sustainability

MDPI

Article

A Hybrid MCDM Framework for Assessing the Strategic Role of Dry Ports in Emergency Logistics Networks: An Integrated Efficiency–Resilience Perspective

Gani Mustafa İnegöl [1,2,*] and Yasin Arslanoğlu [1]

[1] Maritime Faculty, Istanbul Technical University, Tuzla, 34940 Istanbul, Türkiye; arslanoglu@itu.edu.tr
[2] Karamürsel Maritime Vocational School, Kocaeli University, 41500 Karamürsel, Kocaeli, Türkiye
* Correspondence: gani.inegol@kocaeli.edu.tr

Abstract

This study proposes a novel dual-role weighting framework for dry port location selection, bridging the gap between commercial logistics efficiency and strategic disaster resilience. Designed to establish a new theoretical evaluation paradigm, the research utilizes the Fuzzy Rough SWARA (FR-SWARA) method and a 12-person expert panel to weigh a comprehensive set of 31 criteria under high-dimensional uncertainty. The findings reveal a decisive hierarchical shift, where spatial and infrastructure-related dimensions significantly outweigh traditional cost considerations. This empirical evidence substantiates the transition from 'just-in-time' to 'Just-in-Case' logistics architectures. Ultimately, the study reconceptualizes the dry port as a 'strategic stabilizer'—a critical infrastructure node that absorbs systemic shocks and maintains supply chain continuity during diverse crises, including natural disasters and the COVID-19 pandemic. The proposed weighting framework offers a robust theoretical roadmap for policy and managerial decision-making in volatile geographies.

Keywords: dry port; emergency logistics; resilience; multi-criteria decision-making (MCDM); supply chain security

1. Introduction

Maritime transport constitutes the backbone of global trade flows, facilitating over 80% of global commodity trade and ensuring access to international markets. However, recent global shocks have exposed the structural vulnerabilities of these critical networks. The COVID-19 pandemic triggered unprecedented disruptions, precipitating severe port bottlenecks and soaring freight rates, which laid bare the inherent limitations of just-in-time (JIT) models [1,2]. Furthermore, geopolitical tensions, such as the Russia–Ukraine war and trade disputes between major economies, have necessitated a strategic realignment towards alternative trade routes and accentuated the precarity of supply chain security [3–5].

In addition to anthropogenic shocks, maritime logistics infrastructure faces escalating threats from natural disasters and climate change. Alongside the Great East Japan Earthquake and Hurricane Katrina, the recent 2023 Kahramanmaraş and Hatay earthquakes have starkly illustrated how the physical destruction of logistics infrastructure can incapacitate supply chains and vital emergency response operations [6–8]. These compounding pressures necessitate a paradigm shift from purely efficiency-oriented logistics to resilient and adaptive systems capable of withstanding multi-dimensional crises [2].

Check for updates

Academic Editor: Koichi Murata

Received: 8 April 2026
Revised: 20 April 2026
Accepted: 21 April 2026
Published: 24 April 2026

Copyright: © 2026 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license.

The concept of dry ports was developed to alleviate seaport congestion and optimize the operational efficiency of inter-port cargo transportation, driven by the exponential growth in global trade volumes and the surge in containerization [9,10]. In response to these multifaceted challenges, a dry port is defined as an intermodal terminal located inland, typically directly connected to seaports via high-capacity transport modes such as railways [11–14]. The strategic siting of a dry port is paramount for fully unlocking its operational advantages [15]. However, given the vulnerabilities mentioned above, evaluating dry ports solely through a conventional commercial lens remains strategically inadequate. To address these disruptions, emergency logistics has emerged as an indispensable capability for sustaining supply chain continuity.

Consequently, emergency logistics constitutes a vital component of disaster management and risk reduction in extraordinary scenarios such as natural disasters, pandemics, crises, and wars, facilitating the rapid deployment of relief materials and life-saving support during times of crisis [16]. Integrating this capability into dry port location selection transforms these infrastructural nodes from mere cargo buffers into strategic dual-purpose hubs.

Despite extensive research on dry port locations and emergency logistics as independent domains, a critical research gap persists in the extant literature: previous decision-making models have largely evaluated commercial logistics hubs and emergency response centers as mutually exclusive entities. This dualistic treatment fails to capture the systemic operational synergy required when the broader logistics network—including near-port, mid-range, and distant facilities—faces systemic damage, congestion, or incapacitation due to large-scale crises such as earthquakes or pandemics. While conventional studies predominantly emphasize 'just-in-time' (JIT) efficiency, recent global disruptions necessitate a strategic transition toward 'Just-in-Case' (JIC) logistics architectures.

In this context, the conceptual framework presented in Figure 1 illustrates this structural transition. To operationalize this shift, the present study ontologically redefines dry ports as 'strategic stabilizers'. Within this framework, a strategic stabilizer is defined as a logistics node that possesses the structural redundancy and multi-scalar connectivity to maintain supply chain continuity when the overarching logistics system is compromised. Unlike a standard 'resilient node'—which primarily focuses on self-recovery—a strategic stabilizer functions as an integrated hub for both operational coordination and emergency logistics distribution. These stabilizers are specifically designed to absorb systemic shocks by serving as high-capacity staging areas for emergency response network integration, ensuring functional stability across the national logistics network regardless of the specific point of failure.

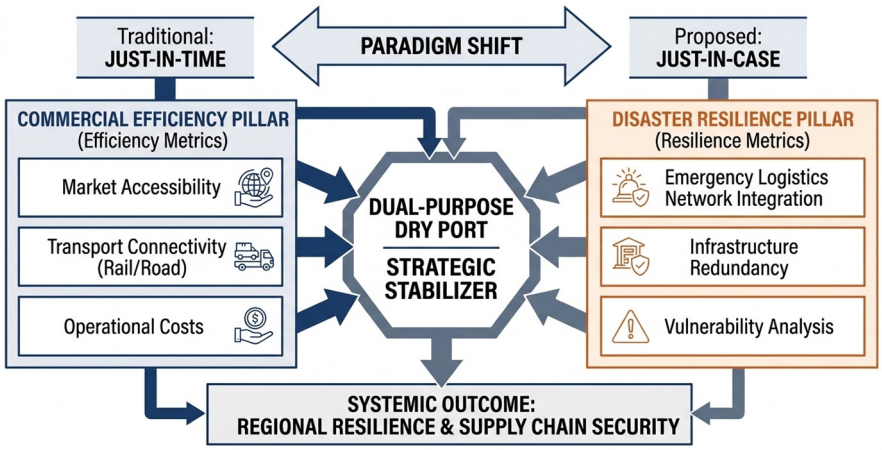


Figure 1. Conceptual framework.

To address these multi-dimensional requirements, rather than executing a standard site-specific location application, this study aims to develop a robust, dual-role strategic weighting framework designed to systematically harmonize inherently conflicting objectives. By employing the Fuzzy Rough SWARA (FR-SWARA) method to prioritize resilience-oriented sub-criteria and encapsulate stakeholder dissonance within a rough boundary structure, the proposed framework seamlessly integrates traditional commercial metrics with critical resilience components. Ultimately, this scientifically grounded infrastructure valuation model extends supply chain resilience theory and provides a strategic roadmap for public policy formulation and targeted incentive allocations.

2. Literature Review

2.1. Dry Port Concept

The concept of a dry port has evolved from simple inland clearance depots to advanced intermodal terminals that facilitate modal shifts and regional development. Early definitions focused on relieving seaport congestion [17] and inland customs processing [18]. In the contemporary literature, a dry port is defined as an inland intermodal terminal directly connected to a seaport by high-capacity transport means, where customers can leave/pick up their standardized units as if they are directly at a seaport [11,19]. Roso et al. [11] further categorized these facilities into close, mid-range, and distant dry ports based on their distance from the seaport, highlighting their function as extended gates.

From a sustainability perspective, dry ports significantly mitigate the negative externalities of seaport operations by shifting freight from road to rail. Several studies have quantified these benefits. For instance, Khaslavskaya and Roso [12] and Carboni and Orsini [20] demonstrated substantial reductions in CO_2 emissions and congestion through effective dry port implementation. Furthermore, these facilities enhance global logistics efficiency by acting as buffer zones during peak periods, thereby optimizing vessel turnaround times and providing competitive advantages to the hinterland industries [21–23].

2.2. Review of Criteria and Methodologies Used in Dry Port Location Selection

Dry port location selection is a complex multi-criteria decision-making (MCDM) problem involving conflicting quantitative and qualitative factors such as cost, accessibility, and environmental impact [24]. Owing to the high capital investment and irreversibility of the decision, the literature offers a wide array of methodological approaches. Early studies predominantly utilized hybrid MCDM models; for instance, Kayikci [25] and Ka [26] employed Fuzzy AHP integrated with Artificial Neural Networks (ANNs) and ELECTRE, respectively, to evaluate macroeconomic and infrastructural criteria.

More recent research has incorporated spatial and environmental dimensions into the decision-making process. Komchornrit [27] and Raad et al. [28] combined MCDM methods with Geographic Information Systems (GISs) to assess spatial–temporal factors alongside traditional economic metrics. Similarly, environmental sustainability has gained prominence, with studies such as Pham and Lee [29] focusing on green routing models to minimize total emissions. The diversity of criteria, ranging from traditional cost metrics to social and political factors, and the evolution of methodologies are summarized in Table 1.

As shown in Table 1, while numerous studies have utilized MCDM methods for dry port location selection, they have predominantly focused on economic and operational criteria. Methodologies have evolved from traditional AHP and ANP to more complex hybrid approaches; however, the integration of resilience and emergency response capabilities as core decision criteria remains limited. This study differentiates itself from the listed literature by introducing a 'dual-use' perspective, evaluating dry ports not only as commercial nodes but also as critical assets for national disaster management.

Table 1. Some dry port location selection studies have been found in the literature.

Author	Year	Country	Method
Lv and Li [30]	2009	China	ANP
Wei et al. [31]	2010	-	Fuzzy ANP
Ka [26]	2011	China	AHP-ELECTRE
Ambrosino and Sciomachen [32]	2014	Italy	Mixed-Integer Linear Programming
Roso et al. [33]	2015	Croatia	AHP
Chang et al. [34]	2015	China	Linear Programming
Wang et al. [35]	2017	China	Integer programming
Komchornrit and Weerawat [27]	2020	Thailand	SEM-MACBETH-PROMETHEE
Tadic et al. [36]	2020	Slovenia	Gray Delphi-AHP-CODAS
Saka and Çetin [37]	2020	Türkiye	AHP
Božicević et al. [38]	2021	Croatia	AHP
Raad et al. [28]	2022	Iran	Fuzzy SWARA, GIS Fuzzy MULTIMOORA
Chowdhury and Munim [39]	2023	Bangladesh	Fuzzy AHP-BWM-PROMETHEE
Wu and Zhang [40]	2023	China	Game Theory
Nguyen et al. [41]	2016	Vietnam	SWING
Bagheri et al. [15]	2024	Iran	Deterministic, Stochastic, and Robust Models
Kine et al. [42]	2025	Ethiopia	GIS-SMART

2.3. Emergency Logistics Concept and Emergency Logistics Centers

Emergency logistics are designed to minimize response times and provide critical materials and services following sudden catastrophic events such as natural disasters, pandemics, and wars [43]. This system constitutes a critical aspect of disaster response and management by coordinating and efficiently transporting resources, relief teams and materials to affected areas. Effective emergency logistics play a pivotal role in mitigating human casualties and enhancing recovery trajectories [44–46]. Owing to its inherently multilayered and complex nature, this process requires effective coordination and collaboration among various actors, such as public institutions, non-governmental organizations, and the private sector [47,48]. The operational intervention of emergency logistics is uniquely challenging, particularly in urban areas with high and dynamic populations. To adapt to these uncertainties, emergency logistics must develop flexible and adaptable supply chain strategies that can respond to sudden changes in resource requirements and distribution channels [47].

Emergency logistics centers are strategic facilities designed to facilitate the rapid and efficient distribution of resources during emergencies such as natural disasters, pandemics, and wars [49]. These facilities must have the capacity to handle a wide range of goods, including food, medical supplies, shelter materials, and rescue equipment, as well as the capabilities to meet demands that may vary depending on the severity and type of emergency [50].

One of the key factors that can directly impact the speed and efficiency of relief efforts is the proximity of emergency logistics centers to the affected areas [51,52]. The location selection of emergency and humanitarian aid logistics facilities is vital in terms of the effectiveness of disaster management processes and the timely delivery of aid to communities affected by disasters [51,53,54]. This strategic decision directly affects the determination of the central points for the storage, distribution, and coordination of relief supplies, as well as disaster preparedness and response capacity. The location selection of emergency logistics centers requires the simultaneous evaluation of uncertainties in demand and conditions, multiple objectives, and various qualitative and quantitative factors [55,56]. Although the criteria considered in the site selection problem vary from study to study, some factors frequently emerge in the literature. Transportation options and

accessibility are considered by many researchers to be critical factors. Yılmaz and Kabak [57] stated in their study on Istanbul that transportation options are the most important main criterion for main distribution centers. Similarly, Geng [58] emphasized the importance of proximity to main transportation networks for rapid response, while Wang and Ma [54] and Boonmee et al. [53] also highlighted the critical role of transportation distances to demand points and access to infrastructure. Pang et al. [59] stated that prioritizing areas with high population density would increase response effectiveness, and Wang and Ma [54] and Geng [58] also included this criterion in their studies. Similarly, Feng et al. [60] identified population density distribution as the most important criterion in their work based on MCDM and GIS integration. Cost factors [55,56], infrastructure [61], physical characteristics of facilities, and potential for cooperation with local/international stakeholders [62] are other important criteria found in the literature. The advancement of humanitarian logistics and emergency response modeling has increasingly integrated fuzzy logic with dynamic simulation techniques to manage stochastic environments. Notably, the synergy between fuzzy clustering and agent-based modeling (ABM) has demonstrated significant efficacy in simulating complex rescuer behavior during large-scale emergencies [63]. Furthermore, fuzzy agent-based expert systems have been successfully utilized to navigate imprecise operational parameters in industrial optimization [64]. Despite these advancements, a profound gap remains in the literature regarding the integrated evaluation of commercial and emergency logistics perspectives. Historically, these two domains have been treated in parallel due to their perceived conflicting goals: commercial efficiency seeks a lean, 'just-in-time' structure with minimal inventory, whereas disaster resilience necessitates intentional 'Just-in-Case' redundancies. Evaluating these in isolation leads to either 'fragile efficiency' or 'uneconomical redundancy'. This study overcomes this isolation by proposing a dual-role model that harmonizes these perspectives beyond the reach of conventional agent-based simulations which typically focus on single-purpose response effectiveness.

3. Materials and Methods

In the development of a robust multi-criteria decision-making model, the rigorous elicitation of criterion weights is paramount for aligning analytical outcomes with the strategic priorities of decision-makers. While a plethora of weighting techniques exists within the MCDM literature, this study deliberately adopts the Fuzzy Rough Stepwise Weight Assessment Ratio Analysis (FR-SWARA) method. The rationale for selecting the FR-SWARA framework over other established fuzzy techniques—such as Fuzzy AHP, Fuzzy BWM, or Fuzzy DEMATEL—is strictly tied to the high-dimensional and deeply uncertain nature of dual-role infrastructure planning.

Conventional matrix-based methods, such as Fuzzy AHP and ANP, rely on exhaustive pairwise comparisons that induce severe cognitive fatigue and consistency issues, particularly when evaluating a complex hierarchy of 31 distinct sub-criteria. Similarly, Fuzzy BWM relies heavily on the absolute identification of single 'best' and 'worst' criteria. This mathematically forces an artificial consensus in a dual-role model where public and private experts hold fundamentally conflicting reference points (e.g., cost versus vulnerability). Furthermore, methods that enforce rigid mathematical consistency thresholds often necessitate the artificial recalibration of expert judgments, thereby compromising the authenticity of the original assessments.

The FR-SWARA method overcomes these limitations by offering a cognitively parsimonious, stepwise approach that eliminates strict consistency constraints and preserves the fidelity of the experts' true priorities. Crucially, the fuzzy rough extension distinguishes itself from standard fuzzy methodologies through endogenous uncertainty modeling. Instead of relying on subjective membership functions, objective 'rough' intervals are derived

directly from the data distribution. This integration captures the true boundary of expert disagreement without diluting it into a single crisp average, making it uniquely suited to harmonize the conflicting paradigms of commercial logistics efficiency and emergency infrastructure resilience.

3.1. Preliminaries

Fuzzy sets capable of utilizing linguistic values have been created to address both qualitative and quantitative information involving uncertainty in the decision-making process [65]. Fuzzy sets have been used in many studies in the literature, and their applicability has been demonstrated [66–73]. Fuzzy logic is a computational methodology derived from the fuzzy set theory proposed by Zadeh [65] that determines degrees of truth instead of binary truth values such as 0 and 1 [74]. These degrees of certainty provide a more quantitative decision-making framework in complex and uncertain environments [75].

