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Optimizing community healthcare coverage in remote Liberia

Paige VonAchen and Karen Smilowitz
Department of Industrial Engineering and Management Sciences, Northwestern University, Evanston, Illinois, USA
Mallika Raghavan
National Community Health Systems, Last Mile Health, Boston, Massachusetts, USA, and
Ross Feehan
Operations Team, Last Mile Health, Boston, Massachusetts, USA

Abstract

Purpose – The purpose of this paper is to present a case study describing a collaboration with Last Mile Health, a non-governmental organization, to develop a framework to inform its community healthcare networks in remote Liberia.

Design/methodology/approach – The authors detail the process of using the unique problem setting and available data to inform modeling and solution approaches.

Findings – The authors show how the characteristics of the Liberian setting can be used to develop a two-tier modeling framework. Given the operating constraints and remote setting the authors are able to model the problem as a special case of the location-routing problem that is computationally simple to solve. The results of the models applied to three districts of Liberia are discussed, as well as the collaborative process of the multidisciplinary team.

Originality/value – Importantly, the authors describe how the problem setting can enable the development of a properly scoped model that is implementable in practice. Thus the authors provide a case study that bridges the gap between theory and practice.

Keywords West Africa, Liberia, Community health workers, Ebola virus disease (EVD), Healthcare network design, Location-routing problems

Paper type Case study

1. Introduction

This case study describes a collaboration between the non-governmental organization, Last Mile Health (LMH), and Northwestern University focused on the development and implementation of operations research models to facilitate decision making in remote Liberia. We detail our process of using the unique problem setting and available data to inform modeling and solution approaches. We explore how the setting details impact the model and solution approach to design a community healthcare network. We use the setting details to develop a two-tier modeling framework, including a simplified special case of the location-routing problem that can be solved with commercial software in remote settings. The resulting reduction in computational complexity provides organizations with limited resources, such as LMH, with the needed ease of implementation. By working directly with available data, results are grounded in the context of the problem and allow for greater impact. Thus, we bridge the gap between research and practice; outlining the importance of close partnerships and providing a guide for future applied operations research in humanitarian logistics.

The paper is organized as follows. Section 2 reviews relevant humanitarian logistics literature and the call to link theory and practice. Section 3 provides details of

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LMH's-specific problem setting and the limited data available to inform the models. Section 4 describes how the data were used to inform the specific solution approach for LMH's operational decisions and the consequent models developed. Section 5 provides an outline of the solutions specific to LMH, and the implications of the described collaboration, including how LMH is using the results. Section 6 concludes the research and describes next steps.

2. Literature review

The field of humanitarian logistics has grown in recent years (Starr and Van Wassenhove, 2014); however, there remains a significant gap in literature linking theory and practice (Bhimani and Song, 2016; Van Wassenhove, 2006). There have been numerous calls for additional applied humanitarian logistics research, particularly in last mile efforts (Starr and Van Wassenhove, 2014; Bhimani and Song, 2016). Additionally there is an explicit gap in applied healthcare development research, as few location-allocation models for developing health systems have reached the implementation phase (Rahman and Smith, 2000). Closing these gaps require increased collaborations and case studies exemplifying the benefits of applied research and suggest best practices (Stuart *et al.*, 2002). Close partnerships allow for data exchange and knowledge about the problem context in order to have a greater impact on operational humanitarian projects (Leiras *et al.*, 2014). This exchange is particularly important in the humanitarian domain due to its unique challenges, including data limitations and barriers to implementation.

A lack of robust and quality data remains a primary issue plaguing efforts in the humanitarian domain (Van Wassenhove and Pedraza Martinez, 2012; Starr and Van Wassenhove, 2014; Martinez *et al.*, 2011). Modeling efforts are often forced to estimate certain parameters and input data (Balcik and Beamon, 2008); leaving solutions inapplicable to the contexts at hand. Other applied modeling efforts have often involved the development of complex modeling techniques and also remain unable to be used in practice (Iannoni *et al.*, 2009; Jia *et al.*, 2007) due to a lack of available data and/or prohibitive amount of CPU time. In certain cases, the use of simulation data has enabled the validation of certain models despite a lack of data (Das and Hanaoka, 2014). However (Van Wassenhove and Pedraza Martinez, 2012) emphasizes the importance of using primary data in the development and application of logistics models. The humanitarian logistics research limitations described above can be resolved by increasing collaboration between academics and practitioners (Bhimani and Song, 2016) from the very beginning of the attachment (Van Wassenhove and Pedraza Martinez, 2012). Understanding the context and data available prior to developing models enables the models to be grounded in the reality of the application and increase the likelihood of implementation.

