Capacitated Location-Allocation Model for Emergency Supply Chain: The Case of Morocco

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Abstract—Recently, Morocco has experienced a series of disasters, including the El Haouz earthquake in 2023, which have brought renewed attention to the country's emergency preparedness and the efficiency of its national emergency supply chain. In addition, this study considers a prospective scenario based on potential flood events in northern Morocco to evaluate future resilience requirements. In this context, improving the strategic planning of Emergency Supply Facilities (ESFs) is essential for strengthening disaster response capabilities. This study develops a capacitated location–allocation optimization model for emergency supply chain planning that incorporates demand uncertainty, flexible allocation of ESFs, and donor contributions. The proposed framework is evaluated through computational experiments using problem instances consisting of multiple candidate ESF locations, demand points, and disruption scenarios, allowing the analysis of different emergency response configurations. The results indicate that the proposed optimization framework can significantly improve the efficiency and responsiveness of Morocco's emergency supply chain. The model provides a practical decision-support tool for policymakers and planners to enhance disaster preparedness and resource allocation in national emergency logistics systems.

Keywords—Emergency logistics; disaster response; location–allocation; stochastic demand; supply chain resilience

I. INTRODUCTION

Over the past two decades, a notable rise in the rate of natural and man-made disasters has been observed, creating unprecedented problems for the existing humanitarian logistics system [1],[2]. Morocco is no exception to the above-mentioned phenomenon. The El Haouz earthquake that struck Morocco in 2023 is a prime example of the structural shortcomings of the emergency logistics system. The natural disaster caused 2,946 deaths, 6,000 injuries, and the destruction of 59,647 buildings. The disaster also devastated 163 villages [3]. The structural shortcomings of the emergency logistics system were reflected through the pre-positioning of stock, the disaster response operations, and the coordination of the response activities of the different government entities, the private sector, and the NGOs [4]. Similar shortcomings were evident during the floods that struck Morocco in 2010. The floods as well as the wildfires that ravaged the Rif region and the Middle Atlas region. In addition to the above-mentioned disasters, the supply chain of the entire nation was also affected due to the COVID-19 pandemic [5].

In response to these challenges, Morocco has diversified its approach to be more proactive and institutionally involved in disaster preparedness. The national strategy for disaster risk management (Stratégie Nationale de Gestion des Risques de Catastrophes 2020-2030) outlines a national vision to address these challenges by promoting decentralization, territorial preparedness, and logistical autonomy [6]. An integral part of this strategy is the development of ESFs at the regional level by risk typology (natural, humanitarian, and accident risks) [7].In this context, the Moroccan government has recently announced its plans to invest more than 7 billion MAD to develop the framework for the national stockpile and upgrade emergency storage infrastructure [8].

However, there are still some structural challenges to be addressed by the Morocco ESF Program. Firstly, there is considerable uncertainty regarding disaster demands in terms of their spatial characteristics and magnitudes. Empirical studies on large-scale disasters worldwide have shown that there are considerable differences between predicted demands and actual demands during disasters. Therefore, it is necessary to consider stochastic models to avoid under-provisioning and over-allocation. Secondly, there were considerable challenges regarding volunteer contributions during the El Haouz earthquake in Morocco. Even though there were sufficient volunteer contributions during emergencies, there were problems with efficiency due to unorganized logistics. Evidence suggests that unorganized delivery can lead to congestion, redundant delivery, excess storage capacity, and considerable differences between demands and supplies during emergencies [9]. This has been experienced during recent earthquakes worldwide in Kermanshah (Iran), Wenchuan (China), and Van (Turkey) [10].

Collectively, these factors highlight the need for the development of an effective emergency logistics system within the Moroccan context, accompanied by a modeling approach that takes into consideration various aspects of uncertainty. In the context of emergency logistics, location-allocation models are recognized as fundamental models for effectively addressing the challenges associated with emergencies [11],[12],[13]. The integration of stochastic factors into location-allocation models for emergency scenario evaluation post-event has been identified as a significant advancement within the emergency logistics literature[14]. Nevertheless, various location-allocation models for emergency response planning failed to incorporate various aspects relevant to the Moroccan context. As such, the objective of this research is to develop a capacitated location-allocation model for strategic emergency supply planning within the context of Morocco, taking into consideration various aspects relevant to the country's emergency response planning, including various

policy guidelines. In addition, the proposed approach aims to improve the decision-making of national disaster management authorities and regional planners while accounting for demand uncertainty within the framework of the disaster management policy guidelines for the country.

The remainder of the study is organized as follows: In Section II, the recent literature on location-allocation modeling techniques is reviewed. In Section III, the proposed optimization model for emergency response planning in the Moroccan context is presented. In Section IV, the simulation approach used for the proposed model is presented. In Section V, the results and discussion are presented, with emphasis on the Moroccan context.

II. Literature Review

Facility Location-Allocation (FLA) models constitute one of the foundational pillars of humanitarian logistics, enabling a systematic framework for determining the location of emergency facilities and ensuring the effective coverage of the affected disaster zones. Recent state-of-the-art publications indicate that the humanitarian facility location problem has evolved gradually, moving from simple deterministic mathematical formulations to incorporate uncertainty elements in disaster scenarios [15]. In particular, two-stage stochastic mixed-integer programming has been used to account for uncertainty in disaster intensity and the probabilistic variability of affected regions to improve the supply pre-positioning resilience[16][17]. Related optimization approaches have simultaneously addressed congestion, network disruptions, and reliability concerns using hybrid approaches, incorporating both stochastic and robust uncertainty [18],[19]. Equity and timeliness have also been integrated to allow the resolution of the FLA problem, focusing on multicriterial mathematical formulations. Those publications aimed to provide a trade-off between the solution quality and related costs [20]. Recent publications have explored the use of robust optimization approaches to deal with the large-scale FLA problems under conditions of deep uncertainty [21]. Overall, these contributions document significant methodological advances to deal with the uncertainty, capacity constraints, and congestion effects related to the FLA mathematical formulation. From a governance perspective, recent studies have considered the importance of aligning facility location-allocation models with national strategies for disaster responses. In the Chinese context, several optimization models have been developed for the strategic placement of emergency material reserves, with objectives aligned with the central government's strategic agendas and the structural frameworks for administrative responsibilities and equity with respect to geographic locations [22], [23]. Similarly, humanitarian logistics research addressing specific types of disasters like the COVID-19 pandemic also reflects the influence of health strategies and institutional rules for coordination at the national level for specific solution approaches in the design of models for the United States healthcare system [24], while vaccine distribution models for Mexico emphasizes the role of specific government policies for optimized facility placement and allocation for delivery [25]. These papers support the rationale for the strategic importance of institutional alignment when applying optimized solutions for location-allocation models in emergency logistics, but provide limited generalization for broader solution application using different national policy strategies. As outlined in Table I, the current literature provides a solid methodological and conceptual foundation but offers comparatively little attention to the direct incorporation of Moroccan disaster risk reduction instruments such as the SNGRC 2020-2030 [1]and the national ESF Program into FLA models.

