number of scenarios and aim to cover a wide range of potential future realizations within the planning stage, typically face computational challenges (Ehrenstein et al., 2019; Suryawanshi & Dutta, 2022). To handle these challenges of large-scale problems, such as the strategic planning of large-scale SCs, the literature has identified decomposition approaches as an appropriate method (Ni et al., 2018; Suryawanshi & Dutta, 2022). For example, Sabri & Beamon (2000) have proposed a decomposition approach for simultaneous strategic and operational planning: after taking initial strategic decisions for a deterministic (baseline) scenario, the results of a strategic model are iteratively fed into an operational sub-model that includes parameter uncertainty. The operational model decisions, in turn, serve as input for adjusting the strategic decisions.

Based on the generally accepted approach of decomposing the SC network design problem into the decision levels, network structure, and operational flows, as well as the resilience curve concept and metrics to assess SC resilience, we propose a three-stage decomposition-based SC design approach: The first stage economically optimizes a deterministic SC design model to provide initial strategic decisions. In the second stage, an exhaustive set of realistic future feedstock supply scenarios is simulated, whereas the network flows are economically optimized. The resulting SC performance represented by the product supply (satisfied demand) over time (i.e., the shape of the resilience curves) provides insights into the SC resilience and allows the identification of impacts on demand regions (i.e., the resilience gap) that are caused by feedstock supply disruptions rippling through the SC. In the third stage, a matheuristic (MH) iteratively identifies potential neighborhood solutions (i.e., initial strategic SC design decisions are strengthened by resilience actions) with a local search (LS) and then evaluates the performance with regard to resilience and economic performance. In this stage, two different LS strategies, three resilience targets, and two approaches for a self-adapting economic lower bound can be combined, resulting in different MH-variants guiding the search process differently. The LS strategies determine which type of resilience action is tested first. The resilience target specifies which aspect of performance improvement is to be prioritized. In this work, we apply the targets reduction of deep impacts, the duration of disruptions, or a combination of both. The economic lower bound is used to control the financial leeway for resilience actions. Altogether, we consider twelve different MH-combinations of LS mechanisms, resilience targets, and economic lower bounds, enabling decision makers to explore the trade-off between resilience and economic performance.

Our approach advances existing research by combining methods from Operations Research (i.e., optimization and matheuristic) with another theoretical concept (i.e., the resilience curve) to enable a more sophisticated, multifaceted decision-making (Alikhani et al., 2023). In this regard, the trade-off between resilience and economic performance has been rarely addressed in existing literature (Heckmann et al., 2015) and has recently regained the attention of researchers and practitioners (Lücker et al., 2025). In summary, we make the following contributions to the literature:

- To account for resource supply disruptions and design resilient SC, we propose a three-stage approach that decomposes strategic (network structure) and tactical/operational (material procurement, inventory, and distribution planning) decisions and that can handle an exhaustive set of future scenarios.
- In the third stage, we present a matheuristic that combines local search with mathematical optimization for decision-making in large-scale problems.
- Within this matheuristic approach, we examine the influence of different combinations of two resilience action types, two different self-adapting economic bounds, and three different resilience targets on strategic network design and the resulting performance regarding resilience and the economic dimension.
- We use the resilience curve concept to assess and validate the effectiveness of our approach and to identify distinct resilience characteristics of resilience actions.

- ❖ We evaluate the proposed approach for the large-scale problem of a climate-vulnerable biofuel production network and provide trade-off solutions between economic performance and different resilience targets to support decision-making.

The structure of the paper is as follows. Section 2.1 briefly summarizes the concept of resilience assessment, while section 2.2 gives an overview of existing literature on resilient SC design. The underlying real-world problem is explained in section 3. Section 4 describes the three-stage decomposition approach in detail and the developed MH variants. Section 5.1 presents the SC designs arising from the MH variants, section 5.2 shows their effectiveness in improving resilience for not-anticipated supply scenarios through an out-of-sample test. First, their aggregated performance and Pareto solutions are analyzed. Second, the resilience curves for representative scenarios reveal the individual characteristics of resilience actions. Section 6 discusses the implications for decision-makers regarding the different variants as well as strengths and weaknesses. Finally, section 7 summarizes the insights and gives an outlook for future research.

2. Theoretical foundation

The following Section, 2.1, briefly describes the fundamentals of resilience assessment and thoroughly explains the concept of resilience curves and metrics. Then, we analyze the most closely related literature on resilient SC design.

2.1 SC resilience assessment at a glance

The resilience curve is an established concept introduced in the early 2000s to quantitatively assess the infrastructure availability after an earthquake (Bruneau et al., 2003). It was initially used to visualize the rapid decline and consecutive recovery of infrastructure availability over time, which enables the quantification of the resilience gap as the area above the curve limited by the horizontal line representing full availability of infrastructure (Bruneau et al., 2003). Over time, the resilience curve concept has evolved through consideration of pre- and during-disruption phases, resulting in a trapezoid-shaped curve (Henry & Ramirez-Marquez, 2012; Panteli et al., 2017; Poulin & Kane, 2021; Umunnakwe et al., 2021). Literature reviews have already harmonized these metrics and their manifold mathematical formulations (Bruckler et al., 2024; Poulin & Kane, 2021). Figure D 1 shows two resilience curves: one with (turquoise curve) and one without resilience actions (purple curve). In line with the idea of Bruneau et al. (2003), the resilience gap (see Figure D 1) represents the lost performance compared to the target performance (as the area over the curve) and is used as a decision criterion of the proposed MH in Stage III, which should be minimized in order to improve SC resilience. The remaining metrics in Figure D 1 serve not only to assess the current state (purple resilience curve without actions, similar to Poulin & Kane (2021)) but also to evaluate the improvement effect by resilience actions (difference between purple and turquoise curves), as they increase absorptive, adaptive, and restorative capacities, which modify the curve's shape (Bruckler et al., 2024, 2025).

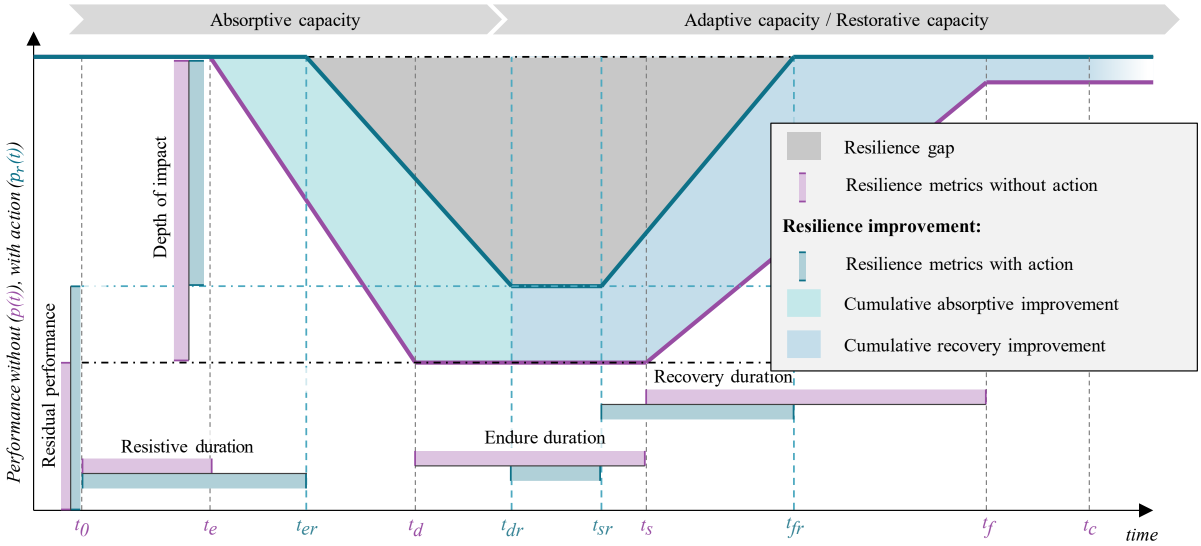

Figure D 1: *Exemplary resilience curves and metrics (based on Bruckler et al. 2024, 2025).*

The basis for assessing the improvement effect of resilience actions are the following characteristic points in time and their corresponding performance values (see Figure D 1): t_0 ≔ start of the observation window, t_e (t_{er}) ≔ start of performance decline (with resilience actions), t_d (t_{dr}) ≔ end of performance decline (with resilience actions), t_s (t_{sr}) ≔ start of performance recovery (with resilience action); t_f (t_{fr}) ≔ end of performance recovery (with resilience action), and t_c ≔ end of the observation window. While absorptive capacity refers to the ability to ideally avoid or at least partially absorb the initial performance decline between t_0 and t_d (t_{dr}), adaptive and restorative capacities relate to the ability to efficiently recover performance between t_d (t_{dr}) and t_c (Bruckler et al., 2024). Table D 1 presents a selection of metrics that can be used to assess the improvements in resilience capacities achieved by implemented actions, based on resilience curves to reduce the resilience gap (i.e., the area above the curve). The improvement effect of these metrics can be categorized into three resilience targets of reducing the duration of disruption (DD) (i.e., by increasing resistive duration/decreasing endure & recovery duration), reducing the depth of performance loss (DI) (i.e., by decreasing the depth of impact/increasing residual performance), and the combined effect of reducing the overall performance loss (CI) (i.e. by increasing cumulative absorptive and recovery improvement). Depending on the resilience target, some resilience actions might be more effective than others: higher inventories, for example, might extend the resistive duration, but don't mitigate the depth of impact.

Table D 1: *Selected resilience curve metrics categorized by the resilience target with description and the improvement effect by resilience actions (cf., Bruckler et al. 2024, 2025).*

Resilience metric	Improvement by resilience actions	Calculation of improvement
DD	*Resistive duration*	Increased resistive duration
DD	*Endure duration*	Reduced duration of disrupted performance before recovery
DD	*Recovery duration*	Reduced duration of recovery
DI	*Depth of impact*	Reduced extent of performance decline
DI	*Residual performance*	Increased remaining performance
CI	*Cumulative absorptive improvement*	Increased area between curves until end of performance decline
CI	*Cumulative recovery improvement*	Increased area between curves during endure & recovery duration

2.2 Related literature on resilient SC design

Literature has already dealt with resilient SC modeling. Table D 2 provides a comprehensive overview of relevant research in this field, structured by the degree of resilience consideration and chronological order. The nomenclature used in Table D 2 is as follows:

- Sources of uncertainty or disruptions: C := costs, D := demand, F := facility availability, L := link availability, and S := supply;
- Model type: Det. := deterministic model, Sto. := stochastic model, and Rob. := robust model;
- Resilience consideration: M := model type and/or formulation (such as constraints) aim at increasing resilience, A := resilience action is explicitly considered within the model, and O := Resilience is considered either as an explicit resilience objective, as part of a combined objective function, or as a decision criterion.

The most crucial distinction between existing articles is the model type, with most articles applying stochastic programming based on predefined scenarios (Alizadeh et al., 2024; Guo et al., 2024; Sabouhi et al., 2021), followed by robust programming (Hu et al., 2025; Nasrollah et al., 2023; X. Zhou et al., 2024), whereas both types allow the consideration of disruption scenarios and/or uncertainty of model parameters. Another distinction is observed in the type of uncertainty parameter: many articles focus solely on uncertainty (Garcia-Herreros et al., 2014; Lotfi et al., 2024; Nikian et al., 2023), followed by partial to complete facility disruption (e.g., Ehrenstein et al., 2019; Fattahi et al., 2017; Lou et al., 2020). Only a few works consider supply disruptions (Chen et al., 2021; Punnathanam & Shastri, 2022) or cost uncertainty (Shekarabi & Mozdgir, 2025; C. Wang & Zhong, 2024). Some articles take a combination of different uncertainties into account (e.g., Guo et al., 2024; Hasani & Khosrojerdi, 2016; Jabbarzadeh et al., 2018; Khezerlou et al., 2021).

Table D 2: *Related literature on resilient SC modeling.*

Reference	Uncertainty / Disruption	Econ. obj.	Resil. obj.	Resil. action	Resilience consideration	Model type	Exact	Metaheuristic	Heuristic	Hybrid appr.	Decomposition	Application case
Holzapfel et al., 2023	-	x		x	A	Det.			x	x	x	Distribution network
Jahed et al., 2024	D,S	x			M	Rob.		x		x		Vaccine SC
Hasani & Khosrojerdi, 2016	C,D,F,S	x		x	M,A	Sto.		x		x		Generic SC
Fattahi et al., 2017	F	x		x	M,A	Sto.	x					Generic SC
Ehrenstein et al., 2019	F	x		x	M,A	Sto.			x		x	Three-echelon SC
Peng et al., 2021	D,L	x		x	M,A	Sto.			x	x		Logistic network
Gholami-Zanjani et al., 2021	D	x		x	M,A	Sto.	x				x	Food SC
Vali-Siar et al., 2021	D,F	x		x	M,A	Sto.		x		x		Closed-loop SC
Vali-Siar & Roghanian, 2022	D,F	x		x	M,A	Sto.			x	x		Closed-loop SC
Aldrighetti et al., 2023	F	x		x	M,A	Sto.			x	x	x	Multi-echelon SC
Nasrollah et al., 2023	D,S	x		x	M,A	Rob.		x	x			Closed-loop SC
C. Wang & Zhong, 2024	C	x		x	M,A	Sto.		x				Four-echelon SC
Hu et al., 2025	D	x		x	M,A	Rob.	x					Multi-echelon SC
Sabouhi et al., 2021	C,D,F,L	x		x	M,A	Sto.	x				x	three-echelon SC
Garcia-Herreros et al., 2014	D	x			M,O	Sto.	x				x	Generic SC
Ghavamifar et al., 2018	D,F,L	x			M,O	Sto.	x				x	SC network
Azad & Hassini, 2019	D,F	x			M,O	Sto.	x				x	Generic SC
Lou et al., 2020	F		x		M,O	Det.		x				Supply network
Cheramin et al., 2021	D	x	x		M,O	Sto.	x				x	Magnet recycling SC
Esmizadeh et al., 2021	D	x	x		M,O	Sto.		x				Three-echelon cold chain
Khezerlou et al., 2021	D,F,L,S	x			M,O	Det.		x				Biofuel SC
Lotfi et al., 2024	D	x			M,O	Rob.	x		x	x	x	Closed-loop SC
Nikian et al., 2023	D	x			M,O	Rob.		x				Steel SC
Pathy & Rahimian, 2023	D	x	x		M,O	Sto.	x				x	Pharmaceutical SC
Alizadeh et al., 2024	D,F	x	x		M,O	Sto.	x				x	Closed-loop SC
Guo et al., 2024	C,D,F	x	x		M,O	Rob.		x				Generic SC
X. Zhou et al., 2024	D	x	x		M,O	Rob.	x			x	x	Hydrogen SC
Zahiri et al., 2017	D,S	x	x	x	M,O,A	Sto.		x		x		Pharmaceutical SC
Jabbarzadeh et al., 2018	C,D,F,S	x		x	M,O,A	Sto./Rob.						Closed-loop SC
Saghaei et al., 2020	D,S	x		x	M,O,A	Sto.		x		x		Four-echelon biomass SC
Chen et al., 2021	S		x	x	M,O,A	Det.		x				Two-echelon SC
Hasani et al., 2021	C,D	x	x	x	M,O,A	Rob.		x		x		Med. device SC
Punnathanam & Shastri, 2022	S	x		x	M,O,A	Sto.			x		x	Biofuel SC
Goodarzian et al., 2022	D	x	x	x	M,O,A	Sto.		x		x		Healthcare SC
Khalili-Fard et al., 2024	D	x	x	x	M,O,A	Sto.		x	x	x		Humanitarian SC
Y. Wang et al., 2024	F	x		x	M,O,A	Rob.	x					Generic SC
Liu et al., 2025	D	x		x	M,O,A	Sto.			x		x	Multi-echelon SC
Müllerklein & Fontaine, 2025	L	x		x	M,O,A	Sto.	x					Supply network
Shekarabi & Mozdgir, 2025	C	x		x	M,O,A	Rob.	x					Food SC
Bruckler et al., 2025	S	x	x	x	M,O,A	Sto.	x					Biofuel SC
Our study	**S**	**x**	**x**	**x**	**M,O,A**	**Sto.**			**x**	**x**	**x**	**Biofuel SC**

Furthermore, the approaches differ in their objective functions: Most models pursue economic objectives to minimize the expected costs under disruption scenarios or parameter uncertainty. Due to the limitation to only one stakeholder–mostly a producing company–one can argue that such approaches only serve the entity applying this modelling to achieve efficient planning under uncertainty, sometimes referred to as 'robust planning'. Some works open towards different stakeholders and consider the consumer resilience in terms of supply security by integrating penalty costs for unsatisfied demand (Ghavamifar et al., 2018; Khalili-Fard et al., 2024; Nikian et al., 2023; Shekarabi & Mozdgir, 2025) or risk metrics like the conditional value at risk (Ehrenstein et al., 2019; Khezerlou et al., 2021) within the economic objective functions.

