Stochastic Benders Optimization for Hurricane Preparedness in Nicaragua *

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Abstract

We study a two-stage stochastic facility location and inventory pre-positioning problem for hurricane preparedness, inspired by real-world collaboration with UNICEF in Nicaragua. The model uses historical hurricane tracks, population density, infrastructure data, and road networks to optimize warehouse placement and stock levels ahead of hurricane season. Disruptions to roads and facilities are scenario-dependent, and the objective minimizes expected costs, including penalties for unmet demand.

To solve large-scale instances efficiently, we implement a parallelized multi-cut Benders decomposition algorithm. Applied to all 20 real hurricane scenarios that impacted Nicaragua's Northeast region, our method solves each instance in under two seconds. Through time-series cross-validation, we demonstrate that disruption-aware stochastic planners reduce total costs on unseen hurricanes by 26% and unmet demand by 27% compared to a non-hurricane-aware baseline. The results highlight the importance of anticipatory planning under uncertainty and show that recency-weighted scenario models can improve robustness without significant added cost.

1 Introduction and Motivation

This project was inspired by our collaboration with UNICEF on hurricane preparedness in Nicaragua in the context of MIT's Capstone Project. The goal is to pre-position emergency supplies—such as water, medicine, and hygiene kits—at fixed warehouses before hurricane season, so that when disasters strike, aid can be delivered efficiently despite damaged infrastructure. The challenge lies in making these decisions under uncertainty: the exact hurricane path is unknown, and each storm disrupts roads and warehouse stock differently.

We formulate the problem as a two-stage stochastic optimization model. In the first stage, we choose which warehouses to open and how much inventory to allocate at each. In the second stage, for each potential hurricane track (a scenario), the model determines optimal shipments to meet demand, considering disruptions the roads and stocks caused by the hurricane. We assume future hurricanes are drawn from the same distribution as past events.

Our implementation is grounded in real data. Hurricane scenarios are generated from historical tracks in the *Hurdat2* database. Demand points are constructed using high-resolution WorldPop population rasters and OpenStreetMap (OSM) tags for schools, hospitals, and clinics. The transportation network is extracted from real OSM road data. The only synthetic inputs are the set of candidate warehouse locations—sampled from points in the network—and the budget constraints on warehouse openings and stock. The demand nodes are scaled from observed population density.

We focus on the north-eastern quadrant of Nicaragua, where hurricane landfalls are most frequent (Fig. 1), enabling high-impact planning while keeping the problem tractable. To efficiently solve this large-scale model, we implement multi-cut Benders decomposition with parallel scenario solves.

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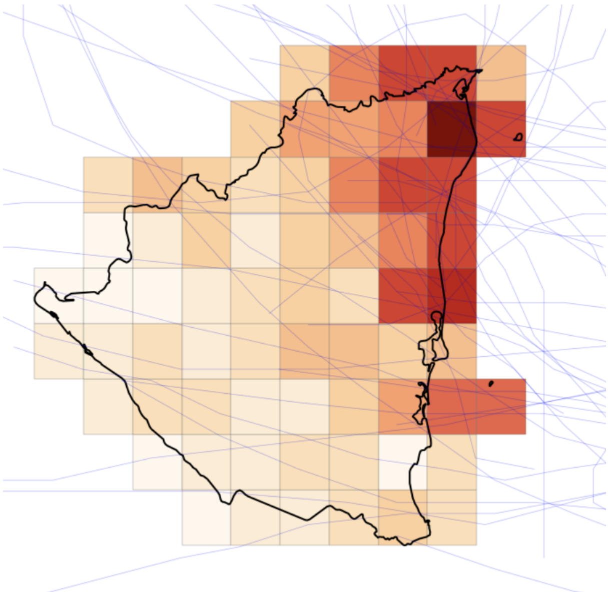


Figure 1: Hurricane intersection density and selected hotspot.

