FUDMA Journal of Sciences (FJS)
ISSN online: 2616-1370
ISSN print: 2645 - 2944
Vol. 10 No. 15, August, 2026, pp 189 – 196
DOI: https://doi.org/10.33003/fjs-2026-1015-5527

A Conflict-Sensitive Mixed Integer Linear Programming Framework for Humanitarian Aid Distribution in Active Conflict Zones

Aliyu, O. Aminu, Maijama'a Bilkisu, Abubakar A. Mohammed, Nweze, N. Obini

*Corresponding authors' email: ohindase11@gmail.com

ABSTRACT
The delivery of humanitarian aid in active conflict zones presents a fundamental operational dilemma: traditional logistics optimization prioritizes cost-efficiency, while conflict sensitivity demands security-aware planning (objectives typically treated as separate rather than integrated concerns). This paper addresses this gap by developing a novel Mixed Integer Linear Programming (MILP) framework that systematically incorporates real-time security data into humanitarian distribution optimization. The model advances beyond static risk proxies by designing a mathematical structure capable of ingesting dynamic conflict event data (e.g., ACLED reports) alongside infrastructure constraints, route-specific delay factors, warehouse capacities, and prioritized demand. The framework operationalizes conflict sensitivity through a multi-objective function that minimizes both tangible transportation costs and intangible security risk exposure, subject to constraints including minimum demand fulfillment (≥80%), supply capacity limits, and maximum acceptable risk thresholds. The model incorporates a calibrated risk-weighting parameter (α) that enables humanitarian planners to explicitly quantify and control the trade-off between operational efficiency and personnel safety. A proof-of-concept validation using data from Northeast Nigeria demonstrates the model's computational tractability and its ability to generate feasible solutions that balance competing objectives. The key methodological contribution lies in the framework's structural readiness for temporally relevant security integration—moving beyond probabilistic planning toward event-driven operational optimization. This research provides humanitarian organizations with a defensible, mathematically rigorous tool for making transparent trade-offs between efficiency, security, and equity in the world's most challenging environments.

Received: 09 June 2026
Accepted: 13 July 2026
Published: 09 Sept. 2026

Keywords: Mixed Integer Linear Programming (MILP), Humanitarian Logistics, Conflict-Sensitive Aid, Optimization, Mathematical Modeling

INTRODUCTION

Humanitarian aid distribution in contemporary conflict zones presents a dual challenge of operational efficiency and conflict sensitivity, a balance that traditional logistics models frequently fail to achieve (Anderson, 1999; Mac Ginty & Richmond, 2013). This failure is increasingly consequential given the rising complexity of crises, marked by a 44% increase in climate-related disasters since 2000 and the persistence of protracted conflicts that severely disrupt aid delivery, as seen in regions like Yemen and South Sudan (UNDRR, 2022; UNOCHA, 2023).

Mixed Integer Linear Programming (MILP) has emerged as a powerful tool for structuring complex humanitarian logistics problems, enabling optimal decisions on facility location, resource allocation, and routing (Ghahremani-Nahr et al., 2022), its application in active conflict zones requires significant advancement.

Current conflict-sensitive MILP models have begun to incorporate security by assigning cost penalties to high-risk areas or using probabilistic planning to handle uncertainty (Hezam et al., 2021; Ghasemi et al., 2022). Furthermore, robust and fuzzy optimization techniques have been integrated to ensure solutions remain viable across a range of possible scenarios and to manage imprecise data (Ghahremani-Nahr et al., 2022).

Despite significant advances in humanitarian logistics optimization over the past decade, a critical and persistent gap remains in the integration of real-time security data into operational decision-making frameworks. This gap has been repeatedly identified in the literature but remains inadequately addressed (Hezam et al., 2021; Akbari & Salman, 2024; Sabbagh et al., 2025).

First, many existing models rely on static or historical risk assessments, which are fundamentally insufficient in the fluid landscape of modern conflicts where threat levels can shift hourly (Khalaj Rahimi & Rahmani, 2024; Walsh et al., 2024). The Armed Conflict Location & Event Data Project (ACLED) and similar platforms provide real-time, geo-referenced data on conflict events, yet this rich stream of information is not systematically or dynamically fed into operational optimization models (Reynaud & Nicosia, 2024; Ekici et al., 2025). As noted by Sabbagh et al. (2025, p. 4), "the temporal lag between data collection and optimization execution remains a critical vulnerability in humanitarian logistics systems."

Second, there is no established, empirically-validated framework for quantifying the trade-off between transportation cost and security risk in a manner that is both mathematically rigorous and operationally actionable (Khalaj Rahimi & Rahmani, 2024; Pashapour et al., 2024). This forces decision-makers to choose between cost-driven efficiency (which may expose personnel to unacceptable danger) and overly conservative security protocols (which may leave vulnerable populations without aid). Recent studies by Ghahremani-Nahr et al. (2024) and Akbari and Salman (2024) have called for more nuanced approaches to risk-cost trade-offs, but empirical validation remains scarce.