Only very few works consider explicit resilience objective functions, with the majority applying so-called network structure metrics: Lou et al. (2020) and Chen et al. (2021) present resilience objectives based on the robustness metric' network connectivity after disruption'. Hasani et al. (2021) minimize the 'centrality of nodes' while Goodarzian et al. (2022) present a resilience objective function by composing several network structure metrics, including 'node complexity' and 'criticality', as well as the efficiency in distribution centers and warehouses. Similarly, Zahiri et al. (2017) combine 'flow and node complexity' with 'node criticality'. Guo et al. (2024) maximize the reliability of selected inventory location and transport edges. Another type of resilience objective is based on metrics assessing the downstream SC performance to represent consumer resilience: Zahiri et al. (2017) use network structure metrics and additionally incorporate customer dissatisfaction to minimize the maximum unmet demand in each period. Esmizadeh et al. (2021) include the maximization of customer satisfaction as a separate resilience objective besides an economic, company-oriented objective. However, less present in existing works are approaches that use resilience curve-related metrics as objective functions, which is also pointed out by Bruckler et al. (2024). Khalili-Fard et al. (2024), for example, minimize the time-to-response between disrupting event and system failure, also referred to as the endure and recovery duration of the resilience curve (Bruckler et al., 2024). Other approaches apply resilience (chance) constraints, such as requiring a minimum level of demand satisfaction regardless of the disruption severity (Bruckler et al., 2025; Cheramin et al., 2021).

Besides the consideration of explicit resilience objectives many existing SC models consider decisions on different resilience strategies such as facility reinforcement or provision of additional backup or production capacities (Gholami-Zanjani et al., 2021; Heidari & Rabbani, 2023; Hu et al., 2025; Peng et al., 2021; Vahid Nooraie & Parast, 2016; Vali-Siar et al., 2022), multiple sourcing (Aldrighetti et al., 2023; Sabouhi et al., 2021; Vali-Siar et al., 2022), backup supplier availability (Aldrighetti et al., 2023; Nasrollah et al., 2023) or storage availability (Bruckler et al., 2025; Punnathanam & Shastri, 2022; Saghaei et al., 2020).

Besides the degree of resilience consideration, existing articles on resilient SC design also differ in their solution strategy. The majority solve their models exactly. A widely used exact decomposition approach for two-stage formulations, such as resilient SC models, is Benders Decomposition, which is well-suited for large instances with complex and continuous variables (Müllerklein & Fontaine, 2025). Many articles apply explicit strategies such as simultaneously adding multiple Benders cuts to the master problem (Cheramin et al., 2021; Pathy & Rahimian, 2023), integrating valid inequalities into the master problem (Azad & Hassini, 2019; Ghavamifar et al., 2018), or providing an improved initial solution (Garcia-Herreros et al., 2014; Müllerklein & Fontaine, 2025; Y. Wang et al., 2024) to speed up the algorithm. Another common approach to handling large-scale SC models is the application of metaheuristic algorithms to solve them nearly optimally. Many articles use genetic algorithms and their variants (Esmizadeh et al., 2021; Nikian et al., 2023; Vali-Siar et al., 2022; Y. Wang et al., 2024), conduct a variable neighborhood search (e.g., Chen et al., 2021; Lou et al., 2020), or an adaptive large neighborhood search (Guo et al., 2024; Hasani et al., 2021) to discover neighborhood solutions of initially selected solutions. Few hybrid approaches first use an exact method, metaheuristic, or heuristic to find an initial solution, which is then improved by a LS (Jahed et al., 2024; Lotfi et al., 2024; Lou et al., 2020; Nasrollah et al., 2023; Zahiri et al., 2017) or other algorithms (Ehrenstein et al., 2019; Goodarzian et al., 2022; Khalili-Fard et al., 2024; Peng et al., 2021) in the aftermath.

In summary, many existing articles on resilient SC design consider resilience by using stochastic or robust models reflecting disruptions and/or parameter uncertainty and optimize economic objectives, taking penalty costs for unsatisfied demand into account. However, even though resilience is a frequently used term in existing literature, only a few approaches integrate an explicit resilience perspective influencing the model decisions (Suryawanshi & Dutta, 2022) through resilience objectives, constraints, or as decision criteria. Although many models deliberately decide on the implementation of resilience actions, they usually do not assess their characteristic effect on resilience (Bruckler et al., 2024; Sharkey et al., 2021). Additionally, while most approaches cover demand uncertainty and facility disruptions, articles on supply disruptions “rippling” downstream the entire SC (Liberatore et al., 2012) are scarce (Govindan et al., 2017). Although many exact solution approaches for two-stage stochastic programming models exist, metaheuristics or combinations of exact and heuristic approaches are worth exploring in order to enable the efficient computation of large-scale resilient supply chain design problems (Govindan et al., 2017; Suryawanshi & Dutta, 2022). In this regard, matheuristics are capable of efficiently identifying solutions for large-scale problems where exact methods are unable to provide appropriate solutions in an acceptable time (Juan et al., 2023). The decomposition of complex supply chain problems is another effective approach to improve computability (Suryawanshi & Dutta, 2022). However, only one of the investigated articles presents an approach utilizing a decomposition-based fix-and-optimize matheuristic (Lotfi et al., 2024). Therefore, to contribute to the existing research, our article considers resilience within supply chain network design modeling via the application of two different resilience actions and explicit resilience targets guiding the solution approach. Methodologically, this work develops a three-stage decomposition-based approach with a matheuristic (MH) that combines local search with network flow optimization guided by different resilience targets to identify effective resilience actions in the SC design stage. From a resilience research perspective, we analyze the impact of different resilience action types, self-adapting economic bounds, and resilience targets during the supply chain design process. Thereby we contribute to a better understanding of the relationship between resilience actions and resilience metrics as conceptually analyzed by Bruckler et al. (2024). In addition, we discuss trade-off solutions between resilience and the economic dimension.

3. THE SC DESIGN PROBLEM FOR SECOND-GENERATION BIOETHANOL PRODUCTION

As the bioeconomy aims at producing goods from renewable and regrowing biogenic resources in order to substitute fossil products (European Commission, 2018), their SC are especially vulnerable to climate change-related extreme weather events impacting feedstock supply. Therefore, to demonstrate and evaluate our resilient SC design approach, we examine the production of second-generation bioethanol (2G-EtOH) in European regions. Specifically, we focus on the production of 2G-EtOH from lignocellulosic biomass using agricultural residue straw as the feedstock (Gnansounou, 2010). The set P of products to be substituted contains fossil fuels and first-generation bioethanol that is made from crops and thereby competes with food security (Solomon, 2010). We generally investigate the problem introduced by Wietschel et al. (2021) and further developed in Messmann et al. (2023) and Bruckler et al. (2025) for designing a 2G-EtOH SC network for several Eastern European regions. Note that the complete optimization model with sets, indices, parameters, decision variables, and constraints is described in detail in Appendix D. Figure D 2 illustrates the 2G-EtOH SC design decisions.

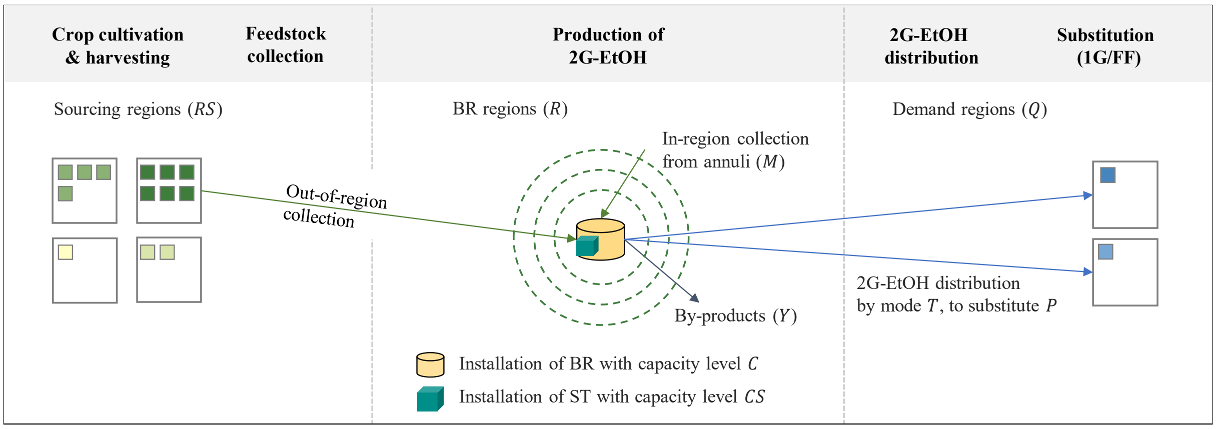

Figure D 2: *Illustration of the 2G-EtOH SC and the decisions to be made (based on Bruckler et al. (2025)).*

The structural decisions in the planning process involve selecting regions from the set of possible regions R in which to install biorefineries (BRs) and determining their capacity by selecting a pre-defined level from the set C. Additionally, feedstock storages (ST) can be installed in these regions R, and their possible capacity levels are given by the set CS. To define regions, the NUTS-1 (Nomenclature of Territorial Units for Statistics) level of the EU-28 was chosen as the geographical resolution because these regions represent sufficiently large socio-economic regions (with populations ranging from three to seven million people (DESTATIS, 2024)). In SC design, the structural decisions must be combined with operational flow decisions to assess the solution quality appropriately. This is particularly true when considering supply disruptions. For the 2G-EtOH network, the feedstock processed by a BR in one period $x \in X$ (e.g., quarter) can either be supplied by a ST in the region of the BR, collected directly from the region where the BR is located (“in-region”), or collected directly from another region (“out-of-region”). All regions where feedstock can be collected are included in the RS set. "Directly" means that the collection and processing occur during the same period. The differentiation between “in-region” and “out-of-region” collection is made to account for different transportation costs. For in-region collections, so-called "sourcing annulus" sectors are defined by set M and corresponding cost factor are given. For out-of-region collections, sourcing annulus are of minor relevance and costs are defined between regions. The maximum available feedstock is given per period and sourcing region and for the sourcing annuli in each BR region. Furthermore, mean and standard deviation of normal distributions representing regional feedstock supplies are available (Bruckler et al., 2025). During the transformation of feedstock into 2G-EtOH (with factor θ) in the BRs, the by-products surplus energy and biomethane (defined by set Y) are produced. The amount of each by-product is linearly related to the amount of 2G-EtOH produced, which in turn is linearly related to the amount of feedstock. On the distribution side of the SC, we have a set of demand regions Q for which the (maximum) demands for each of the substitution products in P are given. Three transportation modes (farm tractor, truck, and rail) are defined by set T for the transportation of feedstock and 2G-EtOH. However, 2G-EtOH cannot be transported by a farm tractor.

The economic performance of the network is measured by the net present value (NPV), which is defined as discounted revenues from product substitutions and by-product sales minus investment costs and discounted sourcing, processing, and transportation costs. See Appendix D 5 for more details on the economic objective criterion, and for details on the parameters, see Appendix D 3 and Bruckler et al. (2025). The resilience of the 2G-EtOH network is measured by its ability to fulfill target demands for the products to be substituted (i.e., the resilience gap). The resilience gap is to be characterized and minimized by following one of three resilience targets (as defined in section 2.1).

4. THREE-STAGE PLANNING APPROACH FOR RESILIENT SC DESIGN

The planning approach for resilient SC design that we propose in this paper consists of three stages, each dedicated to a specific decision problem:

- ❖ Stage I: An initial baseline solution is determined by optimizing a deterministic expected value model (the baseline scenario, or BSC) to maximize the NPV.
- ❖ Stage II: Based on the fixed structural decisions made in Stage I, the operational flows for a comprehensive set of supply disruption scenarios are optimized by maximizing the NPV. This supply disruption simulation provides information about resilience gaps that will be minimized in the next stage.
- ❖ Stage III: different MHs variants combining two different LS strategies, three resilience targets, and two economic lower bounds explore the implementation of resilience actions in different ways to improve resilience without reducing economic performance (i.e., the NPV).

Our three-stage approach is developed to address the computational difficulties posed by the two-stage stochastic model proposed by Bruckler et al. (2025) and thus to handle such large-scale SC problems. Because of the high computational requirements of their approach, the planning horizon was limited to four years (16 quarters), and the optimization model considered only 25 scenarios anticipating feedstock disruptions. In contrast, we propose using a planning horizon of 10 years (40 quarters) as usual for strategic decisions. Furthermore, our three-stage approach provides the possibility to consider an ‘arbitrarily’ large number of supply disruption scenarios in stage II.

The following sections describe the planning parameters, objectives, decisions, and methods for each of the three stages in detail.

4.1 Stage I: Initial SC design

The initial SC design, including the selection of regions for installing BRs and STs and their capacities, is determined by optimizing a deterministic expected value model with the objective of maximizing the NPV. The data basis of this model is given by the baseline scenario BSC ($sc = 0$), and the uncertain feedstock availability is represented by expected values. The corresponding supply parameters $\psi^{0}_{r,x}$ and $\mu^{0}_{r,m,x}$ are determined by historical feedstock (straw) availability data, i.e., the smoothed mean value of historic time series per region and period. The optimization model '*MBase*' consists of the objective function as defined in equation (D.0) (see Appendix D 5) and the constraint sets (D.1) to (D.14) (see Appendix D 6).

The result of Stage I serves as the baseline solution (BS) for the subsequent stages and includes determining a set of regions, $Q^{BS} \subseteq Q$, for which fulfilling any demands ($P_{r,u,t,p,x} > 0$) is economically beneficial. These 'demand regions' are also considered to be most relevant in terms of resilience, and therefore, the amount of bioethanol $\vartheta^{BS}_{u,x}$ ([t 2G-EtOH]) transported to a demand region $u \in Q^{BS}$ in period $x \in X$ are the reference values (i.e., target demand fulfillment) for calculating resilience gaps in the subsequent stages. Naturally, the baseline solution also includes the structural decision on the capacity (denoted with σ) of the installed BRs ($iBR^{BS} = \{\pi^{BS}_{r} = \sum_{c \in C} B_{r,c} \cdot \sigma^{BR}_{c} \mid \forall r \in R\}$) and STs ($iST^{BS} = \{\varrho^{BS}_{r} = \sum_{cs \in CS} \sigma^{ST}_{cs} \cdot S_{r,cs} \mid \forall r \in R\}$). Note that these capacity decisions might be adjusted in Stage III but remain fixed in Stage II.

4.2 Stage II: Simulative resilience gap assessment

To identify potential resilience gaps, we optimize the NPVs for a set S of feedstock supply scenarios (with $sc \in \{1, 2, \ldots, \omega\}$).

To identify and assess resilience gaps, we focus on the three resilience targets introduced in 2.1. Thereby, reducing the resilience gap increases SC resilience, which improves the resilience curve shape and the related metrics presented in 2.1.

The feedstock supply parameters $\psi^{sc}_{r,x}$ and $\mu^{sc}_{r,m,x}$ for the ω scenarios, are drawn from a correlated normal distribution with the mean and standard deviation of trend-adjusted historic data (Bruckler et al., 2025). To fix the structural decision of Stage I during these optimizations, the following two sets of constraints are added to the model:

$$\sum_{c \in C} B_{r,c} \cdot \sigma^{BR}_{c} = \pi^{BS}_{r} \qquad \forall\, r \in R \qquad \text{(D.15)}$$

$$\sum_{cs \in CS} S_{r,cs} \cdot \sigma^{ST}_{cs} = \varrho^{BS}_{r} \qquad \forall\, r \in R \qquad \text{(D.16)}$$

Constraints (D.15) ensure that the BR capacities are fixed, and constraints (D.16) ensure that the ST capacities are fixed. Consequently, only flow variables can be changed in Stage II. These two constraint sets, combined with the constraint sets (D.1) to (D.14) and the optimization criterion of maximizing the NPV, as defined in equation (D.0), define the flow optimization model '*MFlow*'.

In Stage II, this model is used to solve the ω feedstock supply scenarios. This allows us to assess the economic performance and resilience of the baseline solution in the event of a supply disruption. To measure the overall economic performance of the baseline solution with regard to the ω feedstock supply scenarios, the expected net present value is calculated by (D.17):

$$E(NPV^{Stage\ II}) = \sum_{sc \in S} \frac{1}{\omega} NPV_{sc} \tag{D.17}$$

This value is used as an initial reference value (lower bound) for the third planning stage. Regrading SC resilience, the expected resilience gaps are calculated by the equally weighted scenario-based gaps (D.18). The resilience gaps are calculated by three different approaches representing the resilience targets introduced in section 2.1: (D.19) the depth of impact (DI) as representative of performance-based metrics, (D.20) the disruption duration of performance loss (DD) represents the total absorb, endure, and recovery duration, and (D.21) the cumulative impact (CI) represents area-based metrics of cumulative absorptive and recovery improvement. To effectively enforce a decreasing DI, we square the difference between target demand fulfillment ($\vartheta_{u,x}^{BS}$) achieved by the baseline scenario and actual fulfillment realized, and thereby primarily penalize deep disruptions of demand coverage at a demand region. Disruption duration (DD) is calculated as the number of periods during which the total product delivery to a region ($P_{r,u,t,p,x}$) is below its baseline demand. Finally, CI compares the demand fulfillment of the ω scenarios with the target demand over time.

$$E(ResGap^{Stage\ II}) = \sum_{sc \in S} \frac{1}{\omega} Res.Gap_{sc}\,, \tag{D.18}$$

$$\begin{aligned}
&with && \text{(D.19)}\\
&\quad DI{:}\ Res.Gap_{sc} = \sum_{u \in Q_{base}} \sum_{x \in X} \big(\vartheta_{u,x}^{BS} - \sum_{r \in R} \sum_{t \in T} \sum_{p \in P} P_{r,u,t,p,x}\big)^2 &&\\
&\quad DD{:} && \text{(D.20)}\\
&\qquad for\ each\ sc \in S{:} &&\\
&\qquad\quad Res.Gap_{sc} = 0 &&\\
&\qquad\quad for\ each\ u \in Q_{base}, x \in X{:} &&\\
&\qquad\qquad if\ \big(\vartheta_{u,x}^{BS} - \sum_{r \in R} \sum_{t \in T} \sum_{p \in P} P_{r,u,t,p,x}\big) > 0\ then &&\\
&\qquad\qquad Res.Gap_{sc} = Res.Gap_{sc} + 1 &&\\
&\quad CI{:}\ Res.Gap_{sc} = \sum_{u \in Q_{base}} \sum_{x \in X} \big(\vartheta_{u,x}^{BS} - \sum_{r \in R} \sum_{t \in T} \sum_{p \in P} P_{r,u,t,p,x}\big) && \text{(D.21)}
\end{aligned}$$

Note that DI and CI could even be negative if $P_{r,u,t,p,x}$ exceeds $\vartheta_{u,x}^{BS}$ and, consequently, overfulfills the target demand in the baseline scenario. However, fulfilling unsatisfied target demand is prioritized since it depends on the economic optimization in stage 2. If explicit scenario probabilities are known, they could be integrated by replacing $1/\omega$ with the corresponding probabilities.