2 Data and Pre-Processing

2.1 Data

- **Hurricane tracks:** Historical storm paths from the *Hurdat2* archive (via KAGGLE), covering 42 hurricanes that intersected Nicaragua between 1870 and 2023. Each track is rasterized and used to define storm scenarios.
- **Road network:** Downloaded from the OpenStreetMap Overpass API, retaining only roads classified as highways or major paths. After filtering, the resulting network includes 42,836 raw edges (before graph techniques to simplify it).
- **Facilities:** Public service locations extracted from OpenStreetMap using `amenity` and `building` tags, including schools, health centers, and pharmacies. These are used to generate demand nodes.
- **Population:** Raster data from WorldPop 2020 at 100 m resolution, used to estimate local demand and identify population clusters.

2.2 Pre-processing

2.2.1 Study Region and Road Network

As discussed above, we select the hurricane-prone northeastern region of Nicaragua as our study area. Within this region, we extract all major roads from OpenStreetMap and construct a connectivity graph, excluding minor paths such as footways and cycleways. The network is clipped to the region and simplified via degree-2 chain reduction, which collapses sequences of nodes with degree two (i.e., straight segments with no branches) into single edges. This yields a directed road graph with 4,518 edges.

2.2.2 Demand Nodes

Demand nodes are derived from two sources: critical infrastructure (e.g., schools, hospitals, clinics, supermarkets) and high-resolution 2020 population rasters from WorldPop. We identify populated raster cells and assign demand proportional to estimated inhabitants. Both sources are merged using DBSCAN clustering ($\varepsilon = 500$ m), a density-based algorithm that groups nearby points without requiring a fixed number of clusters. Each resulting cluster is assigned a centroid and total demand. Clusters without population receive a small default demand. This process yields $|J| = 34$ demand nodes.

2.2.3 Candidate Warehouse Sites

Candidate warehouse sites are sampled synthetically from the graph with spatial density proportional to local population. Construction costs are simulated to be higher near dense demand areas, reflecting land scarcity and urban constraints. We retain $|I_N| = 100$ candidate warehouse sites.

2.2.4 Hurricane Scenarios and Disruption Modeling

From the 42 hurricanes that impacted Nicaragua, only 20 actually intersect our hotspot region of interest. Therefore, our scenario set $\mathcal{S}$ consists of these 20 historical hurricane tracks that intersect the study region, each defining a distinct disruption realization in the stochastic model. Each hurricane scenario affects the network by damaging roads and facilities within a fixed impact radius. Specifically, a road segment is considered disrupted if any part of it lies within 10 km of the hurricane path. Similarly, a warehouse is considered impacted if its location is within 5 km of the track, in which case a fixed fraction of its inventory is lost (e.g., 30% reduction).

2.2.5 Preprocessing for Post-Storm Logistics

To support fast evaluation of each scenario, we preprocess all disrupted graphs to compute the new shortest paths and update the feasible set of arcs E_s for every $s \in \mathcal{S}$. This ensures that post-hurricane shipment plans are realistic and respect connectivity constraints under disruption.

3 Optimization Model

In this section we present the full two-stage stochastic program, define its master and subproblem, derive the dual and the explicit Benders optimality cuts, and explain why feasibility cuts are never needed.

3.1 Notation and Parameters

We index candidate warehouses by $i \in I$, demand nodes by $j \in J$, and hurricane scenarios by $s \in S$. In each scenario only arcs $(i, j) \in E_s \subset I \times J$ remain usable. Table 1 summarizes all remaining parameters.

3.2 Decision Variables

We choose binary f_i to open warehouse i, nonnegative r_i to pre-position inventory, and auxiliary θ_s to approximate the second-stage cost in each scenario. After a hurricane we ship $x_{ijs} \geq 0$ from i to j or incur unmet demand $u_{js} \geq 0$.

