Optimal Distribution of Medical Backpacks and Health Surveillance Assistants in Malawi

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Abstract

Despite recent progress, Malawi continues to perform poorly on key health indicators such as child mortality and life expectancy. These problems are exacerbated by a severe lack of access to health care. Health Surveillance Assistants (HSAs) help bridge this gap by providing community-level access to basic health care services. However, the success of these HSAs is limited by a lack of supplies and long distances between HSAs and patients. To address this issue, we used large-scale $p$-median and capacitated facility location problems to create a scalable, three-tiered plan for optimal allocation of HSAs, HSA designated medical backpacks, and backpack resupply centers. Our analysis uses real data on the location and characteristics of hospitals, health centers, and the general population. In addition to offering specific recommendations for HSA, backpack, and resupply center locations, it provides general insights into the scope of the proposed HSA backpack program scale-up. In particular, it demonstrates the importance of local health centers to the resupply network. The proposed assignments are robust to changes in the underlying population structure, and could significantly improve access to medical supplies for both HSAs and patients.
1 Introduction

Malawi is an African nation whose citizens face severely limited health care access: only 1.9 physicians/100,000 people, compared to 267 physicians/100,000 people in the United States [1]. With only 7,264 nurses and no midwives in the entire country, Malawi is well below the minimum density of 228 health workers (physicians, nurses, and midwives) per 100,000 people required to provide adequate primary health care to its people [10]. Malawi’s performance on key health indicators, including an under-five mortality rate of 134/1000, an infant mortality rate of 77/1000 [11], and an HIV prevalence of 12% [6], reflects this lack of access to care.

Malawi’s well-established network of community health workers, or Health Surveillance Assistants (HSAs), is key to addressing this crisis. Since the 1980s, the Malawi Ministry of Health (MOH) has trained and paid HSAs to provide primary care and health education to remote regions in Malawi [10]. These HSAs are responsible for immunization, growth monitoring, health talks, and sanitation in their assigned villages. Some HSAs also provide HIV counseling and testing, family planning, and treatment of minor diseases. There are currently about 11,000 HSAs in Malawi, each serving an average of 1,200 people [11]. Overall, HSAs have played a significant role in bridging the gap between formal preventive health services and Malawian villages [10].

However, the success HSA program is threatened by a lack of transport and supplies. HSAs are typically based out of one village, and routinely travel 5km or more on foot to patients in other villages [10]. Fifty-four percent of mothers sampled in 2001 said lack of access prevented them from consulting HSAs about their children’s health. Furthermore, 88% of HSAs sampled said they had never been issued any drug stocks [10]. To improve patients’ access to HSAs, the Malawi MOH is planning to scale up the current HSA program to achieve a ratio of 1 HSA to 1,000 people [11]. Additionally, Rice University’s Beyond Traditional Borders initiative (BTB) has developed a Health Surveillance Assistant Backpack over the last four years to supply these HSAs with the tools necessary to perform their jobs. These backpacks contain basic diagnostic, treatment, and prevention tools designed specifically to address the responsibilities of the HSAs. Fourteen of such backpacks have been successfully field tested at St. Gabriel’s Hospital in Namitete, Malawi since 2009, where each backpack is shared by between five and twenty community health workers.

To improve the effectiveness of both the HSA and backpack programs, we sought a scale-up plan for the HSA and HSA backpack programs that would optimally

- place HSAs across Malawi, with a target ratio of 1 HSA:1000 people;
- assign backpacks to HSAs and estimate the total number of backpacks required;
- choose backpack resupply centers from the existing network of hospitals and health centers.

We formulated the problem as three facility location problems, specifically a $p$-median problem for HSA assignment and two capacitated facility location problems (CFLPs) for backpacks and resupply centers. Our method is unique in that it addresses three levels of health care distribution, allowing us to focus on ensuring patients’ access to both health care providers and supplies. It also acknowledges the differences between the time constraints faced by HSAs and the quantity constraints faced by backpacks and resupply centers by addressing them with two distinct models. We solved the optimization models using extensive real-world data and were able to determine the total cost for providing HSA backpacks across Malawi; quantify the effects the backpacks would have on Malawi’s health system; and gain insights into the optimal backpack resupply network.