Third, the relationship between risk-weighting parameters and actual logistics outcomes remains poorly understood (Vitoriano et al., 2011; Hezam et al., 2021). Specifically, it is unclear whether increasing the penalty for risk in optimization models leads to meaningful reductions in security exposure or simply increases costs without corresponding safety benefits (Ghasemi et al., 2022; Khalaj Rahimi & Rahmani, 2024). This knowledge gap undermines evidence-based policy-making for humanitarian security management. As observed by Sabbagh et al. (2025, p. 12), "the absence of systematic sensitivity analysis on risk parameters represents a significant methodological weakness in the majority of humanitarian logistics models."

Fourth, there is limited empirical evidence on the existence and nature of "risk plateaus" —minimum feasible risk levels that cannot be eliminated through optimization regardless of how heavily risk is penalized (Du et al., 2020; Yin et al., 2024). Understanding whether such plateaus exist, and at what level, is crucial for setting realistic expectations for security management in conflict-zone logistics. Recent work by Pashapour et al. (2024) on the Capacitated Mobile Facility Location Problem with Mobile Demand (CMFLP-MD) suggests that irreducible risk floors may be a general feature of humanitarian logistics in conflict environments, but this hypothesis requires empirical testing across different contexts.

Fifth, and most critically for this study, there is a dearth of empirical research on conflict-sensitive logistics optimization specifically for Northeast Nigeria (Osuji et al., 2024; Global WASH Cluster, 2024). While the BAY states represent one of the world's most complex humanitarian environments, with over two million internally displaced persons and ongoing security threats from multiple non-state armed groups (IOM, 2024; UNDRR, 2025), optimization studies for this context remain extremely limited. The few existing studies (e.g., Osuji et al., 2024) have focused on multi-criteria decision-making for vessel selection rather than comprehensive land-based distribution network optimization.

These interrelated problems are particularly acute in Northeast Nigeria, where humanitarian agencies operate in one of the world's most complex and dangerous environments (Ogungbemi, 2025; UNDRR, 2025). Without a robust, empirically-validated optimization framework that explicitly addresses the cost-risk trade-off and incorporates recent security data, aid delivery will remain suboptimal—either unnecessarily dangerous for personnel or insufficient for affected populations (Global WASH Cluster, 2025; Salawu et al., 2026).

The aim of this study is to develop and empirically validate a conflict-sensitive Mixed Integer Linear Programming (MILP) framework for humanitarian aid distribution that explicitly quantifies and optimizes the trade-off between transportation cost and security risk in active conflict zones, with specific application to Northeast Nigeria.

Specifically, the study seeks to:

i. Formulate a multi-objective MILP model that integrates real-time security data (derived from ACLED and expert assessments) with infrastructure constraints, warehouse capacities, and prioritized demand to generate optimal aid distribution plans.

ii. Quantify the cost-risk trade-off by conducting a systematic sensitivity analysis of the risk-weighting parameter (α) to determine the relationship between risk aversion and total transportation cost.

iii. Determine the optimal calibration of the risk-weighting parameter (α) that provides meaningful risk sensitivity while avoiding economically irrational cost escalation, providing an evidence-based benchmark for humanitarian agencies.

MATERIALS AND METHODS

Literature Review

The relentless pursuit of operational efficiency in complex, constraint-driven environments has propelled Mixed Integer Linear Programming (MILP) and its robust variants to the forefront of decision-support science. These optimization frameworks, capable of modeling discrete choices (e.g., facility opening, vehicle routing) alongside continuous flows (e.g., commodity amounts), provide a mathematically rigorous foundation for tackling some of the most pressing logistical and resource allocation challenges across humanitarian, healthcare, defense, and commercial sectors. The following synthesis elucidates how these sophisticated models are tailored to address specific, high-stakes problems, revealing a common thread of seeking optimality amidst uncertainty, scarcity, and dynamic needs.

In the volatile realm of humanitarian logistics and disaster response, where speed and reliability are paramount, MILP models are indispensable for structuring effective aid delivery. The foundational challenge of minimizing delivery times from temporary warehouses to dispersed demand points was addressed by Acero Condor et al. (2023), who innovatively integrated real-world geospatial data. Their model utilized the Google Maps API Distance Matrix to dynamically incorporate travel times based on actual routes and vehicle density, ensuring the MILP's solutions were grounded in contemporary traffic conditions rather than theoretical distances. This approach was validated through a case study in Chosica, Peru, demonstrating practical applicability. However, post-disaster environments are often characterized by profound uncertainties, including the threat of secondary disasters.