Sets and Indices	
I	candidate warehouse locations
J	demand nodes
S	hurricane scenarios
$E_s \subset I \times J$	feasible shipment arcs in scenario s
Parameters	
h_i	opening cost of warehouse i
c_r	unit cost of pre-positioned stock
C_i	capacity of warehouse i
$\bar{B}_f, \bar{B}_r$	facility-opening and stock budgets
d_j	demand at node j
c_{ijs}	per-unit shipping cost $i \to j$ in scenario s
ρ_{is}	fraction of r_i surviving in s
$a_{ijs} \in \{0, 1\}$	1 if arc (i, j) is available in s
p_s	probability of scenario s
M	large penalty for unmet demand

Table 1: Index sets and model parameters

3.3 First-Stage (Master) Problem

The first-stage objective balances the fixed costs of opening warehouses and holding pre-positioned stock against the expected second-stage cost:

$$\min_{f,r,\theta} \underbrace{\sum_{i \in I} h_i f_i}_{\substack{\text{opening}\\ \text{costs}}} + \underbrace{c_r \sum_{i \in I} r_i}_{\substack{\text{stock}\\ \text{costs}}} + \underbrace{\sum_{s \in S} p_s \, \theta_s}_{\substack{\text{expected}\\ \text{recourse}}}$$

Subject to capacity and budget constraints:

$$r_i \leq C_i \, f_i \qquad \forall i \in I \tag{1}$$

$$\sum_{i \in I} h_i \, f_i \leq \bar{B}_f \tag{2}$$

$$c_r \sum_{i \in I} r_i \leq \bar{B}_r \tag{3}$$

$$\theta_s \geq 0 \qquad \forall s \in S \tag{4}$$

$$f_i \in \{0, 1\}, \; r_i \geq 0 \qquad \forall i \in I. \tag{5}$$

Constraint (1) forces inventory only at opened facilities, (2) and (3) enforces the two-budget structure, and θ_s will be driven by Benders cuts to match the true recourse cost.

3.4 Second-Stage (Scenario) Subproblem

Given a fixed (f, r) and scenario s, we compute the optimal post-storm response by solving:

$$
\begin{aligned}
Q_s(f,r) = \min_{x,u} \quad & \sum_{(i,j)\in E_s} c_{ijs}\, x_{ijs} + M \sum_{j\in J} u_{js} \\
\text{s.t.} \quad & \sum_{j:(i,j)\in E_s} x_{ijs} \le \rho_{is}\, r_i && \forall i \in I && (6)\\
& \sum_{i:(i,j)\in E_s} x_{ijs} + u_{js} \ge d_j && \forall j \in J && (7)\\
& 0 \le x_{ijs} \le M\, a_{ijs}, \quad u_{js} \ge 0 && \forall (i,j) \in E_s && (8)
\end{aligned}
$$

3.5 Dual and Full Benders Optimality Cut

First, we note that since the slack variable u_{js} can always absorb unmet demand, the subproblem is always feasible and only optimality cuts are needed. We introduce dual variables α_{is} for (6), β_{js} for (7), and γ_{ijs} for the upper-bound on x_{ijs}. The dual LP maximises

$$\sum_{j\in J} \beta_{js} d_j - \sum_{i\in I} \alpha_{is}\rho_{is} r_i - \sum_{(i,j)\in E_s} \gamma_{ijs} M\, a_{ijs}$$

subject to

$$-\alpha_{is} + \beta_{js} - \gamma_{ijs} \le c_{ijs} \quad \forall (i,j) \in E_s, \qquad \beta_{js} \le M, \quad \alpha, \beta, \gamma \ge 0.$$

Let α^*, β^*, γ^* denote an optimal dual solution. We then add the following *multi-cut* style Benders cut to the master for each $s \in S$:

$$\boxed{\theta_s \;\ge\; \sum_{j\in J} \beta^*_{js}\, d_j \;-\; \sum_{i\in I} \alpha^*_{is}\, \rho_{is}\, r_i \;-\; \sum_{(i,j)\in E_s} \gamma^*_{ijs}\, M\, a_{ijs}.}$$

This cut enforces θ_s to lie above the supporting hyperplane of the true recourse function at (f, r).