A fuzzy triangular number is a special type of fuzzy number used to represent uncertain or indefinite numerical values. A triangular fuzzy number is represented by three real numbers, denoted as $M = (l, m, u)$, where (l) is the minimum value, (m) is the peak value, and (u) is the maximum value. This structure reflects uncertainty by forming a triangular membership function where membership values increase linearly from (l) to (m) and decrease linearly from (m) to (u) [76].

In fuzzy multi-criteria decision-making problems, criterion evaluations in the form of linguistic values must be converted into fuzzy numbers. Accordingly, the linguistic values and membership degrees used in this study are listed in Table 2.

Table 2. Linguistic variables and TFN values.

Linguistic Variable (LV)	TFN Value
Absolutely Very Important (AVI)	(1, 1, 2)
Important (IM)	(2, 3, 4)
Moderately Important (MI)	(3, 4, 5)
Neutral/Undecided (NE)	(4, 5, 6)
Slightly Less Important (SLI)	(5, 6, 7)
Unimportant (UI)	(6, 7, 8)
Absolutely Insignificant (AI)	(8, 9, 10)

The concept of rough numbers, used particularly in scientific disciplines such as mathematics and decision-making, refers to the representation of uncertain information with lower and upper bounds derived from raw data without resorting to any interpretation. This representation method allows researchers to maintain objectivity during the data integration process of decision models [77].

In the application of fuzzy rough sets, linguistic expressions are first quantified using fuzzy logic, and the resulting values are evaluated within the rough set framework. In this approach, it is assumed that fuzzy values are handled as defined on the universal set U and generally represented as $\widetilde{A}_i = (x_i^l, x_i^m, x_i^u)(i = 1, 2, \ldots, n)$. For a given set of evaluations, $\theta^e = \{x_1^e, x_2^e, \ldots, x_n^e\}$, where the index $e \in \{l, m, u\}$ denotes the specific component (lower bound l, middle value m, and upper bound u) of the fuzzy number, the rough lower and upper limits of the component (c_i^e) can be defined as follows [71,73,78,79]:

$$\underline{Lim}(c_i^e) = \frac{1}{\underline{N^e}} \sum_{k=1}^{\underline{N^e}} \varphi_k \in \underline{Apr}(c_i^e) \tag{1}$$

Here, Equation (1) calculates the rough lower limit ($\underline{Lim}$) of the fuzzy number component (c_i^e). This calculation is performed by taking the average of the values within the lower

approximation set ($\underline{Apr}\ (c_i^e)$), which is formed by all evaluations (φ_k) of the k-th expert (where $k = 1, 2, \ldots, \overline{K}$, and K is the total number of experts) that are equal to or less than the value c_i^e. Furthermore, $\underline{N}^e$ denotes the total number of evaluations contained within this lower approximation set.

$$\overline{Lim}(c_i^e) = \frac{1}{\underline{N}^e} \sum_{k=1}^{\underline{N}^e} \varphi_k \in \overline{Apr}(c_i^e) \tag{2}$$

Similarly, Equation (2) calculates the rough upper limit ($\overline{Lim}$) of the fuzzy number component (c_i^e). This calculation is performed by taking the average of the values within the upper approximation set ($\overline{Apr}(c_i^e)$), which is formed by all evaluations (φ_k) of the experts that are equal to or greater than the value c_i^e. Furthermore, $\underline{N}^e$ denotes the total number of evaluations contained within this upper approximation set.

Using these calculated limits, a fuzzy rough number, FRN, is created, represented by $\widetilde{A}_i$. The structure of the $\widetilde{A}_i$ number is defined by Equation (3).

$$FRN(\widetilde{A}_i) = ([x_i^{lL}, x_i^{lU}], [x_i^{mL}, x_i^{mU}], [x_i^{uL}, x_i^{uU}]) = ([\underline{Lim}(x_i^l), \overline{Lim}(x_i^l)], [\underline{Lim}(x_i^m), \overline{Lim}(x_i^m)], [\underline{Lim}(x_i^u), \overline{Lim}(x_i^u)]) \tag{3}$$

If there are two FRN values, $FRN(\widetilde{A}) = ([a^{lL}, a^{lU}], [a^{mL}, a^{mU}], [a^{uL}, a^{uU}])$ and $FRN(\widetilde{B}) = ([b^{lL}, b^{lU}], [b^{mL}, b^{mU}], [b^{uL}, b^{uU}])$, the following operations are performed on them.

Addition:

$$FRN(\widetilde{A}) + FRN(\widetilde{B}) = ([a^{lL} + b^{lL}, a^{lU} + b^{lU}], [a^{mL} + b^{mL}, a^{mU} + b^{mU}], [a^{uL} + b^{uL}, a^{uU} + b^{uU}]) \tag{4}$$

Subtraction:

$$FRN(\widetilde{A}) - FRN(\widetilde{B}) = ([a^{lL} - b^{uU}, a^{lU} - b^{uL}], [a^{mL} - b^{mU}, a^{mU} - b^{mL}], [a^{uL} - b^{lU}, a^{uU} - b^{lL}]) \tag{5}$$

Multiplication:

$$FRN(\widetilde{A}) \times FRN(\widetilde{B}) = ([a^{lL} \times b^{lL}, a^{lU} \times b^{lU}], [a^{mL} \times b^{mL}, a^{mU} \times b^{mU}], [a^{uL} \times b^{uL}, a^{uU} \times b^{uU}]) \tag{6}$$

Division:

$$FRN(\widetilde{A}) \div FRN(\widetilde{B}) = ([a^{lL} \div b^{uU}, a^{lU} \div b^{uL}], [a^{mL} \div b^{mU}, a^{mU} \div b^{mL}], [a^{uL} \div b^{lU}, a^{uU} \div b^{lL}]) \tag{7}$$

For FR numbers to have a valid structure, there must be a specific ordering relationship between the component limits. Specifically, the lower limit of the lower component must not be greater than the upper limit of the middle component ($a_1^U \leq a_2^L$) and the upper limit of the middle component must not be greater than the lower limit of the upper component ($a_2^U \leq a_3^L$). It is acceptable for these limit values to be equal to each other. However, if these ordering constraints are not met, necessary adjustments to the FR numbers must be made to resolve the resulting mathematical inconsistency [79]. The required adjustments are presented in Equation (8).

$$\begin{aligned} \overline{Lim}(c_i^l) &= \underline{Lim}(c_i^m)\ if\ \overline{Lim}(c_i^l) > \underline{Lim}(c_i^m) \\ \overline{Lim}(c_i^m) &= \underline{Lim}(c_i^u)\ if\ \overline{Lim}(c_i^m) > \underline{Lim}(c_i^u) \end{aligned} \tag{8}$$

3.2. Fuzzy Rough SWARA Method

The Stepwise Weighted Average Ratio Analysis (SWARA) technique, one of the multi-criteria decision-making methods introduced to the literature by Keršuliene et al. [80], is a method used to calculate the weights of criteria in decision problems. This approach

is based on determining and ranking the relative importance levels of criteria based on the assessments of experts or decision-makers. The main objective of this method is to enable actors involved in the decision-making process to first rank the evaluation criteria according to their own perception of importance and then determine their weights through comparisons between criteria based on this ranking [71]. This method has been applied in many fields and has undergone several modifications [81–86].

Chen and colleagues [72] developed the SWARA method using a fuzzy rough number set and proposed the Fuzzy Rough SWARA method. The algorithmic flowchart of the proposed FR-SWARA framework is presented in Figure 2.

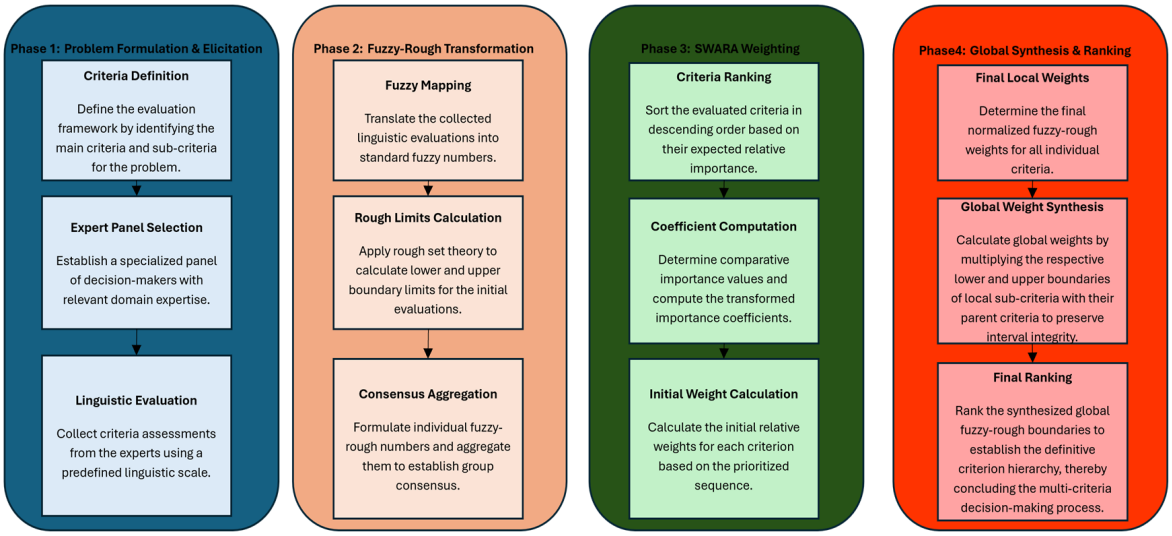


Figure 2. Conceptual flowchart of the proposed FR-SWARA methodology.

The computational procedure is implemented through the following steps:

Step 1. The decision problem, consisting of m evaluation criteria, is defined.

Step 2. A panel of experts is established to evaluate the criteria. The experts evaluate the importance of each criterion using a predefined linguistic scale. For each expert, $(k = 1, 2, \ldots, K \; where \; K \; is \; the \; total \; number \; of \; experts)$, a fuzzy number (F_{kj}) corresponding to the linguistic expression given for each criterion $(j = 1, 2, \ldots, m)$ is used to construct the initial fuzzy evaluation matrix F. The matrix F, of size $K \times m$, is structured as follows:

$$F = [F_{kj}]_{K \times m} = \begin{pmatrix} F_{11} & F_{12} & \ldots & F_{1m} \\ F_{21} & F_{22} & \ldots & F_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ F_{K1} & F_{K2} & \ldots & F_{Km} \end{pmatrix}_{K \times m} \quad (9)$$

Step 3. The conversion of the experts' individual evaluations into a fuzzy rough number $FRN(X_j)_k$ is given in Equation (10).

$$FRN(X_j)_k = [(x_{jk}^{L1}, x_{jk}^{U1}), (x_{jk}^{L2}, x_{jk}^{U2}), (x_{jk}^{L3}, x_{jk}^{U3})] \quad (j = 1, 2, \ldots m), (k = 1, 2, \ldots, K) \quad (10)$$

The initial fuzzy rough decision matrix is obtained using Equation (11), which aggregates the $FRN(X_j)_k$ numbers derived from each expert's evaluation.

$$FRN_{initial} = \begin{pmatrix} FRN(X_1)_1 & FRN(X_2)_1 & \dots & FRN(X_m)_1 \\ FRN(X_1)_2 & FRN(X_2)_2 & \dots & FRN(X_m)_2 \\ \vdots & \vdots & \ddots & \vdots \\ FRN(X_1)_K & FRN(X_2)_K & \dots & FRN(X_m)_K \end{pmatrix}_{K \times m} \tag{11}$$

Step 4. For each criterion in the $FRN_{initial}$ matrix, the individual fuzzy rough evaluations provided by the K experts are aggregated to establish the group fuzzy rough number, $FRN(X_j)_{group}$, which represents the consensus of the expert panel. The components of this group fuzzy rough number are calculated using Equation (12):

$$FRN(X_j)_{\text{group}} = \left[\left(\frac{1}{K}\sum_{k=1}^{K} x_{jk}^{L1}, \frac{1}{K}\sum_{k=1}^{K} x_{jk}^{U1} \right), \left(\frac{1}{K}\sum_{k=1}^{K} x_{jk}^{L2}, \frac{1}{K}\sum_{k=1}^{K} x_{jk}^{U2} \right), \left(\frac{1}{K}\sum_{k=1}^{K} x_{jk}^{L3}, \frac{1}{K}\sum_{k=1}^{K} x_{jk}^{U3} \right) \right] \tag{12}$$

Step 5. The criteria are subsequently ranked in descending order of their importance based on the aggregated group fuzzy rough matrix. This ranking procedure is executed using Equation (13).

$$FRN(X_{(1)})_{\text{group}} \succcurlyeq_{\text{significance}} FRN(X_{(2)})_{\text{group}} \succcurlyeq_{\text{significance}} \cdots \succcurlyeq_{\text{significance}} FRN(X_{(m)})_{\text{group}} \tag{13}$$

The group fuzzy rough numbers corresponding to the ranked criteria form the ranked group matrix (FRN_{RGM}) of size $m \times 1$. Each row of this matrix represents a criterion—ordered by its relative importance—along with its associated group fuzzy rough number, as structured in Equation (14):

$$FRN_{RGM} = \begin{pmatrix} FRN_{group}(X_{(1)}) \\ FRN_{group}(X_{(2)}) \\ \vdots \\ FRN_{group}(X_{(m)}) \end{pmatrix}_{m \times 1} \tag{14}$$

Step 6. Each fuzzy rough number in the FRN_{RGM} matrix is normalized and converted to a $FRN(N_{(j)})$ number. $\text{FRN}(\text{N}_{(1)}) = [(1.00, 1.00), (1.00, 1.00), (1.00, 1.00)]$. The normalized fuzzy rough number value for the criterion ranked first in importance is directly assigned to $(j = 1)$. To calculate the $FRN(N_{(j)})$ values for the subsequent criteria in $j > 1$, the $FRN_{group}(X_{(m)})$ fuzzy rough number for the least important criterion $C_{(m)}$ among all criteria in the FRN_{RGM} matrix is determined as $FRN(Z) = [(z^{L1}, z^{U1}), (z^{L2}, z^{U2}), (z^{L3}, z^{U3})] = \max FRN_{RGM}$. The calculation of the $FRN(N_{(j)})$ numbers is provided by Equation (15).

$$\begin{aligned} FRN(N_{(j)}) &= \tfrac{FRN_{group}(X_{(j)})}{FRN(Z)}, \\ FRN(N_{(j)}) &= \left[\left(\tfrac{x_{(j)}^{L1}}{z^{U3}}, \tfrac{x_{(j)}^{U1}}{z^{L1}} \right), \left(\tfrac{x_{(j)}^{L2}}{z^{U2}}, \tfrac{x_{(j)}^{U2}}{z^{L2}} \right), \left(\tfrac{x_{(j)}^{L3}}{z^{U1}}, \tfrac{x_{(j)}^{U3}}{z^{L1}} \right) \right] \end{aligned} \tag{15}$$

The components of the number $FRN(N_{(j)})$ are shown in Equation (16).

$$FRN(N_{(j)}) = [(n_{(j)}^{L1}, n_{(j)}^{U1}), (n_{(j)}^{L2}, n_{(j)}^{U2}), (n_{(j)}^{L3}, n_{(j)}^{U3})] \tag{16}$$

Step 7. The transformed importance coefficient, denoted as $FRN(\mathfrak{S}_{(j)})$, is calculated. For the most important criterion (ranked first, where $j = 1$), this value is directly assigned

as $FRN(\mathfrak{S}_{(1)}) = [(1.00, 1.00), (1.00, 1.00), (1.00, 1.00)]$. For the subsequent criteria ($j > 1$), the transformed importance coefficients are calculated using Equation (17).

$$FRN(\mathfrak{S}_{(j)}) = [(n_{(j)}^{L1} + 1, n_{(j)}^{U1} + 1), (n_{(j)}^{L2} + 1, n_{(j)}^{U2} + 1), (n_{(j)}^{L3} + 1, n_{(j)}^{U3} + 1)], (j > 1) \quad (17)$$

Step 8. Using the calculated transformed importance coefficient, $FRN(\mathfrak{S}_{(j)})$, the fuzzy rough number $FRN(\Re_j)$, which represents the recalculated weight for each j-th criterion, is computed. The index j indicates the criterion's position in the importance ranking. The structure of $FRN(\Re_j)$ is shown in Equation (18).

$$FRN(\Re_j) = [(\Re_j^{L1}, \Re_j^{U1}), (\Re_j^{L2}, \Re_j^{U2}), (\Re_j^{L3}, \Re_j^{U3})] \quad (18)$$