In a national context such as Morocco, where emergency logistics is shifting towards a decentralized approach and the establishment of a national stockpile network, there is a pressing need for modeling approaches that are directly incorporated in the Moroccan government's stated objectives. To the best of our knowledge, no existing scientific work has explicitly incorporated elements of Morocco DRR governance framework into its formulation, resulting in a significant gap of the broader strategic alignment of current FLA models to the Moroccan context.

TABLE I. Modeling-Oriented Contributions

Reference	Problem Type	Decision Level	Modeling Method	Modeling Approach	Disaster Phase	Relevance to Morocco
[26]	Location–inventory prepositioning	Strategic/Tactical	Stochastic Optimization	Two-Stage Stochastic Programming (MILP) + Scenarios	Preparedness (pre-positioning)	High
[27]	Relief network design (facility + flow)	Strategic	Hybrid Stochastic–Robust Optimization	Stochastic MILP + Robust Optimization (Min–Max / Arc Protection)	Response	High
[28]	Multi-echelon location–allocation with equity	Strategic/Tactical	Stochastic Optimization	Multi-period Stochastic MILP	Multi-phase (preparedness + response)	High
[29]	Facility location & stock pre-positioning with transsshipments	Strategic/ Tactical	Stochastic Optimization	Scenario-based Stochastic MILP with Transsshipments	Preparedness	High
[30]	Facility location + routing	Operational	Risk-Averse Stochastic Optimization	Stochastic MILP with Mean–CVaR Objective	Response	Medium

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[1] Stratégie Nationale de Gestion des Risques des Catastrophes Naturelles 2020-2030

[31]	Emergency facility location (multi-objective)	Strategic	Multi-Objective Optimization	Bi-objective MILP (Cost–Time Trade-off)	Response	High
[32]	Two-stage emergency logistics (reserve + deployment)	Strategic /Tactical	Stochastic Optimization	Two-Stage Stochastic Programming (MILP)	Preparedness & response	High
[33]	Facility location & distribution routing	Operational	Distributionally Robust Optimization	Distributionally Robust MILP (Worst-case Mean–CVaR)	Response	Medium
[34]	Emergency facility location–allocation	Strategic / Tactical	Uncertainty-Theory-Based Optimization	Uncertainty-Theory-Based Bi-objective LP	Response	Medium
[35]	Resource allocation & facility usage coordination	Tactical	Stochastic Optimization	Scenario-based Stochastic MILP	Response	High
[36]	Emergency logistics network design	Strategic	Stochastic Optimization	Stochastic MILP with Reliability Constraints	Response	Medium
[37]	Covering-type facility location for mobile units	Strategic	Scenario-Based Optimization	Set-Covering MILP + Scenario Analysis	Response	Medium
[38]	Dynamic ambulance location / relocation	Operational	Dynamic Stochastic Optimization	Time-dependent Stochastic MILP	Immediate response	Medium
[39]	Logistics center location (ELCs)	Strategic	Robust Optimization	Robust MILP (Interval Uncertainty)	Preparedness	High
[40]	Joint location–allocation–routing	Operational	Stochastic Optimization	Integrated Location–Routing Stochastic MILP	Response	Medium
[41]	Relief-item prepositioning (facility selection & stock levels)	Strategic/ Tactical	Stochastic Optimization	Scenario-based Stochastic Programming (MILP)	Preparedness	High
[42]	Emergency logistics network routing & allocation	Tactical /Operational	Stochastic Optimization	Stochastic MILP + Metaheuristic Solution	Response	Medium
[43]	Governance & coordination of relief logistics	Strategic	Qualitative / Conceptual Modeling	Qualitative Case Study / Conceptual Framework	Response	High
[44]	Risk assessment & relief-chain design	Strategic	Fuzzy Multi-Criteria Decision-Making (MCDM)	Fuzzy AHP / Fuzzy MCDM	Preparedness	High
[45]	Evaluation of earthquake response strategies	Strategic	Multi-Criteria Decision-Making (MCDM)	MCDM Preference Modelling (AHP / TOPSIS / PROMETHEE)	Preparedness & response	High
[46]	Transport-network support to emergency logistics	Operational	Qualitative / Empirical Analysis	Empirical Assessment + Conceptual Analysis	Response & recovery	Medium
[47]	Post-disaster logistics resilience (construction materials)	Tactical	Empirical / Conceptual Modeling	Empirical Statistical Analysis + Conceptual Framework	Recovery	Low

The literature review highlights the critical role of incorporating uncertainty in demand, supply disruptions, and network reliability into the model. Two-stage stochastic programming and robust optimization are repeatedly identified, indicating a methodological preference to handle variability in post-disaster demand and operational constraints [28],[29], [30], [32], [33], [37], [40], [44], [46], [47]. Multiple studies have also focused on multi-objective/hybrid models to balance costs, time, and equity, demonstrating that emergency logistics models extend beyond efficiency to include resilience and fairness. Several studies address multiple planning levels simultaneously, particularly strategic facility location decisions combined with tactical allocation or inventory planning.

This literature is highly relevant to the Moroccan context, particularly for designing the network of ESFs to respond to disasters such as the 2023 El Haouz earthquake [43] and the floods that affected northern Morocco in early 2026. Similar to these studies, our capacitated location–allocation model explicitly accounts for stochastic post-disaster demand, distinguishing between Uniform and Normal distributions, and incorporates local suppliers and donors in resource allocation. The results and discussions in our article confirm that the nature of demand strongly impacts shortage levels, transportation costs, and warehouse utilization, which aligns with the general findings of the literature that scenario-based uncertainty profoundly affects network performance[16],[48]. Additionally, the inclusion of donor contributions in our model mirrors the literature's recognition of multiple supply sources as a key factor for resilience, highlighting the importance of integrating both local and external resources in Morocco's emergency logistics planning.