To navigate this complexity, Du et al. (2020) advanced the field by developing a Three-Stage Mixed Integer Robust Optimization (TS-MIRO) model. This model explicitly accounts for the uncertainty in relief demand and the potential for cascading catastrophic events. Their research quantified the inherent trade-off between cost and reliability: while a deterministic TS-MILO model yielded the lowest cost, it was vulnerable to uncertainty. The robust counterparts (BTS-MIRO, PTS-MIRO, ETS-MIRO) paid a "robust price"—increasing costs by at least 10.05%—but guaranteed supply stability even under worst-case scenarios, with the ETS-MIRO model (using an ellipsoidal uncertainty set) proving most efficient by limiting cost increases to just 44.66% of the box set model's expense in extreme conditions.

Moving from tactical response to strategic network design, Zhang et al. (2020) tackled the pre-positioning and distribution problem through a distributionally robust optimization lens. Their model designed a three-level relief network (suppliers, distribution centers, points of distribution) while incorporating resource reallocation and handling demand uncertainty through a risk measure known as mean absolute semi-deviation (MASD). This approach, which requires only partial knowledge of the probability distribution of uncertainties, provides a tractable yet conservative framework for ensuring network resilience.

At the global strategic level, Eligüzel et al. (2023) conducted a seminal analysis of the United Nations Humanitarian Response Depots (UNHRD) network. By applying classic location-allocation models maximum coverage, P-median, and set covering to real 2018 shipment data, they identified profound inefficiencies. Their application of the P-median model recommended a rebalancing of depot roles, which could reduce the network's total traveled distance by an estimated 58% and highlighted the Accra depot as critically under-utilized, offering actionable managerial insights for capacity investment.

The integration of nutritional objectives into this logistical calculus represents another frontier, as demonstrated by Peters et al. (2021) in their work with the World Food Programme (WFP). Their holistic MILP model simultaneously optimizes food basket composition, sourcing, delivery, and transfer modalities, connecting supply chain mechanics directly to human nutritional outcomes. This allowed for breakthroughs such as reducing operational costs in Iraq by 12% without degrading the nutritional value delivered, proving that cost-efficiency and humanitarian impact are not mutually exclusive.

Similarly, for flood disaster response, Okonta and Olaomi (2023) modeled the problem as a stochastic, multicommodity, multimodal network flow. Their formulation, considering multiple disaster scenarios (mild, medium, severe) with associated probabilities, successfully minimized expected rescue costs while tightly matching supply to demand, demonstrating the power of stochastic programming in anticipatory planning.

The utility of integer programming extends decisively into critical infrastructure management, such as healthcare and national defense. Overcrowding in emergency departments (EDs), a widespread public health issue, was framed as a resource optimization problem by Chouba et al. (2020). Their MILP aimed to minimize the total number of patients waiting throughout the ED care pathway by optimally allocating medical staff and beds. Tested on real data from a French hospital and solved using a Sample Average Approximation (SAA) approach, the model provided evidence-based staffing and capacity plans to alleviate systemic bottlenecks.

In the domain of national security, Odion et al. (2023) applied Mixed Integer Programming to optimize the resource-intensive training of officer cadets at the Nigerian Defence Academy. Their model sought the minimum-cost allocation of resources (instructors, equipment, time) across mission-essential tasks while maintaining required proficiency standards. The solved model yielded an objective function value of 211.5, representing the minimal cost to sustain training excellence, thereby offering a quantitative, scientific basis for defense budget allocation and training schedule design.

In the digital and economic spheres, these optimization techniques guard against modern threats and market disruptions. Akinbowale et al. (2023) confronted the escalating challenge of cyberfraud in the South African banking sector by developing a heuristic-based MILP model. This decision-support system proactively allocates cybersecurity resources, guiding the ordering, sequencing, and assignment of tasks to anti-fraud teams—to ensure a rapid and cost-effective incident response, with their algorithm finding optimal solutions for cost minimization and network connection efficiency.

The global COVID-19 pandemic presented severe logistical disruptions, which Sang et al. (2021) addressed for logistics enterprises in Vietnam. Their MILP model formulated a low-cost freight allocation strategy to navigate social distancing restrictions, ensuring the continued movement of essential goods by minimizing total transportation costs while meeting district-level demand in Ho Chi Minh City.

Humanitarian logistics research increasingly focuses on minimizing the arrival time of relief goods and optimizing services in disaster-affected regions, with recent studies exploring the use of modern transport fleets that include drones. In a study on optimizing relief operations, Khalaj and Rahmani (2024a) introduced a multi-objective hybrid truck-drone routing problem with pickup and delivery services, considering reliability (MHTDRP-PD-R). The problem was formulated as a mixed-integer linear programming (MILP) model with the simultaneous goals of minimizing transportation time and maximizing reliability through routing and inventory decisions made by multiple trucks and drones. To address the complexity of the model, the authors developed an adaptive large neighborhood search (ALNS) algorithm, coupled with a heuristic technique. The ALNS algorithm refined initial solutions through destroy and repair operators and was integrated with multi-objective optimization methods, specifically the ε-constraint method, to create a unified objective function. The solution quality was evaluated using both small and large-scale test problems, with results demonstrating the superiority of the developed ALNS integrated with the ε-constraint method in terms of objective value and solution time.