The specific components of $FRN(\Re_j)$ are obtained as follows using Equation (19):

$$FRN(\Re_j) \begin{bmatrix} \Re_j^{L1} = \begin{pmatrix} 1.00 & j = 1 \\ \frac{\Re_{j-1}^{L1}}{\mathfrak{S}_j^{U3}} & j > 1 \end{pmatrix} , \quad \Re_j^{U1} = \begin{pmatrix} 1.00 & j = 1 \\ \frac{\Re_{j-1}^{U1}}{\mathfrak{S}_j^{L3}} & j > 1 \end{pmatrix} \\ \Re_j^{L2} = \begin{pmatrix} 1.00 & j = 1 \\ \frac{\Re_{j-1}^{L2}}{\mathfrak{S}_j^{U2}} & j > 1 \end{pmatrix} , \quad \Re_j^{U2} = \begin{pmatrix} 1.00 & j = 1 \\ \frac{\Re_{j-1}^{U2}}{\mathfrak{S}_j^{L2}} & j > 1 \end{pmatrix} \\ \Re_j^{L3} = \begin{pmatrix} 1.00 & j = 1 \\ \frac{\Re_{j-1}^{L3}}{\mathfrak{S}_j^{U1}} & j > 1 \end{pmatrix} , \quad \Re_j^{U3} = \begin{pmatrix} 1.00 & j = 1 \\ \frac{\Re_{j-1}^{U3}}{\mathfrak{S}_j^{L3}} & j > 1 \end{pmatrix} \end{bmatrix} \quad (19)$$

Step 9. To determine the final criteria weights, it is first necessary to compute the aggregated fuzzy number $FRN(\aleph)$, which represents the sum of all $FRN(\Re_j)$ values. This aggregated fuzzy number is calculated using Equation (20).

$$\begin{aligned} FRN(\aleph) &= \sum_{j=1}^{m} FRN(\Re_{(j)}) \\ FRN(\aleph) &= \left[\left(\sum_{j=1}^{m} \Re_{(j)}^{L1}, \sum_{j=1}^{m} \Re_{(j)}^{U1} \right), \left(\sum_{j=1}^{m} \Re_{(j)}^{L2}, \sum_{j=1}^{m} \Re_{(j)}^{U2} \right), \left(\sum_{j=1}^{m} \Re_{(j)}^{L3}, \sum_{j=1}^{m} \Re_{(j)}^{U3} \right) \right] \\ FRN(\aleph) &= [(\aleph^{L1}, \aleph^{U1}), (\aleph^{L2}, \aleph^{U2}), (\aleph^{L3}, \aleph^{U3})] \end{aligned} \quad (20)$$

The final fuzzy rough weight $FRN(W_{(j)})$ for each criterion is calculated using Equation (21).

$$FRN(W_{(j)}) = \left[\left(\frac{\Re_{(j)}^{L1}}{\aleph^{U3}}, \frac{\Re_{(j)}^{U1}}{\aleph^{L1}} \right), \left(\frac{\Re_{(j)}^{L2}}{\aleph^{U2}}, \frac{\Re_{(j)}^{U2}}{\aleph^{L2}} \right), \left(\frac{\Re_{(j)}^{L3}}{\aleph^{U1}}, \frac{\Re_{(j)}^{U3}}{\aleph^{L1}} \right) \right], \quad (j = 1, 2, 3, \ldots, m) \quad (21)$$

Subsequent to deriving the final fuzzy rough weighting coefficient $FRN(W_{(j)})$ for each criterion, these local weights are systematically aggregated to construct the overarching strategic hierarchy. Given that the FR-SWARA methodology operates on rough boundaries rather than crisp point estimates, this aggregation necessitates the application of interval arithmetic. Specifically, the global fuzzy rough weight of a sub-criterion is computed by multiplying its local interval bounds by the corresponding global interval bounds of its parent main criterion. To preserve the structural integrity of the uncertainty buffer, scalar multiplication is executed across the lower and upper limits, $L_{global} = L_{parent} \times L_{local}$ and $U_{global} = U_{parent} \times U_{local}$, respectively, thereby formulating the resultant global $[L, U]$ interval. This rigorous hierarchical aggregation ensures that the priority of any specific

resilience or operational metric is mathematically contextualized within its overarching macro-category. The synthesized global boundaries are subsequently utilized to rank the sub-criteria, thereby unveiling the multi-dimensional priorities inherent to the dual-role dry port model.

4. Results

In the application phase of this study, the application of the Fuzzy Rough SWARA method, whose details are given in the Materials and Methods section, to the dry port location selection problem will be addressed. This process begins with the definition of dry port location selection criteria determined based on a comprehensive literature review and expert opinions. The defined criteria were established with a comprehensive perspective, encompassing both the traditional logistics functions of dry ports and their potential roles in disaster situations. The flowchart of the study is presented in Figure 3.

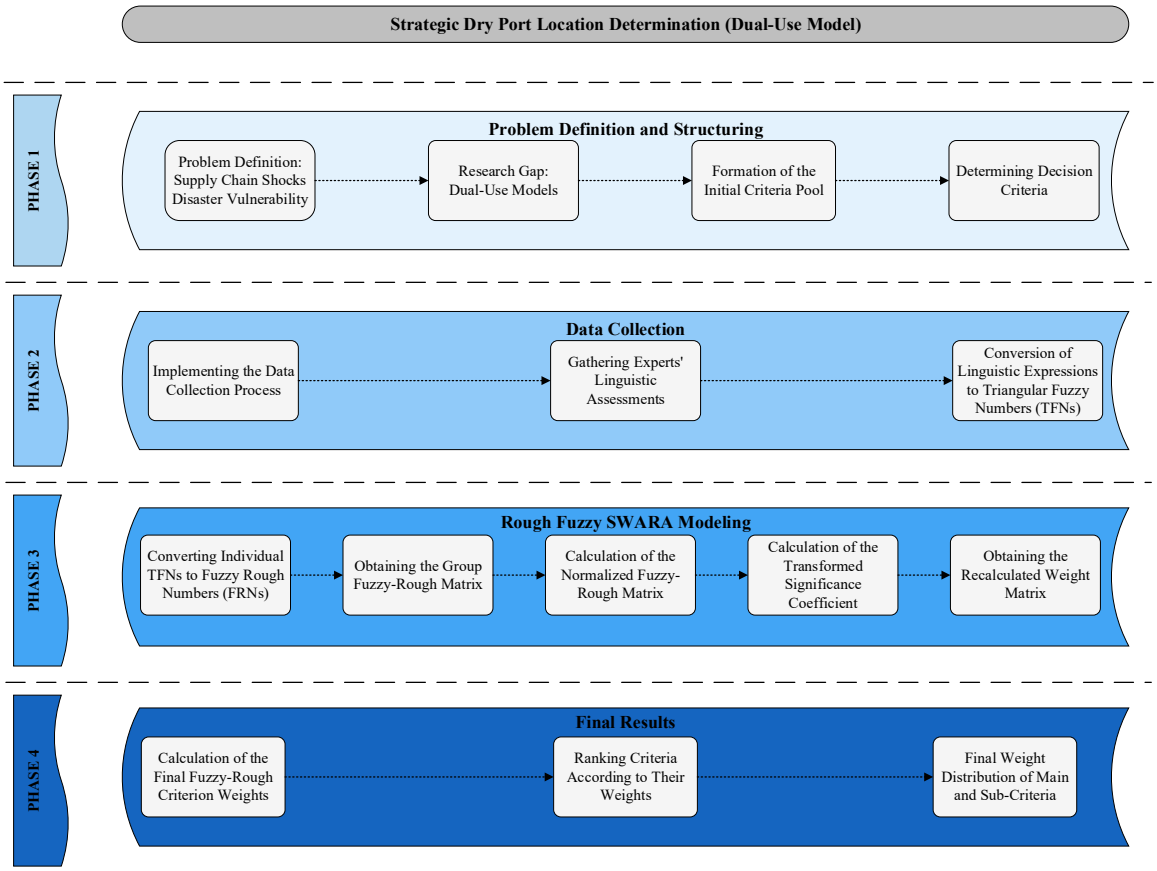


Figure 3. Flowchart of the study.

4.1. Determination of the Criteria Set

Based on the literature review and expert opinions, the criteria set was structured under six main dimensions. The location dimension includes Accessibility to Markets and Production Centers and Proximity to the Logistics Ecosystem for operational efficiency, while economic sustainability is evaluated through Regional Development and Trade Potential. Given the study's dual-purpose nature, this dimension also covers Exposure to Natural Disaster Risks and the Vulnerability Level of the Service Area.

The transport dimension is analyzed through Distance to Seaport, Distance from the Airport, Distance from Major Highway, and Distance from the Existing Railway Line, which determine cost and competitiveness. Additionally, Reliability of Connectivity to Emergency Response Networks is integrated for emergency scenarios. The infrastructure dimension

measures technical sufficiency via Physical Capacity and Expansion Flexibility, Transportation Route Capacity, Transportation Network Integration, and Cargo Handling Diversity. Resilience is ensured through Reliability and Redundancy of Operational Infrastructure, Structural Integrity and Durability of the Facility and the critical Emergency Logistics and Coordination Competence.

The financial dimension, cost, covers initial investment items such as Installation Cost and Land Acquisition Cost, alongside Transportation Cost, Storage Cost, and Operating and Maintenance Costs. The social and political dimension addresses the investment environment through Access to Skilled Labor, Social Acceptance and Stakeholder Relations, Favorability of the Legal and Regulatory Framework, and Financial Incentives and Public Support. Finally, the environmental dimension includes Sustainable Transportation and Emission Management, Waste Management and Circular Economy, and Energy Efficiency and Clean Energy Use, while ecological harmony is secured through Sustainable Land Use and Biodiversity Conservation and Environmental Adaptation and Social Integration. The criteria set is provided in Table 3.

Table 3. Criteria set.

Criterion	Reference	Criterion	Reference
Location		**Cost**	
Accessibility to Markets and Production Centers	[23,24,26,27,47,54,59,60,87–92]	Installation Cost	[26,28,49,56,93–95]
Regional Development and Trade Potential	[25,26,28,31,36,59,87,88,92,95–99]	Transportation Cost	[24–26,28,35,61,62,87–89,92,94]
Proximity to the Logistics Ecosystem	[19,24,25,38,57,90,92,100,101]	Storage Cost	[24,62,89,91,94,102,103]
Exposure to Natural Disaster Risks	[28,53,58,61,62,91,104]	Land Acquisition Cost	[24,26,28,31,39,91]
Vulnerability Level of the Service Area	[53,55,57,105]	Operating and Maintenance Costs	[28,94,95,106,107]
Transport		**Social and Political**	
Distance to Seaport	[24,26,28,36,89,97,108]	Access to Skilled Labor	[13,24,28,31,39,52,62,89,92,99,109–111]
Distance from the Airport	[24,28,57,62,91,97]	Favorability of the Legal and Regulatory Framework	[24,25,28,36,39,62]
Distance from Major Highway	[24,26,27,53,57,60,91]	Financial Incentives and Public Support	[24,26,28,101,111]
Distance from the Existing Railway Line	[24,26,38,61,99,104,108,112]	Social Acceptance and Stakeholder Relations	[24,52,62,95,96,99]
Reliability of Connectivity to Emergency Response Networks	[53,57–60,62,91,113]		

Table 3. *Cont.*

Criterion	Reference	Criterion	Reference
Infrastructure		**Environmental**	
Physical Capacity and Expansion Flexibility	[24,25,49,53,57,58,61,89,93–95,114,115]	Sustainable Transportation and Emission Management	[24,25,29,87,91,93,95,99,112,116–118]
Reliability and Redundancy of Operational Infrastructure	[25,28,31,52,57–59,92,119–121]	Waste Management and Circular Economy	[24,59,93,95]
Transportation Route Capacity	[25,45,54,61,93]	Energy Efficiency and Clean Energy Use	[13,41,122–127]
Transportation Network Integration	[11,19,25,38,57,99,128]	Environmental Adaptation and Social Integration	[24,29,39,102]
Cargo Handling Diversity	[24,38,57,61,101,111]	Sustainable Land Use and Biodiversity Conservation	[24–26,93,95,102,122]
Emergency Logistics and Coordination Competence	[31,48,49,52,53,56,58,60,91,115,120–135]		
Structural Integrity and Durability of the Facility	[55,95,136–139]		

4.2. Application of the Model and Analysis of Results

In the application phase of this study, the Fuzzy Rough SWARA method, which is at the core of the developed model, will be detailed in terms of how it is applied to the strategic dry port location selection problem. The process began with a comprehensive literature review and the presentation of a set of criteria, determined based on the opinions of a 12-person expert team, as input to the model. The evaluation process was conducted by a diversified panel of 12 experts, whose comprehensive demographic and professional profiles are summarized in Table 4 and visualized in Figure 4. To ensure that the proposed model effectively harmonizes commercial logistics efficiency with strategic disaster resilience, the panel was deliberately structured to include balanced representation from public authorities, academia, the maritime port sector, and the logistics industry. As illustrated in Figure 4A, the sectoral distribution reflects a strategic configuration—comprising Public (33.3%), Private/Industry (33.3%), Port (16.7%), and Academia (16.7%)—designed to internalize the complex friction between profit-driven efficiency and public-driven security.

Furthermore, as depicted in Figure 4B, the panel's architecture is characterized by exceptional professional seniority and academic rigor; 100% of the participants possess a minimum of ten years of experience, with 75% holding advanced graduate degrees (MSc or PhD). This heterogeneous composition serves as a structural safeguard against cognitive bias to ground the model in deep operational reality, ensuring that the resultant weighting scheme represents a scientifically rigorous synthesis capable of reconciling conflicting commercial and humanitarian imperatives.

Building upon this robust demographic foundation, the panel was systematically engaged to validate the comprehensiveness and structural integrity of the proposed evaluation framework. An initial pool of factors, extracted from the extant literature, was subjected to a Delphi-inspired filtering process. This iterative refinement systematically eliminated redundant metrics—for instance, consolidating the overlapping dimensions of

'Proximity to the Logistics Ecosystem' and 'Transportation Network Integration'—thereby ensuring that the final set of 31 sub-criteria was both exhaustive and mutually exclusive. Beyond general sectoral diversity, the authoritative capacity of the selected experts was purposefully curated based on their direct operational involvement in managing complex, multi-dimensional supply chain disruptions. Notably, every member of the panel possesses field-validated experience in mitigating severe logistical bottlenecks and supply crises triggered by both major seismic events and the COVID-19 pandemic. This highly specialized domain expertise ensures that the aggregated judgments across all 31 sub-criteria are grounded in pragmatic, dual-role operational reality rather than purely abstract theoretical assumptions.

Table 4. Profiles of the expert panel.

Expert ID	Sector	Institutional Context/Professional Role	Education	Experience (Years)
E1	Private	Senior Freight Forwarding & Logistics Manager	MSc	15–20
E2	Public	Disaster & Emergency Management Authority	PhD	20+
E3	Port	Port Operations & Cargo Handling Specialist	BSc	10–15
E4	Port	Maritime Logistics & Forwarding Consultant	BSc	15–20
E5	Private	Logistics & Crisis Distribution Director	PhD	20+
E6	Public	Municipal Disaster Prevention & Planning Unit	MSc	15–20
E7	Public	Civil Defense & Disaster Coordination Expert	MSc	15–20
E8	Academia	Maritime Transportation & Resilience Professor	PhD	20+
E9	Academia	Supply Chain Risk Management Researcher	PhD	10–15
E10	Industry	Intermodal Transport & Terminal Manager	MSc	10–15
E11	Public	Regional Infrastructure & Transport Policy Specialist	MSc	15–20
E12	Industry	Senior Warehouse & Distribution Operations Manager	BSc	20+

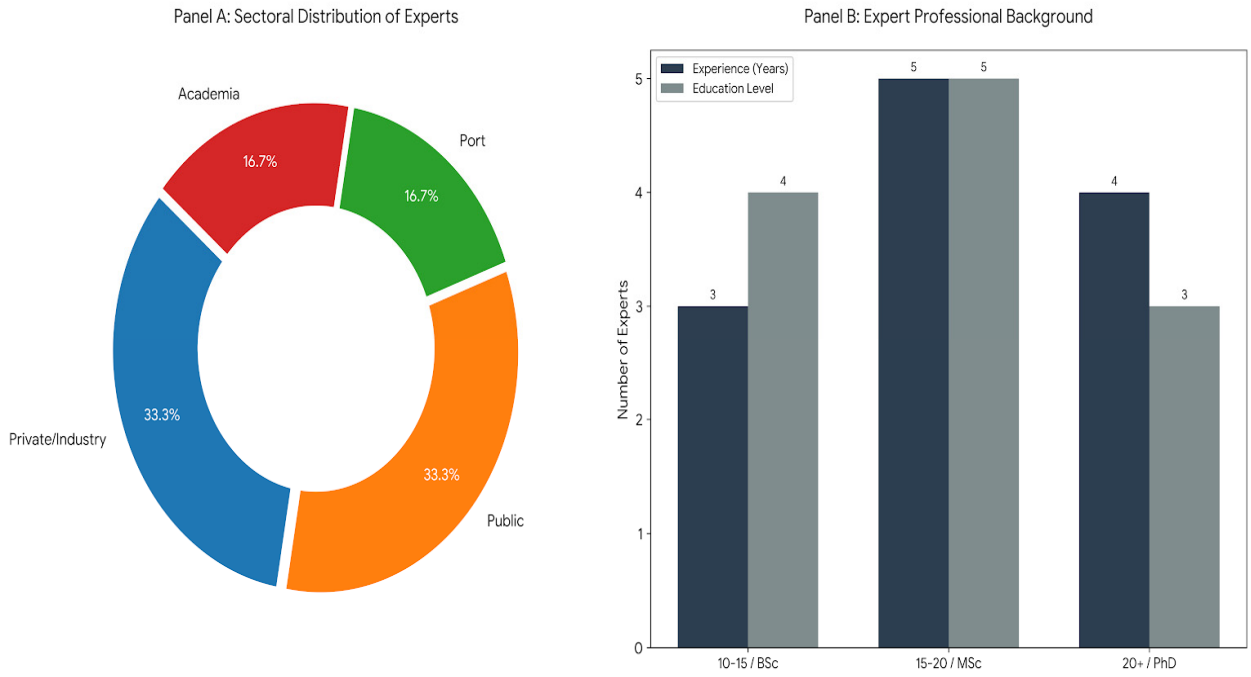


Figure 4. Profile of the expert panel: (**A**) sectoral distribution; (**B**) experience and education levels.