In addition to building models based on available data, applied humanitarian research should involve simple models. Ozdamar and Ertem (2015) noted that while many current proposed logistics planning models have good practical features, most models' computational burden prevent them from being applied. It is critical to develop simple approaches to assist relief efforts (Day *et al.*, 2012). It is suggested that more solvable models would directly benefit humanitarian logistics (Ozdamar and Ertem, 2015). Again, working directly with logisticians in the field allows for a greater understanding of the context. This understanding can directly improve the applicability of models developed, as researchers understand proper assumptions for the models and can scope models appropriately. However, there remains a gap in applied literature further exemplifying how this can be accomplished.

Additionally, increased partnerships and case studies within the humanitarian logistics domain can be mutually beneficial to both practice and theory. Collaboration allows for natural expansion of OR/MS research through the development of novel models (Apte and Mason, 2006; Green *et al.*, 2013). Thus there is further benefit to closer collaboration between non-profit organizations and academics.

In this paper, we describe a collaboration which bridges theory and practice in humanitarian logistics. By doing so, we are able to address gaps in applied OR/MS described above; specifically the need for models grounded in the reality of the data available and the context of the humanitarian efforts. We provide a case study describing our efforts in applied humanitarian logistics. We show how the use of available data and contextual limitations can enable a computationally simplified model that is directly implementable and scoped for the problem at hand. The models developed expand OR/MS research through a particularly useful simplified special case of the location-routing model for use in remote road networks. Thus we contribute to the growing body of knowledge in applied humanitarian logistics and directly improve the operational model of LMH.

3. Problem setting and data

In 2014, the Ebola virus disease (EVD) devastated West Africa and demonstrated that weak, inequitable health systems threaten the entire global community (Kalra *et al.*, 2014). Though Liberia is no longer confronting an EVD emergency, it still faces the need to build a resilient and comprehensive health system. LMH and its partners have thus launched a national expansion of a community healthcare model. This section describes LMH's-specific problem setting and data constraints.

3.1 Problem setting: community healthcare model at LMH

Founded by survivors of Liberia's civil war, LMH saves lives in the world's most remote villages. LMH specializes in the development and management of professionalized community health workers (CHWs) who bridge the gap between clinics and remote villages, bringing critical services to the doorsteps of people living in the last mile. LMH's programs are implemented hand-in-hand with community members, local government officials, national policy makers, and global partners to ensure sustainable impact.

CHWs prevent, diagnose, and treat common health conditions in remote Liberia. Community health worker leaders (CHWLs) supervise and support CHWs. Community clinical supervisors (CCSs) provide clinical oversight of CHWLs at supervision hubs (SHs), where supplies are distributed and trainings occur. Figure 1 illustrates the reporting relationships amongst CCSs, CHWLs, and CHWs.

In the current LMH operational model, CHWs serve as the first point of contact for community members seeking medical care. CHWs live and work within a one-hour walking distance of patients. CHWLs are also located in communities throughout rural Liberia but do not function as CHWs; CHWLs are strictly supervisors, not healthcare practitioners. The CHWLs travel to visit CHWs every week to provide supervision and resources. The CHWLs also travel to SHs for monthly trainings with CCSs. These hubs are centrally located in larger communities. There is one CCS at each SH.

The recruitment of CHWs, CHWLs, and CCSs occurs sequentially in each region. First, local committees nominate qualified persons to LMH and the Ministry of Health & Social Welfare. Those nominees are then screened, interviewed, and tested; a select number