In a related study, Khalaj and Rahmani (2024b) addressed the critical factor of deprivation time in post-disaster logistics by introducing a new hybrid vehicle routing problem with pickup and delivery services. This study aimed to minimize deprivation costs by optimizing routing and inventory decisions made by heterogeneous vehicles, including multiple trucks and drones in a disaster setting. The model was presented as a MILP problem, where deprivation time was categorized into three main classes based on the arrival time of relief goods to affected areas. Given the problem's complexity, an improved ALNS metaheuristic was developed, which employed a heuristic algorithm to generate high-quality initial solutions and utilized 17 destroy and repair operators for solution improvement. The algorithm was tested on a large-scale dataset based on real-world data from a crisis scenario, specifically the Tehran earthquake. The results indicated the algorithm's superiority in providing better-quality solutions with lower solution times.

Expanding the scope of humanitarian logistics to address the needs of en-route refugees, Pashapour et al. (2024) investigated the Capacitated Mobile Facility Location Problem with Mobile Demands (CMFLP-MD). This study aimed to assist humanitarian organizations in cost-efficiently optimizing the logistics of capacitated mobile facilities used to deliver relief aid to transiting refugees in a multi-period setting. In this problem, refugee groups follow specific paths and must receive relief aid at least once every fixed number of consecutive periods to maintain service continuity. The objective was to minimize overall costs, including fixed, service provision, and relocation costs associated with the mobile facilities. The authors formulated an MILP model and proposed two solution methods: an accelerated Benders decomposition approach as an exact solution method and a matheuristic algorithm that relied on an enhanced fix-and-optimize agenda. The methodologies were evaluated using realistic instances based on the Honduras migration crisis that began in 2018. The numerical results revealed that the accelerated Benders decomposition excelled compared to standard MILP, achieving a 46% runtime improvement on average while acquiring solutions at least as good as the MILP across all instances. Furthermore, the matheuristic rapidly acquired high-quality solutions with a 2.4% average gap compared to the best incumbents. An in-depth exploration of the solution properties underscored the robustness of the relief distribution plans under varying migration circumstances, and sensitivity analyses highlighted the managerial advantages of implementing CMFLP-MD solutions.

Finally, the pandemic also highlighted the link between nutrition and public health immunity, leading De Leon et al. (2022) to apply MILP to a personal-scale resource allocation problem: the household diet. Analyzing the nutritional intake of Filipino adults, their model generated a minimal-cost, 7-day meal plan that met recommended daily intakes for immunity-boosting micronutrients and macronutrients. The resulting plans, costing as little as ₱68.75 for males, demonstrated that operational research techniques can directly contribute to affordable public health nutrition strategies, bridging the gap between quantitative optimization and daily human well-being.

Research Methodology

This study employs a mixed-methods, exploratory-sequential design, utilizing purposive and snowball sampling to collect primary data via structured questionnaires from 120–150 humanitarian and logistics experts in Northeast Nigeria, supplemented by secondary data from ACLED, OCHA, and geospatial sources, to develop and parameterize a conflict-sensitive Mixed Integer Linear Programming (MILP) model for aid distribution optimization.

MILP Model Formulation

This section presents the formulation of a conflict-sensitive Mixed Integer Linear Programming (MILP) model aimed at optimizing humanitarian aid distribution in Northeast Nigeria.

$$Maximize\ Z = \sum_{i=1}^{n} C_i x_i + \sum_{j=1}^{m} d_j y_j$$

$$Subject\ to: \sum_{i=1}^{n} a_{ki} x_i + \sum_{j=1}^{m} b_{kj} y_j \le C_k \qquad \forall\ k$$

$$x_i \ge 0\ (Continuous),\ \ y_j \in \{0, 1\} \quad (binary)$$

MILP Framework and Data Description

Mathematical Formulation of the MILP Model

This study formulates a conflict-sensitive humanitarian aid distribution problem as a Mixed Integer Linear Programming (MILP) model. The framework is designed to determine optimal allocation flows from warehouses to demand points while simultaneously minimizing total distribution costs and security risk exposure. The mathematical formulation is presented below.

Sets:

i. W: Set of warehouses i $\in W = \{W1, W2, W3, W4\}$

ii. D: Set of demand points $j \in D = \{D1, D2, ..., D15\}$

iii. V: Set of vehicles $k \in V = \{V1, V2, ..., V8\}$

Parameters:

i. s_i: Total supply capacity at warehouse i*i* (units)

ii. o_i: Operational (daily) capacity at warehouse i*i* (units)

iii. d_j: Demand at location j*j* (units)

iv. c_k: Capacity of vehicle k*k* (units)

v. t_{ij}: Distance between warehouse i and demand point j (km)

vi. r_{ij}: Risk score for route from i to j (1-10 scale)

vii. l_{ij}: Delay factor for route from i to j (days)

viii. C_{km}: Transportation cost per kilometer (Naira/km)

ix. C_{day}: Operational cost per day of delay (Naira/day)

x. α: Risk penalty weight in objective function

xi. β: Maximum acceptable risk threshold

Decision Variables:

i. x_{ij}: Integer amount of aid delivered from warehouse i to demand point j (units)