The criteria were divided into six main groups, each with its own sub-criteria. In line with this structure, the weighting process was carried out separately for the main criteria first, followed by the sub-criteria under each main criterion.

The first and critical step in obtaining the weights of the criteria was for each expert to evaluate the criteria according to their importance levels using the linguistic expressions

presented in Table 2, based on their own assessment opinions. After this evaluation matrix was created, $([F_{kj}]_{e\times m})$, the second step involved converting the linguistic values given by the experts into equivalent fuzzy numbers. For example, as indicated in Table 2, the value Definitely Very Important is represented by the triangular fuzzy number (1, 1, 2), while the value important is represented by the triangular fuzzy number (2, 3, 4). This conversion process allows all linguistic evaluations to be converted into appropriate fuzzy number equivalents, enabling uncertainty to be expressed mathematically.

The next stage of the application process is the conversion of fuzzy numbers obtained from the experts' individual linguistic evaluations into crisp fuzzy numbers. This conversion involves determining crisp lower and upper approximations for the sub (l, m, u) components of each fuzzy number. Based on the assessments of the main criteria, the fuzzy number F_{kj} corresponding to the linguistic expression given by each expert is taken as a basis. In this context, the coarse lower limit $(\underline{Lim}(c_i^e))$ for each component (c_i^e) of the observed fuzzy number is calculated using the formula defined in Equation (1). Similarly, the coarse upper limit $(\overline{Lim}(c_i^e))$ is determined using the formulation in Equation (2). These calculations are performed by taking the average of other expert evaluations that are equal to or smaller/larger than the relevant expert's evaluation value. It is critically important that the obtained coarse fuzzy numbers have a valid structure and that the ordering relationship between the component limits is ensured. To resolve any mathematical inconsistencies that may arise if these ordering constraints are not met, the corrections in Equation (8) must be applied. This procedure is applied separately for each expert's evaluation of each criterion, and, as specified in Equation (10), the fuzzy rough numbers $FRN(X_j)_k$ that form the initial fuzzy evaluation matrix are obtained.

This procedure is explained below using the example of one of the main criteria, location, for Expert 1.

All experts' assessments for the location criterion are provided in Table 5.

Table 5. Experts' assessments of the location criterion, one of the main criteria.

Experts	LV	Fuzzy Evaluations for the Location Main Criterion (l, m, u)		
Expert 1	IM	2	3	4
Expert 2	IM	2	3	4
Expert 3	IM	2	3	4
Expert 4	AVI	1	1	2
Expert 5	IM	2	3	4
Expert 6	AVI	1	1	2
Expert 7	AVI	1	1	2
Expert 8	AVI	1	1	2
Expert 9	AVI	1	1	2
Expert 10	AVI	1	1	2
Expert 11	IM	2	3	4
Expert 12	IM	2	3	4

Expert 1's linguistic expression important (IM) for the location criterion is represented by a triangular fuzzy number according to Table 2 (2, 3, 4). The coarse lower and upper limits for each component of this fuzzy number (l = 2, m = 3, u = 4) are calculated using Equations (1) and (2), utilizing the other expert evaluations in Table 6.

Table 6. Initial decision matrix for main criteria.

Criteria	Initial Group Fuzzy Rough Matrix					
Location	*l*		*m*		*u*	
	L	U	L	U	L	U
	1.25	1.75	1.5	2.5	2.5	3.5
Transportation	*l*		*m*		*u*	
	L	U	L	U	L	U
	1.38163	2.65774	1.660354	3.48413	2.66035	4.4653
Infrastructure	*l*		*m*		*u*	
	L	U	L	U	L	U
	1.83704	3.70337	2.309259	4.64087	3.30926	5.64087
Cost	*l*		*m*		*u*	
	L	U	L	U	L	U
	2.58889	4.1765	3.361111	5.16955	4.36111	6.16955
Social and Political	*l*		*m*		*u*	
	L	U	L	U	L	U
	2.80873	4.04444	3.80873	5.04444	4.80873	6.04444
Environmental	*l*		*m*		*u*	
	L	U	L	U	L	U
	2.92109	4.60972	3.921086	5.60972	4.92109	6.60972

The calculation of the coarse fuzzy number for Expert 1 is as follows:

$$\underline{Lim}(c_1^l) = \frac{2+2+2+1+2+1+1+1+1+1+2+2}{12} = 1.50$$
$$\overline{Lim}(c_1^l) = \frac{2+2+2+2+2+2}{6} = 2.00$$
$$\underline{Lim}(c_1^m) = \frac{3+3+3+1+3+1+1+1+1+1+3+3}{12} = 2.00$$
$$\overline{Lim}(c_1^m) = \frac{3+3+3+3+3+3}{6} = 3.00$$
$$\underline{Lim}(c_1^u) = \frac{4+4+4+2+4+2+2+2+2+2+4+4}{12} = 3.00$$
$$\overline{Lim}(c_1^u) = \frac{4+4+4+4+4+4}{6} = 4.00$$

Applying this principle, the initial fuzzy rough decision matrix ($FRN_{initial}$) is created, which forms the basis for calculating the FR SWARA method. This matrix is shown in Table 6 for the main criteria.

After creating this FRN_{initial} matrix, the criteria were ranked according to their importance level, which is the fifth step of the Fuzzy Rough SWARA method. According to the methodology, the criterion with the lowest value in this decision matrix is determined as the most important criterion. In this context, the location criterion was determined as the most important criterion among the main criteria because it had the lowest value. The transportation and infrastructure criteria follow location in order, while the environmental criterion is ranked as having the highest values. The ranking process was performed according to the principles specified in Equation (13). After ranking the criteria, the FRN_{RGM} matrix is obtained. As Step 6, data normalization of the FRN_{RGM} matrix was performed. This normalization was carried out using Equations (15) and (16), and normalized fuzzy rough numbers ($FRN(N_{(j)})$) were obtained for each criterion. After obtaining the normalized fuzzy rough numbers, the calculation of the $FRN(\mathfrak{S}_{(j)})$, which is Step 7 of the Fuzzy Rough SWARA method, is performed. In this step, the value of the most important criterion is directly assigned as one. The values of the other criteria are calculated based on the determined ranking and normalized values, as shown in Equation (17). These coefficients

reflect the relative influence of each criterion on the decision-making process and form the basis for determining the final weights. The $FRN(\mathfrak{S}_{(j)})$ matrix is given in Table 7.

Table 7. Matrix of main criteria $FRN(\mathfrak{S}_{(j)})$.

Criteria	*l*		*m*		*u*	
	L	**U**	**L**	**U**	**L**	**U**
Location	1.00	1.00	1.00	1.00	1.00	1.00
Transportation	1.20903	1.3374	1.3374	1.67847	1.67847	2.52864
Infrastructure	1.27793	1.46926	1.46926	1.84397	1.84397	2.93109
Cost	1.39168	1.683	1.683	2.11222	2.11222	3.11208
Social and Political	1.42494	1.77396	1.77396	2.22638	2.22638	3.06925
Environmental	1.44194	1.79679	1.79679	2.25503	2.25503	3.26276

After determining these $FRN(\mathfrak{S}_{(j)})$ values, Equation (19) is used to obtain the $FRN(\Re_j)$ matrix shown in Table 8.

Table 8. $FRN(\Re_j)$ matrix.

Criteria	*l*		*m*		*u*	
	L	**U**	**L**	**U**	**L**	**U**
Location	1.00	1.00	1.00	1.00	1.00	1.00
Transportation	0.39547	0.59578	0.59578	0.74772	0.74772	0.82711
Infrastructure	0.13492	0.3231	0.3231	0.50891	0.50891	0.64723
Cost	0.04335	0.15297	0.15297	0.30238	0.30238	0.46507
Social and Political	0.01413	0.06871	0.06871	0.17046	0.17046	0.32638
Environmental	0.00433	0.03047	0.03047	0.09487	0.09487	0.22635

In the final stage of the Fuzzy Rough SWARA method, the final fuzzy rough weights of the main criteria, calculated using Equations (20) and (21), are presented in Table 9.

Table 9. Final fuzzy rough weights of the main criteria.

Criteria	*l*		*m*		*u*	
	L	**U**	**L**	**U**	**L**	**U**
Location	0.28636	0.35407	0.35407	0.46061	0.46061	0.62806
Transportation	0.11325	0.21094	0.21094	0.34441	0.34441	0.51948
Infrastructure	0.03864	0.1144	0.1144	0.23441	0.23441	0.4065
Cost	0.01241	0.05416	0.05416	0.13928	0.13928	0.29209
Social and Political	0.00404	0.02433	0.02433	0.07851	0.07851	0.20499
Environmental	0.00124	0.01079	0.01079	0.0437	0.0437	0.14216

As a result of applying all the steps of the Fuzzy Rough SWARA method detailed above, the final fuzzy rough weights of both the main criteria and the sub-criteria associated with these main criteria were obtained for the dry port site selection and emergency logistics center functions. These weights reflect the relative importance of the relevant main and sub-criteria in the decision-making process. All obtained criterion weights are comprehensively presented in Table 10.

The hierarchical distribution of the global weights and their uncertainty intervals, presented in Table 10, is illustrated in Figure 5, where the bars represent the range between l_L and u_U values to reflect the degree of expert consensus and uncertainty.

Table 10. Fuzzy criteria weights obtained using the Fuzzy Rough SWARA method.

Criteria	*l*		*m*		*u*	
	L	U	L	U	L	U
Location	0.28636	0.35407	0.35407	0.46061	0.46061	0.62806
Transportation	0.11325	0.21094	0.21094	0.34441	0.34441	0.51948
Infrastructure	0.03864	0.11440	0.11440	0.23441	0.23441	0.40650
Cost	0.01241	0.05416	0.05416	0.13928	0.13928	0.29209
Social and Political	0.00404	0.02433	0.02433	0.07851	0.07851	0.20499
Environmental	0.00124	0.01079	0.01079	0.04370	0.04370	0.14216
Location						
Accessibility to Markets and Production Centers	0.09863	0.14338	0.14742	0.23544	0.24343	0.41272
Regional Development and Trade Potential	0.03554	0.07209	0.07706	0.15280	0.16140	0.31217
Vulnerability Level of the Service Area	0.01120	0.03359	0.03743	0.09189	0.09946	0.21853
Exposure to Natural Disaster Risk	0.00354	0.01566	0.01819	0.05529	0.06132	0.15292
Proximity to the Logistics Ecosystem	0.00118	0.00660	0.00830	0.03006	0.03549	0.10189
Transport						
Distance to Seaport	0.03391	0.07169	0.07207	0.14533	0.14634	0.28179
Distance to Major Highway	0.01635	0.04555	0.04606	0.11097	0.11209	0.23356
Distance to the Main Railway Line	0.00784	0.02879	0.02928	0.08426	0.08539	0.19215
Emergency Response Network Connection Reliability	0.00323	0.01564	0.01603	0.05503	0.05602	0.14308
Distance to Airport	0.00119	0.00705	0.00735	0.02981	0.03076	0.09052
Infrastructure						
Physical Capacity and Expansion Flexibility	0.01067	0.03858	0.03901	0.10575	0.10706	0.24904
Reliability and Redundancy of Operational Infrastructure	0.00432	0.02224	0.02273	0.07671	0.07808	0.20009
Transportation Capacity	0.00156	0.01217	0.01258	0.05282	0.05409	0.15471
Structural Integrity and Durability of the Facility	0.00057	0.00637	0.00666	0.03478	0.03586	0.11728
Cargo Handling Diversity	0.00020	0.00305	0.00323	0.02098	0.02179	0.08302
Transportation Network Integration	0.00007	0.00142	0.00156	0.01230	0.01320	0.05867
Emergency Logistics and Coordination Competency	0.00002	0.00062	0.00070	0.00678	0.00742	0.03896
Cost						
Transportation Cost	0.00412	0.02177	0.02177	0.07271	0.07271	0.20290
Installation Cost	0.00124	0.01141	0.01141	0.05023	0.05023	0.15612
Land Acquisition Cost	0.00041	0.00519	0.00519	0.03008	0.03008	0.11376
Operating and Maintenance Cost	0.00013	0.00233	0.00233	0.01778	0.01778	0.08179
Storage Cost	0.00004	0.00100	0.00100	0.01011	0.01011	0.05661
Social and Political						
Access to Skilled Labor	0.00154	0.01014	0.01103	0.04273	0.04762	0.14573
Favorability of the Legal and Regulatory Framework	0.00046	0.00432	0.00551	0.02730	0.03265	0.10786
Financial Incentives and Public Support	0.00013	0.00167	0.00253	0.01586	0.02060	0.07611
Social Acceptance and Stakeholder Relations	0.00004	0.00059	0.00120	0.00836	0.01336	0.05207
Environmental						
Sustainable Transportation and Emissions Management	0.00039	0.00391	0.00398	0.02041	0.02089	0.08654
Energy Efficiency and Clean Energy Use	0.00016	0.00231	0.00000	0.01542	0.01595	0.07071
Waste Management and Circular Economy	0.00006	0.00117	0.04828	0.01001	0.01051	0.05329
Sustainable Land Use and Biodiversity Conservation	0.00002	0.00056	0.01236	0.00610	0.00651	0.03854
Environmental Compliance and Social Integration	0.00001	0.00024	0.00271	0.00334	0.00373	0.02575