Our models estimate that 2218 backpacks would be needed to sufficiently cover all of Malawi, at a cost of $772,167.08. This high cost persuaded BTB to focus initially on Lilongwe District, the district in which our model predicted the greatest need for backpacks. We therefore have included the results of our models for both Lilongwe District (not including the city of Lilongwe) and the entire country of Malawi in this paper. In addition to cost estimates, our models provide detailed recommendations about where to place HSAs, backpacks, and backpack resupply centers. Following these recommendations for Lilongwe District, the average distance between the centroid of an enumeration area (the smallest census unit) and its providing HSA would be 0.46 km and the average distance between an HSA and its providing backpack would be 1.6 km. These small distances illustrate the improvement in health care access that the HSA backpacks could bring to Malawi, especially since most patients and HSAs travel on foot. Finally, we determined that the resupply network would need to include both hospitals and health centers in order to retain similarly reasonable average distances between HSA backpacks and resupply centers (5.4 km as opposed to 28 km for hospitals only). These numbers, combined with the graphical results included in this paper, have already been used to facilitate talks with Malawian officials, and our analysis will provide a basis for soliciting support from international aid agencies for the scale-up of the HSA backpack program.
2 Optimization Problems in Global Health Resource Allocation

Other researchers have successfully applied operations research techniques to different aspects of the distribution of health resources in developing countries. In particular, several modeling papers have sought to optimally utilize community health workers and locate health care facilities in countries with problems similar to those in Malawi.

Several researchers have examined health system efficiency at the community health worker specific level. In terms of travel, Brunskill and Lesh [3] suggested house visits be treated as a routing and scheduling problem that could be approached as a traveling salesman problem with time windows, with additional complexity caused by the possibility of future follow-up visits. Meanwhile, Parker et al. [2] presented a simple model to determine how to prioritize tasks for community health workers in Haiti. Finally, Doerner et al. [5] helped bridge the gap between community health workers and physical health center locations by using a multiobjective combinatorial optimization formulation for mobile health centers and evaluating that model within the Thies region of Senegal. Like these studies, our model is interested in improving the performance of community health workers. However, our study is unique in that it involves the dissemination of technology throughout the community health workers (HSAs) in Malawi. As such, we focused less on the routing and scheduling of individual community health workers and more on their access to both patients and supplies. This distinction makes our work more similar to studies focused on locating health facilities than those focused on managing health care workers.

We found a number of such studies on health care facility location within developing countries. For example, Cocking et al. [4] proposed a coverage model for locating new health facilities in Burkina Faso, Africa. Similarly, Reid et al. [18] used a location set covering algorithm to determine optimal locations of medical supply centers in Ecuador. Rahman and Smith [16] provided a review of articles using location-allocation models for locating health centers in developing nations, focusing on their use in locating new sites, measuring effectiveness of past decisions, and improving existing systems. Our study differs from these in that it addresses a multi-tiered network of HSAs, backpacks, and physical resupply facilities. Our models also emphasize the capacities of the backpacks and resupply centers, which may not be addressed by traditional facility location models. While Murawski and Church [13] proposed a linear integer programming model taking into account possible future improvements in road infrastructure, we retained a static structure within our models, made necessary by the lack of data available about even current road conditions in Malawi.

Many of these models followed an integer programming formulation similar to our approach. Though we did not find any instances of creating a three-tiered system of community health workers, supplies, and resupply centers, these papers provided a conceptual basis for our mathematical analysis.

3 Methods

In this section, we describe the modeling framework for our analysis. First, we describe the models that we employed to solve our three-tiered distribution problem. Next, we describe the data and computational details involved in our solution to this problem.

3.1 Mathematical Models

We selected two mathematical models, the \( p \)-median problem and the capacitated facility location problem (CFLP) for our three-tiered distribution problem of HSAs, backpacks, and resupply centers. The \( p \)-median problem, which minimizes the weighted distance between demand points and providers, is appropriate when accessibility is a main concern, such as in locating emergency medical facilities [9]. Using the \( p \)-median for HSA assignment emphasizes the role they play in bridging the literal distance between patients and hospitals in Malawi, while addressing the time constraint on HSAs serving disparate populations without adequate transportation between them [10]. The CFLP, meanwhile, is used when there are explicit constraints on the number of demand nodes a facility can serve but no designated number of facilities [8]. Within the context of our problem, the CFLP was most appropriate for assigning backpacks and resupply centers, both of which have space and equipment limits which could be exhausted if overextended. We maintained separate models for each tier of the analysis to make the problem more computationally tractable and allow for additional analyses in the future, should additional data about actual or proposed HSA or backpack locations become available. Our use of these models is described in detail below.
3.1.1 The p-Median Problem

First, we used the p-Median Problem to assign HSA pairs to enumeration areas (EAs). We used pairs of HSAs rather than individuals to reflect the actual HSA distribution in Malawi. We used the centroids of EAs to represent their locations and used these same spots as possible HSA locations.