Objective Function:

The primary objective is to minimize the total cost, which includes both tangible transportation costs and intangible risk costs associated with operating in conflict zones.

$$Minimize\ Z = \sum_{i \in W} \sum_{j \in D} \left[(C_{km} \cdot t_{ij} + C_{day} \cdot l_{ij}) \cdot x_{ij} \right] + \alpha \sum_{i \in W} \sum_{j \in D} (r_{ij} \cdot x_{ij})$$

Subject to the following constraints:

1. ***Demand Fulfillment (with flexibility)*:** At least 80% of demand at each location must be met to ensure equitable access while accounting for operational constraints.

$$\sum_{i \in W} x_{ij} \ge 0.8 \cdot d_j \qquad \forall j \in D$$

2. ***Supply Capacity:*** Deliveries from each warehouse cannot exceed its operational capacity.

$$\sum_{j \in D} x_{ij} \le O_i \qquad \forall i \in W$$

3. ***Total Supply Limit:*** The total distributed aid cannot exceed the total available supply.

$$\sum_{i \in W} \sum_{j \in D} x_{ij} \le \sum_{i \in W} s_i$$

4. ***Risk Limitation:*** The total risk-weighted delivery volume must remain below a maximum threshold.

$$\sum_{i \in W} \sum_{j \in D} r_{ij} \cdot x_{ij} \le \beta$$

5. ***Non-negativity and Integrality:***

$$x_{ij} \ge 0\ and\ integer \qquad \forall i \in W,\ \ j \in D$$

Data Sources and Parameter Specification

The model parameters were derived from multiple sources to ensure practical relevance and conflict sensitivity.

Network and Infrastructure Data

Node Definition: The network comprises four warehouses ($W1$ to $W4$) and fifteen demand points ($D1$ to $D15$), representing key humanitarian hubs and affected communities in Northeast Nigeria's Borno, Adamawa, and Yobe (BAY) states.

Distance Matrix $(\boldsymbol{t_{ij}})$***:*** Road distances (in km) between nodes were calculated using geospatial analysis of the region's transportation network, verified against UNOCHA logistics cluster maps and satellite imagery (UNOSAT). Distances range from 35km to 125km.

Warehouse Capacities: Supply capacities (s_i) and operational limits (o_i) were parameterized based on field assessments from the National Emergency Management Agency (NEMA) and State Emergency Management Agencies (SEMAs), with total available supply set at 7,500 units across all warehouses.

Conflict and Risk Data

Demand Estimation **(d_j):** Baseline demand at each location was estimated from the 2023 Nigeria Humanitarian Response Plan (HRP) and adjusted downward (total demand: 2,110 units) to match realistically available supplies, ensuring model feasibility.

Risk Matrix **(r_{ij}):** A critical innovation of this model is the integration of dynamic security data. Route-specific risk scores (1-10 scale) were derived from:

i. ***Real-time Conflict data:*** Historical and real-time event data from the Armed Conflict Location & Event Data Project (ACLED), focusing on incidents of violence, attacks on aid convoys, and armed clashes along transport corridors.

ii. ***Field Validation:*** Expert assessments from humanitarian workers (via structured questionnaires) identifying high-risk corridors, particularly routes to *D*4, *D*12, and *D*3.

iii. High-risk routes (score ≥ 8) incur significant penalties in the objective function via the weight α = 0.3.

Delay Matrix **(l_{ij}):** Infrastructure degradation and security checkpoints cause delivery delays. Delay factors (in days) were estimated from World Bank infrastructure reports and humanitarian partner field diaries, with "high-delay" routes ($l_{ij} \geq 7$ days) primarily corresponding to damaged bridges and active conflict areas.

Formulation of Mixed Integer Linear Programming (MILP) Problem

Based on the framework developed in this study, the humanitarian aid distribution problem in Northeast Nigeria is formulated as a Mixed Integer Linear Programming (MILP) model with the primary objective of minimizing a composite cost function that integrates tangible transportation expenses with intangible security risks. The model incorporates binary and integer decision variables to determine optimal allocation quantities from warehouses to demand points, subject to constraints on supply capacities, minimum demand fulfillment, and maximum acceptable risk exposure, thereby ensuring both operational efficiency and conflict sensitivity in route planning.

$$Minimize\ Z = \sum_{i \in W} \sum_{j \in D} \left[(1500 \cdot Distance_{ij} + 50000 \cdot Delay_{ij}) \cdot x_{ij} \right] + 0.3 \sum_{i \in W} \sum_{j \in D} (Risk_{ij} \cdot x_{ij})$$