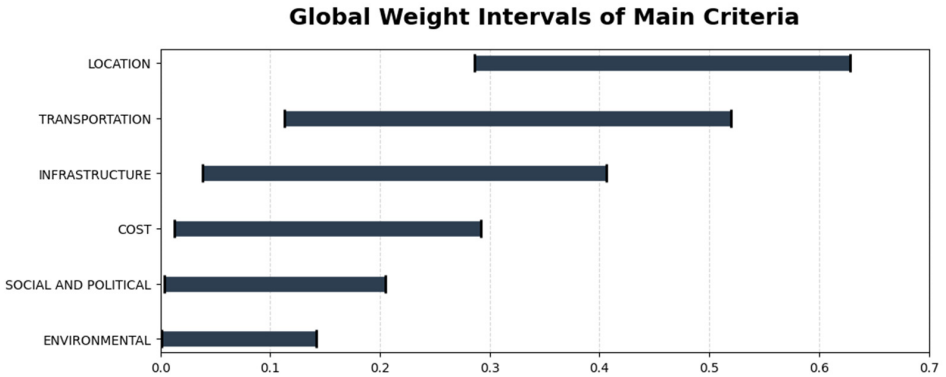


Figure 5. *Cont.*

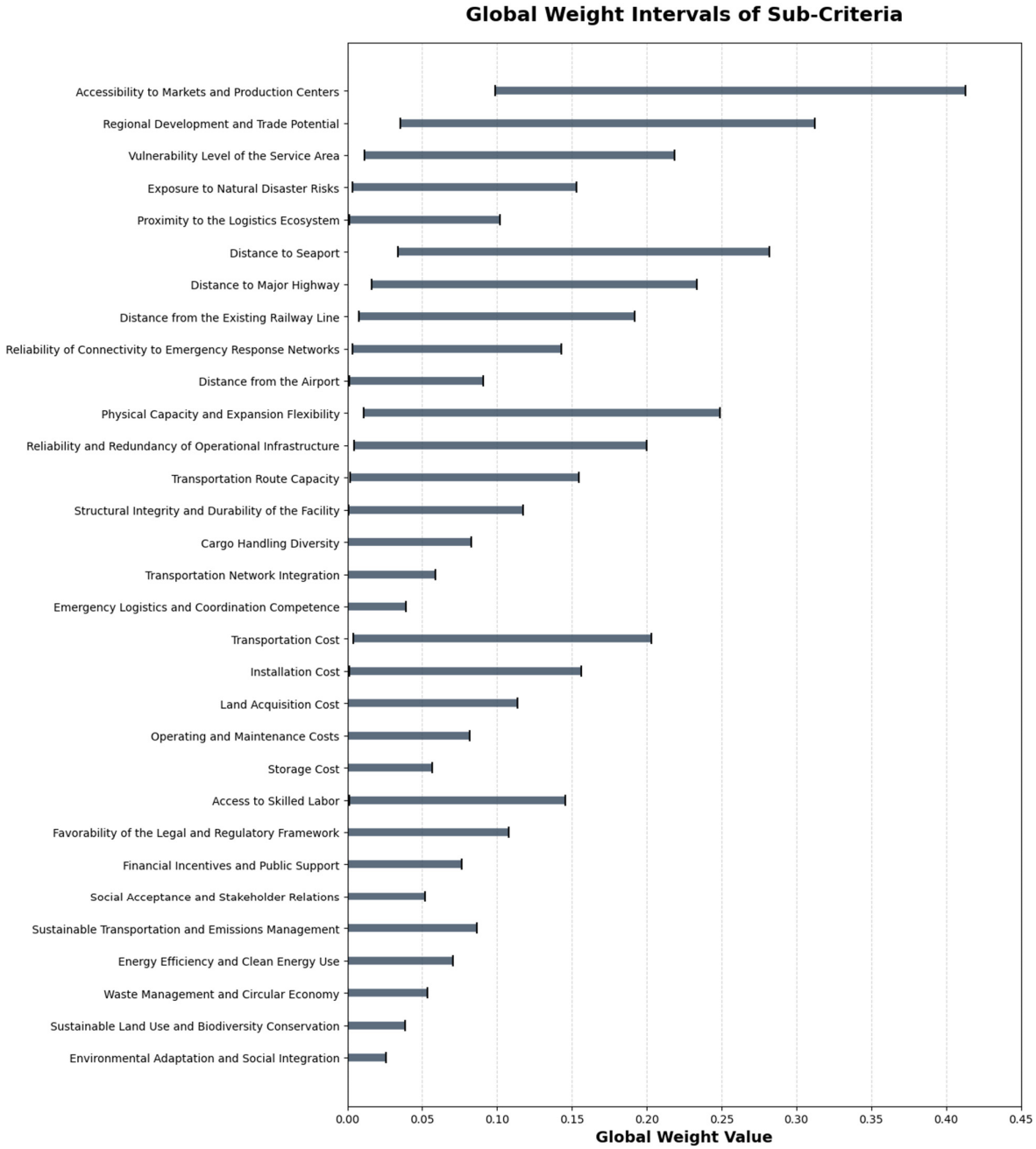


Figure 5. Global weight intervals.

4.3. Comparative Analysis and Methodological Validation

To rigorously validate the stability and theoretical robustness of the proposed FR-SWARA framework, a comprehensive multi-method benchmarking analysis was conducted. The baseline expert evaluations were re-computed using SWARA, the Fuzzy Analytic Hierarchy Process (FAHP), and the Fuzzy Best–Worst Method (FBWM). This comparative approach serves to empirically demonstrate how the dual-role dry port model behaves under distinct mathematical constraints and differing decision-making paradigms.

4.3.1. Methodological Comparison at the Main Criteria Level

At the macro level, the comparison of main criteria weights presented in Table 11 reveals a high degree of stability across all evaluated methodologies. Irrespective of the underlying algorithmic mechanics, the spatial and physical dimensions—namely 'location' and 'transportation'—consistently dominate the decision matrix. This alignment confirms

the foundational reliability of the proposed framework in prioritizing structural resilience over conventional cost metrics.

Table 11. Methodological comparison of main criteria weights.

Main Criteria	FR-SWARA Interval [L, U]	SWARA (Rank)	Fuzzy AHP (Rank)	Fuzzy BWM (Rank)
Location	[0.28636, 0.62806]	0.34517 (1)	0.35049 (1)	0.34000 (1)
Transportation	[0.11325, 0.51948]	0.23884 (2)	0.24252 (2)	0.23526 (2)
Infrastructure	[0.03864, 0.40650]	0.16803 (3)	0.17062 (3)	0.16551 (3)
Cost	[0.01241, 0.29209]	0.11494 (4)	0.08754 (4)	0.14152 (4)
Social and Political	[0.00404, 0.20499]	0.07890 (5)	0.08012 (5)	0.07772 (5)
Environmental	[0.00124, 0.14216]	0.05413 (6)	0.06871 (6)	0.03999 (6)

4.3.2. Global Sub-Criteria Weights and Rank Reversal Analysis

While the macro-level hierarchy remains stable, the distinct mathematical properties of the selected MCDM methods become pronounced at the sub-criteria level. Table 12 details the global weights and corresponding hierarchical ranks for all 31 sub-criteria, exposing critical rank reversals that stem from methodological variations.

Table 12. Global weights and methodological rank comparison of all sub-criteria.

Sub-Criteria	FR-SWARA Interval [L, U]	SWARA (Rank)	Fuzzy AHP (Rank)	Fuzzy BWM (Rank)
Accessibility to Markets and Production Centers	[0.09863, 0.41272]	0.11244 (1)	0.08668 (1)	0.13684 (1)
Regional Development and Trade Potential	[0.03554, 0.31217]	0.07646 (2)	0.05894 (4)	0.09305 (2)
Distance to Seaport	[0.03391, 0.28179]	0.06942 (3)	0.07136 (2)	0.06759 (3)
Physical Capacity and Expansion Flexibility	[0.01067, 0.24904]	0.05711 (4)	0.05870 (5)	0.05560 (4)
Distance to Major Highway	[0.01635, 0.23356]	0.05495 (5)	0.05649 (7)	0.05350 (6)
Vulnerability Level of the Service Area	[0.01120, 0.21853]	0.05052 (6)	0.06491 (3)	0.03689 (9)
Transportation Cost	[0.00412, 0.20290]	0.04552 (7)	0.03509 (12)	0.05540 (5)
Reliability and Redundancy of Operational Infra.	[0.00432, 0.20009]	0.04495 (8)	0.05775 (6)	0.03282 (11)
Distance to the Main Railway Line	[0.00784, 0.19215]	0.04398 (9)	0.04520 (8)	0.04282 (7)
Installation Cost	[0.00124, 0.15612]	0.03460 (10)	0.02668 (15)	0.04211 (8)
Exposure to Natural Disaster Risk	[0.00354, 0.15292]	0.03440 (11)	0.04420 (9)	0.02512 (15)
Transportation Capacity	[0.00156, 0.15471]	0.03436 (12)	0.03532 (11)	0.03346 (10)
Access to Skilled Labor	[0.00154, 0.14573]	0.03238 (13)	0.03329 (14)	0.03153 (12)
Emergency Response Network Connection Reliability	[0.00323, 0.14308]	0.03217 (14)	0.04134 (10)	0.02349 (16)
Structural Integrity and Durability of the Facility	[0.00057, 0.11728]	0.02591 (15)	0.03330 (13)	0.01892 (21)
Land Acquisition Cost	[0.00041, 0.11376]	0.02511 (16)	0.01935 (20)	0.03055 (13)
Favorability of the Legal and Regulatory Framework	[0.00046, 0.10786]	0.02382 (17)	0.02448 (17)	0.02319 (17)
Proximity to the Logistics Ecosystem	[0.00118, 0.10189]	0.02266 (18)	0.01747 (21)	0.02758 (14)
Distance to Airport	[0.00119, 0.09052]	0.02017 (19)	0.02073 (18)	0.01963 (20)
Sustainable Transportation and Emissions Mng.	[0.00039, 0.08654]	0.01912 (20)	0.02456 (16)	0.01396 (24)
Cargo Handling Diversity	[0.00020, 0.08302]	0.01830 (21)	0.01411 (24)	0.02227 (18)
Operating and Maintenance Cost	[0.00013, 0.08179]	0.01801 (22)	0.01389 (25)	0.02192 (19)
Financial Incentives and Public Support	[0.00013, 0.07611]	0.01676 (23)	0.01723 (22)	0.01632 (22)
Energy Efficiency and Clean Energy Use	[0.00016, 0.07071]	0.01558 (24)	0.02002 (19)	0.01138 (26)
Transportation Network Integration	[0.00007, 0.05867]	0.01292 (25)	0.01328 (26)	0.01258 (25)
Storage Cost	[0.00004, 0.05661]	0.01246 (26)	0.00960 (30)	0.01516 (23)
Waste Management and Circular Economy	[0.00006, 0.05329]	0.01173 (27)	0.01507 (23)	0.00857 (28)
Social Acceptance and Stakeholder Relations	[0.00004, 0.05207]	0.01146 (28)	0.01178 (27)	0.01116 (27)
Emergency Logistics and Coordination Competency	[0.00002, 0.03896]	0.00857 (29)	0.01101 (28)	0.00626 (29)
Sustainable Land Use and Biodiversity Conservation	[0.00002, 0.03854]	0.00848 (30)	0.01089 (29)	0.00619 (30)
Environmental Compliance and Social Integration	[0.00001, 0.02575]	0.00566 (31)	0.00728 (31)	0.00414 (31)

The empirical shifts observed in Table 12 provide profound insights into the complexity of harmonizing conflicting priorities within a dual-role logistics model. Notably, the disaster-oriented criterion 'Vulnerability Level of the Service Area' ascends to the third rank

under the FAHP method. This surge is attributable to the FAHP's strict pairwise consistency requirements and inherently risk-averse structure, which naturally amplifies security and resilience parameters. Conversely, under the FBWM approach—which optimizes weights against predefined best/worst reference points—the efficiency-driven 'Transportation Cost' criterion experiences a significant upward shift to the fifth rank, while falling to the 12th rank in the FAHP.

These methodological discrepancies underscore the theoretical limitations of traditional point-estimate techniques, which compel decision-makers to artificially collapse conflicting objectives (commercial efficiency versus disaster resilience) into a singular, rigid hierarchy. In contrast, the theoretical superiority of the FR-SWARA method lies in its capacity to preserve the boundaries of expert cognitive divergence. By yielding an uncertainty interval, the proposed model effectively encapsulates these opposing methodological tendencies. The overlapping boundaries (e.g., between cost and vulnerability metrics) act as a strategic planning buffer, empowering policymakers to seamlessly navigate the transition between 'just-in-time' operations and 'Just-in-Case' disaster responses without mathematically sacrificing either objective.

4.4. Sensitivity Analysis Based on Expert Perspectives: Scenario-Driven Robustness Test

A critical challenge in modeling a dual-role dry port is the inherent cognitive divergence among stakeholders. To empirically test the robustness of the proposed framework and to address how different professional backgrounds influence uncertainty, the 12-person expert panel was theoretically divided into two distinct sub-panels based on their institutional affiliations.

The Fuzzy Rough SWARA (FR-SWARA) aggregation procedure was recalculated for each sub-panel to observe how the rough intervals [L, U] expand, contract, and shift in response to sectoral biases:

Scenario 1 (Public and Academic Experts): Computed using only the judgments of experts affiliated with public disaster management and academia, who theoretically prioritize structural resilience and environmental safety.

Scenario 2 (Private Sector and Industry Experts): Computed using the evaluations of experts from port operations and the private logistics sector, whose primary motivations align with cost minimization and market accessibility.

4.4.1. Expert-Based Sensitivity at the Main Criteria Level

The impact of the expert sub-panels on the rough interval boundaries [L, U] of the main criteria is presented in Table 13. While the boundaries for 'cost' expand significantly upward under the industry panel, the spatial dimensions ('location' and 'transportation') maintain their hierarchical dominance across both expert groups.

Table 13. Rough intervals and rank shifts in main criteria based on expert profiles.

Main Criteria	Baseline (All 12 Experts) [L, U]	Scenario 1 (Public/Academic) [L, U]	Scenario 2 (Private/Industry) [L, U]
Location	[0.28636, 0.62806]	[0.18349, 0.40244]	[0.37692, 0.82669]
Transportation	[0.11325, 0.51948]	[0.12094, 0.55477]	[0.10648, 0.48841]
Infrastructure	[0.03864, 0.40650]	[0.05777, 0.60777]	[0.02180, 0.22931]
Cost	[0.01241, 0.29209]	[0.00795, 0.18716]	[0.01633, 0.38447]
Social and Political	[0.00404, 0.20499]	[0.00604, 0.30648]	[0.00228, 0.11564]
Environmental	[0.00124, 0.14216]	[0.00185, 0.21255]	[0.00070, 0.08019]

4.4.2. Sub-Criteria Rank Reversals and Interval Dynamics

The most profound insights regarding cognitive divergence emerge at the sub-criteria level. Table 14 presents the rough intervals [L, U] and the resulting hierarchical shifts (based on interval midpoints) for all 31 sub-criteria across the different expert sub-panels.

Table 14. Rough intervals and rank shifts in all sub-criteria based on expert profiles.

Code	Sub-Criteria	Baseline [L, U] (Rank)	S1: Public [L, U] (Rank)	S2: Private [L, U] (Rank)
C1.1	Accessibility to Markets and Production Centers	[0.09863, 0.41272] (1)	[0.06035, 0.25255] (4)	[0.13276, 0.55555] (1)
C1.2	Regional Development and Trade Potential	[0.03554, 0.31217] (2)	[0.02175, 0.19102] (8)	[0.04784, 0.42021] (2)
C2.1	Distance to Seaport	[0.03391, 0.28179] (3)	[0.03458, 0.28739] (3)	[0.03043, 0.25287] (4)
C3.1	Physical Capacity and Expansion Flexibility	[0.01067, 0.24904] (4)	[0.00653, 0.15239] (11)	[0.01436, 0.33523] (3)
C2.2	Distance to Major Highway	[0.01635, 0.23356] (5)	[0.01667, 0.23820] (6)	[0.01467, 0.20959] (6)
C1.3	Vulnerability Level of the Service Area	[0.01120, 0.21853] (6)	[0.01828, 0.35660] (1)	[0.00603, 0.11766] (12)
C4.1	Transportation Cost	[0.00412, 0.20290] (7)	[0.00252, 0.12416] (14)	[0.00555, 0.27312] (5)
C3.2	Reliability and Redundancy of Operational Infra.	[0.00432, 0.20009] (8)	[0.00705, 0.32651] (2)	[0.00233, 0.10773] (15)
C2.3	Distance to the Main Railway Line	[0.00784, 0.19215] (9)	[0.00800, 0.19597] (9)	[0.00704, 0.17243] (9)
C4.2	Installation Cost	[0.00124, 0.15612] (10)	[0.00076, 0.09553] (18)	[0.00167, 0.21015] (7)
C1.4	Exposure to Natural Disaster Risk	[0.00354, 0.15292] (11)	[0.00578, 0.24954] (5)	[0.00191, 0.08234] (18)
C3.3	Transportation Capacity	[0.00156, 0.15471] (12)	[0.00095, 0.09467] (19)	[0.00210, 0.20825] (8)
C5.1	Access to Skilled Labor	[0.00154, 0.14573] (13)	[0.00157, 0.14863] (12)	[0.00138, 0.13078] (11)
C2.4	Emergency Response Network Connection Reliability	[0.00323, 0.14308] (14)	[0.00527, 0.23348] (7)	[0.00174, 0.07704] (20)
C3.4	Structural Integrity and Durability of the Facility	[0.00057, 0.11728] (15)	[0.00093, 0.19138] (10)	[0.00031, 0.06315] (23)
C4.3	Land Acquisition Cost	[0.00041, 0.11376] (16)	[0.00025, 0.06961] (23)	[0.00055, 0.15313] (10)
C5.2	Favorability of the Legal and Regulatory Framework	[0.00046, 0.10786] (17)	[0.00047, 0.11000] (16)	[0.00041, 0.09679] (16)
C1.5	Proximity to the Logistics Ecosystem	[0.00118, 0.10189] (18)	[0.00120, 0.10392] (17)	[0.00106, 0.09143] (17)
C2.5	Distance to Airport	[0.00119, 0.09052] (19)	[0.00121, 0.09232] (20)	[0.00107, 0.08123] (19)
C6.1	Sustainable Transportation and Emissions Mng.	[0.00039, 0.08654] (20)	[0.00064, 0.14122] (13)	[0.00021, 0.04660] (25)
C3.5	Cargo Handling Diversity	[0.00020, 0.08302] (21)	[0.00012, 0.05080] (28)	[0.00027, 0.11175] (13)
C4.4	Operating and Maintenance Cost	[0.00013, 0.08179] (22)	[0.00008, 0.05005] (29)	[0.00017, 0.11010] (14)
C5.3	Financial Incentives and Public Support	[0.00013, 0.07611] (23)	[0.00013, 0.07762] (22)	[0.00012, 0.06830] (22)
C6.2	Energy Efficiency and Clean Energy Use	[0.00016, 0.07071] (24)	[0.00026, 0.11538] (15)	[0.00009, 0.03807] (27)
C3.6	Transportation Network Integration	[0.00007, 0.05867] (25)	[0.00007, 0.05984] (26)	[0.00006, 0.05265] (24)
C4.5	Storage Cost	[0.00004, 0.05661] (26)	[0.00002, 0.03464] (31)	[0.00005, 0.07620] (21)
C6.3	Waste Management and Circular Economy	[0.00006, 0.05329] (27)	[0.00010, 0.08696] (21)	[0.00003, 0.02869] (28)
C5.4	Social Acceptance and Stakeholder Relations	[0.00004, 0.05207] (28)	[0.00004, 0.05310] (27)	[0.00004, 0.04673] (26)
C3.7	Emergency Logistics and Coordination Competency	[0.00002, 0.03896] (29)	[0.00003, 0.06357] (24)	[0.00001, 0.02098] (29)
C6.4	Sustainable Land Use and Biodiversity Conservation	[0.00002, 0.03854] (30)	[0.00003, 0.06289] (25)	[0.00001, 0.02075] (30)
C6.5	Environmental Compliance and Social Integration	[0.00001, 0.02575] (31)	[0.00002, 0.04202] (30)	[0.00001, 0.01386] (31)

The empirical interval shifts delineated in Table 14 corroborate theoretical postulates regarding sectoral divergence, simultaneously demonstrating the methodological efficacy of the FR-SWARA approach. Specifically, when priorities are derived exclusively from the Public/Academic sub-panel (S1), the uncertainty bounds for the *'Vulnerability Level of the Service Area'* exhibit substantial expansion ([0.0183, 0.3566]), thereby elevating the criterion to the foremost rank. This adjustment directly mirrors the systemic prioritization of structural resilience inherent to public administration paradigms. Conversely, the private sector sub-panel (S2) markedly amplifies the upper thresholds of commercial determinants, as evidenced by the ascension of *'Transportation Cost'* ([0.0055, 0.2731]) to the fifth rank in the hierarchy.