The literature review results indicate that emergency logistics network problems are largely investigated using stochastic and robust optimization techniques, often employing scenario analysis. Two-stage stochastic programming and distribution robust optimization [32],[33],[39],[41] are frequently used methodologies in addressing emergency logistics problems, which reflects the preference for considering uncertainties in demand after disasters. Some papers also address multi-objective or hybrid problems in emergency logistics [27],[38]which reflects the applicability of these models in addressing not only efficiency but also other aspects of emergency response.

The above literature review results are highly relevant to the Moroccan emergency response scenario, especially in relation to the ESF network that could be used in responding to disasters like the 2023 El Haouz earthquake or floods in northern Morocco in early 2026. Similar to the above papers, the proposed capacitated location-allocation model considers stochastic demand in emergency scenarios, distinguishing between Uniform and Normal distributions. Additionally, the study considers local suppliers as part of the emergency response. The results reported in the study corroborate that demand indeed impacts the emergency response in terms of shortage, cost, and warehouse capacity, as reported in the literature, and that scenario analysis impacts the results in emergency response scenarios. Additionally, the consideration of donor contribution in the study reflects the literature's emphasis on considering various supply chain resources as an essential aspect of emergency response.

III. PROBLEM STATEMENT

Morocco has witnessed various types of disasters in the recent past, including the early 2026 floods in the northern region of the country and the El Haouz earthquake in 2023. The main challenges in the emergency logistics response in Morocco include the uncertainty of demand in terms of both size and location, lack of coordination between the government, volunteers, and donors, as well as the distribution of prepositioned resources, which can lead to unmet demand, congestion, and high operating costs[43].

The literature on emergency logistics response, including the use of facility location-allocation models, suggests that the uncertainties of demand, supply, and the reliability of the response system can be managed using stochastic optimization techniques[49]. Although two-stage stochastic programming and DR-MILP have been the preferred techniques in emergency response models[50], literature on the application of the model in the context of Morocco, including the decentralized ESF network, the role of both local suppliers[51], [52], and donors, are not well represented.

In view of the gaps identified in the literature, the study aims to answer the following research questions:

- How would a capacitated location-allocation model be defined to optimize the placement of Emergency Support Facilities (ESFs) in Morocco in the face of uncertain demands?

- What is the effect of the characteristics of post-disaster demands in terms of Uniform and Normal distributions?

- In what ways can local suppliers and donors be utilized to augment the strength of the emergency response network in Morocco?

- What are the effects of the stochastic characteristics of the demands and the supplies from multiple sources in strategic decision-making in the context of disaster response and preparedness in Morocco?

- What trade-offs are involved in the operations to achieve a lower cost in supplying the disaster response to the diverse regions in Morocco?

These questions provide a framework to improve the efficiency of the disaster response chain in Morocco, enabling prompt delivery of goods during disaster events while promoting resilience in resource management. To address these challenges, a capacitated location-allocation mathematical model is developed to incorporate stochastic post-disaster demand, capacities, as well as multisource supplies, including local suppliers as well as donors. The next section provides a detailed explanation of this model, including variables, constraints, and objective functions that guide strategic decisions for the emergency response chain in Morocco.

IV. MATHEMATICAL MODEL

The proposed mathematical model aims to find the optimal locations and allocations of ESFs under demand uncertainty. The model considers the pre-positioning of inventory from local and international suppliers and incorporates the contributions of donors, as needed, after the disaster strikes.

The model incorporates sets that correspond to candidate warehouses, disaster-affected zones, suppliers, and donors, as well as relevant parameters that correspond to warehouse opening and storage costs, demand before and after the disaster, transportation and logistics costs, storage capacity, and the percentage of local supply that is mandatory, as presented in Fig. 1.
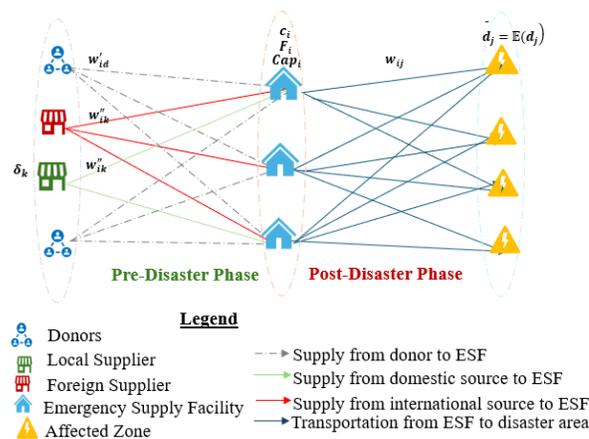

Fig. 1. The conceptual model of emergency supply chain.

The decision variables correspond to the selection of opened warehouses, demand zone allocations, supplier and donor contributions, and quantities of pre-positioned and post-disaster donations.

The objective function aims to minimize the total system cost, which comprises warehouse opening costs, pre-disaster supplier logistics costs, post-disaster donor logistics costs, storage costs of pre-positioned inventory in warehouses, and transportation costs to demand zones based on the expected demand in the aftermath of the disaster [53], [54], [55].

This problem is formulated as a Mixed Integer Linear Programming problem, subject to certain conditions and constraints that need to be met in order for the problem to remain operationally viable.

The constraints include determining the actual number of warehouses that need to be operational, determining the demand zone allocation for a single operational warehouse, ensuring that only operational warehouses receive contributions from suppliers and donors, ensuring that the capacity is not exceeded in the warehouses, ensuring that the minimum level is maintained in the local area, ensuring that donor contributions are activated to cover demand deficiencies, and ensuring that domain conditions are met for binary and continuous variables.

In order to simplify the problem and the model, certain assumptions have been made. The assumptions include the following: the model is static, construction time is not considered for ESFs, storage capacity is limited in the warehouses, donor logistics costs are limited, supplier logistics costs include acquisition, transportation, and storage, post-disaster demand is represented in terms of its expected value, pre-disaster demand is deterministic, donations are activated if post-disaster demand is in excess of pre-positioned stock, to simplify the model, all ESFs are treated as a cluster, and donors may be assigned to a warehouse but may not activate donations if the warehouse is already in possession of sufficient stock. These assumptions, together with the constraints and objectives, allow the model to effectively support decision-making for disaster preparedness and response.

V. MATHEMATICAL FORMULATION

The model aims to identify the location/allocation of ESFs under demand uncertainty. It also plans pre-positioned inventory from local and international sources, as well as donor contributions if needed, after a disaster strikes.

