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Designing a Global Warming-Resilient Humanitarian Welfare Network: A Multi-Objective Optimization Approach to Minimize Cost, Shortage, and Distributional Inequity

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Abstract: This study introduces a multi-objective optimization model for formulating global warming-resilient humanitarian welfare network to minimize total cost, minimize total shortage, and minimize distributional inequity for flood response in flood prone areas. The framework strategically addresses the complexities of disaster relief by considering five key echelons: affected areas, distribution hubs, hospitals, temporary accommodation centers and temporary care centers to integrates casualties costs at temporary care and accommodation centers, transportation cost across all echelons or routes, facilities establishment cost, relief supply shortage ,and distributional inequity .. We employ the epsilon-constraint (ε -constraint), Non-Dominated Sorting Genetic Algorithm-II (NSGA-II) and modified multi-objective particle swarm optimization (MMOPSO) methods to solve the complex optimization problem. The proposed approach for the formulated model efficacy was demonstrated through its application to June/July 2025, real-world case study in Sapele and Amukpe environs, Delta State, Nigeria, a region significantly impacted by perennial floods exacerbated by global warming. Numerical simulations reveal that the MMOPSO method outperforms NSGA-II and ε -constraint methods in terms of solutions quality and computational efficiency to provide Pareto-optimal solutions that balance response time, costs, relief shortage, distributional inequity and community impact. This research contributes to the development of data-driven decision support systems for humanitarian welfare network, enhancing the resilience of communities prone to floods and other disasters. The framework offers policymakers a tool to balance overall costs-efficiency associated with facilities location-allocation, and to minimize distributional inequity in global warming disasters-induced prone regions.

Keywords: Global warming, Resilient Humanitarian Welfare Network, Disaster response.

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1. Introduction

The growing threat posed by extreme weather conditions has significantly heightened the frequency, intensity, and complexity of natural disasters such as floods, droughts, heatwaves, wind and rain storms and hurricanes. These events severely threaten public health in areas prone to flooding and with limited resources. The Intergovernmental Panel on Climate Change (IPCC, 2023) projects a global temperature increase of 1.5–2°C by 2040, which will further exacerbate the risk of climate-induced disasters in low-lying regions such Sapele and Amukpe environs in Delta State, Nigeria. These disruptions challenge the efficiency and effectiveness of emergency welfare network response systems, which are increasingly constrained by limited resources, uncertainty in demand, damaged infrastructure, and conflicting socio-economic priorities. Despite the growing severity of disasters, traditional research on emergency logistics models largely focused on achieving operational efficiency, assuming consistent resource availability and single-objective outcomes like cost or speed [9]. For instance, stochastic optimization strategy has been in use for pre-positioning supplies to manage demand uncertainty [20]. However, a critical limitation confirmation [10] is that such models often overlook equity, leading to insufficient aid distribution for socially vulnerable populations. This creates a

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significant gap between model-based solutions and the complex, ethically-driven needs of real-world disaster response.

In addressing the limitations, recent research has formulated more sophisticated models such as a multi-objective model that integrates climate uncertainty to simultaneously optimize facility location, inventory, and routing, thereby balancing cost, responsiveness, and equity leading to improved preparedness and fairer relief distribution [8]. This aligns with the broader recognition, noted [3], that climate-informed strategies are essential for resilient and equitable responses. Furthermore, tools like the multi-commodity flow models explored [15] show ability for managing diverse relief supplies through damaged networks.

Despite these advances, a significant gap remains: the integrated optimization of location-allocation, multi-period planning, social equity, and welfare network design under dynamic climate risks. To bridge this gap, this paper innovatively build upon the optimization framework [12] to formulate multi-objective optimization model that considered five key echelons: affected areas, distribution hubs, hospitals, temporary accommodation and care centers to integrates casualties costs at temporary care and accommodation centers, transportation cost across all echelons or routes, facilities establishment costs, relief supply shortage ,and distributional inequity . The purpose of this study to minimize total logistics and welfare costs, relief supply shortages, and distributional inequity with a strong emphasis on fairness in aid distribution, and prioritizing flood-prone, resource-constrained regions. This approach offers a practical path toward more resilient, equitable, and climate-adaptive disaster response.

2. Literature Review

A growing segment of the literature recognizes the critical importance of equity in disaster response. An equity-integrated optimization model for shelter allocation that successfully reduces inequality with only a minimal impact on cost was developed [1]. Similarly, [5] proposed an equity-oriented allocation model that leverages social vulnerability data to promote fairness, albeit with a marginal increase in operational costs. Earlier, [11] formulated a multi-objective model that incorporates fairness in facility location and allocation, demonstrating that equity and cost-effectiveness can be pursued simultaneously. More recently, [6] introduced a hybrid fairness-optimization model that employs evolutionary search algorithms with equity metrics. A common limitation across these equity-focused studies is their static nature; they often lack dynamic or multi-period resource flow modeling, fail to address behavioral equity, and do not integrate real-time data or climate-related disruptions.

In response to the increasing frequency of climate-induced disasters, another strand of research has focused on resilience and dynamic planning. A model for dynamic network reconfiguration under climate-induced floods, incorporating advanced environmental modeling [14] also a bi-objective mixed-integer programming model for evacuation that uses climate projections to balance efficiency and fairness under climate risk [13]. In order to advance the field [2] designed a multi-period robust optimization frame work for logistics under global warming threats, offering resilient planning over time. A resilient food distribution, integrating principles of fairness and resilience to ensure supply during crises was addressed by [7]. Despite these advances, a significant gap remains in the literature: the integrated optimization of location-allocation, multi-period planning, social equity, and full welfare network design under dynamic climate risks. No single model simultaneously addresses the five-echelon network structure, the tri-objective of minimizing cost, relief supply shortage, and distributional inequity, and the need for computationally efficient solutions suitable for real-world application. This study seeks to bridge this gap by developing a comprehensive multi-objective optimization framework that incorporates these crucial elements.

3.0 Mathematical Model

3.1.0 Indices and Sets

F_D Temporary care facilities vulnerable to damage from global warming impacts, $F_D = \{1, \dots, F_D\}$

F_R Temporary care facilities resilient to global warming impacts, $F_R = \{1, \dots, F_R\}$

A_D Temporary accommodation centers vulnerable to damage from global warming impacts, $A_D = \{1, \dots . A_D\}$

A_R Temporary accommodation centers resistant to global warming impacts, $A_R = \{1, \dots, A_R\}$

K Index for potential temporary accommodation center sites, k ε $\{1, \dots, K\}$, where $K = A_D \cup A_R$

L Index for potential temporary care facility sites, l ε $\{1, \dots, L\}$, where $L = F_D \cup F_R$

D Index for regions impacted by global warming events, d ε D

H Index for healthcare institutions, h ε H

E Index for distribution hubs, e ε E

V Index for transportation units, v ε V.

C Index for essential commodities, c ε C.

S Index for global warming scenarios, s ε S.

T Index for time periods, t ε T.

M A sufficiently large positive constant.