Notwithstanding these expected dichotomies, the primary theoretical contribution of this sensitivity analysis is articulated through the stability of the baseline (All 12 Experts) parameters. The proposed dual-role framework effectively subsumes the polarized evaluations of both sub-groups. Rather than imposing a rigid, crisp consensus that inherently marginalizes divergent stakeholder priorities, the baseline rough intervals systematically assimilate the cognitive divergence between public and private experts. Even amidst these conflicting motivational drivers, macro-location variables such as *'Distance to Seaport'* and *'Distance to Major Highway'* retain stable operational bounds, consistently occupying the upper echelons of the hierarchy. Consequently, this empirical evidence substantiates that integrating heterogeneous expert profiles within a rough boundary framework yields a highly resilient 'Just-in-Case' logistics architecture, one that remains structurally robust even under extreme stakeholder dissonance.

5. Discussion

The main objective of this study is to develop a hybrid model that integrates the conventional logistics efficiency functions of dry ports with the role they can assume as emergency logistics centers in crisis and disaster situations, and to determine the basic criteria set for the functionality of this model. To this end, the existing literature on dry ports and emergency logistics was first systematically reviewed; then, based on expert opinions, the SWARA method, a multi-criteria decision-making technique, was modified to carry out the process of weighting the criteria. The Fuzzy Rough SWARA approach effectively models the high degree of uncertainty and ambiguity inherent in disaster scenarios. By utilizing rough set theory, the subjective judgments of the 12-expert panel are transformed into an objective and consistent weighting framework, providing more robust insights for crisis-time decision-making compared to traditional MCDM methods.

This study aims to bridge a critical lacuna in the literature by synergizing the logistics efficiency and emergency center functions of dry ports into a singular strategic infrastructure investment. Indeed, the multifaceted shocks experienced in recent years, which have severely destabilized global supply chains, have unequivocally underscored the exigency of this integrated approach. The COVID-19 pandemic exposed the limitations of JIT models by causing unprecedented disruptions in supply chains, bottlenecks at ports, and record increases in freight costs. Similarly, the Russia–Ukraine war in the Black Sea disrupted maritime trade in the region, threatening global food and energy security and increasing the shift towards alternative trade routes. Trade tensions between the US and China have negatively impacted freight costs, increasing the pressure to restructure supply chains.

In addition to these geopolitical and health crises, the devastating effects of natural disasters have demonstrated the fragility of infrastructure. For example, the estimated cost of each day that the Port of Houston in the US was closed due to a hurricane was $322 million, illustrating the magnitude of the economic losses caused by such disruptions. In Türkiye, the collapse and fire disaster at the strategically important Port of Iskenderun following the 6 February 2023, Kahramanmaraş earthquakes painfully demonstrated the vulnerability of critical infrastructure during disasters and its negative impact on national and international supply chains. These global and regional crises prove that logistics infrastructure must be designed not only for commercial efficiency but also to be resilient to shocks and dual use, which is a strategic necessity.

The criterion weights obtained using the Fuzzy Rough SWARA method confirmed the importance of this dual-use approach. Among the main criteria, the fact that the location criterion has the highest weight shows that strategic geographical positioning is indispensable for the success of a dry port. Upon a granular examination of the global weights, the fact that the lower limit of the location criterion nearly intersects the upper

limit of the cost criterion provides empirical validation that site selection supersedes all conventional operational cost considerations in terms of strategic primacy. This finding coincides with the importance of access to markets and production centers, as emphasized by Rodrigues et al. [24] and Ka [26]. From a strategic decision-making perspective, the dominance of the location and transportation criteria implies that physical proximity and connectivity are non-negotiable prerequisites for resilience. While cost reduction is the primary driver in traditional logistics, these results suggest that in a dual-purpose model, investors and public authorities must accept higher initial setup costs to secure long-term operational continuity during crises.

However, in this study, the sub-criterion Accessibility to Market and Production Centers under the main criterion of location has the highest weight, distinguishing it from traditional approaches as it includes not only commercial potential but also disaster-focused sub-criteria such as Vulnerability Level of the Service Area and Exposure to Natural Disaster Risk. This highlights that investment decisions should be made not only based on economic feasibility but also on their potential to contribute to regional resilience. Specifically, the global weight of the Vulnerability Level of the Service Area criterion is significantly higher than fundamental financial indicators such as Installation Cost and Operating and Maintenance Cost, numerically proving the priority of post-disaster resilience over economic efficiency.

The fact that the transportation criterion has the second highest weight reinforces the vital role of intermodal connections for both commercial logistics and emergency operations. In particular, the high weights of the sub-criteria Distance to Seaport and Distance to Major Highway form the basis of an effective hinterland connection, as emphasized by Roso et al. [11] and Yılmaz and Kabak [57]. Additionally, the significant weight assigned to the Reliability of Connection to Emergency Response Networks criterion reflects the expectation that the dry port will support not only its own operations but also regional response capacity in a crisis. These findings are consistent with the work of [132] and Zamiar and Kowalkowski [133], which point to the critical role of public–private sector collaboration in disaster management and logistics planning.

Infrastructure was identified as a key factor in this study. The high weights of sub-criteria such as Physical Capacity and Expansion Flexibility and Reliability and Redundancy of Operational Infrastructure indicate that a dry port must not only meet current demand but also have the critical ability to adapt to unexpected situations such as future growth and sudden flows of relief supplies. This finding parallels the work of Fu and Tang [61], who drew attention to the condition of infrastructure facilities, and Jeevan et al. [52], who emphasized resource availability for emergency centers. In particular, the inclusion of sub-criteria such as Structural Integrity and Resilience of the Facility and Emergency Logistics and Coordination Capability in the model strengthens the study's unique approach of prioritizing resilience to natural disasters such as earthquakes. Furthermore, a critical operational synergy exists between Structural Integrity and Emergency Response Network Connection Reliability. Physical resilience becomes a strategic asset only when integrated with redundant transportation corridors, illustrating that the model treats these criteria as an integrated system rather than isolated variables.

Although the main criteria of cost, social and political, and environmental have lower weights than location, transportation, and infrastructure, they are indispensable for a sustainable and acceptable investment. Notably, this hierarchy deviates from traditional dry port studies, where cost frequently ranks among the top priorities. The fact that location and transport outweigh cost in this study is a unique outcome of the dual-use focus, empirically proving that strategic security and disaster readiness take precedence over immediate economic savings in resilience planning. Notably, the fact that the global

weight of the Accessibility to Markets and Production Centers sub-criterion is higher than the total weight of each of the cost, Social–Political, and environmental main criteria reflects the undisputed superiority of market focus and operational continuity in logistics network design. Social and political sub-criteria, particularly Access to Skilled Labor and Favorable Legal and Regulatory Framework, provide the social operating license and operational ease necessary for the long-term success of the project. The fact that the Sustainable Transportation and Emissions Management criterion has the highest weight under the Environmental main criterion confirms the potential of dry ports to reduce their carbon footprint by promoting environmentally friendly modes such as rail, which is consistent with the findings of Hanaoka and Regmi [112] and Pham and Lee [29].

A core theoretical challenge of the proposed dual-role framework is navigating the inherent friction between commercial efficiency and disaster resilience. The transition to a 'Just-in-Case' (JIC) logistics architecture is empirically justified not merely by the macro-level dominance of location over cost, but by the specific hierarchical shift observed within the sub-criteria. In traditional paradigms, operational costs dictate site selection. However, in this study, disaster-oriented metrics such as the Vulnerability Level of the Service Area and Reliability of Connectivity to Emergency Response Networks strategically outrank fundamental fiscal indicators like Installation and Operating Costs. This indicates that the JIC architecture fundamentally redefines infrastructure valuation: operational continuity during systemic shocks is prioritized over short-term financial optimization. Consequently, when decision-makers face conflicting priorities—such as an optimal market access site located in a high-vulnerability zone—the framework dictates the necessity of 'strategic redundancy'. It mandates accepting higher initial capital expenditures to engineer physical resilience into vulnerable commercial hubs, thereby harmonizing profit-driven utility with public-driven security.

Furthermore, while the mathematical validation in Section 4.3 demonstrates the stability of the results, the theoretical justification for employing FR-SWARA over traditional multi-criteria methods is deeply rooted in the context of this dual-role problem. In integrating commercial and emergency logistics, stakeholders possess inherently conflicting priorities. Traditional pairwise comparison methods often impose strict consistency limits, which can suppress extreme but valid minority opinions—such as a public official's hyper-focus on disaster safety versus a private investor's focus on ROI. The FR-SWARA approach overcomes this by utilizing rough interval boundaries to objectively encapsulate cognitive dissonance. Rather than diluting expert disagreement into a single crisp average, the rough sets map the 'friction' between efficiency and resilience directly into the final fuzzy rough weights, making it uniquely equipped to handle the high-dimensional uncertainty of dual-purpose infrastructure planning.

6. Conclusions

This research presents a comprehensive paradigm shift in dry port location selection by developing a novel hybrid model that harmonizes commercial logistics efficiency with strategic disaster resilience. Through the application of the Fuzzy Rough SWARA (FR-SWARA) method, this study empirically demonstrates that the strategic valuation of dry ports must transcend traditional cost-centric models. The findings reveal a decisive hierarchical shift where the spatial dimensions of location, transportation, and infrastructure significantly overshadow immediate financial obligations. Specifically, the high global weights assigned to factors such as the Vulnerability Level of the Service Area and Reliability of Operational Infrastructure substantiate the empirical transition from 'just-in-time' (JIT) to 'Just-in-Case' (JIC) logistics architectures. In this new paradigm, re-

silience is no longer an auxiliary feature but a foundational prerequisite for national supply chain security.

Central to this study is the reconceptualization of the dry port as a 'strategic stabilizer', a critical infrastructure node designed to absorb systemic shocks rather than propagate them. Unlike traditional hinterland extensions, a strategic stabilizer acts as a multifaceted buffer capable of maintaining operational continuity during diverse crises, ranging from localized natural disasters like the 2023 Kahramanmaraş earthquakes to global disruptions such as the COVID-19 pandemic. By leveraging redundant physical capacity and structural integrity, these facilities ensure that essential relief and commercial flows are coordinated even when primary maritime gateways are compromised. Fundamentally, the strategic stabilizer serves as a 'shock absorber' within the national logistics architecture, preventing the cascading failures that typically follow systemic disruptions.

From a theoretical perspective, this study extends supply chain resilience theory by mathematically embedding disaster-oriented criteria into a classical logistics decision model, offering a robust new lens for infrastructure valuation in volatile geographies. Managerially and politically, the results advocate for a strategic realignment of investment incentives. We argue that public–private partnership (PPP) frameworks must evolve to prioritize facilities offering high-dimensional resilience and rapid response capabilities over those solely focused on initial cost minimization. In an era of increasing geopolitical and environmental volatility, dry ports must be conceptually elevated from passive cargo hubs to active components of national defense and economic security.

Despite its robust framework, this study acknowledges specific limitations. First, the expert panel's primary focus on the Turkish maritime and seismic landscape inherently reflects a regional bias. Future research should recalibrate the model in regions facing distinct threats, such as hurricanes, extreme weather events, or evolving global trade route shifts driven by climate change. Second, while the FR-SWARA method effectively captures high-dimensional uncertainty, it relies on the assumption of criteria independence. Given the complex interdependencies within dual-use systems—where physical capacity directly impacts connectivity—future work should incorporate network-based methodologies to map and quantify these causal feedback loops.

Finally, to transition this static framework into a dynamic operational roadmap, future investigations should integrate the decision model with approaches that combine fuzzy logic and agent-based modeling. Utilizing such dynamic simulations and fuzzy expert systems will allow researchers to model real-time agent-rescuer behaviors and evaluate the effectiveness of logistics responses under varying emergency conditions. This dynamic integration will enable a precise quantification of the trade-offs between proactive resilience investments and potential disaster losses, ensuring that the 'Just-in-Case' architecture remains adaptable to an evolving and unpredictable global threat landscape.

Author Contributions: Conceptualization, G.M.İ.; methodology, G.M.İ.; software, G.M.İ.; validation, Y.A.; formal analysis, G.M.İ.; investigation, G.M.İ.; resources, G.M.İ.; data curation, G.M.İ.; writing—original draft preparation, G.M.İ.; writing—review and editing, Y.A.; visualization, G.M.İ.; supervision, Y.A. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data presented in this study are available on request from the corresponding author. The data are not publicly available due to privacy restrictions.

Acknowledgments: The Istanbul Technical University Scientific Research Projects Coordination Office supported this article (project no MGA-2025-47008).