3.6 Solution Algorithm

We solve the stochastic mixed-integer program using multi-cut Benders decomposition. The method separates the problem into a master problem, which optimizes first-stage decisions (warehouse openings and stock levels), and a set of linear subproblems, one per hurricane scenario, that compute second-stage recourse costs under disruption.

Algorithm 1 Multi-cut Benders Decomposition (with Dual Cuts)

Initialize MP with variables $f_i \in \{0,1\}, r_i \ge 0, \theta_s \ge 0$, no cuts.
repeat
  Solve master problem (MP) $\Rightarrow (f^*, r^*, \theta^*)$, and let LB $\leftarrow$ objective value.
  Compute first-stage cost: $F \leftarrow \sum_i h_i f_i^* + c_r \sum_i r_i^*$
  Set candidate upper bound: $\mathrm{UB}_{\mathrm{cand}} \leftarrow F$
  for each scenario $s \in \mathcal{S}$ **do**
    Solve subproblem $SP_s(r^*)$ and its dual $\Rightarrow Q_s, \alpha^*, \beta^*, \gamma^*$
    Update candidate UB: $\mathrm{UB}_{\mathrm{cand}} \leftarrow \mathrm{UB}_{\mathrm{cand}} + p_s \cdot Q_s$
    Compute cut RHS: $C_s \leftarrow Q_s - \sum_i (-\alpha^*_{is}\rho_{is}) r_i^*$
    Add cut to MP: $\theta_s \ge C_s + \sum_i (-\alpha^*_{is}\rho_{is}) r_i$
  end for
  Update UB: $\mathrm{UB} \leftarrow \min(\mathrm{UB}, \mathrm{UB}_{\mathrm{cand}})$
until $(\mathrm{UB} - \mathrm{LB})/\max\{1, |\mathrm{LB}|\} \le \varepsilon$
return final first-stage solution (f^*, r^*)

Algorithm 1 shows the full algorithm. At each iteration, we solve the master, evaluate all subproblems in parallel, and add one optimality cut per scenario based on dual solutions. The algorithm terminates when the relative optimality gap between the best-known upper and lower bounds falls below a fixed tolerance.

4 Results

4.1 Evaluation Strategy and Planner Variants

To evaluate each planner, we implement a time-series cross-validation procedure inspired by operational forecasting. We sort the 20 historical hurricanes chronologically and, for each index $k = 5, \ldots, 19$, we train the model using the first k storms and evaluate performance on the next one $(k + 1)$. This results in 15 forward-chaining folds. For each fold, we solve the stochastic optimization model with the selected scenario weighting and record performance on the held-out hurricane, mimicking the uncertainty of future events.

We compare the following five planner variants:

- **Stochastic Exponential:** assigns exponentially decaying probabilities to past scenarios ($\pi_s \propto \lambda^{k-s}$ with $\lambda = 0.9$).
- **Stochastic Linear:** assigns linearly decreasing weights to older scenarios.
- **Stochastic Uniform:** assigns equal probability to all past storms used in training.
- **Deterministic (last hurricane):** plans using only the most recent hurricane as the scenario.
- **No-disruption (baseline):** assumes infrastructure is unaffected by hurricanes and solves a simpler deterministic problem.

For each fold, we evaluate the resulting first-stage solution by computing the realized cost under the true test scenario, including unmet demand penalties, shipping cost, and prepositioning investment. All planners are assessed using the same downstream cost computation.

4.2 Time-Series Cross-Validation Results

Figure 2 reports average performance across folds for five planning strategies, measured in terms of total cost, unmet demand, and disaggregated first-stage and shipping costs. The results clearly demonstrate the benefit of accounting for stochasticity: all three stochastic planners outperform the deterministic and baseline heuristics.