A. Sets and Parameters

1) Sets:

I : set of candidate warehouses (ESFs), indexed by i.
J : set of disaster-affected zones, indexed by j.
K : set of suppliers (local and foreign), indexed by k.
D : set of donors, indexed by d.

2) Parameters

F_i	*Fixed cost to open warehouse i*
c_i	Unit storage cost at warehouse i

$\bar{d}_j = \mathbb{E}(d_j)$	Expected post-disaster demand at zone j
w_{ij}	Transportation cost per unit from warehouse i to zone j
w''_{ik}	Logistics cost per unit from supplier k to warehouse i (acquisition + transport + storage)
w'_{id}	Logistics cost per unit from donor d to warehouse i (transport + handling)
Cap_i	Maximum storage capacity of warehouse i
α	Minimum fraction of stock from local suppliers
δ_k	Local supplier indicator $= \begin{cases} 1 & \text{if supplier } k \text{ is local} \\ 0 & \text{otherwise} \end{cases}$

B. Objective Function

$$\min Z = \sum_{i \in I} F_i x_i + \sum_{i \in I} \sum_{k \in K} w''_{ik} q_{ik} + \sum_{i \in I} \sum_{d \in D} w'_{id} q'_{id} + \sum_{i \in I} c_i q_i + \sum_{i \in I} \sum_{j \in J} w_{ij} f_{ij}$$

The first term represents the cost of establishing and running the warehouses.

The second term represents the pre-disaster logistics cost for supplying these warehouses from suppliers, which is proportional to the actual amount shipped.

The third term represents the post-disaster logistics cost for delivering donations to the warehouses, which includes only the transportation of donated materials.

The fourth term represents the storage cost of pre-positioned inventory contained in the warehouses before the disaster.

The fifth term represents the post-disaster transportation cost for delivering relief materials from the warehouses to the demand zones, conditional on the amount shipped.

Although service-oriented objectives such as minimizing unmet demand or response time are often considered primary priorities in humanitarian supply chains, cost optimization remains an important factor in strategic planning due to limited operational budgets and resource constraints. In this study, the objective function focuses on minimizing total logistics costs to support decision-makers in designing an efficient emergency supply network. However, the model also captures service-level considerations indirectly through shortage costs associated with unmet demand in Section VII.

C. Decision Variables

1) Binary variables

Variable	Description
x_i	Equal to 1 if warehouse i is opened, 0 otherwise
y_{ij}	Equal to 1 if zone j is assigned to warehouse i, 0 otherwise

Variable	Description
z_{ik}	Equal to 1 if supplier k supplies warehouse i, 0 otherwise
h_{id}	Equal to 1 if donor d supplies warehouse i, 0 otherwise

2) Continuous flow variables

$q_{ik} \geq 0$	Quantity shipped from supplier k to warehouse i
$q'_{id} \geq 0$	Quantity donated by donor d to warehouse i
$f_{ij} \geq 0$	Quantity shipped from warehouse i to zone j

3) Derived variables

$q_i^L = \sum\limits_{k \in K, \delta_k = 1} q_{ik}$	Local stock stored at warehouse i
$q_i^F = \sum\limits_{k \in K, \delta_k = 0} q_{ik}$	Foreign stock stored at warehouse i
$q_i = q_i^L + q_i^F$	Total pre-positioned stock at warehouse i
$q'_i = \sum\limits_{d \in D} q'_{id}$	Total donations received at warehouse i

D. Constraints

The model is subject to the following MILP constraints:

$$\sum_{i \in I} x_i = P \tag{1}$$

$$\sum_{i \in I} y_{ij} = 1, \forall j \in J \tag{2}$$

$$y_{ij} \leq x_i, \forall i, j \tag{3}$$

$$z_{ik} \leq x_i, \forall i, k \tag{4}$$

$$h_{id} \leq x_i, \forall i, d \tag{5}$$

$$q_{ik} \leq M z_{ik}, \forall i, k \tag{6}$$

$$q'_{id} \leq M h_{id}, \forall i, d \tag{7}$$

$$q_i^L = \sum_{k \in K, \delta_k = 1} q_{ik}, \forall i \tag{8}$$

$$q_i^F = \sum_{k \in K, \delta_k = 0} q_{ik}, \forall i \tag{9}$$

$$q_i = q_i^L + q_i^F, \forall i \tag{10}$$

$$q'_i = \sum_{d \in D} q'_{id}, \forall i \tag{11}$$

$$q_i + q'_i \leq Cap_i x_i, \forall i \tag{12}$$

$$q_i^L \geq \alpha q_i, \forall i \tag{13}$$

$$\sum_{j \in J} f_{ij} \leq q_i + q'_i, \forall i \tag{14}$$

$$f_{ij} \leq M y_{ij}, \forall i, j \tag{15}$$

$$\sum_{i \in I} f_{ij} = \bar{d}_j, \forall j \tag{16}$$

$$q'_i \geq \sum_{j \in J} f_{ij} - q_i, \forall i \tag{17}$$

$$x_i, y_{ij}, z_{ik}, h_{id} \in \{0,1\}, \quad q_{ik}, q'_{id}, f_{ij}, q_i, q'_i \geq 0 \tag{18}$$

The model is composed of a group of constraints that have been designed to ensure the efficient operation of the supply network. Constraint (1) ensures that only P warehouses open from the considered locations. In constraint (2), each zone affected by the disaster is to be assigned to a single warehouse. Constraint (3) ensures that each zone is allocated exclusively to an open warehouse. Constraints (4) and (5) imply that each supplier is allowed to make deliveries only to an open warehouse, as is each donor. Constraints (6) and (7) relate to the flow of materials to the warehouse and to opening the warehouse, where the corresponding decision variable is set to 1. Constraints (8) and (9) relate to the decomposition of pre-positioned inventory between local and foreign sources based on the suppliers, considering the importance of resilience and sovereignty-oriented sourcing strategies, as discussed in [52], while Constraint (10) defines the total pre-positioned inventory in each warehouse. Constraint (11) defines the total donations received by each warehouse. Constraint (12) relates to the capacity of each warehouse and is only applicable if the warehouse is open. Constraint (13) defines the minimum fraction of the pre-positioned inventory that is required to be local. Constraint (14) ensures that the total quantity shipped out from the warehouse does not exceed the sum of its pre-positioned inventory and its donations. Constraint (15) ensures that the goods are shipped only between the warehouse and the zone to which it is assigned. Constraint (16) ensures that the total expected demand of each zone is fully met. Constraint (17) states that the donations may be used for meeting demand only if the pre-positioned inventory is insufficient. Constraint (18) defines the domain of each variable.