To reduce the computation time at this stage, we propose integrating all ω scenarios into a single model by adding a scenario index to all parameters, decision variables, etc., and using (D.17) as the objective function. This reduces computation time because initializing one of the ω models takes as long as solving them to optimum (since only flow decisions need to be made).

4.3 Stage III: Resilience improvement by MH

The proposed MH variants combine different LS strategies comprising neighborhood searches for resilience actions with the optimization model *MFlow* defined in Stage II. The central goal of the MH is to improve the resilience of the 2G-EtOH network while maintaining an appropriate level of economic performance. To improve resilience, i.e., to reduce unfulfilled demands in regions from the set Q^{BS}, the LS takes the current best (incumbent) solution s^* and applies two actions (transformations) to compute neighborhood solutions: BR capacity shifts and ST capacity extensions. These actions aim at improving the absorptive capacity (see section 2.1) and thereby intend to increase resilience by avoiding or absorbing performance decline in an early stage of the disruption. While the three resilience gaps are calculated in Stage II to determine a starting point for resilience improvement, in Stage III, one of these resilience gaps is chosen as the resilience target to guide the LS and the implementation order of resilience actions, while the others are co-calculated for assessment purposes. In the mathematical optimization part of the MH, a solution s is evaluated by solving the *MFlow* model for each scenario in S, along with the currently given structural decisions for installed BR capacities ($iBR^s = \{\pi_r^s | \forall\, r \in R\}$) and installed ST capacities ($iST^s = \{\varrho_r^s | \forall\, r \in R\}$). Then, $E(NPV^s)$ and the three $E(Res.Gap^s)$ are calculated. As in Stage II, only flow decisions need to be made. Therefore, to reduce computation time, we propose integrating all scenarios into one model again. Furthermore, we recommend keeping this integrated model "warm" (i.e., without new model initialization for each new solution) because only the right-hand sides of the constraints (D.15) and (D.16) need updating. With the results of the *MFlow*-based scenario optimization, we can evaluate if a solution s is better than another one. In the heuristic part of the MH of Stage III, a solution s is considered to be better than another solution s', if the expected resilience gap of the chosen target improves, i.e., $E(Res.Gap^s) < E(Res.Gap^{s'})$. Hereby, a necessary condition for a better solution is that its expected economic performance is not worse than an incumbent reference value (lower bound): $E(NPV^s) \geq NPV^{LB}$. At the beginning of the LS, the reference value is set to the value of Stage II: $NPV^{LB} = E(NPV^{Stage\ II})$. In order to continuously address the objective of maximizing the NPV, we have decided to use a self-adapting mechanism for NPV^{LB} (controlled by the parameter ε). As already mentioned, we propose two self-adapting economic lower bound mechanisms. The first uses a tight adaptation mechanism ($\varepsilon = ti$), updating NPV^{LB} to $E(NPV^{s^*})$ whenever a new best solution s^* is found. To provide a wider leeway for resilient action, the second mechanism uses a looser adaptation mechanism ($\varepsilon = lo$) and updates the NPV^{LB} to the mean of the expected NPVs of the new best solution and the current lower bound.

4.3.1 BR CAPACITY SHIFT NEIGHBORHOOD SEARCH (BR-SH-NS)

As evaluating neighborhoods for all combinations of BRs and their potential capacity levels would be very inefficient, we introduce the concept of 'supply-disruption-affected BRs'. With regard to a solution s, a BR installed in region $r \in R$ (with $\pi_r^s > 0$) is said to be disruption-affected if its capacity is not fully exploited in all periods and all scenarios from S.

The unused capacity for such a BR region is defined by $uc_r^s = \sum_{sc \in S} uc_r^{s,sc} \geq 0$ (where $uc_r^{s,sc} = \sum_{x \in X}(\pi_r^s - \sum_{u \in Q} \sum_{t \in T} \sum_{p \in P} P_{r,u,t,p,x})$ for a scenario $sc \in S$). We order all affected regions in decreasing order of uc_r^s to first investigate a BR capacity shift to unaffected regions that would most likely reduce resilience gaps without compromising the economic performance. The resulting list of potential 'capacity senders' is named $BR.SEND^s$. The remaining unaffected BRs form the 'capacity receiver' list named $BR.REC^s$, ordered by descending economic advantageousness based on regionalization (cost) factors for BR installation, transport activities, and labor as defined in Wietschel et al. (2021). This differentiation into sender and receiver regions increases computational efficiency by evaluating only the most promising BR capacity shifts.

For the same reason, only a limited number of BR capacity shifts (i.e., five) are performed and evaluated in the neighborhood. The amount of capacity shifted corresponds to the first five levels as defined in set C, and we follow the first improvement approach within the neighborhood. The following pseudocode illustrates the BR-SH-NS:

```
runBR-SH-NS (s, iBR^s, iST^s, BR.SEND^s, BR.REC^s, E(ResGap^{s*}), NPV^LB, S, ε):
BR^REC := getBestReciever(BR.REC^s )
for BR^SEND ∈ BR.SEND^s do
    for c ∈ {1,2,...,5} do
        s', iBR^{s'} := shiftCapacity (iBR^s, BR^SEND, BR^REC, c)
        E(ResGap^{s'}), E(NPV^{s'}) := evaluateWithMFlow (iBR^{s'}, iST^s, S)
        if E(ResGap^{s'}) < E(ResGap^{s*}) and E(NPV^{s'}) ≥ NPV^LB then        // valid first
            NPV^LB := getNewEconomicLB (E(NPV^{s'}), NPV^LB, ε)                 improvement
            return s', iBR^{s'}, E(ResGap^{s'}), NPV^LB
return s, iBR^s, E(ResGap^{s*}), NPV^LB                                        // no improvement
```

4.3.2 ST CAPACITY EXTENSIONS NEIGHBORHOOD SEARCH (ST-EX-NS)

In general, storage is only installed where BRs are installed, and thus increasing the capacity of STs in the same region as affected BRs is most promising and beneficial for a high solution efficiency. Consequently, we iterate through the $BR.SEND^s$ list to determine the storages where the capacity will be increased. Again, we only investigate a subset of possible capacity extensions, i.e., the first 15 levels as defined in CS. As ST capacity levels are more granular compared to BR capacity levels due to the transformation factor (i.e., θ), we follow the best improvement approach to identify the most promising capacity extension within the neighborhood to ensure a balanced effectiveness of ST capacity extension and BR capacity shift. The following pseudocode illustrates ST-EX-NS:

```
runST-EX-NS (s* := s, iBR^s, iST^s, BR.SEND^s, E(ResGap^{s*}), NPV^LB, S, ε):
for BR^SEND ∈ BR.SEND^s do
    ST := getStorage (BR^SEND)
    for cs ∈ {1, 2, …, 15} do
        s', iST^{s'} := addCapacity (ST, iST^s, cs)
        E(ResGap^{s'}), E(NPV^{s'}) := evaluateWithMFlow (iBR^s, iST^{s'}, S)
        if E(ResGap^{s'}) < E(ResGap^{s*}) and E(NPV^{s'}) ≥ NPV^LB then
            NPV^{LB'} := getNewEconomicLB (E(NPV^{s'}), NPV^LB, ε)
            s* := s', iST^{s*} := iST^{s'}, E(ResGap^{s*}) := E(ResGap^{s'})
    if s* <> s then                                        // valid best
        return s*, iST^{s*}, E(ResGap^{s*}), NPV^{LB'}     improvement
return s, iST^s, E(ResGap^{s*}), NPV^LB                    // no improvement
```

4.3.3 THE MH VARIANTS MH-BR-ST AND MH-ST-BR

The two base variants, MH-BR-ST and MH-ST-BR, use both neighborhood search mechanisms, but in a different order. Variant MH-BR-ST starts each iteration by performing the BR-SH-NS, and only if no improvement can be achieved here, ST-EX-NS is performed in this LS iteration. However, the next LS iteration starts again with BR-SH-NS. The following pseudocode illustrates BR-ST:

```
runMH-BR-ST (s* := BS, iBR^{S*} := iBR^BS, iST^{S*} := iST^BS, E(ResGap^{s*}) := E(ResGap^{Stage II}),
             NPV^LB := E(NPV^{Stage II}), S, ε):
do
    BR.SEND^{s*}, BR.REC^{s*} := getAffectionLists (s*)
    s, iBR^s, E(ResGap^{s*}), NPV^LB :=
            runBR-SH-NS (iBR^{s*}, iST^{s*}, BR.SEND^{s*}, BR.REC^{s*}, E(ResGap^{s*}), NPV^LB, S, ε)
    if s <> s* then              // valid improvement by BR-SH-NS
        s* := s, iBR^{s*} := iBR^s
    else
        s, iST^s, E(ResGap^{s*}), NPV^LB :=
                    runST-EX-NS (iBR^{s*}, iST^{s*}, BR.SEND^{s*}, E(ResGap^{s*}), NPV^LB, S, ε)
        if s <> s* then          // valid improvement by ST-EX-NS
            s* := s, iST^{s*} := iST^s
        else
            terminate            // no improvement
while E(ResGap^{s*}) > 0
```

In the MH-ST-BR variant, the ST-EX-NS is performed first in each LS iteration, followed by BR-SH-NS if no improvement can be achieved by ST-EX-NS. Since the overall logic remains the same as for MH-BR-ST, we will not present a pseudocode for ST-BR. Both variants terminate when the resilience gap closes (becomes zero) or when no improvement can be achieved in an LS iteration.

Both variants are worth exploring because they follow different search principles. First, ST-BR makes ‘larger’ transformations by extending ST capacities, which can be seen as search space exploration. Then, it makes ‘smaller’ transformations by shifting BR capacity, which can be seen as search space exploitation. This sequence of exploration and exploitation is preferred by many metaheuristics. In contrast, VNS first searches the nearest neighborhood using small transformations. If no improvement can be achieved, it moves on to ‘larger’ neighborhoods (Hansen et al., 2010). BR-ST essentially follows this approach.

4.4 SUMMARY

Figure D 3 summarizes the three-stage planning approach:

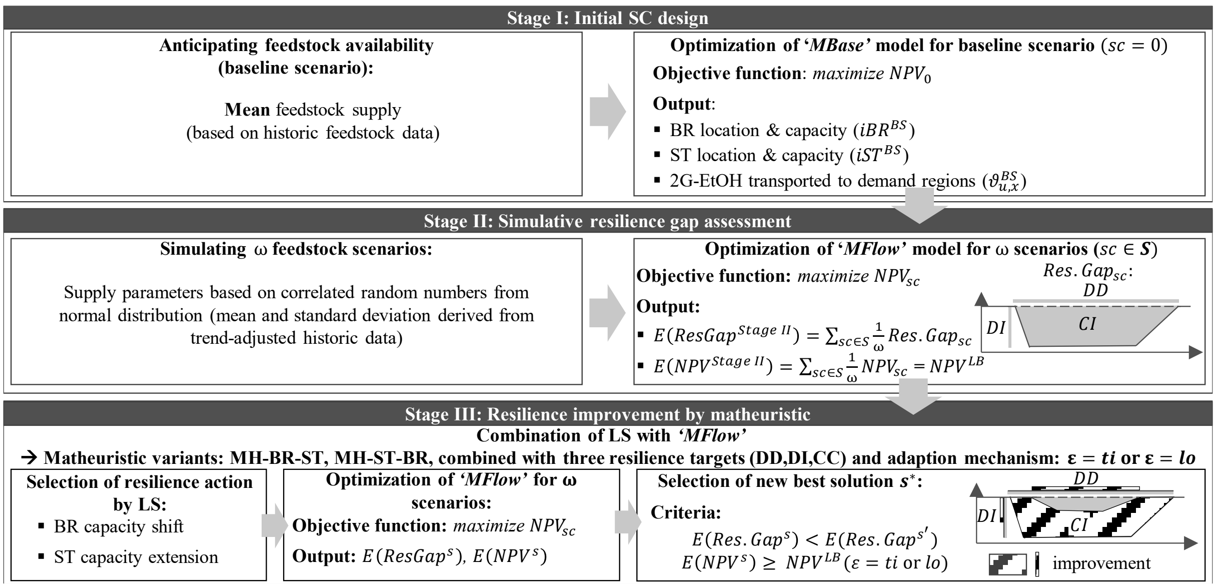

Figure D 3: *The three-stage planning approach.*

In total, we develop twelve MH variants in Stage III to improve SC resilience. Each variant combines one of two LS strategies with one of two NPV^{LB} adaptation mechanisms and one of three resilience targets defining the resilience gap. For example, MH-BR-ST is combined with the loose adaptation mechanism ($\varepsilon = lo$), expressed by MH-BR-ST(lo) and executed for the resilience target depth of impact (DI). The twelve variants were developed to assess the impact of resilience actions and metrics considered in the supply chain design.

5 EVALUATION

To evaluate the proposed three-stage planning approach and the effects of different resilience actions, targets, and economic lower bounds, we apply it to the case of designing a resilient 2G-EtOH SC in Eastern Europe. Details on the case are described in Section 0 and in Bruckler et al. (2025). In section **Fehler! Verweisquelle konnte nicht gefunden werden.**, the planning results for the different stages and, particularly, the behavior of the MH variants in Stage III are discussed. In the following out-of-sample analysis of section 5.2, Pareto-efficient solutions between resilience targets and economic performance are analyzed in more detail. Finally, a resilience curve analysis of scenarios with the best improvement regarding each resilience target is performed.

The proposed three-stage planning approach was implemented in Python 3.9.19, utilizing Gurobi 12.0.2. Experiments are executed on a Desktop PC equipped with a 13th Gen Intel(R) 16-Core(TM) i7-13700 (2.10 GHz) processor and 32 GB RAM.

5.1 MH VARIANT ANALYSIS

The baseline solution BS resulting from the optimization of the baseline scenario BSC with the "*MBase*" model comprises three biorefineries in Romania (RO2, RO3, RO4), three in Hungary (HU1, HU2, HU3), and one in Bulgaria (BG3) with a total production capacity of 693.75 kt 2G-EtOH per period. No storage is installed, and demand is fulfilled in five regions Q^{BS}: two Austrian regions (AT1 and AT2), two Finish regions (FI1 and FI2), as well as the Swedish region (SE2). Solving the Stage I problem takes 111.1 minutes (10 seconds for initializing the model and 111 minutes for solving it).

In Stage II, to identify resilience gaps, ω =100 randomly drawn scenarios are optimized with the *MFlow* model. The simulative optimization reveals unfulfilled demand in the regions FI1, FI2, and AT2 with the following expected resilience gaps for the three different resilience criteria: $E(ResGap^{Stage\ II}) = 4{,}762$ kt EtOH^2 (DI), 26.87 quarter (DD), and 156.033 kt 2G-EtOH (CI). Note that each value corresponds to a 100% resilience gap in the subsequent figures. The initial lower bound on the net present value after Stage II is $NPV^{LB} = E(NPV^{Stage\ II})$= 584.98 Mio €. The total computation time for solving the *MFlow* model with all 100 scenarios integrated is about 24.2 minutes.

Stage III tested all MH variants to investigate how resilience actions, different targets, and economic lower bounds affect the final SC design. Figure 4 visualizes the improvement progress (implementation of resilience actions in BR regions) and the resulting effects on both resilience and economic performance for each variant. The top two charts represent variants with a tight lower bound (ti), while the bottom four charts show variants with loose NPV^{LB} adaptation (lo).

The most remarkable effects arise from the **LS strategies** that test the implementation of actions in a different order: MH-BR-ST variants prioritize the resilience action of BR capacity shifts, which relocate more EtOH capacity to less affected regions rather than installing ST capacity to provide feedstock in affected regions. In contrast, MH-ST-BR variants install more ST capacity, while BR capacity shifts remain comparable. A second considerable effect arises from the **self-adapting economic lower bounds**: ti leads to fewer improvement steps, shorter computation times (i.e., 279 min for MH-BR-ST(ti)), higher economic performance, and less resilience improvement, with no difference among the three targets (DI, DD, CI). The results for lo are more differentiated, with more improvement steps and longer computation times (up to 2112 min for MH-BR-ST(lo)). In general, allowing economic leeway (lo) achieves higher resilience improvements at the cost of a lower economic performance.