The best-performing method overall is the **Stochastic Exponential** policy, which yields the lowest total cost (14.39 M$) and unmet demand (810 units), with 26% lower cost and 27% lower unmet demand than the baseline model (which ignore the hurricane effects). The **Stochastic Linear** and **Uniform** planners follow closely, with slightly higher costs (14.47 M$ and 14.68 M$, respectively) and unmet demand. This indicates that *recency weighting* adds value by emphasizing more recent hurricane patterns, but the performance difference among stochastic variants remains modest.

In contrast, the **Deterministic (last hurricane)** policy incurs significantly higher cost (18.15 M$) and unmet demand (1025 units), confirming that reliance on a single past event leads to under-preparedness. The **No-disruption baseline**, which ignores hurricane effects entirely, performs worst, with a total cost of 19.55 M$ and over 1105 units unmet.

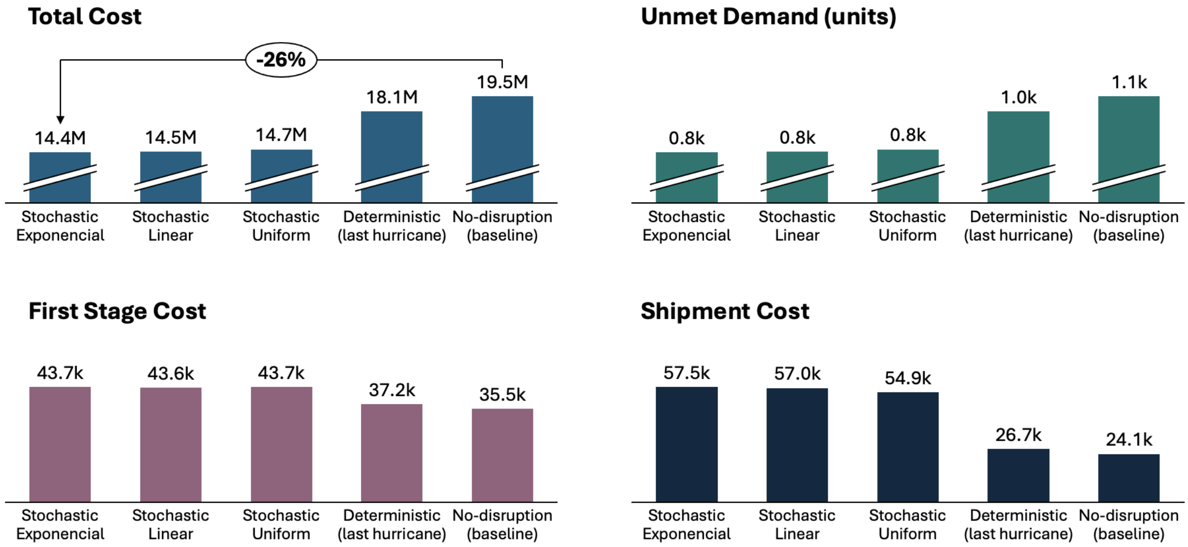


Figure 2: Cross-validation metrics: total cost, unmet demand, first-stage, and shipping costs

Importantly, we observe a trade-off between **proactive investment** (first-stage and shipping costs) and **unmet demand**: planners that invest more upfront tend to reduce the number of unsatisfied units. Stochastic planners allocate more upfront resources to pre-position supplies (e.g., 43.7 k$ in the exponential case) and accept higher distribution cost (57.5 k$), in exchange for improved coverage and lower unmet demand. The deterministic and baseline methods, by contrast, spend less upfront and distribute less, but suffer larger penalties for unmet need.