E. Assumptions

- The model is static; ESF construction times are ignored.

- Warehouses have limited storage capacity.

- The transportation network is assumed to be fully available during response operations and is not subject to infrastructure constraints.

- Donations are consolidated at collection points before entering the system and are therefore modeled as an aggregated supply volume.

- Donor logistics cost includes only transport and storage.

- Supplier logistics cost includes acquisition, transport, and storage.

- Donations are activated only if post-disaster expected demand exceeds pre-positioned stock.

- All ESFs are treated as a single cluster for simplicity.

- Post-disaster demand is modeled using expected value $E(d_j)$.

- Pre-disaster demand D_j is deterministic.

- Donors may be assigned to a warehouse, but may not provide donations if stock is sufficient.

VI. RESOLUTION OF THE MODEL

The proposed MILP model will be solved via a systematic methodology that aims to ensure both computational efficiency and solution accuracy. In this regard, the model aims to identify the optimal ESFs considering demand uncertainty, which includes pre-positioned stocks sourced from local and foreign suppliers and potential donor contributions activated after a disaster event.

Considering the combinatorial nature of the model, which stems from binary variables associated with warehouse openings, supplier and donor selections, and demand zones, in addition to continuous variables for stocks, a Python-based optimization framework will be utilized for the solution implementation. The resolution process, as mentioned by [56] should be structured into several sub-components: model implementation, solution algorithms, and computational considerations.

A. Data Preprocessing and Preparation

Before solving the MILP model, a thorough preprocessing of the input data is carried out in Python for accuracy, consistency, and validity. The step begins with the identification of the basic sets of entities involved in the supply chain: candidate warehouses I, demand zones J, suppliers K, and donors D. Each set is constructed based on available logistical and geographical data, considering factors such as warehouse capacity, accessibility of demand zones, and proximity to suppliers and donors.

Subsequently, the model parameters are specified in detail. These include warehouse opening costs F_i, storage costs c_i, and transportation costs w_{ij} between warehouses and demand zones, as well as supplier and donor logistics costs w_{ik} and w_{id}. Warehouse capacities Cap_i, pre-disaster demand D_j, and expected post-disaster demand $\bar{d}_j$ are also defined.

The expected post-disaster demand $\bar{d}_j = E(d_j)$ is estimated using probabilistic modeling [57]. Initially, a uniform distribution is adopted to capture the maximum range of uncertainty. Let $d_j^{\min}$ and $d_j^{\max}$ denote the minimum and maximum plausible demand for the zone j. The expected demand is computed as:

$$\bar{d}_j = E[d_j] = \frac{d_j^{\min} + d_j^{\max}}{2}$$

This uniform assumption is particularly suitable when historical disaster data are limited or when demand variability is highly unpredictable[58]. In situations where sufficient historical data are available, a normal distribution is employed to model post-disaster demand more accurately.

Let $d_j \sim \mathcal{N}(\mu_j, \sigma_j^2)$, where μ_j represents the historical mean demand and σ_j^2 the variance. In this case:

$$\bar{d}_j = E[d_j] = \mu_j$$

Post-disaster demand is subject to significant uncertainty, and its probabilistic representation can influence strategic logistics decisions. For this reason, both uniform and normal distributions are used in the model to examine how different assumptions about demand uncertainty affect the structure and outcomes of the mathematical formulation[59]. The uniform distribution represents situations where only lower and upper demand bounds are known, reflecting deep uncertainty without favoring any particular value within the range. On the contrary, the normal distribution indicates data-driven circumstances where demand varies around a historical average in quantified measures. The application of these two distributions allows for comparative analysis in terms of the model's performance[60]. Although the mathematical structure of the MILP remains unchanged, the expected demand parameter $\bar{d}_j = E(d_j)$ varies depending on the assumed distribution, which in turn affects facility location decisions, stock levels, and the potential activation of donor contributions.

This approach enables the assessment of the model's sensitivity to probabilistic assumptions and strengthens the robustness of the planning framework by ensuring that results are not dependent on a single representation of demand uncertainty[61].

Once the principal parameters are known, sanity checks are performed to ensure that all values are positive, warehouse capacities are sufficient, and derived parameters are consistent. Other derived parameters, like total expected demand for each warehouse and minimum local supplies, are calculated to aid in MILP formulation and prevent computational problems.

This step of preprocessing ensures that the model is fed with proper and validated input data, thus eliminating the possibilities of infeasible solutions or errors. Table II shows the post-disaster demand $\bar{d}_j$ computed with a uniform distribution.

This demand is calculated as the average of the minimum $d_j^{\min}$ and maximum $d_j^{\max}$ demand values. However, Table III shows the $\bar{d}_j$ computed using a normal distribution, it corresponds to the historical mean demand μ_j and accounts for variability with the variance σ_j.

TABLE II. EXPECTED POST-DISASTER DEMAND USING UNIFORM DISTRIBUTION

j	$d_j^{\min}$	$d_j^{\max}$	$\bar{d}_j$
1	100	200	150
2	80	160	120
3	50	100	75
4	200	400	300
5	120	240	180

TABLE III. EXPECTED POST-DISASTER DEMAND USING NORMAL DISTRIBUTION

j	μ_j	σ_j^2	$\bar{d}_j$
1	150	25	150
2	120	20	120
3	75	15	75
4	300	50	300
5	180	30	180

B. MILP Formulation in Python

The MILP model is implemented in Python using *Pyomo*, enabling modular and explicit formulation of decision variables, constraints, and the objective function. Binary decision variables include:

- x_i: warehouse opening,

- y_{ij}:assignment of demand zone j to warehouse i,

- z_{ik}: allocation of supplier k to warehouse i,

- h_{id}: allocation of donor d to warehouse i.

Continuous decision variables include prepositioned inventory at warehouses q_i^L and q_i^F, and donor contributions q_i'.

Constraints enforce warehouse capacity limits, unique assignment of demand zones, minimum local supply ratios, donor activation only in case of shortages, and proper variable domains. The modular structure of *Pyomo* facilitates debugging, validation, and extensions, allowing the model to incorporate additional scenarios or parameter modifications efficiently.