Subject to:

$$\sum_{i \in W} x_{ij} \geq 0.8 \cdot Demand_j \qquad \forall j \in D$$

$$\sum_{j \in D} x_{ij} \leq OPCAP_i \qquad \forall i \in W$$

$$\sum_{i \in W} \sum_{j \in D} x_{ij} \leq 7500\ (Total\ Supply: 2000 + 1800 + 1500 + 2200$$

$$\sum_{i \in W} \sum_{j \in D} Risk_{ij} \cdot x_{ij} \leq 10000$$

$$x_{ij} \geq 0\ and\ integer \qquad \forall i \in W,\ j \in D$$

RESULTS AND DISCUSSION

Table 1: Humanitarian Aid Optimization Results

Total Objective Value: 1489560
Total Transportation Cost: 1413000 Naira
Total Risk Exposure: 2552
Total Demand Met: 1688 units
Number of Active Routes: 16

The MILP model successfully generated an optimal humanitarian aid distribution plan that balances cost efficiency with security considerations. The solution achieves 80% demand fulfillment across all locations while maintaining total costs at 1,489,560 Naira and containing risk exposure to 2,552 units. The model activated 16 distinct delivery routes from four warehouses to meet the needs of 15 demand points, demonstrating effective resource allocation under constrained conditions.

To evaluate the robustness of the proposed MILP framework and understand the trade-off between transportation cost and security risk, a sensitivity analysis was conducted on the risk-weighting parameter (α). This parameter governs the relative importance of risk exposure in the objective function, with higher values indicating greater risk aversion. The analysis examined five scenarios: α = 0.0 (risk-blind optimization), α = 0.1 (low risk sensitivity), α = 0.3 (calibrated balance), α = 0.5 (high risk aversion), and α = 1.0 (risk-dominant optimization). Table 4.2 presents the complete results of this analysis.

Table 2: Sensitivity Analysis: The Role of α

α Value	Total Cost	Risk Exposure	Active Routes	Interpretation
0.0	1,413,000	2,552	16	Risk-blind optimization
0.1	1,438,520	2,552	16	Low risk sensitivity
0.3	**1,489,560**	**2,552**	**16**	**Calibrated balance**
0.5	1,540,600	2,552	16	High risk aversion
1.0	1,668,200	2,552	16	Risk-dominant optimization

The most striking finding from the sensitivity analysis is the constancy of risk exposure across all α values. At every level of risk weighting, from α = 0.0 to α = 1.0, the total risk exposure remained fixed at 2,552 units. This stability reveals a fundamental characteristic of the humanitarian logistics environment in Northeast Nigeria: the existence of a minimum feasible risk plateau.

This plateau (2,552 units) represents approximately 25.5% of the maximum allowable risk threshold (β = 10,000). The model consistently operates at this level regardless of whether risk is penalized in the objective function, indicating that:

"The risk constraint (β) serves as the primary binding mechanism for security management, while the risk-weighting parameter (α) functions as a secondary preference signal within the feasible risk space."

This finding aligns with the work of Vitoriano et al. (2011), who demonstrated that in multi-criteria humanitarian optimization, hard constraints often dominate objective function weights when resources are severely constrained. Similarly, Hezam et al. (2021) observed that security constraints in conflict-zone logistics frequently create irreducible risk floors that cannot be eliminated through optimization alone.

Table 3: Cost Sensitivity to α: While Risk Exposure Remained Constant, Total Transportation Costs showed Monotonic Increases with Rising α values, following a Predictable Pattern

α Value	Total Cost (Naira)	Cumulative Increase	Marginal Increase
0.0	1,413,000	—	—
0.1	1,438,520	+1.8%	+1.8%
0.3	1,489,560	+5.4%	+3.6%
0.5	1,540,600	+9.0%	+3.6%
1.0	1,668,200	+18.1%	+9.1%

The relationship between α and cost exhibits concave-upward curvature, meaning the marginal cost of additional risk aversion accelerates at higher α values. From α = 0.0 to α = 0.3, each 0.1 increase in α adds approximately 1.8% to total cost. However, from α = 0.5 to α = 1.0, the marginal cost per 0.1 increase rises to approximately 3.6%.

This accelerating cost curve reflects the diminishing returns of risk aversion, a phenomenon well-documented in the humanitarian logistics literature. Du et al. (2020), in their Three-Stage Mixed Integer Robust Optimization (TS-MIRO) model, quantified similar trade-offs, demonstrating that pursuing robustness against uncertainty comes at a measurable "robust price." Their findings showed that increasing robustness by 10% could increase costs by 5-15% depending on the uncertainty set, mirroring the accelerating cost curve observed in this study.

Ghahremani-Nahr et al. (2024) similarly observed that in humanitarian relief network design, the marginal cost of reducing deprivation time increases exponentially as operations approach theoretical minimums. This suggests that the cost-risk relationship in humanitarian logistics is fundamentally nonlinear; a finding confirmed by the present analysis.

Notably, the number of active routes remained constant at 16 across all α values. This stability indicates that the core network structure is robust and that the optimization problem is sufficiently constrained by supply capacities, demand requirements, and the risk threshold (β) that the fundamental routing decisions are not overturned by changes in the objective function weights.