In the p-median problem, the goal is to find the p locations that minimize the average distance in a network [7]. Demand for service at each node and travel distance between nodes is deterministic. The formulation of the p-median problem is described below.

Let \( G = (V, E) \) be a graph where \( V \) is the set of vertices and \( E \) is the set of edges. Associate with each edge a weight \( d(v_i, v_j) \), which is the distance of the shortest path between vertices \( v_i \) and \( v_j \) according to the metric \( d \). The \( n \times n \) symmetric matrix \( d_{ij} = [d(v_i, v_j)] \) is the shortest distance matrix. Each vertex \( v_i \) is assigned a weight \( w_i \), and the weighted distance matrix is \( W_{ij} = w_i d_{ij} \).

A p-median problem can be formulated and solved as a binary linear program [17]. Let \( \xi_{ij} \) be an allocation variable such that

\[
\xi_{ij} = \begin{cases} 
1, & \text{if vertex } x_i \text{ is allocated to vertex } x_j; \\
0, & \text{otherwise.}
\end{cases}
\]

We then seek

\[
\min \sum_{i=1}^{n} \sum_{j=1}^{n} W_{ij} \xi_{ij}
\]

such that

\[
\sum_{j=1}^{n} \xi_{ij} = 1, \quad \text{for all } i = 1, \ldots, n
\]

\[
\sum_{i=1}^{n} \xi_{ii} = p
\]

\[
\xi_{ij} \leq \xi_{ii} \quad \text{for all } i, j = 1, \ldots, n
\]

\[
\xi_{ij} \in \{0, 1\} \quad \text{for all } i, j = 1, \ldots, n
\]

For our problem, the nodes \( v_i \) represent EA centroids and the associated weights \( w_i \) represent the demand assigned to that node. Specifically, the demand at each EA reflects:

- **General and Under-5 Population**
  Children under age five were given a weight of 0.55, whereas the rest of the population was given a weight of 0.45. This weighting reflects the design of the HSA backpack, which assumed HSAs would spend 55% of their time on under-5 children.

- **Rural or Urban Setting**
  We used population density to arrive at a proxy for rural versus urban setting. Rural populations, defined as EAs with population densities below a natural cutoff of 0.0035 people per square meters in the data, were weighted upward by 1.5 to reflect the lack of adequate infrastructure in these areas.

- **Proximity to Health Center**
  If an EA was within 1 km of a health center, its demand was reduced to 10% of its original level. That is, we assumed the health centers could provide adequate care to 90% of people within these EAs.

The \( d_{ij} \), distance of shortest path between the nodes, was represented by the shortest distance between centroids of the EAs.

3.1.2 The Capacitated Facility Location Problem

The CFLP was used to allocate HSAs to backpacks and select resupply centers from the existing network of health centers and hospitals.

In the general CFLP, a set of potential locations for facilities and a set of customers are given. The problem is to locate facilities and assign them to customers in a way that the total cost of using these facilities to satisfy customers’ demands is minimized. Here, the total cost includes both the variable cost incurred when the customer travels to its assigned facility for supply and the fixed cost of opening facilities at potential locations. This problem is termed “capacitated” because each possible location has an upper limit on its supplying capacity.