R Index for resource allocation tiers (0 for primary facilities, 1 to R for backup) facilities, r ε R

3.1.1 Parameters

C_{lsr}^{care} Cost of establishing temporary care facilities at location l at allocation tier r under scenario s.

C_{ksr}^{accomm} Cost of establishing a temporary accommodation center at location k in tier r and scenario s.

C_{vs}^{veh} Operational cost per unit distance for vehicle v under scenario s.

$\prod_{ls}^{care}$ Penalty costs at temporary care center L due to its failure in scenario s.

$\prod_{ks}^{accom}$ Penalty costs at temporary accommodation center K due to its failure due in scenario s.

$D_{ds}^{outpatient}$ Number of individuals requiring outpatient services in affected region d under scenario s.

$\mathrm{D}_{\mathrm{ds}}^{\mathrm{evac}}$ Number of individuals needing evacuation from affected region d under scenario s.

$D_{\mathrm{ds}}^{\mathrm{critical}}$ Number of critically injured individuals requiring treatment in affected region d under scenario s.

$\mathrm{Q}_{\mathrm{kcts}}^{\mathrm{commodity}}$ Demand for commodity C, at temporary accommodation center k during time period t under scenario s.

$\mathrm{M}_{\mathrm{v}}^{\mathrm{patient}}$ Capacity of vehicle type v transporting injured individuals (both critically and non-critically injured).

$\mathrm{M}_{\mathrm{v}}^{\mathrm{evac}}$ Capacity of vehicle type v transporting individuals displaced by global warming events.

$\mathrm{M}_{\mathrm{v}}^{\mathrm{goods}}$ Capacity of vehicle type v transporting commodities from distribution hubs.

$\mathrm{N}_{\mathrm{ects}}^{\mathrm{distrt}}$ Capacity of distribution hub e for commodity type c under scenario s at time t.

$\mathrm{N}_{\mathrm{kcts}}^{\mathrm{shelter}}$ Capacity of temporary accommodation center k for commodity type c under scenario s at time t.

$\mathrm{N}_{\mathrm{lhs}}^{\mathrm{hospital}}$ Patient admission capacity at hospital h across all allocation tiers r in scenario s.

$\mathrm{N}_{\mathrm{lsr}}^{\mathrm{hospital}}$ Patient admission capacity at temporary care facility l across all allocation tiers rin scenario s.

$\mathrm{N}_{\mathrm{ksr}}^{\mathrm{evac}}$ Capacity of temporary accommodation center k for housing evacuees under scenario sat allocation tier r.

$\mathrm{D}_{\mathrm{dlr}}^{\mathrm{affected-care}}$ Distance between affected region d and temporary care facility l at allocation tier r.

$\mathrm{D}_{\mathrm{dkr}}^{\mathrm{affected-accom}}$ Distance between affected region d and temporary accommodation center kat allocation tier r.

$\mathrm{D}_{\mathrm{ekr}}^{\mathrm{dist-accom}}$ Distance between distribution hub e and temporary accommodation center k at allocation tier r.

$\mathrm{D}_{\mathrm{dh}}^{\mathrm{affected-\ hospital}}$ Distance between affected region d and hospital h.

$\mathrm{R}_{\mathrm{lr}}^{\mathrm{care}}$ Coverage radius for temporary care center k at allocation tier r.

$\mathrm{R}_{\mathrm{kr}}^{\mathrm{accom}}$ Coverage radius for temporary accommodation center k at allocation tier r.

$\Xi_{\mathrm{dlsr}}^{\mathrm{equity}}$ Cost incurred when the vulnerable in the affected area d, are inadequately served by temporary care facility l at allocation tier r in scenario s.

$\Xi_{\mathrm{dksr}}^{\mathrm{equity}}$ Cost incurred when the vulnerable in the affected area d, are inadequately served at temporary accommodation center k at allocation tier r in scenario s.

$\mathrm{P}_{\mathrm{l}}^{\mathrm{care-fail}}$ Probability of failure of temporary care facility $\mathrm{l} \in \mathrm{F}_{\mathrm{D}}$ due to global warming impacts.

$\mathrm{P}_{\mathrm{k}}^{\mathrm{accom-fail}}$ Probability of failure of temporary accommodation center $\mathrm{k} \in \mathrm{AD}$ due to global warming impacts.

P_{s} Probability of occurrence for scenario s.

β_{ct} Consumption coefficient for commodity c in time period t.

γ_{k} Minimum required coverage level for commodities at temporary accommodation center k.

$\boldsymbol{\vartheta}_{\mathrm{c}}$ Volume (m^3) of each unit of commodity c.

Ψ_{c} Priority level for fulfilling the demand of commodity c.

ψ_{eksr} Priority level for fulfilling the demand of commodity at temporary accommodation center.

Ω_{ds} Vulnerability index of affected area d in scenario s.

Λ_{dls} Number of non-critically injured individuals transferred from affected region d to temporary care facility l in scenario s.

Λ'_{dks} Number of individuals displaced by global warming impacts transferred from affected region d to temporary accommodation center k in scenario s.

Λ''_{dhs} Number of critically injured individual transferred from the affected region d to the hospital

h in scenario s.

Γ_{ekcts} Quantity of commodity type c transferred at time t from distribution hub e to temporary accommodation center k in scenario s.

$\mathrm{Y}_{\mathrm{vdls}}$ Number of vehicle type v traveling from affected region d to temporary care facility l in scenario s.

$\mathrm{Y}'_{\mathrm{vdks}}$ Number of vehicle type v traveling from affected region d to temporary accommodation center k in scenario s

$\mathrm{Y}''_{\mathrm{vdhs}}$ Number of vehicle type v traveling from affected region d to hospital h in scenario s.

Y_{vekst} Number of vehicle type v traveling at time t from distribution hub e to temporary accommodation center k in scenario s.

ϖ_{kctsr} Amount of shortage for commodity c, at temporary accommodation center k at allocation tier r in scenario s during period t.

Γ_{kcts} Amount of commodity c stored at temporary accommodation center k in period t in scenario s

C^{eq} Predefined societal cost or penalty multiplier associated with equitable service provision.

3.1.2 Decision Variable

Location:

χ_{lsr} Binary, equal to 1 if temporary care facility l is established at allocation tier r in scenario s, 0, if otherwise.

χ'_{ksr} Binary, equal to 1 if temporary accommodation facility k is established at allocation tier r in scenario s, 0, if otherwise.

Assignment:

ζ_{dlsr} Binary, equal to 1 if affected area d is assigned to temporary care facility l at allocation tier r in scenario s. 0, if otherwise.

ζ'_{dksr} Binary, equal to 1 if affected area d is assigned to temporary accommodation facility k is at allocation tier r in scenario s. 0, if otherwise.

ψ_{elsr} Binary, equal to 1 if temporary care facility l is assign to distribution hub e at allocation tier r in scenario s. 0, if otherwise.