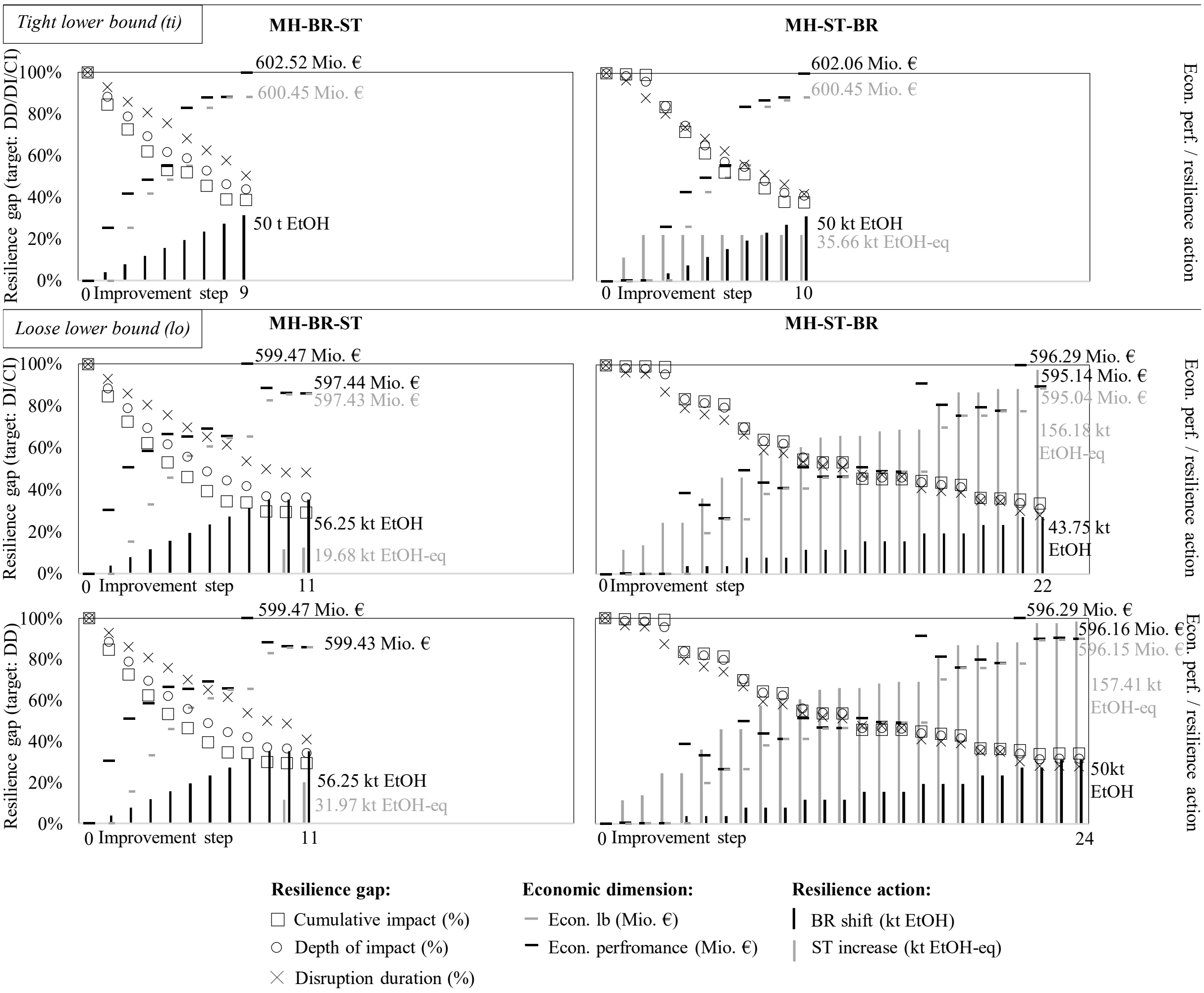

Figure D 4: *Improvement steps for MH-BR-ST and MH-ST-BR with tight and loose NPV^{LB} adaptation and three resilience targets: cumulative impact (CI), depth of impact (DI), and disruption duration (DD).*

MH-BR-ST(lo) shifts slightly more BR capacity and enables ST installation compared to its tight counterpart, achieving the greatest resilience improvements in DI among all MH variants.

Thus, the strategy of prioritizing BR capacity shifts has the characteristic effect of avoiding deep performance declines. When selecting DD as the target, larger ST capacities are installed, which further improves DD. Simultaneously, DI and CI reductions are also slightly higher, as the heuristic local search method gets trapped in a local optimum. Nevertheless, the difference in DI and CI when optimizing DD is marginal, confirming that the target and our approach mainly achieve their intended goal. In addition, choosing CI instead of DI does not change the strategic SC design at all.

In contrast, when prioritizing ST installations (MH-ST-BR(lo)), remarkably more storage is installed, exceeding the shifted BR capacity by more than threefold. This strategy achieves the greatest reduction of DD among all variants, especially with DD as resilience target. However, selecting DI or CI instead intuitively leads to larger reductions in *cumulative impact* and *depth of impact*, while DD is improved less. This behavior confirms the characteristic effect of storage capacity installation on the length of a disruption: In contrast to BR capacity shifts, this action avoids (or at least delays) demand coverage drops to reduce DD.

In summary, the proposed MH approach and the two resilience actions enable the reduction of resilience gaps while improving economic performance. Depending on the MH strategy (MH-ST-BR or MH-BR-ST), different resilience actions are prioritized, revealing their individual characteristics in improving supply chain resilience. Self-adapting economic lower bounds (ti or lo) steer the extent to which resilience actions are implemented, and thus the degree to which economic performance is sacrificed in favor of resilience improvement. Different resilience targets can additionally influence the local search of the MH by either further improving the characteristic effect of the implemented resilience action or by guiding it towards further reductions in another resilience target that differs from this characteristic effect. Nevertheless, **different resilience targets** have only a minor impact on the resulting supply chain design, as they only influence strategic decisions, while flow optimization is exclusively based on the economic objective.

5.2 Out-of-sample analysis

To evaluate the performance of the different MH variants regarding resilience gaps reduction and economic performance without the bias of known scenarios, we conducted an out-of-sample analysis based on 100 new, randomly drawn feedstock supply scenarios. This means that we use the solutions computed by the MHs, i.e., their structural decisions, and the 100 new feedstock supply scenarios to initialize and optimize the six integrated *MFlow* models. This approach is also recommended by similar studies (Bruckler et al., 2025; C. Wang & Zhong, 2024). As a reference value, we use the solution BS computed in Stage I and solve the 100 corresponding integrated *MFlow* models. Table D 3 summarizes the expected economic performance $E(NPV)$ and the expected resilience gaps $E(ResGap)$ with regard to the basic MH variants and ε (i.e. the SC designs), with the best performances highlighted in bold. Additionally, the installed ST capacities are presented.

The out-of-sample results confirm previous findings that an economic leeway (lo) achieves a larger reduction of resilience gaps at the expense of lower economic performance, while a tight economic lower bound (ti) gains the largest economic improvement and less resilience improvement. It is also apparent that shifting BR capacity mainly contributes to the resilience target DI of avoiding deep losses in demand coverage. The installation of large feedstock storage (ST) mainly contributes to resisting disruptions (i.e., reducing DD) and thus delays performance declines.

Table D 3: *Key figures of the out-of-sample analysis for the SC designs.*

		Economic performance		**Resilience performance**						**Resilience actions**	
		NPV		**DD**		**DI**		**CI**		**BR shift**	**ST increase**
ε	MH-Variant	Mio. €	(%)	quarter	(%)	kt EtOH^2	(%)	kt EtOH	(%)	kt EtOH	kt EtOH-eq
	Ref. Values (BS)	591.89	0	27.02	100	3.70E+09	100	141.353	100	0	0
	MH-BR-ST										
ti	DI (CI), DD	**608.68**	**2.84**	13.09	48.5	1.01E+09	27.3	55.54	39.3	50	0
lo	DI (CI)	603.46	1.96	12.33	45.6	6.73E+08	18.2	44.61	31.6	56.25	19.68
	DD	603.56	1.97	10.74	39.8	**6.66E+08**	**18.0**	41.51	29.4	56.25	31.97
	MH-ST-BR										
ti	DI (CI), DD	608.38	2.79	10.67	39.5	9.85E+08	26.6	51.06	36.1	50	35.66
lo	DI (CI)	601.51	1.63	7.07	26.2	9.12E+08	24.6	38.31	27.1	43.75	156.18
	DD	601.44	1.62	**7.01**	**25.9**	8.99E+08	24.3	**37.79**	**26.7**	50	157.41

Consequently, the results of the proposed MH-variants represent trade-off solutions between each resilience target (DD, DI, and CI) and the economic performance (see Figure D 5). The identification and connection of Pareto-efficient points form a Pareto front: each point on the front marks a non-dominated solution, meaning that one objective cannot be improved without degrading the other. Among the Pareto-efficient points, the compromise solution (marked in bold) is defined as the variant with the closest Euclidean Distance to the utopia point (i.e., the theoretical optimum combining the highest economic and resilience performance). Taking the resilience gap DI and economic performance simultaneously into consideration (Figure D 5 I), the variants BR-ST-(lo) are by far most effective in approaching both goals simultaneously. In line with previous findings, the resilience target has only a minor effect on the SC design. Regarding the combined effect of reducing DD and economic performance (Figure D 5 II), a tight economic lower bound combined with a prioritization of ST installations (ST-BR-DD/DI/CI(ti)) marks the compromise solution. Although a loose lower bound would result in a further substantial resilience improvement, ST installation is associated with higher investment costs exceeding the additional revenue from improved demand coverage, which in turn reduces the economic performance. Finally, when aiming at a reduction of uncovered demand (CI) while maintaining high economic performance (Figure D 5 III), the prioritization of BR capacity shift yields the optimal trade-off regarding both objectives. Choosing the resilience target DD of decreasing the disruption duration and allowing an economic leeway (lo) enables further reduction in CI at slightly higher economic performance. Consequently, variant BR-ST-DI/CI(lo) is Pareto-dominated by BR-ST-DD(lo), as the additional ST capacity of this variant leads to higher demand satisfaction and revenues exceeding storage investment.

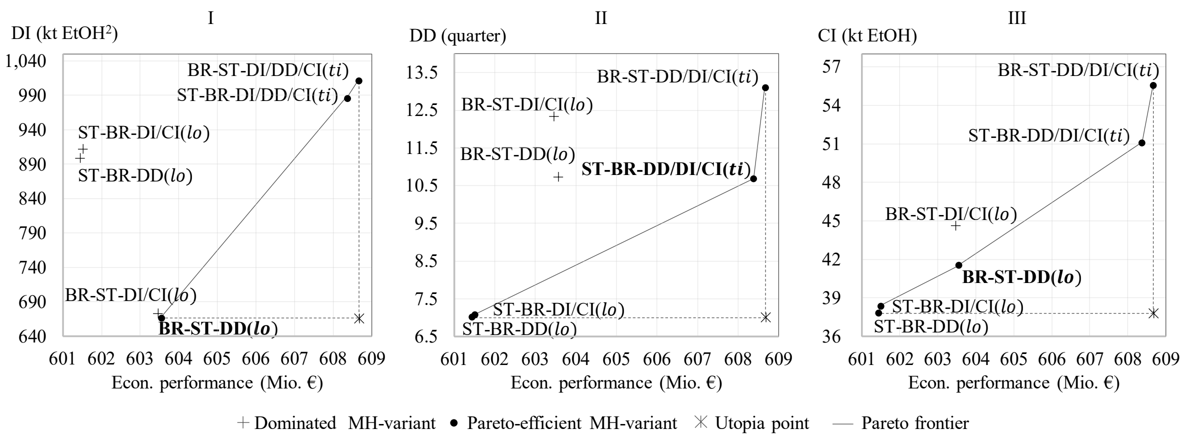

Figure D 5: *Pareto points between resilience targets and economic performance with the compromise solution in bold letters.*

The analysis across all scenarios in Table D 3 allows for an aggregated assessment of resilience performance. However, the characteristic effect of different resilience actions on the resilience curve and related metrics remains unclear. This effect can be explained and differentiated further when analyzing individual scenarios. Therefore, Figure D 6 presents individual resilience curves of the presented variants for three different scenarios (I-III). Each scenario represents the best improvement of each resilience target (DD, DI, CI) compared to the baseline SC design without resilience actions (BS). In addition, the improvement effect of each resilience target is visually indicated by the related resilience metrics.

Feedstock supply scenario I, where DD is improved the most, is mainly characterized by less severe, short-term disruptions affecting single years. Assessing the resilience curves, these disruptions are best anticipated by installing sufficient storage capacities to cover unsatisfied demand (i.e., MH-ST-BR(ti), MH-ST-BR-DD(lo)). For those scenarios with short-term and less severe supply disruptions (i.e., periods 8 and 12 in Figure D 6 I), the analytical Pareto-optimal variants ST-BR(ti) tend to be preferable over ST-BR(lo) variants, as they achieve similar resilience gaps at higher economic performances. Similarly, in many other scenarios dominated by short-term supply disruptions (i.e., only a single year), SC solutions with large storage capacities are more effective in compensating supply disruptions, as long as storage capacities are sufficiently large and inventory can be built up in advance. However, when disruptions extend beyond a single year (e.g., periods 22-28), inventory cannot be replenished, ultimately leaving storage facilities empty. As a result, disruptions break in later, however, the performance falls below that of BR-ST designs, which prioritize the shift of BR capacities, thereby avoiding vulnerable feedstock regions.

Scenario II is characterized by deep disruptions in demand coverage (see the resilience curve of BS). SC designs based on the variants MH-BR-ST-DD(lo) and MH-BR-ST-DI(lo) avoid these deep disruptions most effectively. Consequently, the prioritized shifting of BR capacities to less affected regions achieves greater improvements in the resilience metrics "depth of impact" and the related metric of "residual performance" than prioritizing storage installation in affected regions. Thereby, the preferred variants avoid deep performance losses rather than delay performance drops.

In summary the strategy of prioritizing BR capacity shifts and allowing for economic leeway is most effective in the event of long-term (i.e., consecutive years as in scenario I, periods 22-28) and/or severe (i.e., scenario II, periods 17-20 and 25-28) feedstock supply disruptions in regions where the disruptions cannot be compensated for by the installed storage. In such scenarios, these SC designs often show the highest economic performance among the variants with a loose economic lower bound. This can be attributed to two SC design characteristics. First, these SC have less installed BR capacity in highly affected regions (RO3 and HU3). Thus, severe feedstock disruptions in these regions have a smaller impact on 2G-EtOH demand fulfillment and economic performance. Second, BR-ST(lo)) networks prioritize feedstock "backup sourcing" from other regions over storage installation to compensate for disruptions, sacrificing economic performance that exceeds the lower bound.

Finally, scenario III is characterized by the greatest improvement of the resilience target CI in the face of deep and long-lasting disruptions, which are again best addressed by realizing BR capacity shifts. This strategy (i.e., MH-BR-ST(lo) for DI and DD) leads to the largest improvements of the resilience metrics "cumulative absorptive improvement" and "cumulative recovery improvement". Overall, this individual analysis of resilience curves for different scenario types provides differentiated insights into the characteristic effect and effectiveness of the two resilience action types and can help identify the most suitable strategy among the presented MH variants to combine and implement these actions, as most of them have different strengths and weaknesses.

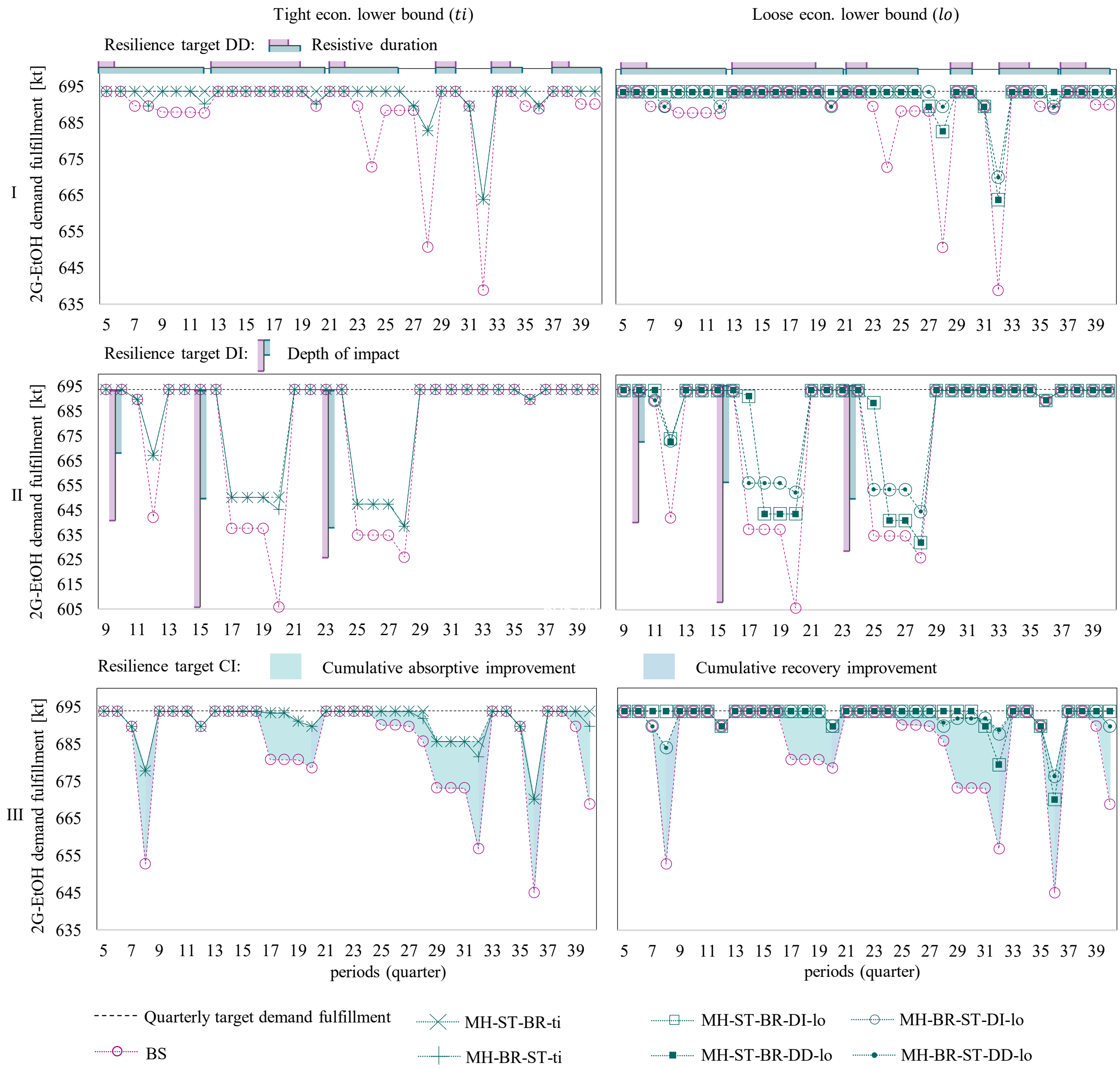

Figure D 6: *Resilience curves for each resilience target for representative scenarios (beginning from the period with the first disruption).*

6 Managerial Insights

The proposed method is demonstrated in the context of advanced biofuels, and although the results are case-specific, many elements are transferable to other large-scale supply chain problems. Therefore, the approach offers guidance and a methodological foundation for practical decision-making. Our findings indicate that the proposed three-stage planning approach can improve both SC resilience, i.e., 2G-EtOH demand fulfillment in the face of supply disruptions, and overall economic performance through network structure adaptations.