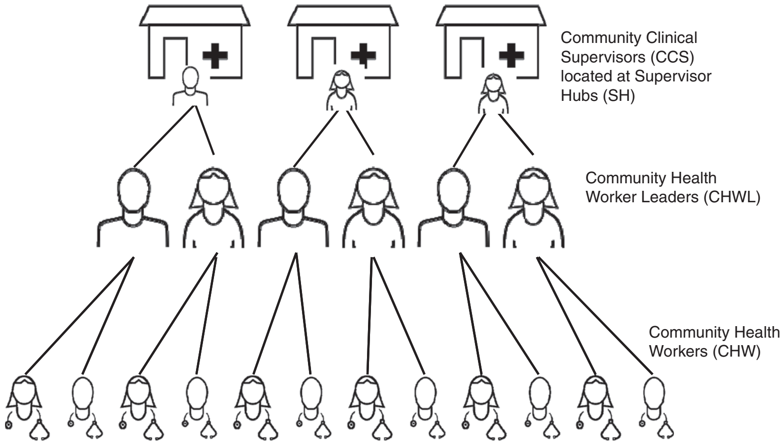

Figure 1.
Current LMH operational model

receive offers for the position of CCS or CHWL. Upon acceptance of their offers, CCSs and CHWLs enroll in a training academy. LMH assesses strengths and capabilities of the trainees to inform placement decisions, which are also guided by the research discussed herein. After CCS and CHWL assignments are determined, CHWLs work within their catchment areas to recruit CHWs. CHWs who receive and accept offers then attend intensive training before serving their communities. Recruitment and launch of the workforce takes nearly four months to complete in each region.

Northwestern University and LMH began their partnership as the CHW program in Rivercess County, Liberia was being developed (see Figure 2).

Rivercess is a remote, coastal county in Liberia with poor infrastructure. Given significant transportation challenges in rural Rivercess and the need to efficiently utilize resources, LMH wanted to carefully design the program's operational model. LMH thus collaborated with Northwestern University to build a decision-making framework that would help inform operational decisions.

Specifically, the operational models within this framework address decisions regarding CHW and CHWL assignments. They determine the optimal CHW location and catchment areas to minimize costs while simultaneously providing coverage to all citizens. Additionally, they determine the optimal CHWL base location, catchment assignments, and route configurations to visit CHWs; again, while minimizing costs.

3.2 Research process

This section presents an overview of the research process. Figure 3 presents a flowchart describing the process used. Data are manually collected, cleaned, and pre-processed for the models using a process described in Section 3.3. Significantly, the data available are used to inform the model and solution approach. As a result, the models are directly applicable to the problem setting and functionally assist LMH with their operational decisions.

3.3 Road/infrastructure data

Throughout rural Liberia, the road network is extremely limited. It has been estimated that an additional 5,700 km of roads need to be built in order to meet rural connectivity standards (linking land responsible for 80 percent of agricultural production value to