φ'_{eksr} Binary, equal to 1 if temporary accommodation facility k is assign to distribution hub e at allocation tier r in scenario s. 0, if otherwise

3.2 Model Formulations

Building upon the established notation, the comprehensive mathematical model, defined by equation (3.1) – (3.4), and equation (3.7) is now presented subject to constraints (1)-(24). The objective function aims to minimize the total cost of humanitarian logistics, relief supply shortage, and distributional inequity in flood prone areas as a result of disaster impacts induced by global warming. It's composed of several parts, such that:

- Casualties Cost at Temporary Care Center.

$$G1 = \sum_{s=1}^{S}\sum_{d=1}^{D} D_{ds}^{outpatient}\ P_s \Pi_{ls}^{care} \left\lfloor \sum_{I \varepsilon FD} \mathrm{P}_{\mathrm{l}}^{\mathrm{care-fail}} \zeta_{\mathrm{dlsr}} + \sum_{I\varepsilon FR}\sum_{r=0}^{R} \left(1 - \mathrm{P}_{\mathrm{l}}^{\mathrm{care-fail}}\right)\zeta_{\mathrm{dlsr}} \right\rfloor \quad (3.1)$$

- Casualties Cost at Temporary Accommodation Center.

$$G2 = \sum_{s=1}^{S}\sum_{d=1}^{D} D_{ds}^{evac} P_s \Pi_{\mathrm{ks}}^{\mathrm{accom}} \left\lfloor \zeta'_{\mathrm{dksr}} + \sum_{I\varepsilon FR}\sum_{r=0}^{R} \left(1 - \mathrm{P}_{\mathrm{k}}^{\mathrm{accom-fail}}\right)\zeta'_{\mathrm{dksr}} \right\rfloor \quad (3.2)$$

- Transportation Costs Across all Routes or Echelons.

$$G3 = \sum_{s=1}^{S}\sum_{v=1}^{V} \left\lfloor \sum_{d=1}^{D}\sum_{r=0}^{R}\sum_{k\varepsilon AD} \mathrm{D}_{\mathrm{dkr}}^{\mathrm{affected-accom}} . \Upsilon'_{\mathrm{vdks}} + \sum_{d=1}^{D}\sum_{r=0}^{R}\sum_{I\varepsilon FD\mathrm{UFR}} \mathrm{D}_{\mathrm{dlr}}^{\mathrm{affected-care}} . \Upsilon_{\mathrm{vdls}} + \sum_{d=1}^{D}\sum_{h=1}^{H} \mathrm{D}_{\mathrm{dh}}^{\mathrm{affected-\ hospital}} . \Upsilon''_{\mathrm{vdhs}} \right.$$
$$\left. + \sum_{e=1}^{E}\sum_{r=0}^{R}\sum_{\mathrm{I\varepsilon ADUAR}}\sum_{t=1}^{T} \mathrm{D}_{\mathrm{ekr}}^{\mathrm{dist-accom}}\ \Upsilon_{\mathrm{vekst}} \right\rfloor \quad (3.3)$$

- Cost of Temporary Facilities Establishment, Shortage Cost, and Penalty for Distributional Inequity.

$$G4 = \sum_{s=1}^{S} P_s \left\lfloor \sum_{r=0}^{R}\sum_{\mathrm{I=FDUFR}} C_{lsr}^{care} .\ \chi_{lsr} + \sum_{r=0}^{R}\sum_{ADUAR} \mathrm{C}_{\mathrm{ksr}}^{\mathrm{accomm}} . \chi'\mathrm{ksr} \right\rfloor + \left\lfloor \sum_{k=1}^{K}\sum_{\mathrm{c=1}}^{\mathrm{C}}\sum_{\mathrm{t=1}}^{T}\sum_{s=1}^{S}\sum_{r=0}^{R} P_s \Psi_{\mathrm{c}}\ \omega_{\mathrm{kctsr}} \right\rfloor$$
$$+ \sum_{s=1}^{S}\sum_{d=1}^{D} P_s \left(\sum_{I\varepsilon FDUFR} \Xi_{dlsr}^{equity} . \zeta_{\mathrm{dlsr}} + \sum_{k\varepsilon AD\mathrm{UAR}} \Xi_{dksr}^{equity} .\ \zeta'_{\mathrm{dksr}} \right) \quad (3.4)$$

To bolster the realism of the model, within the critical context of global warming impacts, we introduce a component that explicitly accounts for social equity. This addition discourages solutions that in advertently leave vulnerable populations underserved, reflecting a more holistic and ethical approach to humanitarian logistics. We define a penalty term, Ξ_{dlsr}^{equity}, which quantifies the cost incurred when vulnerable groups in affected area d are inadequately served by temporary care facility l at allocation tier r in scenarios. This penalty should be a function of the vulnerability index of the affected area. Ω_{ds}, and could also consider factors like the distance to the facility or its capacity to serve the specific needs of vulnerable individuals. A mathematical equation for this equity-based penalty is:

$$\Xi_{dlsr}^{equity} = C^{eq} . \Omega_{\mathrm{ds}} \mathrm{x} \left(\frac{\mathrm{D}_{\mathrm{dkr}}^{\mathrm{affected-care}}}{\mathrm{R}_{\mathrm{lr}}^{\mathrm{care}}} + \frac{1}{\sum_{r=0}^{R} N_{lsr}^{hospital}} \right) \quad (3.5)$$

Here, C^{eq} represents Predefined societal cost or penalty multiplier associated with equitable service provision.. This value would need to be determined based on ethical and policy considerations. Ω_{ds} is the vulnerability index of affected area d in scenario s. A higher value indicates greater vulnerability, leading to a larger penalty if service is inadequate. This index could integrate various socio-economic, demographic, and health factors. $\mathrm{D}_{\mathrm{dls}}^{\mathrm{affected-care}}$ is the distance between affected area d and temporary care facility l in scenario s. A greater distance could imply increase difficulty in access for vulnerable groups. $\mathrm{R}_{\mathrm{lr}}^{\mathrm{care}}$. The ratio $\frac{\mathrm{D}_{\mathrm{dlr}}^{\mathrm{affected-care}}}{\mathrm{R}_{\mathrm{lr}}^{\mathrm{care}}}$ would penalize allocations where the affected area is at the fringes or beyond the optimal service range. $\sum_{r=0}^{R} N_{lsr}^{hospital}$

, represents the total patient admission capacity of temporary care facility l across all allocation tiers r in scenario s. including the inverse of capacity ensures a higher penalty if a facility with limited capacity is disproportionately assigned vulnerable populations. Similarly, the concept of Ξ_{dlsr}^{equity} is directly applicable to temporary accommodation centers as well. We can define a similar penalty term, Ξ_{dksr}^{equity} to ensure equitable service at temporary accommodation centers. Its mathematical expression would follow an analogous structure:

$$\Xi_{dksr}^{equity} = \mathrm{C}^{\mathrm{eq}} \text{ x } \Omega_{\mathrm{ds}} \text{ x } \left(\frac{\mathrm{D}_{\mathrm{dkr}}^{\mathrm{affected-accom}}}{\mathrm{R}_{\mathrm{kr}}^{\mathrm{accom}}} + \frac{1}{\sum_{r=0}^{R} N_{ksr}^{evacuee}}\right) \tag{3.6}$$

Here, $\mathrm{D}_{\mathrm{dlr}}^{\mathrm{affected-care}}$ is the distance to the temporary accommodation center k, $\mathrm{R}_{\mathrm{kr}}^{\mathrm{accom}}$ is its coverage distance, and $\sum_{r=0}^{R} N_{ksr}^{evacuee}$ represents its capacity for housing evacuees. By including both Ξ_{dlsr}^{equity} and Ξ_{dksr}^{equity} in the objective function, the model is encouraged to develop solutions that are not only cost-effective but also socially responsible to minimize distributional inequity, and relief shortage, prioritizing the needs of vulnerable populations in global warming induce disasters.