The investigated problem is large-scale, encompassing a long-term time horizon, strategic and tactical decision levels, and a wide range of scenarios. However, exact solution approaches often reach their computational limits depending on the model specifications. Therefore, the three-step approach with different matheuristic variants is proposed to ensure computational efficiency. Different SC designs result from the matheuristic variants, which combine two local search strategies that prioritize different types of resilience actions (i.e., shifting production capacity to less affected regions, and storage installation) with two self-adapting economic lower bounds (i.e., tight and loose), which vary the economic leeway, and three resilience targets guiding the local search (i.e., minimizing the depth of performance losses, the disruption duration, or the overall performance loss). The results demonstrate that there is no universally preferable combination among these variants. Rather, depending on individual preferences, certain combinations perform better than others in terms of the willingness to sacrifice economic gains for resilience improvements.

Focusing on ST capacity installation is, on average, remarkably more effective in reducing the disruption duration (DD) than avoiding deep performance drops across various supply scenario types, though it is also the more expensive strategy. For individual supply scenarios, installing storage is effective in absorbing the initial disruption impacts, as indicated by the resilience curve shape and metrics. However, for prolonged disruptions (consecutive years), storage may eventually deplete. Thus, resilience actions focused on ST capacity extension are especially effective in compensating for short-term disruptions of small or medium severity. In general, the strategy of extensively implementing both resilience actions (MH-ST-BR) is suitable for decision-makers who strive for a high average expected supply security across various supply scenario types while accepting lower economic performance. However, in scenarios with large and/or long-lasting supply shortages, this strategy is less effective. In these scenarios, prioritizing BR capacity shifts towards regions less susceptible to supply disruptions and installing less storage capacity (BH-BR-ST) results in immediate but milder performance declines. This seems to be more economically beneficial and more effective in achieving the resilience target of reducing the depth of a performance drop (DI) because supply disruptions are avoided rather than buffered. Although this strategy leads to a different resilience curve profile than an extensive storage installation, it also increases absorptive capacity and overall SC resilience. Even without prioritizing costly storage capacity extensions – and thus without the ability to buffer disruptions initially – backup sourcing with available economic leeway can counteract supply disruptions.

In total, the resilience metric and curve analysis for different SC designs has revealed important insights into the characteristic effects of the resilience actions. These findings highlight the importance of differentiated resilience assessments that go beyond a single aggregate resilience metric, as also emphasized by other authors (Poulin & Kane, 2021; Sharma et al., 2018). However, the influence of different resilience targets on the strategic supply chain design was limited in our matheuristic approach, as tactical/operational decisions were exclusively based on the economic objective of the flow optimization.

Remarkable effects on SC design and resilience arise from the self-adapting economic lower bound. When restricting the economic leeway for SC design ($\varepsilon = ti$), fewer resilience actions (especially fewer storage installations) are implemented. Nevertheless, the expected NPV is higher, making this approach preferable for decision-makers focused on economic performance. A scenario analysis shows that this strategy performs well in scenarios with only minor supply disruptions. On the contrary, decision-makers who prioritize greater overall SC resilience in the event of various medium to severe disruptions may accept higher costs for resilience actions, such as the costs associated with ST capacity extensions. Consequently, they may select a loose economic lower bound adaptation. Comparing different trade-off solutions regarding resilience targets and economic performance and deriving the Pareto front can help decision-makers to identify the best compromise between both objectives. Especially if decision-makers are indifferent regarding the two objectives, restricting the economic leeway and preferring economically beneficial strategic resilience actions (e.g., installing production capacities in less vulnerable regions) can be a meaningful decision, as major disruptions are avoided and minor disruptions are tolerated in favor of higher economic performance.

7 CONCLUSION AND FURTHER RESEARCH DIRECTION

This article proposes a resilient SC planning approach that decomposes the SC structure and flow decisions and uses a MH that combines different local search strategies with network flow optimization to design resilient SCs. The resulting SC designs are analyzed to assess the effect of resilience actions, different resilience targets, and different economic leeways in strategic planning. The solution approach is applied and evaluated for the case of 2G-EtOH production, whose SCs are particularly vulnerable to extreme weather events and therefore to an ongoing climate change (Bruckler et al., 2025). Unlike exhaustive exploration and exploitation of neighborhood solutions, the presented MH variants narrow the search space by focusing on neighborhoods with resilience actions (i.e., shifting BR capacity to unaffected regions, extending feedstock ST capacity) at highly affected production nodes and thereby enable an efficient computation.

The strategic planning approach comprises three stages. Stage I economically optimizes a deterministic expected value model to establish initial strategic SC decisions. Stage II simulates a set of randomly drawn supply disruption scenarios and assesses the resilience gap (i.e., unmet target 2G-EtOH demand) by economically optimizing SC flows. The MHs in Stage III then reduce the resilience gap to improve SC resilience while simultaneously keeping the economic performance at an appropriate level. Here, the network flow decisions are determined by the same optimization model used in Stage II. In this regard, we propose MH combinations of two different local search strategies, three different resilience targets, and two mechanisms for the self-adapting economic lower bounds. Depending on the local search strategy, either a shift in production capacity to less affected regions or storage installation in affected regions is prioritized. Resilience targets additionally influence the local search strategy depending on which resilience curve shape is desired. The two mechanisms restrict the economic leeway for implementing further resilience actions, thereby directly influencing the resulting SC design. The proposed MH variants and resulting SC designs allow the determination of Pareto-efficient points between resilience targets and economic performance, providing decision-makers with the opportunity to select from different trade-off solutions or to identify the most suitable compromise point. Prioritizing ST extensions increases expected resilience (and reduces the resilience gap) across many supply scenarios, though it results in lower economic performance. In contrast, prioritizing the shift of BR capacities focuses on higher economic performance with less SC resilience. Further insights are gained regarding the self-adapting lower bound mechanisms: by selecting a tighter or looser bound, decision-makers can regulate the economic flexibility that may be sacrificed for resilience. The least remarkable influence on the SC design arises from the resilience target.

The detailed resilience assessment using resilience curves and metrics for a single scenario visualizes the impact of the different SC designs on overall resilience and clarifies the individual characteristics of the resilience actions. This supports decision-making for addressing distinct supply disruption patterns. Short-term supply disruptions of small or medium impact are effectively absorbed through initial buffering by SCs with larger ST capacities, thus protecting production nodes within the SC. In contrast, long-term and/or high-impact disruptions that cannot be mitigated through storage are better managed by SC designs that prioritize production capacity shifts, thereby reallocating production capacity throughout the SC.

The proposed three-stage approach contributes to existing literature as it efficiently improves SC resilience from different perspectives and, therefore, can handle extensive scenario sets to design a large-scale SC resilient against supply disruptions. Future research could apply and validate this approach for other vulnerable SCs or benchmark it against other heuristic approaches. Besides guiding the local search and influencing strategic decisions as presented in this work, resilience targets could further be integrated into the flow optimization to additionally affect tactical/operational decisions. Consequently, the influence of resilience targets would be increased.

Methodologically, our approach contributes to existing research by incorporating both economic performance and resilience in SC design–an emerging topic in response to existing global challenges (Lücker et al., 2025). In this context, the presented approach can help decision-makers design supply chains that strike a balance between competitiveness, which is necessary for economic survival, and supply chain resilience, which is necessary to cope with an increasingly uncertain world.

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3

CONCLUSION & OUTLOOK

This section summarizes the key results of each *contribution A–D*, discusses the insights that can be gained by academia, practitioners, and policy-makers, and outlines directions for future research. This dissertation addresses the following aspects of designing resilient supply chains: supply risk quantification (A); resilience quantification (B); methodological design approaches and implication analysis (C & D).

Contribution A evaluates existing supply risk assessments and thereby identifies, harmonizes, and categorizes supply risk indicators, measurements, and their normalization approaches. The results reveal that the most commonly used indicator categories in existing assessment approaches are market concentration, scarcity, and political instability. Although research has called for harmonization in criticality assessments (Graedel & Reck, 2016), indicator measurements and normalization methods vary substantially for the same criterion. Further key drawbacks of existing assessments include the lack of transparency in normalization methods and missing data disclosure (Hool et al., 2024; Malinauskienė et al., 2018; Pfleger et al., 2015; Schneider et al., 2014; Schrijvers et al., 2020; Y. Zhou et al., 2019, 2020). Consequently, contradictory results of assessment approaches and challenges in reproduction emerge (Althaf & Babbitt, 2021; Blagoeva et al., 2016; Nassar et al., 2020; Pell et al., 2019; Schrijvers et al., 2020). Particularly problematic are normalization procedures with individual bounds that depend on minimum or maximum values, which result in incomparability as different normalized scores can correspond to the same indicator value (Bach et al., 2017; Pell et al., 2019; N. Zhou et al., 2020). Furthermore, infrequent update cycles of supply risk assessments create remarkable information gaps regarding the temporal development of supply risk (Graedel & Reck, 2016). For example, the EU provides updates every three years (European Commission, 2020, 2025; Graedel & Reck, 2016). Given trade restrictions, increasing demand, and escalating geopolitical conflicts, risks which arise primarily from the aforementioned main indicator categories (i.e., market concentration, scarcity, and political instability) have recently turned into a real threat to European supply security regarding critical raw materials and warrant careful monitoring, as demanded by the EU Critical Raw Materials Act (European Commission, 2023; Wietschel et al., 2025). *Contribution A* thus raises awareness regarding the variance and limitations in indicator measurements and normalization approaches of existing supply risk assessments. Thereby, it lays the foundation for developing harmonized assessment methodologies that enable EU member states, companies, and their supply chains to support monitoring and facilitate cross-study interpretability.

Supply risk monitoring constitutes the initial building block of a systematic supply chain resilience management. Nevertheless, if a risk materializes, resilience (i.e., the extent of vulnerability and recoverability (Wietschel et al., 2025)) must be assessed quantitatively. This quantification, in turn, provides a basis for evaluating the effect of potential counteractions.

Therefore, *contribution B* adds to existing research by deriving general formulae to quantify not only current supply chain resilience based on absorptive, adaptive, and restorative capacities in place, but also the effects of resilience actions to improve these capacities. In addition, several resilience actions are derived from the reviewed literature and categorized alongside the supply chain planning matrix and the resilience capacities they intend to improve. Specifically, visualizing the improvement effect of actions on the resilience curve can support decision-making by revealing which resilience curve characteristics can be modified by which actions, and thus guides the achievement of their desired resilience profile.

Contributions C and *D* focus on the application of these resilience curve metrics in strategic supply chain design modeling and the analysis of the resulting implications. The two presented approaches are exemplified for the case of 2G EtOH production in the EU and thereby provide insights for stakeholders at the political and institutional levels.

Contribution C presents an exact optimization approach that first designs a resilient supply chain regarding climate change-related supply fluctuations, and second, assesses their economic, resilience, and environmental performance for unanticipated supply scenarios through an out-of-sample test. This contribution adds to existing literature by explicitly incorporating the resilience curve concept in resilient supply chain design modeling and by assessing its economic, resilience, and environmental implications. The results indicate that deliberately considering a curve characteristic (i.e., residual performance after a disruption) as a resilience objective within the mathematical model achieves the intended improvement in the curve shape even for unanticipated scenarios. Furthermore, resilience and environmental benefits appear to be complementary goals in bioeconomic supply chains, as their bio-based products substitute fossil ones. Consequently, policy-makers can derive from this approach that efforts to strengthen the resilience of bioeconomic supply chains can yield environmental benefits and should thus be actively supported to drive climate change mitigation (Pizzol, 2015). In addition, decision-makers can assess the effect of integrating the resilience dimension in supply chain design modeling on the economic, resilience, and environmental dimensions.

Contribution D provides a three-stage approach with a matheuristic (i.e., a hybrid method combining mathematical optimization and local search) to explore trade-off solutions between resilience and economic performance for the design of resilient supply chains. Depending on the local search strategy, the resilience target, and the applied self-adaptive economic lower bound, the decisions on the type and extent of resilience actions vary, and consequently, either resilience or economic performance is prioritized. Different resilience curve metrics (e.g., the resilience gap as the area above the resilience curve) have been selected as resilience target guiding the matheuristic and achieve the intended improvement in resilience. In addition, an analysis of the different matheuristic variants reveals the individual effect of the two resilience actions–storage installation and production capacity shifts–on the resilience curve shape regarding different supply disruption patterns. Long-term or high-impact disruptions are most effectively managed through actions that mitigate their effects, such as reallocating production capacity. In contrast, short-term small or moderate disruption scenarios are best addressed by resilience actions that aim to absorb their effects, such as installing storage. *Contribution D* thereby emphasizes the importance of gaining knowledge about the characteristic effect of resilience actions for informed decision-making on resilient supply chain design.

Ultimately, summarizing *contributions B–D*, the following key insights emerge: the resilience curve and the underlying theory constitute a valid concept for a general assessment of the current state and the improvement effect of actions on supply chain resilience. It serves as an effective tool for integrating the resilience dimension into mathematical models alongside the economic objective, thereby supporting strategic supply chain decision-making regarding the trade-off between economic performance and resilience. A single aggregated resilience curve metric (i.e., residual performance after disruption (*contribution C*), or the area above the curve (*contribution D*)) can serve as a resilience objective or decision criterion to select appropriate actions for improving overall resilience, which may also yield several environmental benefits in bioeconomic supply chains by substituting fossil-based products. However, if a specific curve shape (or characteristic) is desired, selecting the resilience objective (i.e., the resilience curve metric) is crucial, as it influences decisions on appropriate actions to achieve this goal. In turn, the (pre-)selection of actions must be undertaken with care to achieve specific resilience characteristics.

Based on *contributions A–D* and their individual recommendations for future research, an overall research agenda can be derived. Three distinct pathways emerge from this dissertation: (1) *framework conceptualization*: *development of a comprehensive supply risk and resilience framework*; (2) *methodological advancement*: multi-criteria optimization balancing economic, resilience, and environmental dimensions simultaneously; incorporation of multiple resilience objectives; and exploration of alternatives to stochastic modeling; (3) *contextual development*: empirical characterization of how specific resilience actions influence the curve shapes; quantification of climate change impacts on supply chain model parameters to reduce epistemic uncertainty and consideration of multiple uncertainty sources.

(1) *Framework conceptualization*: although criticality (constituted by supply risk and vulnerability (U.S. National Research Council, 2008)) and supply chain resilience (i.e., the vulnerability and recoverability (Bruckler et al., 2024; Hosseini et al., 2019; Wietschel et al., 2025)) have usually been examined in isolation from each other, their fundamental interconnection becomes apparent through their mutual dimension of vulnerability, which is a central construct to both concepts (Wietschel et al., 2025). Consequently, the integrated framework of Wietschel et al. (2025) establishes the foundation for a more holistic analytical approach ranging from risk monitoring to the implementation and evaluation of resilience actions. The elaboration of this concept requires further specification and empirical validation through relevant case studies in academic, corporate, and political contexts.

(2) *Methodological advancement*: *contributions C* and *D* have demonstrated the integration of resilience curve metrics as an objective alongside the economic objective, while the environmental dimension has been assessed simultaneously. Thereby, further combinations of these multi-objective models are worth exploring. In particular, multi-criteria optimization of economic, resilience, and environmental objectives for other bioeconomic supply chains could provide valuable insights and validate the complementary relationship between resilience and environmental dimensions. Therefore, exact solution methods such as Benders Decomposition are required to handle the two-stage model structure and associated complexity (Govindan et al., 2017). Furthermore, integrating multiple resilience metrics as individual objectives to capture different resilience characteristics simultaneously can be a promising approach to deliberately achieve decision-makers' preferred resilience profiles when designing resilient supply chains. Besides stochastic optimization, as utilized in *contributions C* and *D*, future research could also investigate alternative methods. In this regard, robust decision-making can handle inherent (deep) uncertainty, e.g., disruptions from climate change (Stanton & Roelich, 2021). This approach is especially effective when insufficient historical data is available to estimate parameter distributions (Govindan et al., 2017; Stanton & Roelich, 2021). However, robust optimization mainly focuses on the worst-case performance (Govindan et al., 2017), which can lead to conservative strategic decisions that excessively compromise economic performance (Bertsimas & Sim, 2004; Roos & den Hertog, 2020). Therefore, future research can focus on integrated approaches combining stochastic and robust optimization–such as presented by Ash et al. (2022)–to combine the advantages of both methods.