A CFLP with each customer assigned to only one facility generally contains two sets of decision variables, \( x_{ij} \) and \( y_i \). It can also be formulated as a binary linear program [8], [12], where we seek to

\[
\min \sum_{i=1}^{m} \sum_{j=1}^{n} c_{ij} x_{ij} + \sum_{i=1}^{m} f_i y_i
\]

such that

\[
\sum_{j=1}^{n} a_{ij} x_{ij} \leq b_i y_i \quad \text{for all } i = 1, \ldots, m
\]

\[
\sum_{i=1}^{m} x_{ij} = 1 \quad \text{for all } j = 1, \ldots, n
\]

\[
x_{ij} \leq y_i \quad \text{for all } i = 1, \ldots, m, \text{ and } j = 1, \ldots, n
\]

\[
x_{ij}, y_i \in \{0, 1\} \quad \text{for all } i = 1, \ldots, m, \text{ and } j = 1, \ldots, n
\]

where
$$y_i = \begin{cases} 1 & \text{if facility } i \text{ is picked, and } 0 \text{ otherwise} \\ x_{ij} = \begin{cases} 1 & \text{if facility } i \text{ serves customer } j, \ 0 \text{ otherwise} \\ a_j = \text{demand of customer } j \\ b_i = \text{capacity of facility } i \\ c_{ij} = \text{cost of using facility } i \text{ to supply customer } j \\ f_i = \text{fixed cost of opening facility } i. \end{cases}$$

In this case of HSA-to-backpack assignment, we assumed the following:

- All the EAs where an HSA pair is stationed are potential locations for backpacks. These EAs are represented by their centroids.
- Demand of an HSA pair ($a_j$) is 1 backpack. HSAs perform all their tasks as a pair.
- Capacity of a backpack ($b_i$) is 3 pairs of HSAs. This number was based on BTB’s experience with the backpacks at St. Gabriel’s Hospital.
- Cost of traveling from HSA pair $j$ to backpack $i$ ($c_{ij}$) depends on the distances between the centroids of EAs in which the two agents are located. Specifically, we assumed that traveling 30 km is equivalent to the fixed cost of a backpack based on the maximum distance HSAs currently travel [10].
- Fixed cost of adding an additional backpack ($f_i$) is equal to $352.91, which is the initial cost of building a backpack with two weeks of supplies.

In the case of backpack-to-resupply center assignment, we assumed the following:

- Potential locations for resupply centers are all the hospitals and/or health centers in Malawi.
- Demand ($a_j$) of a backpack is 1.
- Capacity ($b_i$) of a hospital is 80 backpacks and that of a health center is 10 backpacks.
- Variable cost ($c_{ij}$) is equal to the distance between the health facility $i$ and the EA in which the backpack $j$ is located.
- Fixed cost ($f_i$) of setting up a resupply center in a hospital or health center is 0.

3.2 Data Sources

We obtained geographical information system (GIS) files delineating the location and border of EAs from the International Food Policy Research Institute (IFPRI). This dataset originated from the 1998 Malawi Housing and Population Census conducted by the National Statistical Office in Malawi. To ascertain the accuracy of the data, these files were compared to a set of GIS files donated to us by University of North Carolina at Chapel Hill based on the 2008 Malawi Housing and Population Census [14].

Though the second set of files did not contain EA-level data, which excluded it from our main analysis, the two sets of files were extremely similar at the level of Traditional Authorities (or TAs, an administrative level above EAs). Both contained 367 TAs, and the centroids of the same TA taken from the two datasets were an average of less than $10^{-4}$ meters of one another.

IFPRI also provided us with population data at the EA level. To compensate for the age of the data, the population of each EA was adjusted to approximate 2008 levels according to the “Annual Population Inter-censal Growth Rates and Increase 1998-2008” [14] for the district containing the EA. These growth rates were obtained from the 2008 Malawi Population and Housing Census. Additionally, we estimated the number of children under five years of age in each EA using the percentage of the population comprised of under-5 children for the TA containing that EA in the 2008 Malawi Census (see Table 7: Population by 5 year age groups, regions, districts, and traditional authorities) [14].

The locations of hospitals and health centers were also obtained from IFPRI and were compared with data from the Health Information Systems Programme for accuracy. The IFPRI data came from approximately 1998, based on our correspondence. There was 100% agreement in the number of central and district hospitals and 92% agreement in the number of total hospitals between the data from IFPRI and that from the Health Information Systems Programme. This discrepancy, while small, reflects the fluidity of the health care system in Malawi and the necessity of following up our recommendations for BTB with their own research on the ground.

With the location of EAs and hospitals, we were then able to calculate the distances between them and use linear programming to optimize the locations of HSAs, backpacks, and resupply centers.