Objective Function:

$$\mathrm{Min G} = (G_1 + \mathrm{G}_2 + \mathrm{G}_3 + \mathrm{G}_4) \tag{3.7}$$

Subject to

$$\sum_{e=1}^{\mathrm{E}} \sum_{r=0}^{\mathrm{R}} \Gamma_{\mathrm{ekcts}} \cdot \psi_{\mathrm{eksr}} + \omega_{\mathrm{kctsr}} + \Gamma_{\mathrm{kcts}}(\mathrm{t}-1) - \Gamma_{\mathrm{kcts}} \leq \mathrm{Q}_{\mathrm{kcts}}^{\mathrm{commodity}} \qquad \forall \mathrm{e}, \mathrm{c}, \mathrm{t}, \mathrm{s} \tag{1}$$

$$\sum_{r=0}^{R} \sum_{\mathrm{k\varepsilon ADUAR}} \Gamma_{\mathrm{kcts}} \cdot \boldsymbol{\vartheta}_{\mathrm{c}} \leq \sum_{\boldsymbol{r=0}}^{\boldsymbol{R}} \sum_{\boldsymbol{ADUAR}} \mathrm{N}_{\mathrm{kcts}}^{\mathrm{shelter}} \cdot \chi'_{kcts} \qquad \forall \mathrm{k}, \mathrm{c}, \mathrm{s}, \mathrm{t}, \mathrm{r} \tag{2}$$

$$\sum_{d=1}^{D} \Lambda''_{dhs} \leq N_{lhs}^{hospital}, \qquad \forall \mathrm{l}, \mathrm{h}, \mathrm{s} \tag{3}$$

$$\sum_{k\varepsilon AD\mathrm{UAg}} \Gamma_{\mathrm{ekcts}} \leq N_{ects}^{dist} \qquad \forall \mathrm{e}, \mathrm{c}, \mathrm{t}, \mathrm{s} \tag{4}$$

$$\sum_{d=1}^{D} \Lambda'_{\mathrm{dks}} \cdot \beta_{\mathrm{ct}} = Q_{kcts}^{commodity} \qquad \forall \mathrm{k}, \mathrm{c}, \mathrm{t}, \mathrm{s} \tag{5}$$

$$\Lambda_{\mathrm{dls}} \leq \mathrm{Y}_{\mathrm{vdls}} M_{v}^{patient} \qquad \forall \mathrm{d}, \mathrm{l}, \mathrm{s} \tag{6}$$

$$\Lambda'_{dks} \leq \sum_{v=1}^{V} Y'_{vdks} M_{v}^{evacuee} \qquad \forall \mathrm{d}, \mathrm{k}, \mathrm{s} \tag{7}$$

$$\Lambda''_{dhs} \leq \sum_{v=1}^{V} Y''_{vdhs} M_{v}^{patient} \qquad \forall \mathrm{d}, \mathrm{h}, \mathrm{s} \tag{8}$$

$$\sum_{c=1}^{C} \Gamma_{\mathrm{ekcts}} \leq \sum_{v=1}^{V} \mathrm{Y}_{vekst} M_{v}^{goods} \qquad \forall \mathrm{v}, \mathrm{e}, \mathrm{k}, \mathrm{t}, \mathrm{s} \tag{9}$$

$$\sum_{d=1}^{D} \zeta_{\mathrm{dlsr}} D_{dlr}^{aff\mathrm{ected-care}} \leq R_{lr}^{care} \qquad \forall \mathrm{l}, \mathrm{r}, \mathrm{s} \tag{10}$$

$$\sum_{d=1}^{D} \zeta'_{dksr} D_{dkr}^{aff\mathrm{ected-accom}} \leq R_{kr}^{accom} \qquad \forall \mathrm{k}, \mathrm{r}, \mathrm{s} \tag{11}$$

$$\sum_{d=1}^{D} \chi_{lsr} \leq \chi_{ls0} \qquad \forall \mathrm{l}, \mathrm{s} \tag{12}$$

$$\sum_{r=1}^{R} \chi'_{ksr} \leq \chi'_{ks0} \qquad \forall \mathrm{k}, \mathrm{s} \tag{13}$$

$$\sum_{I\varepsilon \mathrm{F_R}} \sum_{r=1}^{R} \zeta_{dlsr} + \sum_{i\varepsilon F_D} \zeta_{\mathrm{dls0}} = 1 \qquad \forall \mathrm{d, s} \qquad (14)$$

$$\sum_{k\varepsilon A_g} \sum_{r=1}^{R} \zeta'_{\mathrm{dksr}} + \sum_{i\varepsilon FD} \zeta'_{dks0} = 1 \qquad \forall \mathrm{d, r} \qquad (15)$$

$$\Lambda_{\mathrm{dls}} \le \mathrm{M}\zeta_{\mathrm{dlsr}} \qquad \forall \mathrm{d, l, s, r} \qquad (16)$$

$$\Lambda'_{dks} \le M\zeta'_{dksr} \qquad \forall \mathrm{d, k, s, r} \qquad (17)$$

$$\zeta_{\mathrm{dlsr}} \le \chi_{lsr} \qquad \forall \mathrm{l, d, r, s} \qquad (18)$$

$$\zeta'_{dksr} \le \chi'_{ksr} \qquad \forall \mathrm{k, d, s, r} \qquad (19)$$

$$\sum_{h=1}^{H} \Lambda''_{dhs} = D_{ds}^{critical} \qquad \forall \mathrm{d, s} \qquad (20)$$

$$\sum_{I\varepsilon \mathrm{F_{DUF_R}}} D_{ds}^{outpatient} = \sum_{\mathrm{I\varepsilon F}_{DUF_\mathrm{R}}} \zeta_{dlsr} \ x\Lambda_{\mathrm{dls}} \qquad \forall \mathrm{d, r, s} \qquad (21)$$

$$\sum_{k\varepsilon \mathrm{A_D U}A_\mathrm{R}} D_{ds}^{evac} = \sum_{k\varepsilon \mathrm{A}_{DUA_\mathrm{R}}} \zeta'_{dksr} \, x \, \Lambda'_{dks} \qquad \forall \mathrm{d, r, s} \qquad (22)$$

$$\chi_{\mathrm{lsr}}, \chi'_{\mathrm{ksr}}, \zeta_{\mathrm{dlsr}}, \zeta'_{dksr}, \psi_{\mathrm{eksr}} \ \varepsilon \ \{1.0\} \qquad \forall \mathrm{d, r, s, l, k, e} \qquad (23)$$

$$\Lambda_{\mathrm{dls}}, \Lambda'_{dks}, \Lambda''_{dhs}, \Upsilon_{\mathrm{vdls}}, \Upsilon'_{\mathrm{vdks}}, \Upsilon''_{\mathrm{vdhs}}. \Upsilon_{vekst}, \omega_{\mathrm{kctsr}}, \Gamma_{\mathrm{ekcts}}, \Gamma_{\mathrm{kcts}} \ge 0, \text{integer}$$

$$\forall,\mathrm{d,r} \quad \mathrm{s}, l, k, c, t, h, e, v, \qquad (24)$$

The objective function (3.7) minimizes the total cost of humanitarian logistic, relief shortage and distributional inequity by integrating cost of casualties at temporary care and accommodation Centers, transportation cost across all routes or echelons, facilities establishment cost, relief shortage, and distributional Inequity.