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Notteboom, T.; Pallis, T.; Rodrigue, J.P. Disruptions and Resilience in Global Container Shipping and Ports: The COVID-19 Pandemic versus the 2008–2009 Financial Crisis. *Marit. Econ. Logist.* **2021**, *23*, 179–210. [CrossRef]
2. Ivanov, D. Viable Supply Chain Model: Integrating Agility, Resilience and Sustainability Perspectives—Lessons from and Thinking beyond the COVID-19 Pandemic. *Ann. Oper. Res.* **2022**, *319*, 1411–1431. [CrossRef]
3. Chkhenkeli, A.; Kapanadze, N.; Khishtovani, G.; Kosse, I.; Kostiv, B.; Matcharashvili, S.; Sirbiladze, I. *Maritime Trade in the Black Sea in the Context of the Russo-Ukrainian War*; PMC Research Center: Tbilisi, Georgia, 2023.
4. Melas, K.D.; Michail, N.A.; Louca, K.G. Trade Uncertainty, Economic Policy Uncertainty and Shipping Costs. *Ger. Econ. Rev.* **2025**, *26*, 15–33. [CrossRef]
5. Hlovor, I.; Mawuko-Yevugah, L. Lord The Current World-System and Conflicts Understanding the U.S.-China Trade War. *J. World-Syst. Res.* **2024**, *30*, 583–609. [CrossRef]
6. Strategy and Budget Office of the Turkish Presidency. *2023 Kahramanmaraş and Hatay Earthquakes Report*; T.C. Cumhurbaşkanlığı Strateji ve Bütçe Başkanlığı: Ankara, Türkiye, 2023.
7. Folkman, D.; Galvao, C.B.; Gharehgozli, A.; Mileski, J. Port Resiliency and the Effects of Hurricanes on Port Operations. *Int. J. Adv. Oper. Manag.* **2021**, *13*, 409. [CrossRef]
8. Park, Y.W.; Hong, P.; Roh, J.J. Supply Chain Lessons from the Catastrophic Natural Disaster in Japan. *Bus. Horiz.* **2013**, *56*, 75–85. [CrossRef]
9. Jeevan, J.; Roso, V. Exploring Seaport—Dry Ports Dyadic Integration to Meet the Increase in Container Vessels Size. *J. Shipp. Trade* **2019**, *4*, 8. [CrossRef]
10. Haezendonck, E.; Langenus, M. Integrated Ports Clusters and Competitive Advantage in an Extended Resource Pool for the Antwerp Seaport. *Marit. Policy Manag.* **2019**, *46*, 74–91. [CrossRef]
11. Roso, V.; Woxenius, J.; Lumsden, K. The Dry Port Concept: Connecting Container Seaports with the Hinterland. *J. Transp. Geogr.* **2009**, *17*, 338–345. [CrossRef]
12. Khaslavskaya, A.; Roso, V. Outcome-Driven Supply Chain Perspective on Dry Ports. *Sustainability* **2019**, *11*, 1492. [CrossRef]
13. Roso, V.; Russell, D.; Rhoades, D. Diffusion of Innovation Assessment of Adoption of the Dry Port Concept. *Trans. Marit. Sci.* **2019**, *8*, 26–36. [CrossRef]
14. Li, Q.; Ru, Y.; Zhang, L.; Yan, B. Empirical Study on Improving International Dry Port Competitiveness Based on Logistics Supply Chain Integration: Evidence from China. *Int. J. Logist. Manag.* **2021**, *33*, 1040–1068. [CrossRef]
15. Bagheri, M.; Abbasi, H.; Yaghoubi, S.; Pishvaee, M.S.; Fallahi, M. Optimizing Dry Port Locations: A Comparative Analysis of Deterministic, Stochastic, and Robust Models. *Transp. Res. Rec.* **2024**, *2679*, 1922–1940. [CrossRef]
16. Jiang, Y.; Yuan, Y. Emergency Logistics in a Large-Scale Disaster Context: Achievements and Challenges. *Int. J. Environ. Res. Public Health* **2019**, *16*, 779. [CrossRef] [PubMed]
17. Munford, C. Buenos Aires-Congestion and the Dry Port Solution. *Cargo Syst. Int. J. ICHCA* **1980**, *7*, 26–27.
18. UNCTAD Multimodal Transport and Containerisation. *TD/B/C.4/238/Supplement 1, Part Five: Ports and Container Depots*; United Nations Conference on Trade and Development: Geneva, Switzerland, 1982.
19. Witte, P.; Wiegmans, B.; Ng, A.K.Y. A Critical Review on the Evolution and Development of Inland Port Research. *J. Transp. Geogr.* **2019**, *74*, 53–61. [CrossRef]
20. Carboni, A.; Orsini, F. Dry Ports and Related Environmental Benefits: A Case Study in Italy. *Case Stud. Transp. Policy* **2020**, *8*, 416–428. [CrossRef]
21. Zain, R.M.; Salleh, N.H.M.; Zaideen, I.M.M.; Menhat, M.N.S.; Jeevan, J. Dry Ports: Redefining the Concept of Seaport-City Integrations. *Transp. Eng.* **2022**, *8*, 100112. [CrossRef]
22. Jeevan, J.; Maskey, R.; Chen, S.-L.; Sharma, R.; Zaideen, I.M.M. Comparative Analysis of Dry Port Operations in Coastal and Landlocked Countries. *Trans. Marit. Sci.* **2022**, *11*, 6. [CrossRef]
23. Oláh, J.; Nestler, S.; Nobel, T.; Popp, J. Evolution of Freight Villages and Dry Ports from the Macro Logistics Perspective Based on European Benchmarking 2020. *Period. Polytech. Transp. Eng.* **2021**, *49*, 382–393. [CrossRef]
24. de Almeida Rodrigues, T.; Maria de Miranda Mota, C.; Manuele dos Santos, I. Determining Dry Port Criteria That Support Decision Making. *Res. Transp. Econ.* **2021**, *88*, 100994. [CrossRef]
25. Kayikci, Y. A Conceptual Model for Intermodal Freight Logistics Centre Location Decisions. In *Proceedings of the Procedia—Social and Behavioral Sciences*; Elsevier Ltd.: Amsterdam, The Netherlands, 2010; Volume 2, pp. 6297–6311.

26. Ka, B. Application of Fuzzy AHP and ELECTRE to China Dry Port Location Selection. *Asian J. Shipp. Logist.* **2011**, *27*, 331–353. [CrossRef]
27. Komchornrit, K. The Selection of Dry Port Location by a Hybrid CFA-MACBETH-PROMETHEE Method: A Case Study of Southern Thailand. *Asian J. Shipp. Logist.* **2017**, *33*, 141–153. [CrossRef]
28. Raad, N.G.; Rajendran, S.; Salimi, S. A Novel Three-Stage Fuzzy GIS-MCDA Approach to the Dry Port Site Selection Problem: A Case Study of Shahid Rajaei Port in Iran. *Comput. Ind. Eng.* **2022**, *168*, 108112. [CrossRef]
29. Pham, H.T.; Lee, H. Developing a Green Route Model for Dry Port Selection in Vietnam. *Asian J. Shipp. Logist.* **2019**, *35*, 96–107. [CrossRef]
30. Lv, R.S.; Li, C. Analysis on Location Selection of Dry Ports Based on ANP. In Proceedings of the 2009 16th International Conference on Industrial Engineering and Engineering Management, Beijing, China, 21–23 October 2009; pp. 638–641.
31. Wei, J.; Sun, A.; Zhuang, J. The Selection of Dry Port Location with the Method of Fuzzy-ANP. In *Advances in Wireless Networks and Information Systems*; Springer: Berlin/Heidelberg, Germany, 2010; Volume 72, pp. 265–273.
32. Ambrosino, D.; Sciomachen, A. Location of Mid-Range Dry Ports in Multimodal Logistic Networks. *Procedia Soc. Behav. Sci.* **2014**, *108*, 118–128. [CrossRef]
33. Roso, V.; Brnjac, N.; Abramovic, B. Inland Intermodal Terminals Location Criteria Evaluation: The Case of Croatia. *Transp. J.* **2015**, *54*, 496–515. [CrossRef]
34. Chang, Z.; Notteboom, T.; Lu, J. A Two-Phase Model for Dry Port Location with an Application to the Port of Dalian in China. *Transp. Plan. Technol.* **2015**, *38*, 442–464. [CrossRef]
35. Wu, Q.; Zhang, H.; Wang, Y. Optimal Location of Dry Ports in the Pan-Pearl River Delta. *Matec Web Conf.* **2017**, *124*, 05001. [CrossRef]
36. Tadic, S.; Krstic, M.; Roso, V.; Brnjac, N. Dry Port Terminal Location Selection by Applying the Hybrid Grey MCDM Model. *Sustainability* **2020**, *12*, 6983. [CrossRef]
37. Saka, M.; Cetin, O. Comparing Two Judgment Scales of AHP with a Case Study: Reaching a Decision on a Dry Port Location. *WMU J. Marit. Aff.* **2020**, *19*, 427–461. [CrossRef]
38. Božičević, J.; Lovrić, I.; Bartulović, D.; Steiner, S.; Roso, V.; Škrinjar, J.P. Determining Optimal Dry Port Location for Seaport Rijeka Using AHP Decision-Making Methodology. *Sustainability* **2021**, *13*, 6471. [CrossRef]
39. Chowdhury, M.M.H.; Haque Munim, Z. Dry Port Location Selection Using a Fuzzy AHP-BWM-PROMETHEE Approach. *Marit. Econ. Logist.* **2023**, *25*, 301–329. [CrossRef]
40. Wu, Y.; Zhang, R. Game-Theoretical Method Toward Dry Port Multilevel Location Considering Capacity Constraints and Shippers' Choice Behavior. *Transp. Res. Rec.* **2023**, *2677*, 64–82. [CrossRef]
41. Nguyen, T.M.H.; van Binsbergen, A.; Dinh, C.T. Dry Port Location Selection for Integration with Inland Waterway Transport in Developing Countries: A Case Study in Northern Vietnam. *J. Supply Chain Manag. Sci.* **2024**, *5*, 1–29. [CrossRef]
42. Kine, H.Z.; Shiferaw, Z.; Gebresenbet, G.; Tavasszy, L.; Ljungberg, D. GIS Based Multi-Criteria Decision-Making Approach for Dry Port Location Analysis: The Case of Ethiopia. *Res. Transp. Bus. Manag.* **2025**, *60*, 101370. [CrossRef]
43. Jiang, X.; Hu, D. Construction and Optimization Strategy of Urban Emergency Logistics System. *Int. J. Glob. Econ. Manag.* **2024**, *2*, 353–359. [CrossRef]
44. Armaghan, N.; Pazani, M.Y. A Model for Designing a Blood Supply Chain Network to Earthquake Disasters (Case Study: Tehran City). *Int. J. Qual. Res.* **2019**, *13*, 605–624. [CrossRef]
45. Merciu, C.; Ianoş, I.; Merciu, G.-L.; Jones, R.; Pomeroy, G.M. Mapping Accessibility for Earthquake Hazard Response in the Historic Urban Centre of Bucharest. *Nat. Hazards Earth Syst. Sci.* **2018**, *18*, 2011–2026. [CrossRef]
46. Sventeková, E.; Dvořák, Z. Medical Provision of Crises Situations Solving. *Mest J.* **2013**, *1*, 82–93. [CrossRef]
47. Zhao, H.; Niu, C.; Zhang, T.; Cai, S. Review and Prospect of Emergency Logistics Under Uncertainty Conditions. *J. Risk Anal. Crisis Response* **2018**, *8*, 101. [CrossRef]
48. Malik, M.H.A.; Omar, E.N.; Daud, A. Malaysia Humanitarian Logistics: A Successful Collaboration in Humanitarian Relief Works Between NGOs in Malaysia. *Int. J. Acad. Res. Bus. Soc. Sci.* **2022**, *12*, 46–63. [CrossRef]
49. Ge, J.; Li, X.; Wu, Z.; Sun, Y.; Kanrak, M. The Distribution of Emergency Logistics Centers Under the COVID-19 Lockdown: The Case of Yangtze River Delta Area. *Sustainability* **2022**, *14*, 10594. [CrossRef]
50. Tang, Y.Y.; Zhao, X.; Yan, L.; Xiao-juan, S.; Zhao, H. Study on Location of Emergency Logistics Center Based on Improved TOPSIS, Shannon Entropy and Coordinated Development Degree Model. In Proceedings of the 2nd International Conference on Engineering Management and Information Science, EMIS 2023, Chengdu, China, 24–26 February 2023. [CrossRef]
51. Liu, J. Study on the Location of Emergency Logistics Center Under Public Health Events—A Case Study of Huai'an City. In Proceedings of the 2nd International Conference on Information, Control and Automation, ICICA 2022, Chongqing, China, 2–4 December 2022. [CrossRef]
52. Jeevan, J.; Salleh, N.H.M.; Hanafiah, R.M.; Ngah, A.H. Emergence of Emergency Logistics Centre (Elc): Humanitarian Logistics Operations at the Straits of Malacca. *Trans. Marit. Sci.* **2020**, *9*, 279–292. [CrossRef]

53. Boonmee, C.; Arimura, M.; Asada, T. Facility Location Optimization Model for Emergency Humanitarian Logistics. *Int. J. Disaster Risk Reduct.* **2017**, *24*, 485–498. [CrossRef]
54. Wang, H.; Ma, X. Research on Multiobjective Location of Urban Emergency Logistics under Major Emergencies. *Math. Probl. Eng.* **2021**, *2021*, 5577797. [CrossRef]
55. Xu, F.; Ma, Y.; Liu, C.; Ji, Y. Emergency Logistics Facilities Location Dual-Objective Modeling in Uncertain Environments. *Sustainability* **2024**, *16*, 1361. [CrossRef]
56. Liu, H.; Zhang, X. Study on Location Selection of Multi-Objective Emergency Logistics Center Based on AHP. *Proc. Procedia Eng.* **2011**, *15*, 2128–2132.
57. Yılmaz, H.; Kabak, Ö. Prioritizing Distribution Centers in Humanitarian Logistics Using Type-2 Fuzzy MCDM Approach. *J. Enterp. Inf. Manag.* **2020**, *33*, 1199–1232. [CrossRef]
58. Geng, J. An Overview of Emergency Logistics Routing and Location: Models and Future Research Directions. *SHS Web Conf.* **2024**, *181*, 03005. [CrossRef]
59. Pang, X.; Yang, W.; Miao, W.; Zhou, H.; Min, R. Study on Site Selection Evaluation of Emergency Material Storage Based on Improved TOPSIS. *Kybernetes* **2024**, *54*, 5181–5206. [CrossRef]
60. Feng, Z.; Li, G.; Wang, W.; Zhang, L.; Xiang, W.; He, X.; Zhang, M.; Wei, N. Emergency Logistics Centers Site Selection by Multi-Criteria Decision-Making and GIS. *Int. J. Disaster Risk Reduct.* **2023**, *96*, 103921. [CrossRef]
61. Fu, D.; Tang, X. Research on Location Model of Emergency Logistics Based on AHP/DEA. In Proceedings of the 2011 International Conference on Information Management, Innovation Management and Industrial Engineering, ICIII 2011, Shenzhen, China, 26–27 November 2011; Volume 3, pp. 472–474.
62. Ak, M.F.; Acar, D. Selection of Humanitarian Supply Chain Warehouse Location: A Case Study Based on the MCDM Methodology. *Eur. J. Sci. Technol.* **2021**, *22*, 400–409. [CrossRef]
63. Beklaryan, A.L.; Akopov, A.S. Simulation of Agent-Rescuer Behaviour in Emergency Based on Modified Fuzzy Clustering: (Extended Abstract). In *Proceedings of the 2016 International Conference on Autonomous Agents & Multiagent Systems (AAMAS '16), Singapore, 9–13 May 2016*; International Foundation for Autonomous Agents and Multiagent Systems: Richland, SC, USA, 2016; pp. 1275–1276. Available online: https://dl.acm.org/doi/10.5555/2936924.2937117 (accessed on 20 April 2026).
64. Zarandi, M.H.F.; Ahmadpour, P. Fuzzy Agent-Based Expert System for Steel Making Process. *Expert Syst. Appl.* **2009**, *36*, 9539–9547. [CrossRef]
65. Zadeh, L.A. The Concept of a Linguistic Variable and Its Application to Approximate Reasoning—I. *Inf. Sci.* **1975**, *8*, 199–249. [CrossRef]
66. Yildirim, U.; Inegol, G.M. Seafarer Selectıon For Sustaınable Shıppıng: Case Study For Turkey. *Trans. R. Inst. Nav. Archit. Part A Int. J. Marit. Eng.* **2023**, *165*, A71–A88. [CrossRef]
67. Inegol, G.M.; Yildirim, U. Conflicts Due to Cultural Differences in Multicultural Ships. *Aust. J. Marit. Ocean Aff.* **2024**, *17*, 67–93. [CrossRef]
68. Canımoğlu, R.; Yıldırım, U.; İnegöl, G.M. Analysis of Draught Survey Errors by Extended Fuzzy Analytic Hierarchy Process. *J. Eta Marit. Sci.* **2021**, *9*, 51–63. [CrossRef]
69. Hashemkhani Zolfani, S.; Görçün, Ö.F.; Küçükönder, H. Evaluating Logistics Villages in Turkey Using Hybrid Improved Fuzzy SWARA (IMF SWARA) and Fuzzy MABAC Techniques. *Technol. Econ. Dev. Econ.* **2021**, *27*, 1582–1612. [CrossRef]
70. Puška, A.; Štilić, A.; Nedeljković, M.; Božanić, D.; Biswas, S. Integrating Fuzzy Rough Sets with LMAW and MABAC for Green Supplier Selection in Agribusiness. *Axioms* **2023**, *12*, 746. [CrossRef]
71. Wang, N.; Xu, Y.; Puška, A.; Stević, Ž.; Alrasheedi, A.F. Multi-Criteria Selection of Electric Delivery Vehicles Using Fuzzy–Rough Methods. *Sustainability* **2023**, *15*, 15541. [CrossRef]
72. Chen, X.; Zhou, B.; Štilić, A.; Stević, Ž.; Puška, A. A Fuzzy–Rough MCDM Approach for Selecting Green Suppliers in the Furniture Manufacturing Industry: A Case Study of Eco-Friendly Material Production. *Sustainability* **2023**, *15*, 10745. [CrossRef]
73. Stojanović, I. Selection of a Green Contractor for the Implementation of a Solar Power Plant Project. *Symmetry* **2024**, *16*, 441. [CrossRef]
74. Nikravesh, M. Evolution of Fuzzy Logic: From Intelligent Systems and Computation to Human Mind. *Soft Comput.* **2008**, *12*, 207–214. [CrossRef]
75. Miao, Y.; Potts, R.; Huang, X.; Elliott, G.; Rivett, R. A Fuzzy Logic Fog Forecasting Model for Perth Airport. *Pure Appl. Geophys.* **2012**, *169*, 1107–1119. [CrossRef]
76. Kaufmann, A. Theory of Expertons and Fuzzy Logic. *Fuzzy Sets Syst.* **1988**, *28*, 295–304. [CrossRef]
77. Jia, F.; Wang, X. Rough-Number-Based Multiple-Criteria Group Decision-Making Method by Combining the BWM and Prospect Theory. *Math. Probl. Eng.* **2020**, *2020*, 8738327. [CrossRef]
78. Zhu, G.N.; Ma, J.; Hu, J. A Fuzzy Rough Number Extended AHP and VIKOR for Failure Mode and Effects Analysis under Uncertainty. *Adv. Eng. Inform.* **2022**, *51*, 101454. [CrossRef]