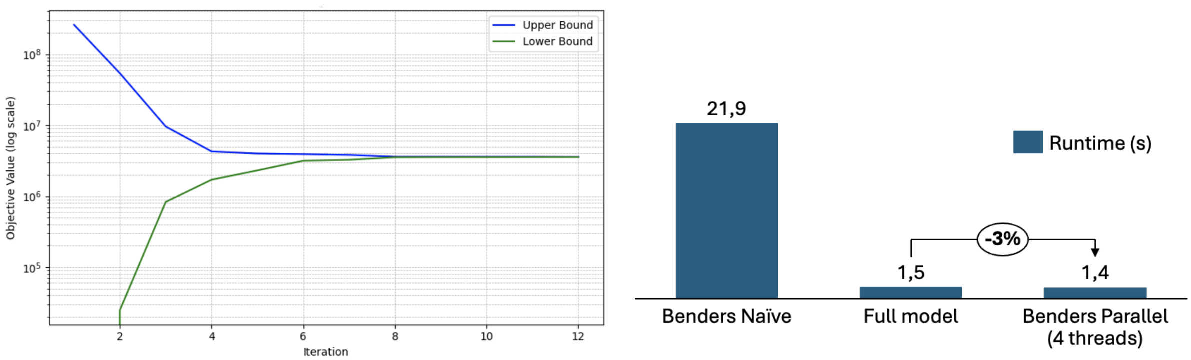
Note, however, that total cost is dominated by unmet demand penalties, which are intentionally inflated to reflect humanitarian urgency but do not correspond to literal monetary costs. This makes total cost a "polluted" objective: valuable for ranking policies but less interpretable in absolute terms.

These findings confirm that scenario-aware stochastic planning is crucial for effective disaster preparedness and that modest recency-based weighting improves robustness without substantially increasing cost.

4.3 Benders Convergence and Runtime

Figure 3a shows the progress of the non-parallelized Benders decomposition algorithm, with the lower and upper bounds converging to a relative gap of 10^{-2} within 12 iterations. While this naive serial implementation incurs substantial overhead—requiring 21.91 s compared to 1.45 s for solving the full extensive MIP with Gurobi—the benefits of decomposition become apparent once parallelism is introduced. Using four threads to solve the scenario subproblems concurrently, parallel Benders achieves convergence in just 1.41 s, outperforming the complete model Gurobi solve.

This performance gap is expected to widen substantially as the problem scales. In our current experiments, the number of scenarios is modest (20), and the full MIP remains tractable. However, for national-scale deployments (e.g., all of Nicaragua), where more than 40 scenarios and thousands of arcs are required to capture geographic and temporal variability, the structure-exploiting decomposition becomes essential. Parallel Benders not only provides faster solve times but also enables distributed computation, making it a scalable and practical solution for real-world disaster logistics planning.



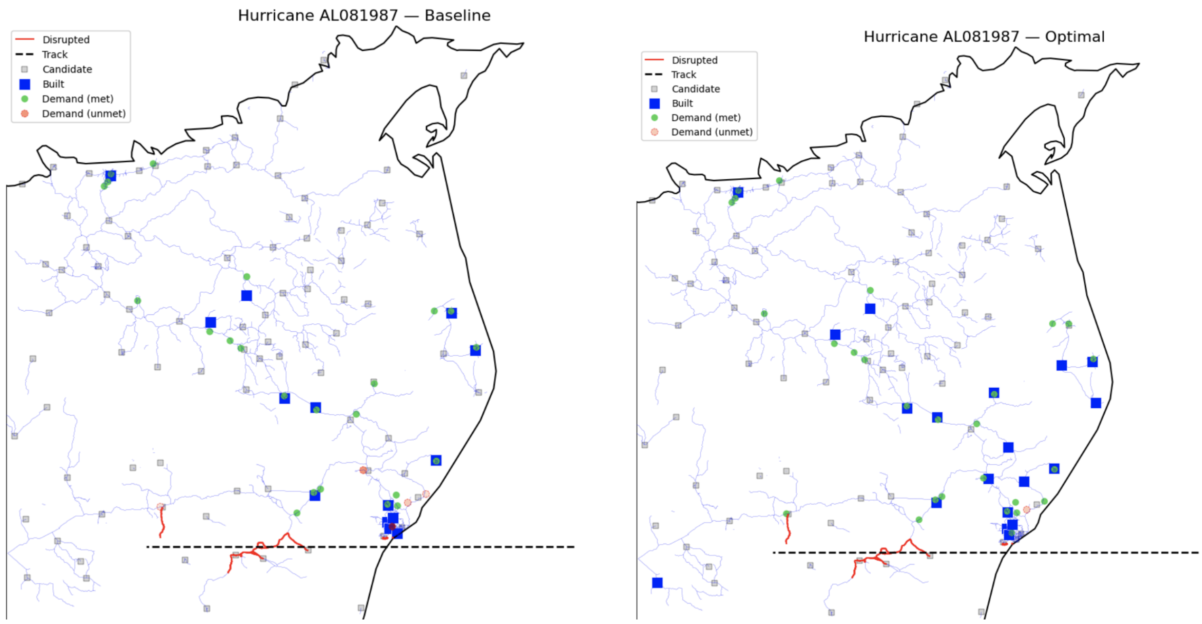
(a) LB/UB convergence (log scale).