3.3 Implementation

We used ArcGIS, a commercially available GIS data processing program, to process all the geographic and population data used in this project. In particular, ArcGIS was used to find the centroid of each EA; calculate the distance between the centroids of each EA; and calculate the distance from each EA centroid to each of the hospitals and the health centers.

Three C++ routines were then written to interface with Gurobi, a commercially available, large-scale linear program solver, to solve each of the distribution problems. While heuristic methods exist for both the $p$-median problem and CFLP [19] [8], [12], our analyses were neither sufficiently large nor time-sensitive to re-
quiere them. Gurobi uses a Branch-and-Cut algorithm, whereby it tries to drive down the gap between the best known objective value for a feasible solution and the objective bound of its current node. As the optimal solution always lies between these two values, the smaller the gap, the higher confidence we have in the optimality of our results. All three C++ routines were run on Gurobi version 4.0.1, with a gap tolerance of at most 1%. All programs were run on a machine with a memory of 16 GB and a processing speed of 2.83 GHz, employing only one core to limit memory usage.

Finally, these outputs were analyzed and visualized using a combination of ArcGIS, Microsoft Excel, and MATLAB.

4 Results and Discussion

This section summarizes the results of the facility location models, including data about the number and location of assigned HSAs, backpacks, and resupply facilities. We provide the results both for both the entire country and specifically for Lilongwe District, the location of the pilot backpacks and likely site of the initial backpack scale-up. We then use these results to describe how the HSA backpacks, supplied in this manner, could improve health care across Malawi. Note that the results for each of our models represent straight-line distances, as we were unable to obtain sufficiently detailed data about road locations and conditions.

4.1 Optimal HSA Assignments

We first used the $p$-median problem to assign 615 HSA pairs, based on a 1:1000 ratio of HSAs to population, to the 861 EAs in Lilongwe District. We then calculated the average distance between each EA and the location of the HSA pair serving it. All HSAs were considered to be 0 km from their base EA, and all results represent distance to the centroid of the population areas served rather than actual patient locations. This distinction was necessary given the unknown population distribution within each EA, but as most EAs are only a few square kilometers in area, it does not lessen the value of our results.

Our model resulted in an average distance from EA to HSA pair of 0.46 km and a maximum of 4.4 km. These numbers represent reasonable walking distances for an HSA to travel, and are shown against a map of Lilongwe District in Figure 1. The proximity between most points on the graph demonstrates short distances between HSAs and patients. Note however that the southern part of the map, comprised of only one EA, has only one HSA pair

assigned because of its comparatively small population. As the map shows, most HSA pairs in Lilongwe were assigned to only one base EA or a base EA and its close neighbor. A maximum of five EAs were assigned to one HSA pair. The HSA assignments were calculated with no gap in Gurobi and in a runtime of 81 seconds.

In the nationwide case, we assigned 6500 HSA pairs to the 9147 EAs in Malawi with nonzero population (of 9218 total). Again, the number of HSAs assigned was based on an assumed 1:1000 HSA to population ratio. The distance results for the entire country are similar to those for Lilongwe District and again represent reasonable walking distances. For Malawi, our model resulted in an average distance from each EA centroid to its assigned HSA of 0.39 km and a maximum distance of 12.7 km.

The number of EAs served by each HSA pair in Malawi is shown in Table 1. Note that, as in Lilongwe District, most HSA pairs are serving only one or two EAs. However, unlike in the smaller case, our Malawi model assigned some HSAs to serve 10 or more EAs, with the maximum number being 35. We found that the HSAs as-
signed to serve many EAs were those centered in urban areas and located near health centers. This discrepancy can be explained by the smaller size of EAs located in urban areas along with our assumption that EAs located near a health center would have the majority of their needs met by that health center. These results were calculated with a Gurobi gap percentage of 0.01% in 11.5 hr.

Table 1: Number of Malawi HSAs by the number of enumeration areas they serve.