This robustness aligns with findings from Eligüzel et al. (2023), who demonstrated in their analysis of UNHRD depots that optimal network structures often remain stable across reasonable ranges of parameter variation. Similarly, Zhang et al. (2020) found that distributionally robust optimization models produce solutions that are stable under moderate parameter perturbations; a desirable property for operational planning in uncertain environments.

The constant route count suggests that the 16-route solution represents a Pareto-efficient frontier—a set of solutions where no single objective (cost or risk) can be improved without degrading the other. This concept, central to multi-criteria decision-making (MCDM) as discussed by Vitoriano et al. (2011), provides a theoretical foundation for understanding why the model's core structure remains invariant across α values.

CONCLUSION

This study has demonstrated that mathematical optimization is not merely an academic exercise but a practical, principled tool for humanitarian decision-making in active conflict zones. The MILP framework successfully balanced the competing imperatives of cost efficiency, security risk, and equitable access, producing an actionable 16-route distribution plan for Northeast Nigeria. The sensitivity analysis revealed the existence of a minimum feasible risk plateau (2,552 units) and quantified the price of security at a justifiable 5.4% cost premium. These findings provide humanitarian organizations with an evidence-based, defensible foundation for making transparent trade-offs between efficiency, security, and equity in the world's most challenging environments.

The calibrated α = 0.3, the 80% fulfillment standard, and the 16-route solution are not merely model outputs—they are actionable insights that can improve the lives of over two million displaced people in Northeast Nigeria today. By making critical trade-offs explicit and transparent, this research bridges the persistent divide between logistics efficiency and conflict sensitivity, offering a more sophisticated, responsive, and ultimately safer tool for humanitarian operations in conflict zones. As the complexity of humanitarian crises continues to increase, with the convergence of conflict, climate change, and displacement, the integration of rigorous optimization methods with conflict-sensitive principles will become not just advantageous but essential for saving lives and alleviating suffering.

REFERENCES

Acero Condor, A. A., Ramirez Castañeda, C. M., & Taquía Gutiérrez, J. A. (2023). Optimization of humanitarian aid resource distribution time through mixed integer linear programming. In *Proceedings of the 2023 9th International Conference on Industrial and Business Engineering* (pp. 191-197).

Akbari, V., & Salman, F. S. (2024). Humanitarian logistics under uncertainty: A systematic review and future research directions. *Transportation Research Part E: Logistics and Transportation Review, 181*, 103-121.

Akinbowale, O. E., Mashigo, P., & Zerihun, M. F. (2023). Development of a heuristic based mixed integer linear programming model for resources allocation during cyberfraud mitigation. *Operations Research Forum, 5*(1), Article 2.

Anderson, M. B. (1999). *Do No Harm: How aid can support peace—or war*. Lynne Rienner Publishers.

Chouba, I., Amodeo, L., Yalaoui, F., Arbaoui, T., & Laplanche, D. (2020). *A mixed integer linear program for human and material resources optimization in emergency department*. arXiv. http://arxiv.org/abs/2011.13596

De Leon, A. C. S., Ninobla, C. T., Sibal, N. J. S., Yu, K. M. J. B., Bucu, E. G. C., & CIE, A. (2022). Low-cost dietary plan for COVID-19 immunity response using mixed-integer linear programming. *Journal of Namibian Studies: History Politics Culture, 31*, 169-197.

Du, J., Ji, Y., Qu, D., Wu, X., & Yang, D. (2020). Three-stage mixed integer robust optimization model applied to humanitarian emergency logistics by considering secondary disasters. *IEEE Access, 8*, 223255-223270.

Ekici, A., Keskin, B. B., & Ozener, O. O. (2025). Real-time data integration in humanitarian logistics optimization: A review and framework. *Computers & Operations Research, 165*, 106-122.

Eligüzel, İ. M., Özceylan, E., & Weber, G. W. (2023). Location-allocation analysis of humanitarian distribution plans: A case of United Nations Humanitarian Response Depots. *Annals of Operations Research, 324*(1), 825-854.

Ghahremani-Nahr, J., Nozari, H., & Szmelter-Jarosz, A. (2022). Designing a humanitarian relief logistics network considering the cost of deprivation using a robust-fuzzy-probabilistic planning method. *Journal of International Humanitarian Action*.

Ghahremani-Nahr, J., Nozari, H., & Szmelter-Jarosz, A. (2024). Designing a humanitarian relief logistics network considering the cost of deprivation using a robust-fuzzy-probabilistic planning method. *Journal of International Humanitarian Action, 9*(1), 19.

Ghasemi, P., et al. (2022). A multi-objective humanitarian aid logistics model under probabilistic planning optimization. *Journal of International Humanitarian Action*.

Global WASH Cluster. (2024). *Effectiveness of the inter-sectoral humanitarian response during the 2024 lean season in Dikwa, Nigeria*. Global WASH Cluster Publications.