(3) *Contextual development*: beyond framework and methodological development, future research should also focus on contextual advancements in supply chain resilience. Particularly worth exploring are (a) *the relationships between resilience actions and*

specific curve shapes, and (b) *the relationship between climate change-induced extreme events and consequent supply chain uncertainties*.

(a) Although demanded by the literature (Behzadi et al., 2020), few studies have examined the relationship between resilience actions and curve shapes. In this regard, both quantitative analyses of the effect of resilience actions on the curve shape, such as those undertaken for storage and production capacity shift in *contribution D*, and conceptual works are needed. Nevertheless, these insights are essential for supply chain decision-makers who need practical decision support to improve resilience and are unable to implement mathematical models. In addition, knowledge of the characteristic effects of resilience actions provides the basis for further methodological advancements in resilient supply chain modeling.

(b) Particularly in light of climate change-induced weather extremes, the relationship between such events and consequent disruptions needs to be further investigated, as resilient supply chains must be prepared for unanticipated events that affect key supply chain model parameters such as supply, demand, or prices. Although the strategic decisions regarding a single uncertainty source (i.e., supply) in *contributions C* and *D* were successfully validated by out-of-sample tests, developing scenarios that accurately reflect multiple sources of parameter uncertainty in the context of potential climate change-induced developments remains challenging (Sun et al., 2024). Therefore, future research should further develop early-warning systems and forecasts for predicting climate change-related impacts on socio-economic systems by applying machine learning beyond meteorological data (Reichstein et al., 2025). Consequently, more accurate parameterization of supply chain models can be a success factor for designing resilient supply chains. While epistemic parameter uncertainty can thereby be reduced, aleatoric (inherent) uncertainty remains in future realizations even with a complete understanding of the system dynamics (Senge et al., 2014). This deep uncertainty requires the development of decision-making approaches that cover uncertainty beyond probabilistic future developments (Gambhir et al., 2025; Stanton & Roelich, 2021).

In conclusion, this dissertation contributes to homogeneity in the quantification of supply risk and resilience and advances the combination of supply chain resilience theory with methods from Operations Research to design resilient supply chains. Nevertheless, further research on resilient supply design is essential to cope with unforeseen developments in an ever-changing world.

CONTRIBUTION APPENDICES

MANUSKRIPT APPENDIX A

Appendix A 1: *List of studies. Additional information is provided in Supporting Information A.*

Short name	Year	Type	Ref.
Adibi et al. 2017	2017	assessment	(Adibi et al., 2017)
Alonso et al. 2007	2007	collection of indicators	(Alonso et al., 2007)
Althaf and Babbit 2020	2020	assessment	(Althaf & Babbitt, 2020)
Apple 2019	2019	collection of indicators	(Apple, 2019)
Ashby 2016	2016	collection of indicators	(Ashby, 2016)
Bach et al. 2016	2016	assessment	(Bach et al., 2016)
Bach et al. 2017 RESPOL	2017	assessment	(Bach, Finogenova, et al., 2017)
Bach et al. 2017 Sustainability	2017	assessment	(Bach, Berger, et al., 2017)
Bach et al. 2018	2018	assessment	(Bach et al., 2018)
Bastein and Rietveld 2015	2015	assessment	(Bastein & Rietveld, 2015)
Bauer et al. 2011	2011	assessment	(Bauer et al., 2011)
Behrendt et al. 2007	2007	assessment	(Behrendt et al., 2007)
Beylot and Villeneuve 2015	2015	assessment	(Beylot & Villeneuve, 2015)
BGS 2015	2015	assessment	(BGS, 2015)
Blagoeva et al. 2016	2016	assessment	(Blagoeva et al., 2016)
Blengini et al. 2017 RESPOL	2017	assessment	(Blengini et al., 2017b)
Brown 2018	2018	assessment	(Brown, 2018)
Buchert et al. 2009	2009	assessment	(Buchert et al., 2009)
Calvo et al. 2018	2018	assessment	(Calvo et al., 2018)
Ciacci et al. 2016	2016	assessment	(Ciacci et al., 2016)
Cimprich et al. 2017	2017	assessment	(Cimprich et al., 2017)
Cimprich et al. 2018	2018	assessment	(Cimprich et al., 2018)
Coulomb et al. 2015	2015	assessment	(Coulomb et al., 2015)
Daw 2017	2017	assessment	(Daw, 2017)
DERA 2019	2019	assessment	(DERA, 2019)
Duclos et al. 2010	2010	assessment	(Duclos et al., 2010)
European Commission 2014	2014	assessment	(European Commission, 2014)
Eggert et al. 2000	2000	assessment	(Eggert et al., 2000)
Eheliyagoda et al. 2020	2020	assessment	(Eheliyagoda et al., 2020)
Erdmann et al. 2011	2011	assessment	(Erdmann et al., 2011)
Frenzel et al. 2017 RESPOL	2017	assessment	(Frenzel et al., 2017)
Frondel et al. 2006	2006	single indicator	(Frondel et al., 2006)
Fu et al. 2019	2019	assessment	(Fu et al., 2019)
Gemechu et al. 2016	2016	assessment	(Gemechu et al., 2016)
Glöser–Chahoud et al. 2016	2016	assessment	(Glöser–Chahoud et al., 2016)
Goddin 2019	2019	assessment	(Goddin, 2019)
Goe and Gaustad 2014	2014	assessment	(Goe & Gaustad, 2014)
Graedel et al. 2012	2012	assessment	(Graedel et al., 2012)
Graedel et al. 2015	2015	assessment	(Graedel, Harper, Nassar, Nuss, et al., 2015)
Grebe et al. 1977	1977	assessment	(Grebe et al., 1977)
Habib and Wenzel 2016	2016	assessment	(Habib & Wenzel, 2016)
Habib et al. 2016	2016	single indicator	(Habib et al., 2016)
Hatayama and Tahara 2015	2015	assessment	(Hatayama & Tahara, 2015)
Helbig et al. 2016	2016	assessment	(Helbig, Bradshaw, et al., 2016)
Helbig et al. 2017	2017	assessment	(Helbig et al., 2017)
Helbig et al. 2018	2018	assessment	(Helbig et al., 2018)
Helbig et al. 2020	2020	assessment	(Helbig et al., 2020)
Ioannidou et al. 2019	2019	assessment	(Ioannidou et al., 2019)
Jasinski et al. 2018	2018	assessment	(Jasiński et al., 2018)
Kim et al. 2019	2019	assessment	(Kim et al., 2019)
Kolotzek et al. 2018	2018	assessment	(Kolotzek et al., 2018)
Kosmol et al. 2018	2018	assessment	(Kosmol et al., 2018)

Short name	Year	Type	Ref.
Li et al. 2019	2019	assessment	(Li et al., 2019)
Malinauskiene et al. 2018	2018	assessment	(Malinauskienė et al., 2018)
Marscheider–Weidemann et al. 2016	2016	single indicator	(Marscheider–Weidemann et al., 2016)
Martins and Castro 2019	2019	assessment	(Martins & Castro, 2019)
Mayer and Gleich 2015	2015	assessment	(Mayer & Gleich, 2015)
Miyamoto et al. 2019	2019	assessment	(Miyamoto et al., 2019)
Morley and Eatherley 2008	2008	assessment	(Morley & Eatherley, 2008)
Moss et al. 2013	2013	assessment	(Moss et al., 2013)
Nansai et al. 2015	2015	assessment	(Nansai et al., 2015)
Nansai et al. 2017	2017	assessment	(Nansai et al., 2017)
Nassar et al. 2015	2015	collection of indicators	(Nassar et al., 2015)
Nassar et al. 2016	2016	assessment	(Nassar et al., 2016)
Nassar et al. 2020	2020	assessment	(Nassar et al., 2020)
NRC 2008	2008	assessment	(U.S. National Research Council, 2008)
Parthemore 2011	2011	assessment	(Parthemore, 2011)
Pell et al. 2019	2019	assessment	(Pell et al., 2019)
Pfleger et al. 2015	2015	assessment	(Pfleger et al., 2015)
Roelich et al. 2014	2014	assessment	(Roelich et al., 2014)
Rosenau–Tornow et al. 2009	2009	assessment	(Rosenau–Tornow et al., 2009)
Schneider et al. 2014	2014	assessment	(Schneider et al., 2014)
Shammugam et al. 2019	2019	assessment	(Shammugam et al., 2019)
Simon et al. 2014	2014	assessment	(Simon et al., 2014)
Spörri and Wäger 2017	2017	assessment	(Spörri & Wäger, 2017)
Sun et al. 2019	2019	assessment	(Sun et al., 2019)
Thomason et al. 2010	2010	assessment	(Thomason et al., 2010)
Tuma et al. 2014	2014	assessment	(Tuma et al., 2014)
van den Brink 2020	2020	assessment	(van den Brink et al., 2020)
Viebahn et al. 2015	2015	assessment	(Viebahn et al., 2015)
Wentker et al. 2019	2019	assessment	(Wentker et al., 2019)
Yan et al. 2020	2020	assessment	(Yan et al., 2020)
Yuan et al. 2019	2019	assessment	(Yuan et al., 2019)
Zepf et al. 2014	2014	assessment	(Zepf et al., 2014)
Zhou et al. 2019	2019	assessment	(Y. Zhou et al., 2019)
Zhou et al. 2020 JCLEPRO	2020	assessment	(Y. Zhou et al., 2020)
Zhou et al. 2020 RESPOL	2020	assessment	(N. Zhou et al., 2020)

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Appendix B 1: *Overview of the reviewed articles. Nomenclature: SCR supply chain resilience | SR system resilience | SC supply chain.*

Authors	Year	Context	Application	Disruption	Capacities: absorptive	adaptive	restorative	adapt. / restor.	original terminology for respective capacities	Metrics: time-based	performance-based	rate-based	integral-based
Abdelmalak et al.	2023	SR	electric power system	meteorological	x			x	recovery	x	x	x	
Abdin et al.	2019	SR	electric power system	meteorological	x				mitigation ability				x
Aghababaei et al.	2021	SR	road network	geophysical				x	robustness; redundancy				x
Aghabegloo et al.	2023	SR	integr. energy system	generic disruption	x	x	x		absorptive capacity; adaptive capacity; restoration capacity		x		x
Ahmadi et al.	2022	SR	electric power system	meteorological	x			x	robustness; recovery; readjust ability	x	x		x
Ahmadi et al.	2021	SR	electric power system	meteorological	x			x	recovery; readjust ability	x			x
Ahmadian et al.	2020	SR	electric power system	production disruption	x		x	x	responsiveness; restoration; criticality		x		x
Alguacil et al.	2014	SR	electric power system	generic disruption	x				vulnerability		x		
Alizadeh et al.	2022	SR	other	generic disruption			x		restoration				x
Amin et al.	2023	SR	electric power system	generic disruption	x				-		x		
Amirioun et al.	2019	SR	electric power system	meteorological	x			x	robustness; vulnerability; resistance; restoration efficiency	x	x		x
Anderson	2018	SR	electric power system	meteorological	x				sustainability	x			x
Appasani et al.	2022	SR	electric power system	generic disruption				x	redundancy	x			
Arab et al.	2015	SR	electric power system	meteorological				x	-				x
Arab et al.	2016	SR	electric power system	generic disruption			x		restoration				x
Arjomandi-Nezhad et al.	2021	SR	electric power system	meteorological	x			x	recovery rapidity			x	x
Ash et al.	2022	SCR	multi-echelon SC	biological	x			x	-				x
Ayala-Cabrera et al.	2019	SR	water supply system	technical	x				responsiveness		x		
Ayyub et al.	2014	SR	community	generic disruption	x			x	redundancy; robustness; resourcefulness; rapidity				x
Azimian et al.	2021	SR	electric power system	generic disruption	x			x	-		x		
Badr et al.	2023	SR	integr. energy system	generic disruption	x			x	-	x	x		x
G. Bai et al.	2021	SR	electric power system	generic disruption				x	recovery				x
Y. Bai et al.	2022	SR	integr. energy system	technical	x	x	x		degradation; adaption; restoration				x
Bao et al.	2019	SR	production site	terrorist attack				x	recovery				x

					Capacities					Metrics			
Authors	**Year**	**Context**	**Application**	**Disruption**	**absorptive**	**adaptive**	**restorative**	**adapt. / restor.**	**original terminology for respective capacities**	**time-based**	**performance-based**	**rate-based**	**integral-based**
Baroud et al.	2014	SR	water supply system	meteorological			x	x	recovery capability; restoration	x	x		
Behzadi et al.	2020	SCR	multi-echelon SC	technical	x			x	-	x			x
Belhadi et al.	2021	SCR	multi-echelon SC	biological	x			x	-	x			
Beyza & Yusta	2021	SR	electric power system	generic disruption	x			x	recovery		x		
Blagojevic et al.	2022	SR	community	generic disruption	x			x	-				x
Borghei & Ghassemi	2020	SR	electric power system	meteorological	x			x	-				x
Bruneau et al.	2003	SR	community	geophysical				x	rapidity				x
Burton et al.	2017	SR	community	geophysical	x			x	recovery	x	x		x
Carvalho et al.	2012	SCR	multi-echelon SC	supply disruption	x			x	-		x		
Carvalho et al.	2022	SCR	multi-echelon SC	supply disruption; production disruption	x			x	recovery	x	x		
Castillo et al.	2020	SR	other	technical			x		restorability		x		
Cavdaroglu	2013	SR	electric power system; other	generic disruption			x		restoration				x
Chan & Schofer	2016	SR	rail transportation	meteorological	x			x	preparedness; recovery effort; rebound ability	x			x
Chandrasekaran & Banerjee	2016	SR	other	geophysical				x	-				x
C. Chen et al.	2021	SCR	production site	terrorist attack	x	x	x		resistance capability & mitigation capability; adaptive capability; restoration capability				x
H. Chen et al.	2017	SR	port	terrorist attack				x	redundancy; efficiency		x		
L. Chen & Miller-Hooks	2012	SCR	freight transportation	meteorological				x	recovery ability		x		
Cheng et al.	2020	SR	other	generic disruption	x		x		absorptive capacity; restorative capacity		x		x
Cimellaro et al.	2010	SR	hospital	geophysical	x			x	rapidity; robustness		x	x	x
Cimellaro et al.	2015	SR	integr. energy system	geophysical	x			x	sustainability				x
Confrey et al.	2020	SR	electric power system	meteorological				x	-		x		
Cubillo & Martinez-Codina	2019	SR	water supply system	meteorological	x			x	response capacity				x
Das et al.	2020	SR	road network	hydrological				x	recovery effort				x
Didier et al.	2018	SR	community	generic disruption	x			x	redundancy; robustness; resourcefulness; rapidity	x	x		x
Dixit et al.	2016	SR	freight transportation	meteorological				x	-		x		

Authors	Year	Context	Application	Disruption	Capacities: absorptive	adaptive	restorative	adapt. / restor.	original terminology for respective capacities	Metrics: time-based	performance-based	rate-based	integral-based
Dong et al.	2022	SR	road network	generic disruption	x			x	robustness; adaption; recovery capability				x
Dui et al.	2023	SR	freight transportation	transport disruption				x	recovery				x
Fan et al.	2023	SR	integr. energy system	supply shock	x			x	withstanding capacity; recovery capacity	x	x		
Fang et al.	2016	SR	integr. energy system	meteorological				x	recoverability				x
Fang et al.	2015	SR	electric power system	cyber attack	x				vulnerability		x		
Fang & Sansavini	2019	SR	electric power system	generic disruption			x		restoration				x
Fang & Sansavini	2017b	SR	electric power system	generic disruption			x				x		x
Fang & Sansavini	2017a	SR	electric power system	cyber attack				x	recovery capability		x		
Fang & Zio	2019	SR	electric power system	generic disruption	x			x	robustness; recovery rapidity				x
Fattahi et al.	2017	SCR	multi-echelon SC	distribution disruption				x	responsiveness		x		
Fattahi et al.	2020	SCR	multi-echelon SC	distribution disruption				x	recovery				x
Faturechi et al.	2014	SR	airport	generic disruption				x	-		x		
Feng et al.	2022	SR	other	terrorist attack				x	-				x
Figueroa-Candia	2018	SR	electric power system	meteorological				x	restoration ability				x
Filippi et al.	2019	SR	other	technical	x			x	-				x
Francis & Bekera	2014	SR	electric power system	meteorological	x	x		x	absorptive capacity; adaptive capacity; recoverability	x	x		
Gabrielli et al.	2022	SCR	multi-echelon SC	generic disruption	x			x	mitigation ability; recovery possibility				x
Galbusera et al.	2016	SR	other	generic disruption	x			x	recovery ability				x
Garifi et al.	2022	SR	electric power system	meteorological	x			x	-				x
Gerges et al.	2023	SR	community	generic disruption	x			x	-				x
Ghorbani-Renani et al.	2020	SR	integr. energy system	terrorist attack	x			x	vulnerability; recoverability				x
Ghosh & De	2022	SR	electric power system	meteorological	x			x	-				x
Goldbeck et al.	2019	SR	rail transportation; electric power system	meteorological	x			x	robustness; rapidity	x	x		x
Gong & You	2018	SR	production site	generic disruption					-				x
Gotangco et al.	2016	SR	community	meteorological	x	x			adaptive capacity		x		
Haeri et al.	2020	SCR	multi-echelon SC	generic disruption	x			x	-		x		