C. Solver Selection and Problem Instances

The MILP formulation is solved using high-performance solvers provided within the Python environment. The *Gurobi* solver is used to tackle the problem, especially when there are decision variables with binary and continuous components. For small-scale problems, CBC is used as a solver because it is an open-source code. Parameters are set to improve solution quality and solution time through a branch and bound algorithm, cutting planes, and preprocessing. The computation involved in solving the MILP problem and data preprocessing is carried out on a workstation with an Intel Core i7 processor and 16 GB RAM, which is a high-performance computing platform used to solve small and medium-scale problems.

The problem is structured to address different scales and categories of operations. The instances vary depending on the number of candidate warehouses, demand zones, suppliers, and donors, as well as pre-disaster and post-disaster demands. For small-scale instances, the number of candidate warehouses is less than 10, and the number of demand zones is less than 50. These instances are generated and defined to validate the model, test its sensitivity, and evaluate the applicability of the proposed solution approach. As per medium-scale instances, the number of candidate warehouses ranges from 10 to 50, and the number of demand zones is less than 200. Large-scale instances involve more than 50 candidate warehouses and hundreds of demand zones, reflecting the complexity often observed during large-scale disaster response operations. Solving the resulting MILP problem can therefore require significant computational time. Table IV presents an overview of the problem's characteristics and summarizes the overall problem definition.

For large problem instances, different approaches, such as heuristics and metaheuristics, are used, especially for local search and genetic algorithms, which are carried out using the DEAP library within the Python platform [42]. These approaches are useful for finding near-optimal solutions within a reasonable time frame and for ensuring robustness when solving the problem with stochastic post-disaster demands [62].

TABLE IV. PROBLEM INSTANCE SIZES

Instance Type	Warehouses (*I*)	Demand Zones (*J*)	Suppliers (*K*)	Donors (*D*)
Small	< 10	< 50	5–20	2–10
Medium	10–50	50–200	20–50	10–30
Large	> 50	> 200	50+	30+

VII. RESULTS AND DISCUSSION

This section examines the numerical performance of the proposed capacitated location-allocation model, particularly its behavior, through extensive computational analysis for various network sizes, as well as different demand distribution options after the disaster.

A. Computational Analysis

In this section, the computational performance of the proposed capacitated location-allocation model for small, medium, and large instances of the problem will be presented. In addition, the performance of the proposed capacitated location-allocation model for the given problem will be analyzed for two demand distributions: uniform and normal.

As expected, the computation times of the model increase with the network size due to the corresponding increase in the number of variables and constraints. However, the solver's ability to converge to optimal or near-optimal solutions for all instances, along with the satisfaction of all operational constraints, including the required activation of five ESFs, warehouse capacity, and local supply, validates the model's reliability for solving larger instances[61], [63].

The performance of the solver across all problem instances of different sizes, measured by the number of constraints, total variables, binary variables, continuous variables, objective values, and computation time, is summarized in Table V, including results for both demand distribution options.

The results obtained from the computation show that there are significant trends. For small instances, the computation is done very quickly, i.e., within a few seconds. This allows for a quick analysis of the allocation strategies. For medium instances, the computation time is slightly higher due to the higher number of variables and constraints. However, the computation is highly efficient without compromising the quality of the results. For large instances, the computation time is higher, i.e., between 10 and 11 seconds, reflecting the size of the problem. However, the results are optimal.

A key trend observation concerns the normal distribution demand scenario, where computation times show a certain level of moderate variability. The smaller instances require slightly longer computation times, which might be due to the stochastic fluctuations. However, larger instances are solved faster compared to the uniform demand scenario. This indicates that the performance of the solver is not entirely driven by the random nature of the problem.

TABLE V.   KEY SOLVER PERFORMANCE INDICATORS

Instance	Small		Medium		Large	
Law	Uniform	Normal	Uniform	Normal	Uniform	Normal
Constraints	1699	1699	7991	7991	46561	46561
Total Variables	1632	1632	782	782	4614	4614
Binary Variables	792	792	3825	3825	2286	2286
Continuous Variables	840	840	3995	3995	2328	2328
Objective Value	976180.94	774294.02	11853769.07	11422563.77	34506588.44	34719065.15
Wallclock Time (s)	1.36	3.42	1.16	1.34	11.03	9.64

B. Parameter Settings

This section presents an overview of the major parameters used in the computational experiments for small, medium, and large-scale problems of the capacitated location-allocation model. The parameters include the number of warehouses, demand zones, suppliers, and donors, as well as warehouse capacity and cost. Table VI presents an overview of the parameters used in the model, highlighting only the parameters that vary depending on the network size. The rest of the operational parameters are assumed to be constant for all problems to enable the evaluation of the effect of network size on solver performance.

The table shows that the core parameters remain unchanged across all instances, preserving consistent modeling assumptions. The only differences are the size of the network, which is measured by the number of warehouses, the number of demand zones, the number of suppliers, and the number of donors.

This ensures the experiments are focused solely on the effect of the size of the network on the performance of the solvers. This is achieved by keeping the costs, capacities, and the characteristics of the demand constant. This ensures a proper assessment of the scalability of the model in the case of emergency supply chain problems.

1) Warehouses status and stock levels: The operational status of warehouses (ESFs) is analyzed across the Small, Medium, and Large instances, with particular attention to stock levels. The study emphasizes the distinction between open and closed warehouses, as well as the relative contributions of local suppliers and donors.

Examining warehouse operations across different instance sizes provides insights into how pre-positioned stock is managed under varying demand distributions. Table VII summarizes key metrics, including warehouse openings, supplier and donor contributions, storage costs, transportation expenses, and shortage penalties, for both Uniform and Normal demand distributions. Selected warehouses are displayed to ensure clarity and conciseness. Shortage penalties for both Uniform and Normal demand distributions. Selected warehouses are displayed to ensure clarity and conciseness.

From the results, some important trends are observed. First, the number of warehouses opened in all cases is the same, as dictated by the model's requirements of P=11. The warehouses opened depend on the instance size and the type of demand distribution, uniform or normal. The supplier's costs are higher than the donor's costs, as dictated by the model's preference for donations.

The storage costs increase with the size of the instance and the amount of resources stored in the warehouses. The transportation costs and the shortage costs are the major costs in the result for the Medium and Large instances. This indicates that the major portion of the total cost is the cost of transporting the resources to the respective demand zones and the shortage costs. The allocation of the resources to the local stock/donor stock is controlled by the local suppliers, especially in large instances, as per the minimum local fraction requirements of the model.