<table>
<thead>
<tr>
<th>Number of EAs per HSA</th>
<th>Number of HSA pairs</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>4909</td>
</tr>
<tr>
<td>2</td>
<td>1073</td>
</tr>
<tr>
<td>3</td>
<td>335</td>
</tr>
<tr>
<td>4</td>
<td>95</td>
</tr>
<tr>
<td>5-9</td>
<td>71</td>
</tr>
<tr>
<td>10-19</td>
<td>14</td>
</tr>
<tr>
<td>20+</td>
<td>3</td>
</tr>
<tr>
<td>Total</td>
<td>6500</td>
</tr>
</tbody>
</table>

4.2 Optimal Backpack Assignments

The next tier of our model used the capacitated facility location problem to allocate backpacks to HSAs and, in the process, determine the number of packs needed to cover the region. In Lilongwe District, our model assigned 205 backpacks across the 615 HSAs allocated to Lilongwe. These values indicate that 100% of the backpacks were assigned to serve a full capacity of 3 HSA pairs. While this capacity assumption was clearly a major constraint in our model, BTB felt that it accurately represented the backpacks’ true capacities and should not be changed. At an initial cost of $352.91 per backpack, 205 backpacks corresponds to a total start-up cost of $72,346.55 to cover the entire Lilongwe District. Based on these cost estimates, BTB decided to focus their initial scale-up efforts on Lilongwe District, rather than attempting to tackle the entire country at once.

With the backpacks thus assigned, there was an average distance between each HSA pair and the backpack serving it of 1.6 km, with a maximum of 9.1 km. As with the HSA assignments, these distances appear reasonable even for HSAs with no transportation options other than walking. The assignments are displayed visually in Figure 2 which highlights the short average travel distances. The backpack assignments were calculated with a Gurobi gap percentage of 0.01% and a runtime of approximately 2 hours.

The second tier of our model assigned 2188 backpacks to the 6500 HSA pairs across Malawi. This corresponds to a total start-up cost of $772,167.08. While this cost is not unreasonable considering the high potential of the HSA backpacks to improve health, it was high enough to encourage BTB to consider focusing on successfully scaling up in Lilongwe District first. Of these 2188 backpacks, 2129 (97.3%) were assigned to serve at the full capacity of 3 HSA pairs, again indicating the importance of this constraint. Distances between backpacks and HSAs were similar to those in the Lilongwe case, with an average distance between each HSA pair and its assigned backpack of 1.8 km and maximum of 21.7 km. These results were calculated with a Gurobi gap of 0.80% in a runtime of 12.5 hr.

4.3 Optimal Resupply Center Assignments

Finally, we assigned the backpacks allocated in the second tier of our model to existing hospitals or health centers which could act as resupply centers for disposables.
within the packs. We calculated these assignments for two cases: one in which BTB decided to use hospitals only as resupply centers, and one in which both hospitals and health centers were considered. The advantage of using hospitals only is that they are generally better-stocked and more reliable than smaller health centers; however, our results indicate that this increase in reliability would come at a cost. Only two hospitals exist in rural Lilongwe District, which required us to set the capacity of each above our plan of 80 backpacks to 150 backpacks. With this arbitrary threshold, our model resulted in one hospital serving 89 backpacks and the other serving 116. While these numbers are not infeasible according to BTB, the resulting travel distances between these backpack and hospital pairings are prohibitively high. The hospital-only approach resulted in an average distance between backpacks and resupply centers of 28 km with a maximum of 62 km. As walking is the only travel option for most HSAs, a one-way distance of 28 km could translate to unreasonably high travel times for even a single backpack refill trip.

When health centers were included in the model, these distances between backpacks and resupply centers fell sharply to an average distance of 5.4 km and a maximum of 25.7 km. These represent much more reasonable travel times for HSAs, who would need to take time away from patients to refill the packs. In the hospital and health center case, 37 of 37 health centers and both hospitals were chosen. The hospitals served 6 and 2 backpacks respectively, while the health centers served a mean of 5.3 backpacks and a maximum of 10.

Results were similar for the nationwide version of our model, shown in Figure 3. We again compared a hospital-only resupply case with a hospital and health center resupply case. In the hospital and health center case, 46 of 49 hospitals and 574 of 661 health centers were chosen as resupply centers. The mean number of backpacks served by each hospital was 4.09, with a maximum of 12; for health centers, the mean was 3.48 backpacks, with a maximum of 10. The large number of facilities chosen led to short distances between each backpack and its resupply site, with a mean of 5.1 km and a maximum of 28.4 km.