Authors	Year	Context	Application	Disruption	Capacities: absorptive	Capacities: adaptive	Capacities: restorative	Capacities: adapt. / restor.	original terminology for respective capacities	Metrics: time-based	Metrics: performance-based	Metrics: rate-based	Metrics: integral-based
Q. Han et al.	2023	SR	other	-	x			x	responsiveness; survivability; recovery capability	x	x		x
Hao et al.	2023	SR	rail transportation	generic disruption				x	recovery ability				x
Hashemifar et al.	2022	SR	electric power system	generic disruption	x			x	-				x
Heath et al.	2016	SR	electric power system	meteorological			x		-				x
Henry & Ramirez-Marquez	2012	SR	road network	geophysical			x		restoration		x		
Hishamuddin et al.	2013	SCR	multi-echelon SC	meteorological				x	recovery				x
Hong et al.	2021	SR	community	meteorological	x			x	-				x
Y. Hosseini et al.	2023	SR	road network	geophysical				x	recovery				x
Hosseini-Motlagh et al.	2020	SCR	multi-echelon SC	generic disruption	x			x	-		x		
Y. H. Huang	2021	SR	electric power system	generic disruption	x			x	-				x
Huang & Pang	2014	SCR	multi-echelon SC	meteorological	x			x	rapidity; redundancy		x		x
Hulse et al.	2021	SR	other	generic disruption	x			x	resistance; absorption; restoration; recovery				x
Iloglu & Albert	2020	SR	road network	meteorological				x	-				x
Ivanov	2018	SCR	multi-echelon SC	supply disruption				x	-		x		
Jeong et al.	2006	SR	water supply system	terrorist attack	x				-		x		
Kalinowski et al.	2015	SR	-	generic disruption	x			x	-				x
Khalili et al.	2017	SCR	multi-echelon SC	generic disruption				x	-				x
Khayatzadeh et al.	2022	SR	integr. energy system	generic disruption	x			x	withstanding ability; restoration ability				x
Kim & Yeo	2016	SR	road network	generic disruption	x				vulnerability		x		
Kwasinski	2016	SR	electric power system	generic disruption	x			x	withstanding capability; recovery	x		x	
Kyriakidis et al.	2018	SR	integr. energy system	meteorological				x	recovery	x			x
Ladipo et al.	2019	SR	other	meteorological	x			x	-				x
Lau et al.	2018	SR	electric power system	generic disruption	x			x	-				x
Lei et al.	2019	SR	electric power system	meteorological				x	-				x
H. Li	2023	SR	other	terrorist attack	x			x	resistance; recovery ability		x		x
M. Li et al.	2019	SR	rail transportation	generic disruption				x	recovery				x
R. Li et al.	2017	SCR	multi-echelon SC	generic disruption	x			x	withstand disruption; recovery				x
Y. Li & Zobel	2020	SCR	multi-echelon SC	generic disruption	x		x	x	robustness; restorative capacity; recovery speed	x	x		x
L. Liao & Ji	2020	SR	electric power system	meteorological	x			x	-				x

Authors	Year	Context	Application	Disruption	absorptive	adaptive	restorative	adapt. / restor.	original terminology for respective capacities	time-based	performance-based	rate-based	integral-based
					Capacities					Metrics			
T. Liao et al.	2018	SR	road network	terrorist attack	x			x	-				x
X. Liu et al.	2021	SR	integr. energy system	generic disruption	x			x	mitigation; recovery				x
Z. Liu & Wang	2021	SR	electric power system	cyber attack	x			x	reliability; recovery speed	x	x		x
Losada et al.	2012	SR	production site	generic disruption	x			x	-	x			
Lücker & Seifert	2017	SCR	multi-echelon SC	production disruption	x			x	mitigation				x
Maheshwari et al.	2017	SCR	multi-echelon SC	meteorological	x			x	-		x		
Malek et al.	2023	SR	electric power system	generic disruption	x			x	-	x	x		x
Mao et al.	2021	SR	road network	meteorological				x	recovery rapidity	x			x
Marasco et al.	2022	SR	community	meteorological	x			x	withstanding capacity; recovery capacity		x		x
Mari et al.	2014	SCR	multi-echelon SC	generic disruption	x			x	vulnerability				x
Matisziw et al.	2010	SR	other	generic disruption	x		x		restoration				x
Miller-Hooks et al.	2012	SR	freight transportation	generic disruption				x	recovery capability		x		
Mishra et al.	2022	SR	electric power system	generic disruption	x			x	coping capacity; recovery				x
Munoz & Dunbar	2015	SCR	-	-	x			x	recovery	x	x		x
Najarian & Lim	2019	SR	electric power system	generic disruption	x	x		x	absorption; adaptation; recovery	x			x
Najarian & Lim	2020	SR	electric power system	generic disruption	x	x	x		absorption; adaptation; rapidity	x			x
Nan & Sansavini	2017	SR	electric power system	meteorological	x	x	x	x	absorptive capability; adaptive capability; restorative capability; recovery capability		x	x	x
Nan et al.	2016	SR	electric power system	meteorological	x	x		x	absorptive capability; adaptive capability; restorative capability; recovery ability		x	x	x
Ni et al.	2018	SR	production site	generic disruption			x		restoration				x
Niu et al.	2023	SR	road network	geophysical	x		x		vulnerability; restoration				x
Nozhati	2021	SR	electric power system	geophysical	x			x	-				
Nurre et al.	2012	SCR	electric power system; other	meteorological			x		restoration				x
Nurre & Sharkey	2018	SR	electric power system	meteorological			x		restoration				x
Ojha et al.	2018	SCR	multi-echelon SC	generic disruption	x	x			vulnerability; adaptability				x
Omer et al.	2009	SR	other	geophysical				x	vulnerability reduction		x		
Omidian & Khaji	2022	SR	other	geophysical				x	sustainability				x

Authors	Year	Context	Application	Disruption	Capacities: absorptive	Capacities: adaptive	Capacities: restorative	Capacities: adapt. / restor.	original terminology for respective capacities	Metrics: time-based	Metrics: performance-based	Metrics: rate-based	Metrics: integral-based
Ouyang et al.	2012	SR	electric power system	biological	x		x		resistant capacity; absorptive capacity; restorative capacity				x
Ouyang & Fang	2017	SR	electric power system	terrorist attack	x			x	-				x
Pant et al.	2014	SR	port	transport disruption			x		restoration	x			
Panteli et al.	2017	SR	electric power system	meteorological	x			x	-	x	x	x	x
Paseka et al.	2018	SR	water supply system	meteorological	x			x	-	x			
Podesta et al.	2021	SR	community	meteorological	x			x	recovery capacity		x	x	x
Poudel et al.	2020	SR	electric power system	meteorological	x			x	-				x
Rajesh	2016	SCR	multi-echelon SC	supply disruption	x			x	flexibility; responsiveness		x		
Reed et al.	2009	SR	electric power system	meteorological	x			x	robustness; rapidity; recovery		x	x	x
Ren et al.	2017	SR	other	generic disruption	x			x	rapidity	x			
Ribeiro & Barbosa-Povoa	2022	SCR	multi-echelon SC	supply disruption				x	responsiveness		x		
Roach et al.	2018	SR	water supply system	meteorological	x			x	absorption; recovery	x	x		x
Sabouhi et al.	2021	SCR	multi-echelon SC	generic disruption	x				-		x		
Salehi et al.	2022	SCR	multi-echelon SC	production disruption	x			x	-				x
Salmeron et al.	2009	SR	electric power system	terrorist attack	x				-		x		
Salmeron & Wood	2015	SR	electric power system	terrorist attack				x	-				x
Sanchis et al.	2020	SCR	production site	generic disruption	x				-		x		
Sanci & Daskin	2019	SR	other	transport disruption			x		-				x
Sang et al.	2021	SR	integr. energy system	generic disruption	x			x	restoration				x
Sawik et al.	2017	SCR	production site	supply disruption	x			x	-				x
Schmitt & Singh M.	2012	SCR	multi-echelon SC	supply disruption	x			x	recovery speed; responsiveness	x	x		
Senkel et al.	2021	SR	integr. energy system	distribution disruption	x			x	recovery	x	x		x
Shahbazi et al.	2021	SR	electric power system	meteorological	x			x	-		x		
Shang et al.	2022	SR	hospital	geophysical	x			x	redundancy; resourcefulness	x	x		x
Sharkey et al.	2015	SR	electric power system; water supply system; other	meteorological			x		restoration				x

Authors	Year	Context	Application	Disruption	Capacities: absorptive	adaptive	restorative	adapt. / restor.	original terminology for respective capacities	Metrics: time-based	performance-based	rate-based	integral-based
Shen et al.	2023	SR	electric power system	generic disruption	x			x	recovery response				x
Simonovic & Arunkumar	2016	SR	water supply system	meteorological				x	-				x
P. Singh et al.	2023	SR	other	meteorological	x			x	-				x
Smith et al.	2020	SR	electric power system; water supply system	geophysical				x	recovery				x
Song et al.	2022	SR	water supply system	geophysical				x	recovery capacity	x			x
Soualah et al.	2023	SR	electric power system	generic disruption	x			x	-				x
Spiegler et al.	2012	SCR	multi-echelon SC	supply disruption	x			x	readiness; responsiveness; recovery				x
Sun et al.	2022	SCR	production site	generic disruption	x			x	-				x
J. Sun et al.	2023	SR	other (infrastructure system: road network, electric power system, wastewater system)	meteorological	x			x	-				x
W. J. Tan et al.	2020	SCR	multi-echelon SC	generic disruption	x			x	effectiveness; resistance ability; recovery ability	x			x
Y. Tan et al.	2018	SR	electric power system; water supply system	meteorological			x		restoration				x
Y. Tan et al.	2019	SR	electric power system; water supply system	meteorological			x		restoration				x
Tang et al.	2023	SR	other	generic disruption	x			x	-				x
Tang et al.	2021	SR	rail transportation	transport disruption	x			x	-				x
Tao et al.	2022	SR	road network	technical	x			x	resistance ability; recovery ability; robustness		x		x
Tariverdi et al.	2019	SR	hospital	generic disruption				x	-		x		
Tofani et al.	2021	SR	electric power system	generic disruption				x	recovery				x
Tofani et al.	2018	SR	electric power system	generic disruption	x			x	withstanding capability				x
Di Tommaso et al.	2023	SR	other	generic disruption	x			x	recovery		x	x	
Torabi et al.	2015	SCR	multi-echelon SC	geophysical				x	robustness; rapidity				x
Touzinsky et al.	2018	SR	port	meteorological	x			x	preparation; resistance; recovery; adaption				x
Tran et al.	2017	SR	other	meteorological	x			x	absorption; recovery; responsiveness; recovery speed	x	x		
Uday & Marais	2014	SR	airport	generic disruption				x	recoverability importance; disruption importance				x
Ulusan & Erugn	2018	SR	other	geophysical			x		restoration				x

					Capacities					Metrics			
Authors	Year	Context	Application	Disruption	absorptive	adaptive	restorative	adapt. / restor.	original terminology for respective capacities	time-based	performance-based	rate-based	integral-based
Valenzuela et al.	2018	SCR	-	-	x				absorption		x		
Veit et al.	2023	SR	other	cyber attack	x			x	absorption; recovery; performance capacity	x	x		x
Verleysen et al.	2023	SR	production site	supply disruption	x			x	-				x
Vugrin et al.	2011	SR	multi-echelon SC	meteorological	x	x	x		absorptive capacity; adaptive capacity; restoration efficiency				x
J. Wang & Liu	2019	SR	road network	meteorological	x				absorbing ability				x
J. W. Wang et al.	2010	SR	other	cyber attack				x	recovery ability	x			
X. Wang et al.	2022	SR	airport	meteorological	x	x	x	x	susceptibility; absorptive capability; rapidity; recovery capability; adaptive capability;	x	x	x	x
Y. Wang & Wang	2020	SR	road network	generic disruption				x	recovery effectiveness		x		
Watson et al.	2022	SR	other	generic disruption				x	responsiveness				x
Jinyi et al.	2020	SR	other	cyber attack	x			x	absorptive capacity; recovery ability; stable state capability	x	x		x
Xu et al.	2023	SR	electric power system	meteorological	x			x	-				x
Y. Yang et al.	2018	SR	electric power system	meteorological	x		x		resistant capacity; absorptive capacity; restorative capacity				x
Z. Yang & Marti	2022	SR	electric power system	generic disruption			x		restoration				x
Yao et al.	2023	SR	electric power system	meteorological	x			x	robustness	x	x		x
Yarveisy et al.	2020	SR	electric power system	generic disruption	x	x	x		absorptive capacity; adaptive capacity; restorative capacity	x	x	x	
Yu & Baroud	2019	SR	community	meteorological				x	recovery capacity		x		
Yuan et al.	2014	SR	electric power system	terrorist attack	x				-		x		
Zahiri et al.	2017	SCR	multi-echelon SC	generic disruption	x			x	-		x		
Zarghami & Zwikael	2022	SR	other	generic disruption	x			x	-				x
Zavala et al.	2019	SCR	multi-echelon SC	distribution disruption				x	capability to recover		x		
C. Zhang et al.	2022	SR	water supply system	technical	x			x	sustainability	x	x		x
H. Zhang et al.	2019	SR	electric power system	meteorological				x	responsiveness; recovery efficiency; restoration economics	x	x		x

Authors	Year	Context	Application	Disruption	Capacities: absorptive	adaptive	restorative	adapt. / restor.	original terminology for respective capacities	Metrics: time-based	performance-based	rate-based	integral-based
H. Zhang et al.	2018	SR	electric power system	meteorological	x			x	toughness; resistance; responsiveness; restoration efficiency; restoration economics	x	x		x
Zhang, Li et al.	2023	SR	community	geophysical	x			x	recovery	x	x		
J. Zhang et al.	2022	SR	rail transportation	technical				x	recovery		x		x
Zhang, Ren et al.	2023	SR	rail transportation	technical				x	recovery				x
J. M. Zhang & T. Wang	2023	SR	other	biological	x			x	-				x
M. Zhang et al.	2022	SR	other	geophysical				x	recovery	x			x
Q. Zhang et al.	2020	SR	water supply system	geophysical				x	rapidity	x			x
X. Zhang et al.	2021	SR	electric power system	meteorological				x	restoration		x		
X. G. Zhang et al.	2022	SR	production site	meteorological				x	-		x		
Z. Zhang et al.	2023	SR	rail transportation	biological	x			x	vulnerability; robustness; response; recovery	x	x		
Zhao et al.	2017	SR	water supply system	biological	x	x		x	adaptive capacity; absorptive capacity; recovery capacity	x	x		x
Zhao et al.	2016	SR	water supply system	biological	x	x		x	absorptive capacity; adaptive capacity; recovey capacity; recovery ability	x	x		x
S. Zhao & You	2019	SCR	multi-echelon SC	generic disruption	x			x	recovery				x
J. X. Zheng & Huang	2023	SR	electric power system	meteorological	x			x	-				x
Zhou et al.	2021	SR	airport	generic disruption	x			x	-				x
Zhou & Chen	2020	SR	airport	meteorological				x	rapidity	x			
Zobel et al.	2021	SR	community	meteorological				x	resistance ability; recovery ability				x
Zong et al.	2022	SR	integr. energy system	geophysical	x			x	-				x
Zukhruf & Frazila	2018	SR	port	technical				x	recovery response		x		

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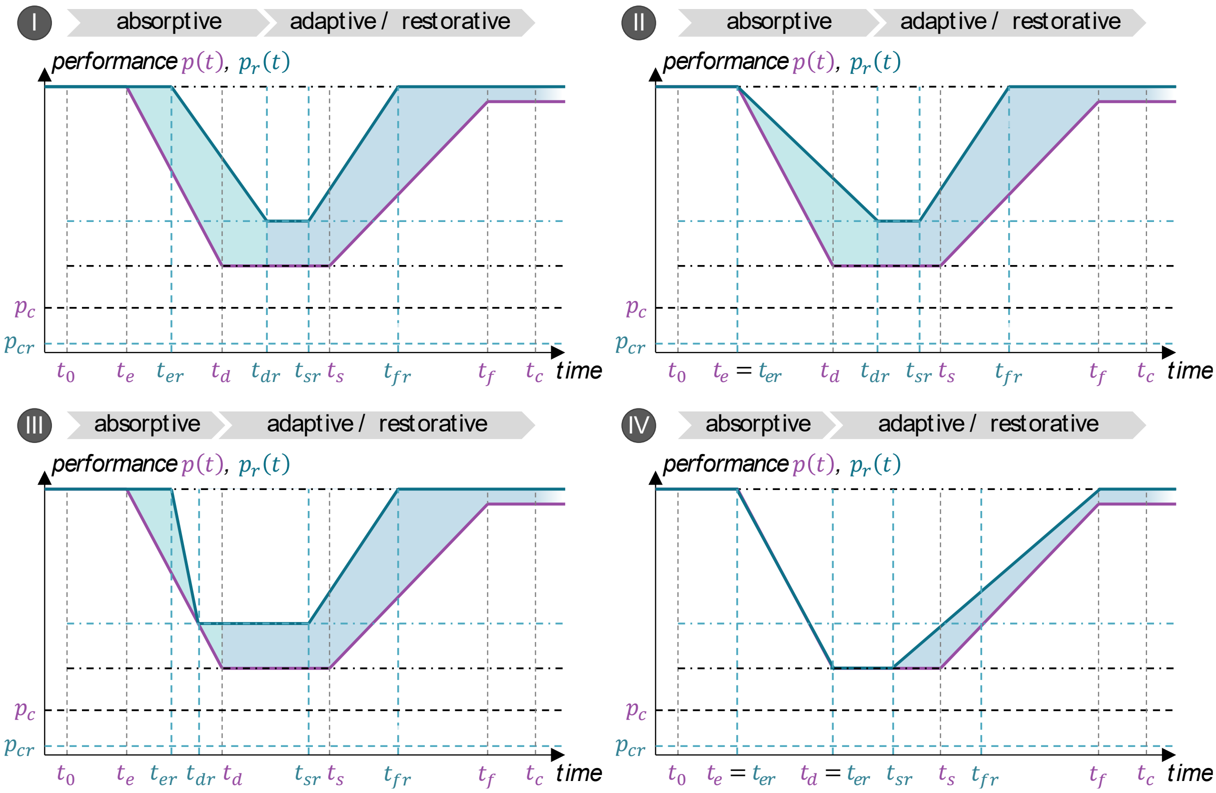
Appendix B 2: *Nomenclature used within this article.*

Explanation	Without implementation of resilience actions	With implementation of resilience actions
Begin of control interval	t_0	
Exposure to hazard	t_{h0}	
Initial system disruption	t_e	t_{er}
End of performance degradation	t_d	t_{dr}
Begin of system recovery	t_s	t_{sr}
End of system recovery	t_f	t_{fr}
End of exposure to hazard	t_{h1}	
End of control interval	t_c	
Performance	$p(t)$	$p_r(t)$
Performance based on the output	$p_o(t)$	$p_{or}(t)$
Performance based on number of system components	$p_n(t)$	$p_{nr}(t)$
performance based on technical system parameters	$p_t(t)$	$p_{tr}(t)$
Performance based on economic parameters	$p_e(t)$	$p_{er}(t)$
Critical threshold	p_c	p_{cr}

Appendix B 3: *Alternative trajectories of the resilience curve.*



Case (I) Resilience curve as illustrated and described in Section 3.3.