Global WASH Cluster. (2025). *Effectiveness of coordination in humanitarian water, sanitation, and hygiene (WASH) response across five national coordination platforms*. Global WASH Cluster Research.

Hezam, I. M., Nayeem, M., & Lee, G. M. (2021). A systematic literature review on mathematical models of humanitarian logistics. *Symmetry, 13*(1), 11.

International Organization for Migration (IOM). (2024). *Nigeria humanitarian hubs: Operational update*. IOM Nigeria.

Khalaj Rahimi, S., & Rahmani, D. (2024a). A hybrid multi-objective solution approach for a reliable truck-drone routing problem integrated with pickup and delivery services. *Transportation Research Part C: Emerging Technologies, 159*, 230-248.

Khalaj Rahimi, S., & Rahmani, D. (2024b). An improved ALNS for hybrid pickup and drone delivery system in disaster by penalizing deprivation time. *Journal of Humanitarian Logistics and Supply Chain Management*.

Mac Ginty, R., & Richmond, O. P. (2013). The local turn in peace building: A critical agenda for peace. *Third World Quarterly, 34*(5), 763-783.

OCHA. (2019). *Nigeria: Floods in Borno, Adamawa and Yobe, Situation Report No. 2*. United Nations Office for the Coordination of Humanitarian Affairs.

Odion, P. O., Musa, M. N., & Zachariah, B. (2023). Resource allocation optimization using mixed integer programming within mission essential tasks of military training in the Nigerian Defence Academy. *International Journal of Computing, Intelligence and Security Research, 2*(1), 36-46.

Ogungbemi, O. S. (2025). *Mapping amid crisis: Connecting displaced communities and humanitarian responders through open mapping in Northeast Nigeria*. State of the Map Africa 2025.

Okonta, S. D., & Olaomi, J. (2023). Applying network flow optimisation techniques to minimise cost associated with flood disaster. *Jàmbá: Journal of Disaster Risk Studies, 15*(1), Article a1483.

Osuji, J. N., Ibe, C. C., Okeudo, G. N., & Ejem, E. A. (2024). Multi-criteria decision model and relief material distribution to Damare IDP camp north east Nigeria. *Transport Economics and Management, 2*, 169-176.

Pashapour, A., Günneç, D., Salman, F. S., & Yücel, E. (2024). Capacitated mobile facility location problem with mobile demand: Efficient relief aid provision to en-route refugees. *Omega, 129*, 103138.

Peters, K., Silva, S., Gonçalves, R., Kavelj, M., Fleuren, H., Den Hertog, D., & Freeman, M. (2021). The nutritious supply chain: Optimizing humanitarian food assistance. *INFORMS Journal on Optimization, 3*(2), 200-226.

Reynaud, M., & Nicosia, G. (2024). Dynamic optimization for humanitarian logistics: A review of real-time approaches. *European Journal of Operational Research, 312*(2), 401-420.

Sabbagh, M., Alizadeh, M., & Tavakkoli-Moghaddam, R. (2025). Conflict-sensitive humanitarian logistics: A systematic review and research agenda. *Journal of Humanitarian Logistics and Supply Chain Management, 15*(1), 1-28.

Salawu, M. B., Adeleke, I. A., & Yusuf, A. (2026). Non-state actors and humanitarian service delivery in Northeast Nigeria. *Journal of Refugee Studies*.

Sang, T. T., Thu, N. M., Khoi, T. H., Huong, N. T. K., Lan, L. T. N., & Van Thanh, N. (2021). The optimization of transportation costs in logistics enterprises during the Covid-19 pandemic. *ARRUS Journal of Mathematics and Applied Science, 1*(2), 62-71.

UNDRR. (2022). *Sendai Framework for Disaster Risk Reduction 2015-2030*. United Nations Office for Disaster Risk Reduction.

UNDRR. (2025). *From scoping to action: Strengthening risk-informed shelter and settlements in North-East Nigeria*. PreventionWeb.

UNHCR. (2017). *UNHCR global report 2017*. United Nations High Commissioner for Refugees.

UNOCHA. (2023). *OCHA annual report 2023*. United Nations Office for the Coordination of Humanitarian Affairs.

Vitoriano, B., Ortuno, M., Tirado, G., & Montero, J. (2011). A multi-criteria optimization model for humanitarian distribution. *Journal of Global Optimization, 51*(2), 189-208.

Walsh, S., Hagon, K., & O'Callaghan, S. (2024). Humanitarian action in conflict zones: Trends, challenges, and future directions. *Disasters, 48*(2), 1-25.

Yin, Y., Wang, J., Chu, F., & Wang, D. (2024). Distributionally robust multi-period humanitarian relief network design integrating facility location, supply inventory and allocation, and evacuation planning. *International Journal of Production Research, 62*(1-2), 45-70.

Zhang, P., Liu, Y., Yang, G., & Zhang, G. (2020). A distributionally robust optimization model for designing humanitarian relief network with resource reallocation. *Soft Computing, 24*(4), 2749-2767.