(b) Optimization model runtimes.

Figure 3: Benders decomposition performance.

4.4 Spatial Insights

Figure 4 offers a qualitative comparison between the baseline and optimized designs under hurricane scenario AL072012. The *no-disruption baseline*, which ignores hurricane risks during planning, concentrates inventory in a few coastal locations. When those sites are impacted, large pockets of unmet demand emerge near the landfall region, as visible in the figure: many demand nodes turn red, indicating failure to serve those communities. In contrast, the *stochastic optimized design* proactively distributes warehouses more broadly, shifting stock inland and introducing spatial redundancies. This leads to higher first-stage investment—as discussed in Section 4—but greatly improves resilience. A much larger fraction of demand nodes remain green, even near the impact zone, highlighting the model's ability to maintain coverage despite disruptions. These visual patterns confirm how scenario-aware stochastic planning mitigates risk through better geographic diversification and redundancy.



(a) No-disruption baseline

(b) Fully trained stochastic model

Figure 4: Facility locations and resulting unmet demand (in red) for hurricane AL072012: (a) non-disruption-aware baseline places most warehouses coastally, (b) disruption-aware design spreads them inland and adds redundancy, reducing stock loss.

5 Conclusion and Future Work

Conclusion. This work introduces a scalable, data-driven pipeline for hurricane preparedness, initially developed in collaboration with UNICEF to support child-focused emergency response in Nicaragua. By combining real data sources—population density, infrastructure, and road networks—with stochastic optimization, our model captures realistic disruption scenarios and delivers actionable preparedness plans.

The stochastic model reduces total cost by **26%** relative to a non-hurricane-aware baseline, largely by reducing unmet demand through proactive and diversified stock placement. Our results highlight the importance of accounting for probabilistic disruptions: the optimized model distributes warehouses inland and builds redundancy to maintain service coverage near high-risk coastal areas. Parallelized multi-cut Benders decomposition further enables rapid solution times, solving 20-scenario problems in under two seconds—faster than full MIP and readily extensible.

Future Work. Building on these results, future directions include scaling the model to cover the full geography of Nicaragua and expanding the scenario library to capture a broader range of possible storm behaviors. A key priority is to incorporate *dynamic recourse* mechanisms that adapt plans as new information about a storm's trajectory becomes available—particularly by leveraging the evolving cone of uncertainty provided in hurricane forecasts. This would enable real-time adjustment of shipments and allocations as landfall nears. Finally, we plan to explore more risk-averse formulations, such as robust optimization and Conditional Value at Risk (CVaR), to better hedge against worst-case impact paths and ensure resilience even under severe disruptions.

Code and data: `https://github.com/iglesiascaio/nicaragua-hurricane-benders`

References

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