Case (II) the resilience actions lead to a performance disruption starting at $t_e = t_{er}$ and ending at $t_{dr} > t_d$. As a result, the *resistive duration* is not affected by a resilience action, but i.a., the *absorb duration* has been increased and thus improved (cf. formulations in), strengthening the absorptive capacity. Likewise, the adaptive and/or restorative capacity have been strengthened by shorter *endure* and *recovery phases* and a higher *restored performance* and *recovery rate*, resulting in a higher cumulative recovery performance.

Case (III) the resilience actions lead to a performance disruption starting at $t_{er} > t_e$ and ending at $t_{dr} < t_d$. As a result, i.e., the *resistive duration, residual performance*, and *depth of impact* are positively affected by the resilience actions, strengthening the absorptive capacity. However, the *absorb duration* has been shortened, and the *failure rate* has increased, offsetting improvement in the *cumulative absorptive performance* to some degree. The adaptive and/or restorative capacities have been strengthened regarding a higher *restored performance*, *recovery rate,* and *residual performance*, correlating with a higher *cumulative recovery performance*. Some resilience metrics remain almost unchanged (e.g., *endure duration*).

Case (IV) the absorptive capacity remains entirely unchanged by the resilience actions. Only the adaptive and/or restorative capacities are strengthened by a shorter *endure duration*, a higher restored performance, and, consequently, a higher *cumulative recovery performance*.

MANUSCRIPT APPENDIX D

Basic network optimization model

The optimization model used by the proposed three-stage planning approach bases on the work of Bruckler et al. (2025) (*contribution C*), wherefore the indices, parameters, decision variables, and economic objective function (NPV) as well as the constraints were adopted. The related data can be found in the Supporting Information D.

Appendix D 1: *Sets and indices.*

$R = \{7, 8, 56, 57, 58, 83, 84, 85, 86\}$	Regions where biorefineries (BR) or storages can be installed	NUTS-1 level regions in 27 EU member states: Bulgaria BG3 (7), BG4 (8); Hungary HU1 (56), HU2 (57), HU3 (58); Romania RO1 (83), RO2 (84), RO3 (85), RO4 (86)
$RS = \{1, 2, 7, 8, 31, 55, 56, 57, 58, 83, 84, 85, 86, 90, 91\}$	Sourcing regions	NUTS-1 level regions in 27 EU member states: 9 BR regions + 6 additional regions; East & South Austria AT1 (1), AT2 (2); Slovakia SK0 (91); Slovenia SL0 (90); Croatia HR0 (55); North Greece EL5 (31)
$M = \{1, 2, \ldots 50\}$	Sourcing annulus	10 km, 20 km, …, 500 km
$MR = \{1, 2, \ldots 50, 57, 58, 106, 107, 108, 133, 134, 135, 136\}$	Combined index for M & R	M represented from 1 … 50 and R represented from 50+7, 50+8, 50+56 … 50+86
$Q = \{1, 2, \ldots 91\}$	Demand regions	NUTS-1 level regions in 27 EU member states
$C = \{1, 2, \ldots 32\}$	BR capacity levels	6,250, 12,500, …, 200,000 metric tons (output per quarter)
$CS = \{1, 2, \ldots 80\}$	Storage capacity levels	5,562.5, 11,125, …, 444,998 metric tons (input)
$P = \{1, 2\}$	Substituted products	Fossil fuel and first-generation bioethanol (1G-EtOH)
$Y = \{1, 2\}$	By-products	Surplus energy, biomethane
$T = \{1, 2, 3\}$	Transport modes	Farm tractor, truck, rail
$X = \{1, 2, \ldots, 40\}$	Time periods	1, 2, …, 40 quarters (10 years)

Appendix D 2: *Basic parameters.*

$\zeta_{u,p}$	t / t EtOH eq.	Demand for substituted product $p \in P$ in region $u \in Q$
$\psi_{r,x}^{sc}$	t Straw	Available feedstock in region $r \in RS$ in period $x \in X$ (in scenario $sc \in S$)
$\mu_{r,m,x}^{sc}$	t Straw	Available feedstock in sourcing annulus $m \in M$ in region $r \in R$ in period $x \in X$ (in scenario $sc \in S$)
θ	t 2G-EtOH / t Straw	Transformation factor from feedstock to 2G-EtOH
σ_c^{BR}	t 2G-EtOH	Maximum capacity of a BR with capacity level $c \in C$ in one period
σ_{cs}^{ST}	t Straw	Maximum capacity of a ST with capacity level $cs \in CS$
ν		Storage loss of feedstock

Appendix D 3: *Economic parameters.*

α_u^{1G}	€ / t 2G-EtOH	Revenues of 2G-EtOH in region $u \in Q$ for substitution of 1G-EtOH
α_u^{FF}	€ / t 2G-EtOH	Revenues of 2G-EtOH in region $u \in Q$ for substitution of fossil petrol
$\alpha_{r,y}^{byp}$	€ / t 2G-EtOH	Revenues of by-products $y \in Y$ in region $r \in R$
$\kappa_{r,c}^{depr,BR}$	€ / BR	10-year depreciated costs of installing a BR in region $r \in R$ with capacity level $c \in C$ (lifetime 20 years)
$\kappa_{r,cs}^{depr,ST}$	€ / Storage	10-year depreciated costs of installing a ST in region $r \in R$ with capacity level $cs \in CS$ (lifetime 33 years)
$\kappa_{r,c}^{pers}$	€ / BR	Quarterly costs for personnel of a BR in region $r \in R$ with capacity level $c \in C$.
κ_c^{oper}	€ / BR	Quarterly fixed costs of operating a BR with capacity level $c \in C$
κ^{var}	€ / t 2G-EtOH	Variable costs of refining bioethanol at a BR
$\varphi_{r,x}$	€ / t Straw	Costs of feedstock at farms in region $r \in RS$ in period $x \in X$
ε_t^{fix}	€ / t Straw	Fixed costs of transporting feedstock with transport mode $t \in T$
$\varepsilon_{r,m,t}^{var,in}$	€ / t Straw	Variable costs of transporting feedstock from sourcing annulus $m \in M$ in region $r \in R$ with transport mode $t \in T$
$\varepsilon_{r,m,t}^{var,out}$	€ / t Straw	Variable costs of transporting feedstock from region $r \in RS$ to BR in region $m \in MR{:}\, m > 50$ with transport mode $t \in T$
η_t^{fix}	€ / t 2G-EtOH	Fixed costs of transporting 2G-EtOH with transport mode $t \in T$
$\eta_{r,q,t}^{var}$	€ / t 2G-EtOH	Variable costs of transporting 2G-EtOH from region $r \in R$ to demand region $q \in Q$ with transport mode $t \in T$
i		Interest rate

Appendix D 4: *Decision variables.*

$B_{r,c}$	$\in \{0,1\}$	1 indicates a construction of BR in region $r \in R$ with capacity level $c \in C$.
$S_{r,cs}$	$\in \{0,1\}$	1 indicates a construction of ST in region $r \in R$ with capacity level $cs \in CS$.
$F_{r,m,t,x}$	$\in \mathbb{Q}_0^+$	Transported amount of feedstock from sourcing annulus $m \in MR{:}\, m \leq \lvert M \rvert$ in region $r \in R \subseteq RS$ to BR in the same region or from another sourcing region $r \in RS$ to BR in region $m \in MR{:}\, m > \lvert M \rvert$ with transport mode $t \in T$ in period $x \in X$.
$P_{r,u,t,p,x}$	$\in \mathbb{Q}_0^+$	Transported amount of 2G-EtOH from BR in region $r \in R$ to fulfill demand in region $u \in Q$ with mode $t \in T$, substituting product $p \in P$ in period $x \in X$.
$S_{r,x}^{in}$	$\in \mathbb{Q}_0^+$	Amount of feedstock to be stored in feedstock storage in region $r \in R$ in period $x \in X$.
$S_{r,x}^{out}$	$\in \mathbb{Q}_0^+$	Amount of feedstock extracted from feedstock storage in region $r \in R$ for production of 2G-EtOH in period $x \in X$.
$S_{r,x}^{stor}$	$\in \mathbb{Q}_0^+$	Amount of feedstock available in feedstock storage in region $r \in R$ at the end of period $x \in \{0,\dots,40\}$ (0 is necessary for initialization).

Appendix D 5: *Economic objective criterion.*

$NPV_{sc} =$	(D.0)
$\sum_{r\in R}\sum_{u\in Q}\sum_{t\in T}\sum_{x\in X}(P_{r,u,t,1G,x}\cdot \alpha_u^{1G})\,/(1+i)^{\frac{x}{4}}$	Revenues from substituting 1G EtOH
$+\sum_{r\in R}\sum_{u\in Q}\sum_{t\in T}\sum_{x\in X}(P_{r,u,t,FF,x}\cdot \alpha_u^{FF})\,/(1+i)^{\frac{x}{4}}$	Revenues from substituting fossil fuels
$+\sum_{r\in R}\sum_{u\in Q}\sum_{t\in T}\sum_{p\in P}\sum_{x\in X}\sum_{y\in Y}(P_{r,u,t,p,x}\cdot \alpha_{r,y}^{byp})\,/(1+i)^{\frac{x}{4}}$	Revenues from by-products
$-\sum_{r\in R}\sum_{c\in C}B_{r,c}\cdot \kappa_{r,c}^{depr,BR}$	BR installation costs
$-\sum_{r\in R}\sum_{c\in C}\sum_{x\in X}(B_{r,c}\cdot \kappa_{r,c}^{pers})\,/(1+i)^{\frac{x}{4}}$	BR personnel costs
$-\sum_{r\in R}\sum_{c\in C}\sum_{x\in X}(B_{r,c}\cdot \kappa_{c}^{oper})\,/(1+i)^{\frac{x}{4}}$	BR operating costs
$-\sum_{r\in R}\sum_{cs\in CS}S_{r,cs}\cdot \kappa_{r,cs}^{depr,ST}$	ST installation costs
$-\sum_{r\in R}\sum_{u\in Q}\sum_{t\in T}\sum_{p\in P}\sum_{x\in X}(P_{r,u,t,p,x}\cdot \kappa^{var})\,/(1+i)^{\frac{x}{4}}$	Process costs
$-\sum_{r\in RS}\sum_{m\in MR}\sum_{t\in T}\sum_{x\in X}(F_{r,m,t,x}\cdot \varphi_{r,x})\,/\,(1+i)^{\frac{x}{4}}$	Feedstock costs
$-\sum_{r\in RS}\sum_{m\in MR}\sum_{t\in T}\sum_{x\in X}(F_{r,m,t,x}\cdot \varepsilon_t^{fix})\,/(1+i)^{\frac{x}{4}}$	Collection costs fixed
$-(\sum_{r\in RS}\sum_{m\in M}\sum_{t\in T}\sum_{x\in X}(F_{r,m,t,x}\cdot \varepsilon_{r,m,t}^{var,in})\,/(1+i)^{\frac{x}{4}}+$ $\sum_{r\in RS}\sum_{\{u\in MR\,\mid MR>\mid M\mid\}}\sum_{t\in T}\sum_{x\in X}(F_{r,u,t,x}\cdot \varepsilon_{r,u,t}^{var,out})\,/(1+i)^{\frac{x}{4}})$	Collection costs variable
$-\sum_{r\in R}\sum_{u\in Q}\sum_{t\in T}\sum_{p\in P}\sum_{x\in X}(P_{r,u,t,p,x}\cdot \eta_t^{fix})\,/(1+i)^{\frac{x}{4}}$	Distribution costs fixed
$-\sum_{r\in R}\sum_{u\in Q}\sum_{t\in T}\sum_{p\in P}\sum_{x\in X}(P_{r,u,t,p,x}\cdot \eta_{r,u,t}^{var})\,/(1+i)^{\frac{x}{4}}$	Distribution costs variable

Appendix D 6: *Constraints.*

Restriction of bioethanol production according to the BR capacity:

$$\sum_{u \in Q} \sum_{t \in T} \sum_{p \in P} P_{r,u,t,p,x} \leq \sum_{c \in C} B_{r,c} \cdot \sigma_c^{BR} \qquad \forall\, r \in R\,, x \in X \qquad \text{(D.1)}$$

Restriction of feedstock storage:

$$S_{r,x}^{stor} \leq \sum_{cs \in CS} \sigma_{cs}^{ST} \cdot S_{r,cs} \qquad \forall\, r \in R, x \in X \qquad \text{(D.2)}$$

Restriction of feedstock collection according to feedstock availability:

$$\sum_{m \in MR} \sum_{t \in T} F_{r,m,t,x} \leq \psi_{r,x}^{sc} \qquad \forall\, r \in RS, x \in X \qquad \text{(D.3)}$$

Flow constraint (transport flows):

$$\left(\sum_{m \in M} \sum_{t \in T} F_{u-|M|,\, m,t,x} + \sum_{r \in RS} \sum_{t \in T} F_{r,u,t,x} + S_{u-|M|,x}^{out} - S_{u-|M|,x}^{in}\right) \cdot \theta \ = \sum_{v \in Q} \sum_{t \in T} \sum_{p \in P} P_{u-|M|,v,t,p,x} \qquad \forall\, u \in MR{:}\, u > |M|,\ x \in X \qquad \text{(D.4)}$$

Restriction of feedstock collection in sourcing annuli:

$$\sum_{t \in T} F_{r,m,t,x} \leq \mu_{r,m,x}^{sc} \qquad \forall\, r \in R, m \in M, x \in X \qquad \text{(D.5)}$$

Bioethanol production is not allowed to exceed the demand of substitute (1G, FF):

$$\sum_{r \in R} \sum_{t \in T} P_{r,u,t,p,x} \leq \zeta_{u,p} \qquad \forall\, u \in Q, p \in P, x \in X \qquad \text{(D.6)}$$

No out-of-region sourcing in the BR region:

$$F_{r,r+|M|,t,x} = 0 \qquad \forall\, r \in R, t \in T, x \in X \qquad \text{(D.7)}$$

In-region sourcing is not allowed in sourcing regions where no BR is constructed:

$$\sum_{m \in M} F_{r,\, m,t,x} = 0 \qquad \forall\, r \in RS \setminus R, t \in T, x \in X \qquad \text{(D.8)}$$

Transport mode ‘tractor ‘is not allowed for bioethanol transport:

$$P_{r,u,1,p,x} = 0 \qquad \forall\, r \in R, u \in Q, p \in P, x \in X \qquad \text{(D.9)}$$

Only one BR per region is allowed:

$$\sum_{c \in C} B_{r,c} \leq 1 \qquad \forall\, r \in R \qquad \text{(D.10)}$$

Only one storage per region is allowed:

$$\sum_{cs \in CS} S_{r,cs} \leq 1 \qquad \forall\, r \in R \qquad \text{(D.11)}$$

Flow constraint (storage flows):

$$S_{r,x}^{stor} = S_{r,x-1}^{stor} \cdot (1-\nu) + S_{r,x}^{in} - S_{r,x}^{out} \qquad \forall\, r \in R, x \in X \qquad \text{(D.12)}$$

Storage outflow needs to be lower than the feedstock amount available at the beginning of the current period (feedstock available at the end of the previous period minus feedstock storage loss):

$$S_{r,x}^{out} \leq S_{r,x-1}^{stor}\,(1-\nu) \qquad \forall\, r \in R, x \in X{:}\, x > 1 \qquad \text{(D.13)}$$

Initial and end states: No storage at the end of period 0; No stock outflow in period 1; No storage inflow in period 40:

$$S_{r,1}^{out} + S_{r,0}^{stor} + S_{r,40}^{in} = 0 \qquad \forall\, r \in R \qquad \text{(D.14)}$$

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