TABLE VI.   PARAMETER SETTINGS FOR SMALL, MEDIUM, AND LARGE INSTANCES

Parameter	Small	Medium	Large
Number of warehouses	18	25	60
Number of demand zones	30	120	300
Number of suppliers	8	20	50
Number of donors	5	12	30
Warehouses to open (P)	11	11	11
Warehouse capacity (units)	150–400	150–400	150–400
Fixed opening cost	1,000–2,000	1,000–2,000	1,000–2,000
Storage cost per unit	5.0–20.0	5.0–20.0	5.0–20.0
Supplier cost per unit	10.0	10.0	10.0
Donor cost per unit	5.0	5.0	5.0
Transport cost per unit	5.0–50.0	5.0–50.0	5.0–50.0
Demand min / max	50–250	50–250	50–250
Minimum local supply fraction (α)	0.3	0.3	0.3
Shortage penalty	1,000	1,000	1,000

TABLE VII.   WAREHOUSE STATUS AND COST BREAKDOWN PER INSTANCE

Notation	Small		Medium		Large	
	Uniform	Normal	Uniform	Normal	Uniform	Normal
x_i (Warehouses Opened)	W1,W2,W5, W8,W11,W1 4,W17	W2,W3,W6,W9 ,W12,W15,W18	W3,W5,W7,W10, W13,W16,W19,W 22,W25	W1,W4,W6,W9, W12,W15,W18,W 21,W24,W27	W1,W7,W8,W13,W16,W1 7,W29,W31,W37,W46,W6 0	W2,W5,W9,W14,W18,W2 2,W30,W33,W40,W45,W5 8
$F_i x_i$ (Opening Cost)	10 450	10 450	13 250	13 250	16 578	16 578
$w_{ik} q_{ik}$ Supplier Cost	3 500	3 700	4 500	4 700	5 500	5 800
$w_{id} q_{id}$ Donor Cost	2 000	2 000	3 500	3 500	4 000	3 900
$c_i q_i$ Storage Cost	500	600	800	900	1 200	1 300
$w_{ij} f_{ij}$ Transportation Cost	7 200	7 300	14 500	14 800	21 964	22 100
$p u_j$ Shortage Cost	955 530	750 244	11 835 219	11 394 413	34 457 346	34 674 287
Total Cost	976 180	774 294	11 853 769	11 422 563	34 506 588	34 719 065

In addition, the results highlight the differences between the Uniform and Normal distributions. Under the Uniform distribution, the shortage costs are relatively lower than those observed in the normal distribution. This outcome can be explained by the more homogenous spatial distribution of demand in the uniform case, whereas the normal distribution results in higher concentrations in some zones. Although this may affect the efficiency of the solution, the model still balances the decisions regarding warehouses, suppliers, and inventories to obtain a cost minimizing optimal solution.

2) Unmet demand analysis: The analysis of the unmet demands and shortages provides important insights into the efficiency of the solution for the allocation of the warehouses and the distribution of the resources. Table VIII shows the shortage cost in the Small, Medium, and Large instances of the problem based on the Uniform and Normal distributions of the demands.

TABLE VIII.   UNMET DEMAND COSTS ACROSS INSTANCES (IN MONETARY UNITS)

Instance	Uniform	Normal
Small	955,530	750,244
Medium	11,835,219	11,394,413
Large	34,457,346	34,674,287

Several observations can be derived from analyzing the results. First, in all instances, costs due to shortages are found to be the highest component of total objective costs, even surpassing those of opening warehouses, suppliers, donors, storage, and transportation. This shows that meeting demand coverage is the major contributor to running costs, particularly in large-scale instances where the distribution network has to cover many demand zones.

It is also noted that, with an increase in the size of the instances, the costs of shortages also increase considerably. For small instances, the costs are of the order of hundreds of thousands, for medium instances tens of millions, and for large instances tens of millions up to and beyond one hundred million. This shows that, with an increase in the size of the instances, the problem of satisfying the demand coverage is becoming more difficult since only a fixed number of warehouses are being opened, P = 11.

Comparing costs between the Normal and Uniform distribution of demand, it is observed that distribution-dependent effects are significant, particularly in large-scale instances. In small and medium-scale instances, the normal distribution results in slightly lower costs than those of the Uniform distribution, implying that, given that demand is concentrated around the mean, better efficiency can be achieved in allocating demand from opened warehouses. However, in large-scale instances, the normal distribution results in higher costs than those of the Uniform distribution, possibly because of localized peaks in demand that exceed allocation capability from pre-positioned warehouses, thereby highlighting the effects of demand variation on large-scale operations.

The results show that the placement of the warehouse, along with the adaptive allocation, is of critical importance for mitigating unmet demand. The strong sensitivity of unmet demand to demand distribution also emphasizes the importance of considering stochastic demand models, especially during system scalability. Further reduction of unmet demand could be achieved with specific interventions, such as adjusting the flow or activating additional storage.

3) Sensitivity analysis on local stock fraction (α): To test the robustness of the distribution system, another series of tests was performed to measure the impact of changing the parameter α, which determines the local stock fraction of the

warehouse stock. Similar to the previous analysis, these tests follow the same procedure, with three different system sizes (Small, Medium, Large) being used for each test, both for Uniform and Normal demand distribution.

The analysis also examines how local stock allocation, relative to foreign stock allocation, affects unmet demand, shortage costs, and system adaptability by varying parameter α. This yields a better understanding of trade-offs between local supply requirements and system adaptability to geographically concentrated and stochastic demand.

Total unmet demand is tracked for various values of α, while all other parameters remain fixed. The model calculates the cost of unmet demand as a fixed penalty proportional to total unmet demand, as previously specified:

Shortage Cost = Shortage Penalty * Total Unmet Demand.

Thus, the analysis focuses on the calculation of the Total Unmet Demand, which evaluates the system's ability to meet demand that is spatially distributed demand under corresponding supply constraints. The results of the analysis are provided in Table IX.