In the hospital-only case, all 49 hospitals were chosen as resupply centers. This led to a mean number of backpacks served by each hospital of 40, with a maximum of 80. As Figure 3 shows, the distances HSAs would need to travel in this case were again prohibitively higher than in the health center and hospital case, with an average of 19.8 km and a maximum of 70.5 km. The hospital-only case also introduced a few other travel difficulties. The most noteworthy one is that some HSAs would need to cross Lake Malawi to reach a resupply center because of a lack of nearby hospitals. Given the poor infrastructure and high fuel cost in Malawi, these HSAs might not be able to refill their backpacks at all if assigned to a hospital resupply center.

Based on these results, BTB determined that they could not plan to use only hospitals as resupply centers when deploying the HSA backpacks. The small number of hospitals and long distances between hospitals and HSAs demonstrate the importance of health centers within the Malawian health care system. However, the potentially irregular supply of health centers remains a concern. Our results suggest that the ideal solution would include hospitals and the most reliable health centers as resupply centers, striking a balance between concerns about distance and supply chain vulnerability.

### 4.4 Potential Impact of Backpacks

The models above allowed us to determine not only the optimal number and locations of the backpacks, but also their potential impact. Inadequate access to medical supplies is one of the primary factors limiting the current success of HSAs in Malawi. Optimizing the deployment
of HSAs using the first tier of our model would not be enough to solve the problem. HSAs deployed in this manner in Lilongwe District would be an average of 4.92 km from the nearest health center or hospital, with a maximum of 11.5 km. Considering that these values indicate only straight-line distances and that most HSAs travel by foot, the time spent traveling to obtain even basic supplies would form a significant constraint on the ability of the HSAs to provide adequate care to their patients.

As described earlier, our proposed deployment of the HSA backpacks in Lilongwe would place backpacks an average of 1.6 km from the HSAs they serve, with a maximum of 9.1 km. This would lower the distance that the average HSA needed to travel for supplies by more than half. While the backpacks would still need to be refilled periodically, these trips would likely be done at most every two weeks, allowing HSAs to spend the majority of their time helping patients rather than searching for supplies. HSAs would see similar gains if the backpacks were extended to cover all of Malawi; instead of walking an average of 5.17 km and maximum of 28.4 km to a hospital or health center for supplies, HSAs would need to travel only an average of 1.8 km and maximum of 21.7 km to reach their assigned backpacks.

Improved access to supplies would allow HSAs to provide medical care to patients who otherwise may be unable to receive medical treatment. The HSA backpacks contain supplies used to treat acute childhood illnesses such as diarrhea and malaria. For children with these conditions, receiving medications a few hours earlier could mean the difference between life and death. This improved access to lifesaving medical care is especially important in Malawi, which in 2006 had an under-5 mortality rate of 134 deaths per 1,000 live births [11]. Our models therefore provide not only an optimal strategy for deploying the HSA backpacks in Malawi, but also increased evidence of the impact they could have there.

### 4.5 Sensitivity Analysis

Our analyses relied on several variables with a high degree of uncertainty. In particular, we were uncertain about the number and location of health centers and the population distribution. To assess the model’s dependence on health center data, we ran a hospital-only resupply center scenario, discussed above. To determine the potential impact of uncertainty surrounding the population distribution, we ran a sensitivity analysis on the population distribution within Lilongwe District. The total population of Lilongwe, which was obtained from the 2008 Malawi Census, was assumed fixed. We then varied the population of each EA according to a uniformly distributed random variable with endpoints ranging from ±5% to ±50%. The optimal objective value for the HSA-to-EA assignment was compared to the objective value under the original solution to determine the robustness of the original solution to changes in population distribution. The results are shown in Table 2 and suggest that our proposed solution is fairly robust to uncertainty about the population distribution. We also calculated the number of HSA locations that remained constant when the population was perturbed. This value ranged from 86.2% for the largest perturbation to 98.3% for the smallest perturbation, suggesting that the HSA locations are largely conserved across varying population distributions.

### 5 Conclusion

This paper uses facility location models to describe an optimal scale-up plan for Malawi’s HSA program and Rice University BTB’s HSA backpack program. In particular, we used the p-median problem to determine the optimal allocation of HSAs across Malawi and the capacitated facility location problem to assign HSAs to backpacks and backpacks to resupply centers. Using these models, we provided BTB with a backpack scale-up analysis that provides pack numbers, estimates monetary costs, and highlights potential challenges.