3.3 Model constraints

The model is governed by series of constraints that shows real world limitations and to ensure its optimal function**.** Constraints (1) ensures that for every temporary shelter, the amount of goods received plus any existing supplies and shortages is enough to meet the demand for each type of commodity. Constraints (2) restricts the storage of goods to established distribution hubs. Constraints (3) restricts the number of critically injured individuals admitted to any hospital to its maximum patient intake. Constraints (4) ensures the outflow of commodities from any distribution hubs does not exceed its designated capacity. Constraints (5) calculates the demand for each commodity at each shelter based on the per-person consumption rate and the number of affected individuals. Constraints (6**)** limits the evacuation of non-critically injured persons to care centers based on vehicle capacity. Constraints (7) imposes a vehicle capacity limit for moving displaced persons to temporary accommodation centers. Constraints (8) limits the evacuation of critically injured persons to hospitals by vehicle capacity. Constraints (9) specifically governs the movement of relief commodities. Constraints (10) permits the assignment of an affected area to a temporary care center only if it is within the center's coverage distance. Constraints (11**)** imposes the same coverage distance requirement for assigning affected areas to temporary accommodation centers. Constraints (12) and (13) ensure that backup (resilient) facilities can only be established if a corresponding primary facility exists. Constraints (14) permits the assignment of an affected area to o**ne** resilient care center. Constraints (15) permits the assignment of an affected area to one resilient accommodation center. Constraints (16) and (17) enforce the movement of people and commodities based on the assignment variables. Constraints (18) and (19**)** enforce that facilities must be established before they can be allocated for use. Constraints (20) ensures all critically injured individuals are transferred to hospitals. Constraints (21**)** ensures all non-critically injured individuals are transferred to care centers. Constraints (22) ensures all displaced persons are transferred to accommodation centers. Finally, Constraints (23) and (24) define the nature of the decision variables, specifying whether they are binary or non-negative integers.

4.0 Solution Methodology

In this research three distinct methodologies are utilized for solution generation and analysis:

4.1.1 Non-Dominated Sorting Genetic Algorithm (NSGA-II) Method

NSGA-II is a leading metaheuristic for multi-objective optimization, widely used for its reliable performance across domains**.** The model uses multiple chromosome encoding segments for: Status of temporary care and accommodation facilities (binary ending for 1= active, 0=inactive).Allocation of injured individuals to care centers, accommodation, and hospital, lastly deployment of the type of vehicles$(\mathrm{v_{1,} v_2, v_{3,}})$. The genetic operator used in this study is a three-step hybrid crossover process with a double-point crossover technique. The mutation operator varies depending on the chromosome dimensionality. For single- dimensional chromosomes, a random selected gene within the chromosome is replaced with an alternative gene. For two dimensional chromosome, a row is randomly chosen has its gene order reversed to introduce variation. The solutions for NSGA-II method, the solutions for the multi-objective model (equations 1-27) are assessed through a fitness function based on the objective functions and ranked through non-dominated sorting procedure. The various operational constraints (equations 6-27) embedded within the proposed model are addressed through the application of a penalty function approach. Should the NSGA-II algorithm generate a solution that violates any of these constraints during its iterative search, a predefined penalty is imposed on the corresponding objective function values, effectively discouraging in feasible outcomes. In essence, the technique optimize one primary objective function while constraining the other objective functions using upper bound epsilon (ε), repeated iteratively to trace all the Pareto solutions.

Table 1.1.Turned parameters for NSGA-II algorithm for flood relief optimization.

Mutation rate	Crossover rate	Population Size	Max Iterations
0.06	0.5	100	120

4.1.2 Modified Multi-Objective Particle Swarm Optimization (MMOPSO) Method

Building on the traditional Multi-Objective Particle Swarm Optimization (MOPSO) method for tackling multi-objective problems. This study introduces Modified Multi-Objective Particle Swarm Optimization (MMOPSO) that retain and update Pareto front dynamically. The (MMOPSO) particle movement is governed by three major components: Inertia defined by particle's velocity from the preceding iteration, local accelerator influenced by the particle's current position and its personal Pareto front effectively representing its historical best location and the global accelerator conversely shaped by the particle's current position and the collective Pareto front of the swarm representing swarm's best positions. The combined inertia, local, and global component to update particle movement mechanism or particle velocity each iteration is defined by the equation (3.8) with the operational parameters table1.2.

$$V^{t+1} = V^{t} + c_1 r_1 (p_{best} - x^{t}) + c_2 r_2 (g_{best} - x^{t}) \quad (3.8)$$

Table 1.2. Parameters of MMOPSO algorithm.

PARAMETER	NOTATION	VALUE
Number of iteration	t_{max}	500
Number of particles	N	50
Inertia Weight	ω	0.6
Cognitive (local) accelerator constant	c_1	0.6
Social (global) accelerator constant	c_2	0.7

4.1.3 Epsilon-Constraint (ε -constraint) Method

The epsilon-constraint method stands as a highly recognized and effective technique for navigating multi-objective optimization challenges. This methodology is particularly adept at generating the complete Pareto Front, which represents the set of optimal trade-off solutions. A pronounced strength of the epsilon-constraint method, distinguishing it from other multi-objective optimization techniques like the weighted sum approach, lies in its robust performance within non-convex solution spaces, where alternative methods often prove less effective. In this study, the total cost objective (Eq. 3.7, composed of G1-G4) was selected as the primary function to be minimized. The remaining two objectives, total relief supply shortage and distributional inequity, were converted into constraints. The mathematical formulation for the ε-constraint version of the model is as follows:

Primary Objective:
Minimize G (Total Cost from Eq. 3.7)

Subject to:
All original constraints (1) to (24)
Plus the new ε-constraints:
Total Relief Shortage ≤ ε shortage
Distributional Inequity ≤ ε inequity