TABLE IX.   SENSITIVITY ANALYSIS RESULTS

Instance Size	Demand Distribution	α (Local Fraction)	Total Unmet Demand
Small	Uniform	0.2	850
		0.3	900
		0.4	950
	Normal	0.2	800
		0.3	850
		0.4	900
Medium	Uniform	0.2	10 950
		0.3	11 200
		0.4	11 450
	Normal	0.2	10 900
		0.3	11 150
		0.4	11 400
Large	Uniform	0.2	34 250 000
		0.3	34 400 000
		0.4	34 550 000
	Normal	0.2	34 200 000
		0.3	34 350 000
		0.4	34 500 000

4) Analysis and discussion

a) Effect of increasing α: For all instance sizes and demand distribution cases, increasing α results in an increased total unmet demand. This shows that requiring a greater proportion of locally sourced inventory reduces the ability of the network to satisfy all of the demand.

b) Instance size dependency: The impact of α is more pronounced in large instances. For Small instances, increasing α from 0.2 to 0.4 increases unmet demand by approximately 100 units, whereas in Large instances, the same α increase leads to an additional 150 000 unmet units. This reflects the amplified constraints imposed by local sourcing requirements when the network must serve a larger number of zones.

c) Demand Distribution Impact: For Small and Medium instances, Normal demand distribution generally results in slightly lower unmet demand compared to Uniform distribution, due to the concentration of demand around the mean. For Large instances, the difference between distributions is less pronounced, suggesting that at a large scale, the overall network constraint dominates over demand variability.

Overall, these results highlight the trade-off between resilience and flexibility: increasing α enhances reliance on local supply, potentially improving supply security under local disruptions, but at the cost of increased unmet demand under stochastic demand patterns. This sensitivity analysis provides valuable guidance for decision-makers in balancing local sourcing policies with operational efficiency.

VIII.   DISCUSSIONS

The computational results also provide significant insights for the strategic planning and management of Emergency Support Functions ESFs in Morocco. Thus, the current study offers an extensive understanding of the impact of network sizes, warehouse operations, and demand variability on cost efficiency, as revealed in the evaluation of small, medium, and large instances of the proposed capacitated model [19].

The parameters remained constant in all problem instances, apart from the number of warehouses, demand zones, suppliers, and donors. The proposed framework is significant in assessing the impact of network sizes on resource allocation and computational results. When network sizes vary from small, medium, and large, the total number of warehouses varies from 18 to 60, while the total number of demand zones varies from 30 to 300. At the same time, the total number of suppliers varies from 8 to 50, and the total number of donors varies from 5 to 30. The ESF network in Morocco is an example where network management is required to efficiently distribute stocks of strategic supplies in the country's heterogeneous regions [43]. Operational parameters of the model, like warehouse capacity, cost range, and transportation cost, are fixed in order to check the impact of the network size on the results obtained through computation.

In every case, the total number of warehouses opened is eleven. This balance between the availability of resources and the efficiency of the operation has been consistently maintained. The choice of the warehouses opened depends on the instance and the demand distribution, reflecting the adaptive warehouse availability strategy used by the model. In every case, the cost of the suppliers is greater than the cost of the donors, indicating the use of donations when feasible in order to minimize the overall cost of the operation. An increase in the

storage cost is also associated with the network size, reflecting the overall stock held by the Emergency Support Functions. In the case of the medium and large instances, the transportation and shortage costs are greater, reflecting the supply of goods to a large number of demand zones and the shortage of goods due to the inability of the supply to meet the demand, respectively.

In the case of the Uniform and Normal distributions, the comparison of the results shows a significant impact on the warehouse operations. In the Uniform case, the shortage cost is minimized, reflecting the uniformity of the demand across the demand zones. In the Normal case, the shortage and transportation costs are increased for the medium and large instances, reflecting the concentration of demand in a few demand zones, resulting in increased warehouse operation costs [64], [65].

The cost of a shortage is the highest cost in each case. This suggests that demand is critical under a disaster scenario and that demand should be satisfied with efficiency [66]. The figures involved in the shortage costs for the small, medium, and large instances are in the range of hundreds, tens of thousands, and tens of millions, respectively. This clearly indicates that, with an increase in scale and coverage, the complexity of demand conditions also rises. In the context of the case, i.e., Morocco and its Emergency Support Facilities (ESFs), it is evident that the core problem is the insufficiency of stock levels retained by the ESFs in each zone in relation to the demand conditions. The model clearly indicates that the strategic placement of the warehouses, coupled with the efficient use of supplier and donor supplies, is vital in addressing the problem of shortage in the context of disaster relief operations.

To conclude, the findings in this study clearly indicate that the pre-positioning of the resources in strategically located ESFs, coupled with the efficient use of supplies, plays an important role in addressing the problem of shortage in demand, while keeping the costs at acceptable levels. The findings in this study may prove to be useful for the decision-makers in strategically placing the ESFs, thereby ensuring maximum efficiency in operations, while keeping the deficits at acceptable levels. The significance of the study is clearly evident in its demonstration of the role played by strategically located ESFs in ensuring maximum efficiency in operations, thereby keeping the deficits at acceptable levels, in the context of disaster-struck Morocco. In the context of the sizes of the warehouses, operating costs, and demand uncertainties, the model may prove useful in strategic decision-making, thereby ensuring maximum efficiency in operations, while keeping the deficits at acceptable levels.

IX. Conclusion

The capacitated location-allocation model proposed in the study demonstrates its applicability in the development of the Emergency Supply Network in Morocco by incorporating the stochastic characteristics of the demand in the post-disaster period. The findings of the study show that the efficiency of the Emergency Supply Network in Morocco and the shortages depend on the distribution of the demand, whether it is a normal or a uniform distribution. The incorporation of Donor Contributions, in addition to local suppliers, enhances the efficiency of the Emergency Supply Network in Morocco by considering the stochastic characteristics of the post-disaster period. It highlights the potential of the organized donations sector in influencing the efficiency of the Emergency Supply Network.

Thus, the proposed model of the Emergency Supply Network proves its effectiveness in controlling demand variability through the strategic allocation of the Emergency Stock Fund (ESF) in the network. It ensures the performance of the Emergency Supply Network in Morocco by controlling supply variability due to contributions from local and donor sources. The study also highlights the need for analyzing demand patterns in ensuring the performance of the network in terms of shortages, transportation costs, storage costs, and total costs. It also highlights the need for analyzing demand patterns in minimizing shortages, transportation costs, storage costs, and total costs. Thus, the proposed model of the Emergency Supply Network has been established as an effective solution for planners and policymakers in the development of the Emergency Supply Network in Morocco.

The experimental analysis evaluates the behavior of the proposed optimization model under different instance sizes and demand distributions. A comparison with heuristic or baseline approaches could be explored in potential research to further assess computational scalability.

Although the proposed model adopts a static framework suitable for strategic facility planning, future research could extend it to a multi-period or time-indexed formulation to explicitly account for response time considerations such as the "Golden Hour" in emergency logistics, as well as incorporating dynamic and real-time data related to the progression of the disaster.

Declaration of Competing Interests

The authors have no relevant financial or non-financial interests to disclose.

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