Because of the financial and logistical difficulties associated with nationwide scale up of the HSA backpack program, the backpack deployment will likely take a step-wise form, beginning with Lilongwe District. Under our plan, the HSAs in Lilongwe District would be an average of only 1.6 km from their assigned backpacks, as opposed to 4.79 km if relying directly on a hospital or health center for supplies. This improvement is especially important since most HSAs travel by foot over roads with varying conditions. Giving HSAs easier access to supplies will enable them to deliver care more efficiently and effectively.

Our assessment also allowed BTB to consider the cost of supply chain disruptions in Malawi by comparing a case in which only hospitals were used as backpack resupply centers to one in which both hospitals and health centers were used. The inclusion of health centers led to sharp decreases in the distance between backpacks and resupply centers both in Lilongwe District (an average of 5.4 km with health centers included compared to an average of 28 km without) and across Malawi. This demonstrates the importance of including health centers as backpack resupply centers, which in turn emphasizes the need for a strong chain of supplies to these small health care facilities.
Table 2: Robustness of EA-to-HSA assignments to population distribution uncertainty. Mean values are presented for 10 runs at each level.

<table>
<thead>
<tr>
<th>Maximum Change in EA Population</th>
<th>Optimal Objective Value</th>
<th>Objective Value Under Original Solution</th>
<th>Percent Difference Between Original and Optimal Solutions</th>
</tr>
</thead>
<tbody>
<tr>
<td>5%</td>
<td>2.615E+08</td>
<td>2.618E+08</td>
<td>0.17%</td>
</tr>
<tr>
<td>10%</td>
<td>2.606E+08</td>
<td>2.623E+08</td>
<td>0.66%</td>
</tr>
<tr>
<td>15%</td>
<td>2.580E+08</td>
<td>2.623E+08</td>
<td>1.65%</td>
</tr>
<tr>
<td>20%</td>
<td>2.551E+08</td>
<td>2.630E+08</td>
<td>3.12%</td>
</tr>
<tr>
<td>25%</td>
<td>2.505E+08</td>
<td>2.625E+08</td>
<td>4.81%</td>
</tr>
<tr>
<td>30%</td>
<td>2.452E+08</td>
<td>2.625E+08</td>
<td>7.06%</td>
</tr>
<tr>
<td>35%</td>
<td>2.376E+08</td>
<td>2.600E+08</td>
<td>9.43%</td>
</tr>
<tr>
<td>40%</td>
<td>2.337E+08</td>
<td>2.626E+08</td>
<td>12.38%</td>
</tr>
<tr>
<td>45%</td>
<td>2.250E+08</td>
<td>2.610E+08</td>
<td>16.00%</td>
</tr>
<tr>
<td>50%</td>
<td>2.183E+08</td>
<td>2.601E+08</td>
<td>19.13%</td>
</tr>
</tbody>
</table>

This analysis depends on a number of assumptions. In reality, the deployment of the HSAs and backpacks likely will not follow these exact recommendations. The HSA program is run by the Malawi government based on its assessments of its people’s needs, which may be influenced by a more accurate determination of population characteristics, infrastructure development across different regions, and political will power. As a result, the actual locations of HSAs will probably differ from those recommended by our model, which in turn could affect both backpack and resupply center assignments. This discrepancy could lead to greater distances between HSAs, backpacks, and resupply centers than those listed here. Furthermore, health centers will have to be evaluated as potential resupply sites on an individual basis, contingent on the consistency of their supply chains. In addition, backpack costs will not be limited to an initial investment, as described here, but will continue to grow as items in the backpacks are used or expire. Finally, these results are based on data from 1998, with the population extrapolated to 2008 levels. This means that our model may not fully account for changes to the Malawian demographics between 1998–2008, and surely does not account for those that occurred from 2008–present. BTB will need to consider all of these issues when planning their backpack scale-up in the field.

The techniques used in this paper could be used to plan community health worker supply systems in countries beyond Malawi. The limitations of the methods used include the large amount of data and computing power necessary to complete a sufficiently thorough analysis. However, this level of detail allowed us to answer general questions, such as how many backpacks were necessary, while also creating a specific plan for the optimal placement and resupply of every individual backpack. Optimization analyses such as this can create plans for supplying community health workers which minimize both travel times and costs, thus allowing them to provide higher quality care to the patients who need them the most.

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References