5.1 Real World Application

Nigeria faced a devastating flood disaster in 2024 that impacted millions and claimed hundreds of lives, prompting urgent national calls for improved mitigation strategies. The destructive trend continued into 2025, with first-quarter reports from the National Emergency Management Agency (NEMA) revealing that flooding had killed 165 people, left 82 missing, and injured 138 others. The disaster affected 119,791 individuals, displaced 43,936, and caused extensive damage to 8,594 houses and 8,278 farmlands across 19 states, with children and women being the most affected groups. To effectively understand and respond to such large-scale disasters, localized case studies are essential. One critical case is the Sapele and Amukpe environs in Delta State, which experienced severe flooding from intense rains in June/July 2025, leading to major displacement. This area's designation by the Nigerian Hydrological Services Agency (NIHSA) as a priority for humanitarian response reinforces its importance as a case study. By focusing on Sapele and Amukpe, researchers and policymakers can move beyond broad generalizations to analyze the specific socio-economic, environmental, and infrastructural dynamics that heighten flood vulnerability in the region. For the purposes of this research, the affected area is divided into 8 distinct, flood-prone zones, each representing a demand point for aid. A strategic response plan has been developed, identifying crucial facilities for emergency operations. This plan includes existing hospitals, designated relief distribution centers, and potential sites for establishing temporary accommodation centers for evacuees, with each temporary accommodation center accompanied by its own care center for the injured and displaced Table1.3 and figure1 is the map of Sapele and Amukpe environs showing the five echelons considered in this study. This coordinated framework aims to tailor effective strategies for Sapele and Amukpe environs, which can serve as a model for other vulnerable areas across Nigeria.

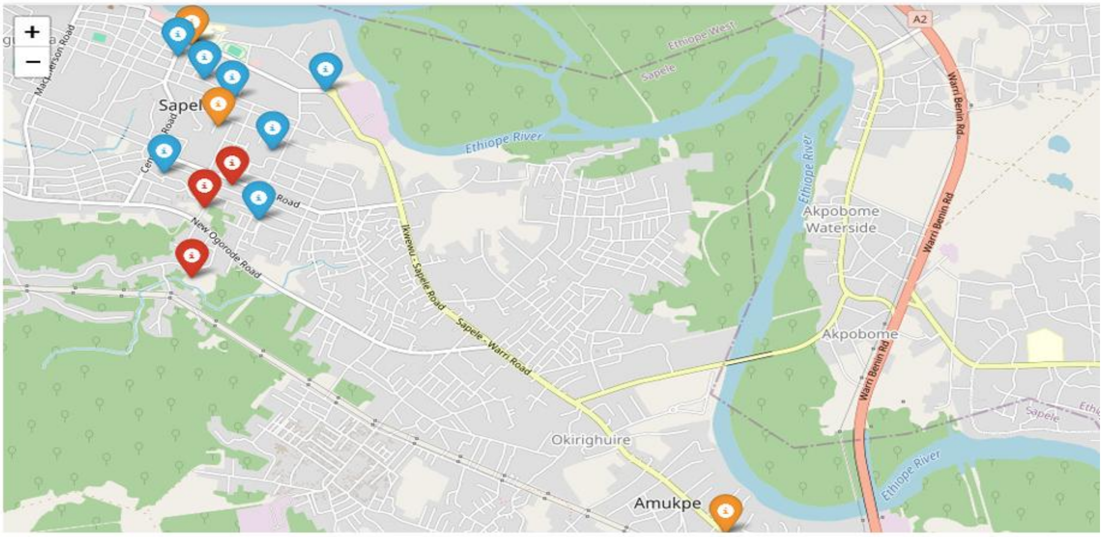

Figure 1. Map of Sapele and Amukpe Environs, showing flood-prone areas and locations of critical facilities: Red Icons (Hospitals/Medical Posts), Orange Icons (Relief Distribution Centers), Blue Icons (Temporary Care and Accommodation Centers).

Table 1.3. Sapele and Amukpe environs Flood Affected areas, Potential Temporary care / Accommodation Centers, Hospitals and Distribution Hubs.

Affected Area	Temporary Care/Accommodation centers	Hospitals	Distribution Hubs
Amukpe	Sapele Technical College	Central Hospital Sapele	Local Govt. Sec. Comp.
Okrigba	Sapele Township Stadium	Okparavero Memorial Hospital	Sapele Dev. Center Compressive Road Ibada
Secondary School	Imene-Eferakeya Medical Center	Main Market	
Ogorode	Okotie- Ebor Secondary School	Sapele Cottage Hospital	
Owumi Road	Malachy Grammar School		
Shell Road	Orodje Secondary School		
Otakpo	Ozue Secondary School		
Orakpo	Igbuya Primary School		

Table 1.4. Different flood scenario for Sapele and Amukpe environs their estimated probability of occurrence.

Flood Scenario	Intense Rainfall		River Overflow		Coastal Surge		Combined Event	
Severity of occurrence	Moderate		High		Moderate to High		Very High	
Time of occurrence	Day	Night	Day	Night	Day	Night	Day	Night
Probability of occurrence	0.250	0.150	0.100	0.080	0.0700	0.05	0.180	0.120
Percentage of affected area	15%		35%		20%		60%	

Table 1.5. Relief commodities for flood response.

Commodity	Priority (%)	Quantity	Unit	Estimated Transportation Cost (10^3 N)	Shortage Penalty (%)
Rice	0. 98	800 Bags	50kg	78	0.79
Flour	0.67	600 Bags	25kg	58	0.45
Vegetable Oil	0.77	200 Gallon	25ltr	62	0.51
Soap	0.78	400 Cartoons	10kg	32	0.60
Bottle Water	0.92	8000 Packs	900cl	45	0.70
Salt	0.65	500 Bags	25kg	43	0.49
Sugar	0.48	30 Bags	50kg	39	0.45
Mosquito net	0.82	2000 Pieces		29	0.71
Mattresses	0.84	3000 Pieces		72	0.60
Bucket	07.6	4000 Pieces		15	0.55
Kerosene stove	0.64	500 Pieces		27	0.43
Cooking Pots	0.73	1000 Pieces		24	0.65
Plastic Bowl	0.59	2000 Pieces		17	0.49
Drugs(Antibiotic, PPIS)	0.89	500 Cartons		14	0.74

5.2. Experimental Methodology

To thoroughly evaluate the effectiveness of the proposed solution approaches in the context of flood relief welfare networks, the following experimental methodology has been adopted. Initially, a set of ten random small and medium-scale test instances, representative of flood scenarios in Sapele and Amukpe environs, are generated. The specific configurations and characteristics of these random instances are detailed in Table 1.6.

Table 1.6. Dimensions of the flood-response instances to verify the solution approaches.

Problem number	Problem scale	Affected areas	Temporary accommodation centers	Distribution centers	Healthcare facilities
1	Small	3	1	1	1
2	Small	4	1	2	2
3	Small	5	2	1	1
4	Small	6	2	2	2
5	Small	7	3	1	1
6	Medium	8	3	3	2
7	Medium	9	4	3	2
8	Medium	11	4	2	3
9	Medium	12	5	3	
10	Medium	13	6	3	3

5.3 Performance Evaluation of, ε-Constraint, NSGA-II and MMOPOS Algorithms for Flood Relief Optimization.

To rigorously evaluate and discuss the numerical computational results of the proposed solution methods in this study, two key performance metrics are employed: Spread Metric (SM) and the Mean Ideal Distance (MID). These metrics collectively measures the convergence and diversity of the obtained Pareto fronts, providing a holistic view of each algorithm's performance in balancing the three conflicting objective.