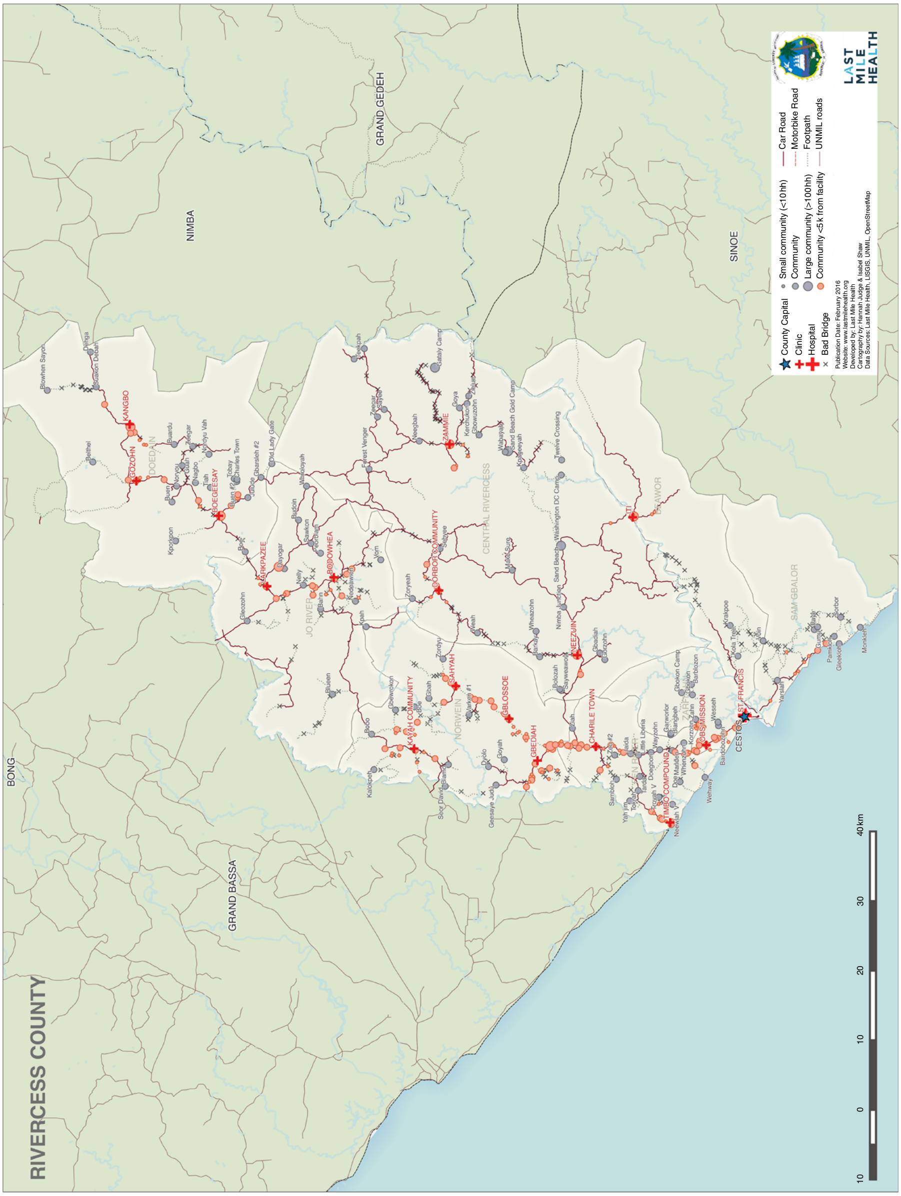

Figure 2.
Logistics and health facilities in Rivercess County, Liberia

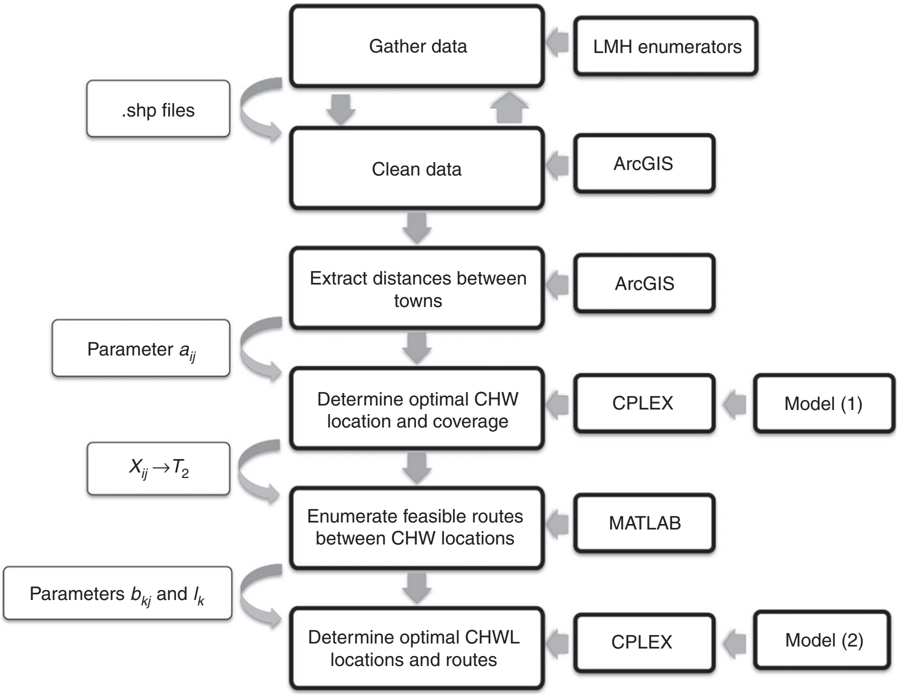

Figure 3.
Decision-making framework flowchart

the national network) (The World Bank, 2011). The majority of roads are unpaved and over 60 percent of the road network is in "good" or "fair" condition. In addition to poor road conditions, the networks in the areas served by LMH often have not been mapped by standard mapping sources; e.g., Google and OpenStreetMap. Thus LMH faces an issue of limited and poor quality data to inform their operational decisions.

In order to provide healthcare access in these remote regions, LMH conducts a rigorous, iterative mapping process for each region. The mapping team consists of enumerators to collect data in the field, a mapping coordinator to manage data collection, and a GIS specialist to compile and process GPS data. Enumerators traverse roads with a GPS device to collect information about communities and the transportation network. Enumerators manually record road conditions and features, as well as community locations, names, and demographic data. These data points are assigned geographic coordinates with GPS devices. As a result, the geographic coordinates of data points representing communities are sensitive to the location of the enumerator when recording data. The GIS specialist then compiles all GPS data into single shape files that can be viewed and analyzed with standard GIS software. In total, for a region the size of Rivercess County, the process takes multiple months and dozens of people to complete. The Appendix describes common data issues encountered in this process. As regions served by humanitarian efforts face similar data constraints, particularly the last mile of the supply chain; these data issues may benefit future manual mapping efforts.