79. Pamučar, D.; Petrović, I.; Ćirović, G. Modification of the Best–Worst and MABAC Methods: A Novel Approach Based on Interval-Valued Fuzzy-Rough Numbers. *Expert Syst. Appl.* **2018**, *91*, 89–106. [CrossRef]
80. Keršuliene, V.; Zavadskas, E.K.; Turskis, Z. Selection of Rational Dispute Resolution Method by Applying New Step-wise Weight Assessment Ratio Analysis (Swara). *J. Bus. Econ. Manag.* **2010**, *11*, 243–258. [CrossRef]
81. Deveci, M.; Varouchakis, E.A.; Brito-Parada, P.R.; Mishra, A.R.; Rani, P.; Bolgkoranou, M.; Galetakis, M. Evaluation of Risks Impeding Sustainable Mining Using Fermatean Fuzzy Score Function Based SWARA Method. *Appl. Soft Comput.* **2023**, *139*, 110220. [CrossRef]
82. Sivageerthi, T.; Bathrinath, S.; Uthayakumar, M.; Bhalaji, R.K.A. A SWARA Method to Analyze the Risks in Coal Supply Chain Management. *Mater. Today Proc.* **2022**, *50*, 935–940. [CrossRef]
83. Seikh, M.R.; Mandal, U. Interval-Valued Fermatean Fuzzy Dombi Aggregation Operators and SWARA Based PROMETHEE II Method to Bio-Medical Waste Management. *Expert Syst. Appl.* **2023**, *226*, 120082. [CrossRef]
84. Ojha, R.; Agarwal, A. People-Centric Variables in the Fourth Industrial Revolution: An Application of SWARA Methodology. *J. Adv. Manag. Res.* **2024**, *21*, 398–420. [CrossRef]
85. Almeida, V.V.A.; Gomes, C.F.S.; Pinochet, L.H.C.; dos Santos, M. Prioritization of Investment Order in Brazil among Renewable Energy Sources: An Analysis Using the SWARA-MOORA-3NAG Method. *J. Model. Manag.* **2024**, *20*, 620–647. [CrossRef]
86. Toygar, A.; Yildirim, U.; İnegöl, G.M. Investigation of Empty Container Shortage Based on SWARA-ARAS Methods in the COVID-19 Era. *Eur. Transp. Res. Rev.* **2022**, *14*, 8. [CrossRef]
87. Wang, C.; Chen, Q.; Huang, R. Locating Dry Ports on a Network: A Case Study on Tianjin Port. *Marit. Policy Manag.* **2017**, *45*, 71–88. [CrossRef]
88. Ng, A.K.Y.; Cetin, I.B. Locational Characteristics of Dry Ports in Developing Economies: Some Lessons from Northern India. *Reg. Stud.* **2012**, *46*, 757–773. [CrossRef]
89. Mohan, V.G.; Naseer, M.A. Dry Port Location Factor Determination Using Delphi in Peninsular Region. *Trans. Marit. Sci.* **2022**, *11*, 169–184. [CrossRef]
90. Abdoulkarim, H.T.; Fatouma, S.H.; Kalgora, B. The Selection of Dry Port Location by Analytic Network Process Model: A Case Study of Dosso-Niger. *J. Transp. Technol.* **2019**, *9*, 146–155. [CrossRef]
91. Guo, Y.; Matsuda, T. Study on the Multi-Criteria Location Decision of Wide-Area Distribution Centers in Pre-Disaster: Case of an Earthquake in the Kanto District of Japan. *Asian Transp. Stud.* **2023**, *9*, 100107. [CrossRef]
92. Mohan, V.G.; Naseer, M.A. Prioritisation of Dry Port Locations Using MCDM Methods: A Case of Cochin Port. *J. Inst. Eng. (India) Ser. A* **2022**, *103*, 841–856. [CrossRef]
93. Rodrigues, A.C.; Macedo, R.d.C.; Martins, R.S. Technological Drivers of Dry Port Efficiency in Brazil. *Rev. De Gestão* **2023**, *30*, 176–189. [CrossRef]
94. Xu, H.; Liu, J.; Qi, S. Incentive Policy for Rail-Water Multimodal Transport: Subsidizing Price or Constructing Dry Port? *Transp. Policy* **2024**, *150*, 219–243. [CrossRef]
95. Asadi Dalivand, A.; Torabi, S.A. Sustainable-Resilient Seaport-Dry Port Network Design Considering Inter-Modal Transportation. *J. Clean. Prod.* **2024**, *452*, 141944. [CrossRef]
96. Lovrić, I.; Bartulović, D.; Steiner, S. Influence of Dry Port Establishment on Regional Development Through Regional Development Index. *Trans. Marit. Sci.* **2020**, *9*, 293–315. [CrossRef]
97. Bhatti, O.K.; Hanjra, A.R. Development Prioritization through Analytical Hierarchy Process (AHP)—Decision Making for Port Selection on the One Belt One Road. *J. Chin. Econ. Foreign Trade Stud.* **2019**, *12*, 121–150. [CrossRef]
98. Abdoulkarim, H.T.; Fatouma, S.H.; Munyao, E.M. Dry Ports in China and West Africa: A Comparative Study. *Am. J. Ind. Bus. Manag.* **2019**, *9*, 448–467. [CrossRef]
99. Golghamat Raad, N.; Rajendran, S. A Hybrid Scenario-Based Fuzzy Stochastic Model for Closed-Loop Dry Port Network Design with Multiple Robustness Measures. *Transp. Res. E Logist. Transp. Rev.* **2024**, *183*, 103417. [CrossRef]
100. Schulz, S.F.; Blecken, A. Horizontal Cooperation in Disaster Relief Logistics: Benefits and Impediments. *Int. J. Phys. Distrib. Logist. Manag.* **2010**, *40*, 636–656. [CrossRef]
101. Ng, A.K.Y.; Gujar, G.C. Government Policies, Efficiency and Competitiveness: The Case of Dry Ports in India. *Transp. Policy* **2009**, *16*, 232–239. [CrossRef]
102. Facchini, F.; Digiesi, S.; Mossa, G. Optimal Dry Port Configuration for Container Terminals: A Non-Linear Model for Sustainable Decision Making. *Int. J. Prod. Econ.* **2020**, *219*, 164–178. [CrossRef]
103. Qiu, X.; Lam, J.S.L.; Huang, G.Q. A Bilevel Storage Pricing Model for Outbound Containers in a Dry Port System. *Transp. Res. E Logist. Transp. Rev.* **2015**, *73*, 65–83. [CrossRef]
104. Kurnia, G.; Adzkia, H.F.; Rachmawati, N.L. Rachmawati Dry Port Location Selection: A Case Study of Tanjung Intan Port. *J. Emerg. Supply Chain Clean Energy Process Eng.* **2023**, *2*, 45–58. [CrossRef]
105. Liu, H.Z.; Liu, L.N. Multi-Objective Location Model Research and Application in the City Emergency Logistics Based on Different Product Materials. *Appl. Mech. Mater.* **2011**, *63–64*, 277–280. [CrossRef]

106. Awad-Núñez, S.; Camarero, A.; Awad Núñez, S.; Cancelas, N.G.; Orive, A.C. Setting of Weighting Factors Influencing the Determination of the Location of Dry Ports Using a DELPHI Methodology. In *Proceedings of the 1st International Virtual Scientific Conference*; University of Zilina: Zilina, Slovakia, 2013; pp. 505–510.
107. Black, J.; Roso, V.; Marušić, E.; Brnjac, N. Issues in Dry Port Location and Implementation in Metropolitan Areas: The Case of Sydney, Australia. *Trans. Marit. Sci.* **2018**, *7*, 41–50. [CrossRef]
108. Roso, V. The Emergence and Significance of Dry Ports: The Case of the Port of Goteborg. *World Rev. Intermodal Transp. Res.* **2009**, *2*, 296–310. [CrossRef]
109. Allen, A.M.; Kovács, G.; Masini, A.; Vaillancourt, A.; Wassenhove, L.V. Exploring the Link Between the Humanitarian Logistician and Training Needs. *J. Humanit. Logist. Supply Chain Manag.* **2013**, *3*, 129–148. [CrossRef]
110. Rohmawati, S.; Saleh, H.H.M.; Syamsuddin, S. The Distribution Model of Humanitarian Logistics in Optimizing Disaster Management in Pasigala in Central Sulawesi. *Tadulako Int. J. Appl. Manag.* **2021**, *3*, 47–59. [CrossRef]
111. Roso, V.; Lumsden, K. A Review of Dry Ports. *Marit. Econ. Logist.* **2010**, *12*, 196–213. [CrossRef]
112. Hanaoka, S.; Regmi, M.B. Promoting Intermodal Freight Transport Through the Development of Dry Ports in Asia: An Environmental Perspective. *Iatss Res.* **2011**, *35*, 16–23. [CrossRef]
113. Wang, W.; Wu, S.; Wang, S.; Zhen, L.; Qu, X. Emergency Facility Location Problems in Logistics: Status and Perspectives. *Transp. Res. E Logist. Transp. Rev.* **2021**, *154*, 102465. [CrossRef]
114. Li, L.; Wen, H.; Zhang, Q. Characterizing the Role of Weibo and WeChat in Sharing Original Information in a Crisis. *J. Contingencies Crisis Manag.* **2022**, *31*, 236–248. [CrossRef]
115. Zhang, R. Multi-Level Site Selection of Mobile Emergency Logistics Considering Safety Stocks. *Appl. Sci.* **2023**, *13*, 11245. [CrossRef]
116. Feng, X.; Zhang, Y.; Li, Y.; Wang, W. A Location-Allocation Model for Seaport-Dry Port System Optimization. *Discret. Dyn. Nat. Soc.* **2013**, *2013*, 309585. [CrossRef]
117. Facchini, F.; Digiesi, S.; Ranieri, L. A Model for Economic and Environmental Evaluation of Inter-/Intra-Terminal Containers Flows. In *Proceedings of the 24th International Conference on Production Research (ICPR 2017), Poznan, Poland, 30 July–3 August 2017*; DEStech Publications: Lancaster, PA, USA, 2018; pp. 732–737. [CrossRef]
118. Roso, V. Evaluation of the Dry Port Concept from an Environmental Perspective: A Note. *Transp. Res. D Transp. Environ.* **2007**, *12*, 523–527. [CrossRef]
119. Li, H.; Yang, J.; Xiang, Z. A Fuzzy Linguistic Multi-Criteria Decision-Making Approach to Assess Emergency Suppliers. *Sustainability* **2022**, *14*, 13114. [CrossRef]
120. Zain, R.M.; Zahari, H.M.; Zainol, N.A.M. Inter-Agency Information Sharing Coordination on Humanitarian Logistics Support for Urban Disaster Management in Kuala Lumpur. *Front. Sustain. Cities* **2023**, *5*, 1149454. [CrossRef]
121. Das, R. Disaster Preparedness for Better Response: Logistics Perspectives. *Int. J. Disaster Risk Reduct.* **2018**, *31*, 153–159. [CrossRef]
122. Agostinelli, S.; Cumo, F.; Nezhad, M.M.; Orsini, G.; Piras, G. Renewable Energy System Controlled by Open-Source Tools and Digital Twin Model: Zero Energy Port Area in Italy. *Energies* **2022**, *15*, 1817. [CrossRef]
123. Wang, S.; Luo, Y.; Liu, Z.; Lu, B. Analysis on Energy Conservation and Emission Reduction Efficiency and Influencing Factors for Ports around Bohai in China under the Low Carbon Target. *Sustainability* **2022**, *14*, 14765. [CrossRef]
124. Mata-Lima, H.; Galuzzi Silva, M.C.; Emilien, M.; Silveira, A.P.; Sacht, H.M.; Vettorazzi, E.; Morgado-Dias, F. Identifying and Ranking Environmental Aspects of a Dry Port in Foz Do Iguaçu City, Paraná-Brazil. *Environ. Qual. Manag.* **2019**, *29*, 57–62. [CrossRef]
125. Popp, J.; Nestler, S.; Nobel, T.; Olah, J. Development of Dry Ports in Europe. *Int. J. Appl. Manag. Sci.* **2018**, *10*, 269–289. [CrossRef]
126. Kurtuluş, E.; Çetin, İ. Assessing the Environmental Benefits of Dry Port Usage: A Case of Inland Container Transport in Turkey. *Sustainability* **2019**, *11*, 6793. [CrossRef]
127. Wang, N. Development of a Comprehensive Evaluation Method in Energy Efficiency and CO2 Emission Levels for Dry Bulk Terminals. In *Proceedings of the Fourth International Conference on Intelligent Traffic Systems and Smart City (ITSSC 2024), Xi'an, China, 23–25 August 2024*; SPIE: Bellingham, WA, USA, 2025; Volume 13422, p. 134222O. [CrossRef]
128. Awad-Núñez, S.; González-Cancelas, N.; Camarero-Orive, A. Application of a Model Based on the Use of DELPHI Methodology and Multicriteria Analysis for the Assessment of the Quality of the Spanish Dry Ports Location. *Procedia Soc. Behav. Sci.* **2014**, *162*, 42–50. [CrossRef]
129. Muravev, D.; Rakhmangulov, A.; Hu, H.; Zhou, H. The Introduction to System Dynamics Approach to Operational Efficiency and Sustainability of Dry Port's Main Parameters. *Sustainability* **2019**, *11*, 2413. [CrossRef]
130. Negi, S. Humanitarian Logistics Challenges in Disaster Relief Operations: A Humanitarian Organisations' Perspective. *J. Transp. Supply Chain Manag.* **2022**, *16*, 691. [CrossRef]
131. Ping, L.; Fan, X.P. The Application of the Improved Jellyfish Search Algorithm in a Site Selection Model of an Emergency Logistics Distribution Center Considering Time Satisfaction. *Biomimetics* **2023**, *8*, 349. [CrossRef] [PubMed]

132. Diehlmann, F.; Lüttenberg, M.; Verdonck, L.; Wiens, M.; Zienau, A.; Schultmann, F. Public-Private Collaborations in Emergency Logistics: A Framework Based on Logistical and Game-Theoretical Concepts. *Saf. Sci.* **2021**, *141*, 105301. [CrossRef]
133. Zamiar, Z.; Kowalkowski, S. Selected Aspects of Military Logistic Support to Public Administration in Eliminating the Effects of Crisis Situations. *Logist. Transp.* **2021**, *49*, 59–72. [CrossRef]
134. Masudin, I.; Lau, E.; Safitri, N.T.; Restuputri, D.P.; Handayani, D. The Impact of the Traceability of the Information Systems on Humanitarian Logistics Performance: Case Study of Indonesian Relief Logistics Services. *Cogent Bus. Manag.* **2021**, *8*, 1906052. [CrossRef]
135. Regis-Hernández, F.; Mora-Vargas, J.; Ruiz, A. A Multi-Criteria Vertical Coordination Framework for a Reliable Aid Distribution. *J. Ind. Eng. Manag.* **2017**, *10*, 789. [CrossRef]
136. Padgett, J.E.; DesRoches, R. Bridge Functionality Relationships for Improved Seismic Risk Assesment of Transportation Networks. *Earthq. Spectra* **2007**, *23*, 115–130. [CrossRef]
137. Tak, H.Y.; Suh, W.; Lee, Y.J. System-Level Seismic Risk Assessment of Bridge Transportation Networks Employing Probabilistic Seismic Hazard Analysis. *Math. Probl. Eng.* **2019**, *2019*, 6503616. [CrossRef]
138. Mason, D.; Brabhaharan, P. Characterisation of Transport Resilience and Measures to Enhance Resilience in the Recovery after the 2016 Kaikōura Earthquake. *Bull. New Zealand Soc. Earthq. Eng.* **2021**, *54*, 69–81. [CrossRef]
139. Liu, Z.; Suzuki, T. Using Agent Simulations to Evaluate the Effect of a Regional BCP on Disaster Response. *J. Disaster Res.* **2018**, *13*, 387–395. [CrossRef]

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.