5.3.1 Spread Metric (SM)

The spread metric (SM) quantifies the standard deviation of the distances between consecutive solutions on the Pareto front [41], indicating the uniformity of the distribution and spread of the non-dominated set solutions along the Pareto front. It can be calculated using the formula below:

$$\mathrm{SM} = \sqrt{\frac{1}{n-1}\sum_{i=0}^{n}(\mathrm{d_i} - d)^2} \qquad (3.9)$$

Here, $\mathrm{d_i}$ represents the Euclidean distance between two adjacent Pareto solutions in the objective space, and d denotes the average Euclidean distance among all adjacent solutions. A smaller SM value signifies a lower dispersion of Pareto points, indicating a more evenly distributed and well-spread Pareto front. Ideally, when SM approaches zero, the distances between all adjacent solutions on the Pareto front are approximately equal.

5.3.2 Mean Ideal Distance (MID)

The mean Ideal distance (MID), measures the convergence rate of the generated Pareto fronts towards an ideal point (0, 0) in the objective space [42], reflecting how close the solutions are to the optimal front solutions. MID metric is utilized to assess the proximity of the generated Pareto solutions to the ideal point in the objective space.

$$\mathrm{MID} = \sqrt{\sum_{i=0}^{n}\frac{\left(\mathrm{f_{ji}} - \mathrm{f_j^*}\right)^2}{\mathrm{R_j^2}} + \frac{(\mathrm{f_{2i}} - \mathrm{f_2^*})^2}{\mathrm{R_2^2}}} \qquad (3.10)$$

In this equation, n refers to the total number of Pareto solutions obtained. $\mathrm{f_{ji}}$, represents the value of the j-th objective for the, i-th solution in the Pareto frontier. $\mathrm{f_j^*}$, denotes the ideal (maximum or minimum, depending on the objective type) value of the j-th objective observed among all solutions in the Pareto frontier. $\mathrm{R_J}$, represents the range of the j-th objective. According to this definition, an algorithm that yields a lower value for the MID demonstrates superior convergence and performance, as its solutions are closer to the ideal trade-off point. All these generated instances are then solved using the epsilon-constraint method, NSGA-II, and MMOPSO algorithms. The performance evaluation metrics, specifically MID, SM, and CPU Time, are computed for all solution approaches across these instances and are presented in Table 1.7.

Table 1.7: Numerical results of multi-objective performance metrics for flood –response in-stance test problems.

No	ε- Constraint			NSGAII			MMOPOSO		
	MID	SM	Time(s)	MID	SM	Time(s)	MID	SM	Time(s)
1	2.450	0.375	4	2.580	0.380	4	2.180	0.378	4
2	2.290	0.370	35	2.350	0.380	6	2.280	0.380	6
3	2.550	0.205	68	2.610	0.210	8	2.570	0.210	7
4	2.980	0.220	95	3.050	0.230	12	2.910	0.235	10
5	3.320	0.435	310	3.380	0.440	21	3.320	0.450	14
6	4.750	0.400	700	4.850	0.410	28	4.810	0.410	18
7	4.820	0.415	1600	4.930	0.420	38	4.840	0.425	28
8	5.010	0.430	2550	5.080	0.450	45	5.040	0.440	30
9	5.180	0.460	5700	5.450	0.475	70	5.220	0.470	35
10	5.400	0.490	8900	5.850	0.500	105	5.500	0.510	52
Ave.	3.875	0.380	1996.2	4.013	0.390	33.7	3.867	0.391	20.4

6.0 Results and Discussion

Given the three objectives are to minimize total cost, minimize total relief supply shortage, and minimize distributional inequity. The epsilon-constraint method, tailored for multi-objective optimization, is implemented using GAMS24.9.1 software. For metaheuristic approaches, MATLAB R2017a v9.2.0.53 software is utilized to code the NSGA-II and MMOPOS algorithms. The computational environment for these simulations includes a laptop equipped with 8GBRAM, an Intel Core i57200U processor, and running Win1064bit. The NSGA-II algorithm, a prominent multi-objective evolutionary algorithm, is applied with various configurations of its parameters. Table1.7 details the numerical results of multi-objective performance metrics for flood –response in-stance test problems used in this study.

6.1 Results Discussion using Mean Ideal Distance (MID)

The MID (3.867) of the MMOPSO has found the pareto- front contains set of pareto-optimal solutions that are, on average, the closest to the ideal point of (Cost=0, Shortage=0, Inequity=0). This is, of course, unachievable, but it serves as the benchmark and is used in obtaining the objectives of this study.

- Minimization of Total Cost: The Pareto front found by MMOPSO contains solutions that are, on average, closer to the minimal possible cost than the fronts found by other algorithms. This mean for any given level of shortage or inequity that a planner is willing to accept, MMOPSO will likely provide an option that achieves that level at a lower financial cost than the other algorithms. This is crucial for efficient budget allocation in large-scale disasters where resources are limited.

- Minimization of Total Shortage: The solutions are also, on average, closer to the goal of zero shortage compare to other two algorithms. This means better coverage of demand for resources (e.g., medical supplies, food, and shelter). This means for any given budget constraint or level of accepted inequity, MMOPSO provides plans that result in less demand satisfaction across the affected areas. This directly translates to more lives saved and reduced human suffering.

- Minimization of Distributional Inequity: This is a particularly important result. A lower MID means the solutions are closer to perfect equity (Inequity=0). MMOPSO's superior performance indicates it is better at finding solutions that balance resource allocation fairly across different affected areas than the remaining solution methods.

6.2 Spread Metric (SM)

- NSGA-II and MMOPSO are virtually tied with average SM values of 0.390 and 0.391**,** respectively. These values are excellent and very low, indicating both algorithms produce a diverse and evenly spread set of solutions with MMOPSO. In terms of computational efficiency speed time fig3, MMOPSO have the least average computation speed time (20.4 s), a better improvement over NSGA-II and ε-Constraint with SM of 0.390 and 0.380 respectively. When evaluating against the three objectives of minimizing cost, shortage, and inequity, the results clearly demonstrate that MMOPSO is the superior algorithm for this large-scale flood response problem table 1.8. Also figure shows the computational solution speed (time) efficacy.

Table 1.8. Performance comparison of the solution methods using MID and SME

Criteria	ε -Constraint	NSGA-II	MMOPSO	Best approach
Solution Quality (MID)	3.875	4.013	3.867	MMOPSO
Solution Diversity (SM)	0.380	0.390	0.391	**E** -Constraint
Computational Speed(Time)	1996.2(s)	33.7(s)	20.4(s)	MMOPSO

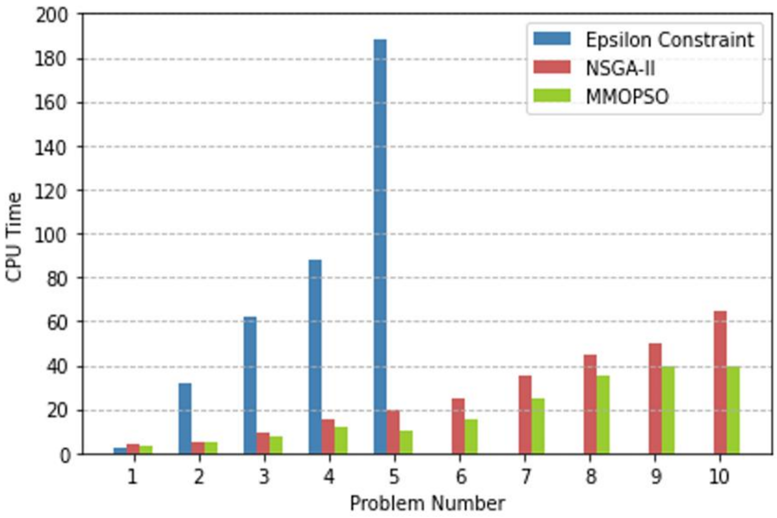

Figure2: Computational solution speed (Time) graph

7 Conclusion and Future Work

7.1 Conclusion

This study set out to address a critical gap in humanitarian logistics by designing a global warming-resilient welfare network that simultaneously minimizes total cost, total shortage, and distributional inequity. The research successfully achieved its primary objectives through the development of a sophisticated multi-objective, multi-period, multi-echelon optimization model, tested on a real-world case study of flood-prone regions in Delta State, Nigeria.

The findings robustly demonstrate that the proposed Modified Multi-Objective Particle Swarm Optimization (MMOPSO) algorithm is the most effective solution method for this complex problem. As quantified by the performance metrics, MMOPSO outperformed both the well-established NSGA-II and the exact ε-Constraint method. Its superior convergence, evidenced by the lowest Mean Ideal Distance (MID = 3.867), signifies that the Pareto-optimal solutions it generates provide the most efficient trade-offs. This translates to actionable plans for policymakers where, for any given level of investment (cost), the solutions offered by MMOPSO achieve a lower shortage of relief supplies and a more equitable distribution of aid compared to the other methods. Furthermore, MMOPSO's exceptional computational efficiency (20.4 seconds average) proves its practical viability for rapid decision-making in time-sensitive disaster response scenarios.

Therefore, this research makes a significant contribution to the field by providing a validated, data-driven framework and a superior computational tool (MMOPSO) for designing humanitarian networks. It moves beyond traditional cost- or efficiency-focused models by explicitly embedding social equity as a core objective, thereby ensuring that the needs of the most vulnerable populations are prioritized in climate-induced disaster planning. The framework offers policymakers a practical tool to balance fiscal responsibility with operational effectiveness and ethical fairness, ultimately enhancing the resilience of communities most threatened by global warming.

7.2 Feature Work Suggestion

Based on the findings of this study, several promising directions for future research are proposed to advance the field of humanitarian logistics optimization:

1. Dynamic Modeling with Real-Time Data Integration: Future research should develop multi-period dynamic frameworks capable of incorporating real-time data. Integrating live information on weather patterns, infrastructure status, and evolving demand would significantly enhance the model's practical applicability for adaptive disaster response.

2. Decision Support System Development: A crucial next step involves implementing the MMOPSO algorithm within an interactive decision support system. Such a platform would enable emergency planners to visualize Pareto-optimal solutions, dynamically explore trade-offs between objectives, and facilitate stakeholder-driven selection of optimal response strategies.

3. Model Expansion with Additional Objectives: The framework could be extended by incorporating supplementary optimization criteria such as: • Minimization of emergency response time• Enhancement of supply network resilience to sequential disruptions• Reduction of environmental impacts from relief operations

This expansion would create more comprehensive decision-making tools.

5. Cross-Context Validation and Application: Future studies should validate the proposed framework across diverse disaster scenarios (e.g., droughts, hurricanes) and various socio-economic contexts to evaluate its robustness and generalizability, thereby strengthening its global applicability.

Pursuing these research directions will contribute to developing more adaptive, responsive, and equitable systems for addressing the growing humanitarian challenges posed by climate change.

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References

1. Chen J., Zhang Y., Liu W., Huang Y., “An equity-integrated model for shelter resource allocation in disaster response”, Annals of Operations Research, 2022.

2. Daneshvar M., Khadem M., “A robust multi-period optimization model for humanitarian relief supply under climate change uncertainty”, Sustainable Operations and Computers, 2022, 3, 112–122.

3. Djalante R., Shaw R., DeWit A., “Building resilience against biological hazards and pandemics: COVID-19 and its implications for the Sendai Framework”, Progress in Disaster Science, 2020, 6, 100080.

4. Kellermann A.L., Savić M., Jones M., “Equity in disaster response: A critical perspective on distributional fairness in emergency logistics”, Disasters, 2018, 42 (S1), S99–S121.

5. Li H., Wang Y., Wu J., “Equity-oriented humanitarian logistics model incorporating social vulnerability data”, Computers & Industrial Engineering, 2022, 171, 108432.

6. Liu Y., Ma J., Zhang Z., Gao H., “Hybrid evolutionary optimization for equitable disaster relief logistics”, Applied Soft Computing, 2023, 129, 109658.

7. Moradi M., Manzouri M., “Resilient food distribution network design during climate-induced crises”, Sustainable Production and Consumption, 2024, 41, 201–213.

8. Rahmani D., Ghasemi P., “Integrated location-inventory-routing optimization for climate-induced disaster logistics”, Computers & Industrial Engineering, 2022, 169, 108233.

9. Rawls C.G., Turnquist M.A., “Pre-positioning of emergency supplies for disaster response”, Transportation Research Part B: Methodological, 2010, 44 (4), 521–534.

10. Rawls C.G., Turnquist M.A., “Stochastic optimization for pre-disaster planning of emergency supply chains”, Journal of Infrastructure Systems, 2016, 2 (1), 04015016.

11. Tofighi S., Torabi S.A., Mansouri S.A., "Humanitarian logistics network design under mixed uncertainty", European Journal of Operational Research, 2016, 250 (1), 239–250.

12. Wang B.C., Qian Q.Y., Gao J.J., Tan Z.Y., Zhou Y., "The optimization of warehouse location and resources distribution for emergency rescue under uncertainty", Advanced Engineering Informatics, 2021, 48, 101278.

13. Wu Y., Cui N., "A bi-objective flood evacuation planning model integrating climate projections", Natural Hazards, 2021, 108 (1), 1001–1027.

14. Yazdani M., Zavadskas E.K., Chatterjee P., "Dynamic network reconfiguration in flood-affected logistics systems", Journal of Cleaner Production, 2021, 283, 124597.

15. Yuan Z., Gao L., Zhang X., Liu Y., "Equity in humanitarian logistics: A Gini-based optimization approach", Operations Research for Health Care, 2023, 39, 100387