Data pre-processing involves the extraction of distances between all town pairs from the shape files. To extract these distances, a road and town network is created using the Network Analyst toolbox in ArcGIS. The importance and impact of using road network distances vs the common Euclidean estimation is described in Section 5.

4. Models for the design of community health networks

This section presents the models and solution approach that together provide a comprehensive decision-making tool for LMH's operational model. The models developed draw from the facility-location and location-routing literature. Reid *et al.* (1986) cite several applications of set covering models to health facility and health worker location problems; e.g., Harvey *et al.* (1974) and Bennett *et al.* (1982). Cocking *et al.* (2006) use a modified max covering model to locate health facilities in Burkina Faso. As noted in Kunkel *et al.* (2014), much of the prior work on community healthcare networks focus on a single tier of facilities; however, Kunkel *et al.* (2014) consider a multiple tier network of health surveillance assistances and medical backpacks in Malawi. The authors formulate both a decomposed model that designs two tiers separately and an integrated model in which the tiers are determined simultaneously. The CHW and CHWL decisions faced by LMH represent a two-tier system. However, the CHWL tier involves multi-stop routes, which is better modeled as a location-routing problem.

The problem is decomposed into the following two sub-problems: CHW location and assignments, and CHWL location, routing and assignments. The first model uses a capacitated set coverage model to determine the optimal location and assignment of CHWs. The goal is to minimize the number of CHWs while ensuring each town is served, each CHW serves a maximum number of households, and no community is located further than 2.5 km from its CHW. The output of this sub-problem (the set of CHW locations) becomes a parameter for the second sub-problem. In the second sub-problem, we determine the location of CHWLs, the set of CHWs each CHWL supervises, and the schedule of routes each CHWL uses to visit these CHWs.

The models make use of the constraints specific to LMH and the context of rural Liberia. Most significantly, we capitalize on the limited road network to enumerate all possible CHWL routes and use said routes as a parameter in the model. This vastly reduces computational complexity and reduces the barrier to implementation, enabling a greater impact.

4.1 Community healthcare workers model

At the first tier, to determine the optimal location for CHWs, a capacitated set coverage model (Daskin, 2011; Guha *et al.*, 2002) is developed that minimizes total CHWs while simultaneously honoring LMH's capacity and distance constraints.

4.1.1 CHW model formulation. Let T represent the set of towns in the district under consideration. This set represents both the towns needing service by a CHW and potential base locations for CHWs, since CHWs are recruited from their home towns. Each town $i \in T$ has a population p_i, measured in number of households (each household is assumed to represent five people). A CHW can serve at most C_1 households and members of a community can travel at most D_1 kilometers to reach a CHW. Given a distance parameter, d_{ij}, between towns i and j, $i, j \in T$, we define a coverage parameter a_{ij} which takes a value of 1 if town i can be served by a CHW in town j (if $d_{ij} \leqslant D_1$), and 0 otherwise.

We introduce the following decision variables:

$$Y_j \text{ number of CHWs in town } j \in T$$

$$X_{ij} = \begin{cases} 1 & \text{if CHW in town } j \in T \\ & \text{serves town } i \in T \\ 0 & \text{otherwise} \end{cases}$$

With this notation, the CHW model with a modified capacitated set covering model is formulated as follows:

$$\min \sum_{j \in T} Y_j \tag{1}$$

subject to:

$$\sum_{j \in T} a_{ij} X_{ij} \geqslant 1 \quad \forall i \in T \tag{2}$$

$$\sum_{i \in T} p_i X_{ij} \leqslant C_1 Y_j \quad \forall j \in T \tag{3}$$

$$M X_{jj} \geqslant Y_j \quad \forall j \in T \tag{4}$$

$$p_i X_{ij} \leqslant p_j X_{ij} \quad \forall i,\, j \in T : i \neq j \tag{5}$$

$$X_{ij} \in \{0, 1\} \quad \forall i,\, j \in T \tag{6}$$

$$Y_j \text{ integer} \quad \forall j \in T \tag{7}$$

where:

$$M = \left(\frac{\sum_{i \in T} p_i}{C_1} \right).$$

The objective function (1) minimizes the number of CHWs needed to serve the population. Constraints (2) are coverage constraints that require each town to be served by a CHW within the distance limit, D_1. Constraints (3) ensure that sufficient CHWs are located in a town to meet the needed coverage capacity. Constraints (4) and (5) are added to the traditional capacitated set covering model to reflect LMH preferences in CHW assignment. Constraints (4) require that a town with a CHW is served by a CHW from that town; given a town with a CHW, the CHW provides care for its own community members, in addition to other communities in the catchment area. Constraints (5) place the CHW in the largest town within its catchment area to reduce travel and assist with recruiting. Finally, constraints (6) and (7) define the X variables to be binary and the Y variables to be integer, respectively.

4.1.2 CHW implementation. When applying Model (1) to Rivercess County, the CHW capacity, C_1, is set to 50 households and the maximum distance between a CHW a community within its catchment, D_1, is set to 2.5 km, given the size of the districts in Rivercess County. The Liberia Ministry of Health & Social Welfare has set a standard of one CHW for every 350 people to maintain quality care. LMH hopes to maintain one CHW for every 250 people, thus a constraint of one CHW for every 250 people is used. Assuming five people per household, this leads to the limit of 50 households per CHW. Model (1) can be solved efficiently with commercial software.

4.2 Community healthcare worker leaders model

At the second tier, to determine optimal CHWL location, assignment, and routing, a location-routing model was developed. The location-routing problem with distance constraints (Berger *et al.*, 2007) allows multi-stop routes from chosen depots; see recent reviews in Albareda-Sambola (2015) and Drexl and Schneider (2015). These reviews highlight advances in modeling and solution approaches (both exact and heuristic) for the LRP. Given the significantly large sets of feasible routes, these models require complex solution approaches. Considering Liberia's limited road network and CHWL travel constraints, there exists a small set of feasible routes for any given CHWL location.

4.2.1 CHWL model formulation. Here, we present an adaption of the location-routing model formulation that is a special case of the formulation of Berger *et al.* (2007). As in those formulations, a set of (not necessarily exhaustive) feasible CHWL routes is specified, R, a priori and the routes and CHWL bases are selected within the model. However, as shown in Figure 4, this formulation differs in that the depot choice is not specified in the set of routes. Figure 4(a) shows the traditional route definition in which the CHWL base is specified in the route definition, as marked by the shaded node in the figure. For a set of three towns, each a possible base location, the set R would include three distinct routes. Figure 4(b) depicts the proposed route representation that does not specify the choice of CHWL base among towns on the route. The route is simply a cycle through the towns. The CHWL selection is determined by the model. In the LMH setting, defining routes in this way reduces the number of possible routes to a level at which all routes can be enumerated a priori and more complex solution methods, such as column generation, are not needed.

From the solution to Model (1), let T_2 denote the set of towns which serve as a base location for at least one CHW; where $T_2 \subseteq T$. Let F_j denote the weekly fixed cost associated with adding a CHWL at location j. This cost includes the cost of travel to the closest SH to location j.

For each route $k \in R$, let l_k denote the distance (in kilometers) of route k, and b_{kj} which takes the value of 1 if route k visits town $j \in T_2$, and 0 otherwise. Let r_2 denote the maximum number of routes a CHWL can perform visiting CHWs each week.

The following decision variables are introduced:

$$W_j = \begin{cases} 1 & \text{if CHWL is located in town } j \in T_2 \\ 0 & \text{otherwise} \end{cases}$$

$$Z_k = \begin{cases} 1 & \text{if route } k \in R \text{ is selected} \\ 0 & \text{otherwise} \end{cases}$$

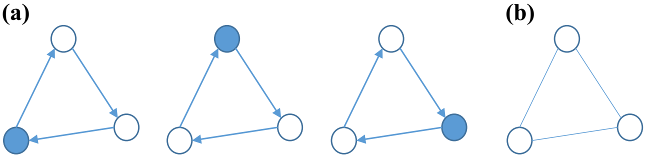

Figure 4. Route definitions for location-routing problem formulations

Notes: (a) Traditional route definition with specified base; (b) proposed route definition without specified base

With the above notation, the CHWL model is formulated as follows:

$$\min \sum_{j \in T_2} F_j W_j + \sum_{k \in R} l_k Z_k \tag{8}$$

subject to:

$$\sum_{k \in R} b_{kj} Z_k \geqslant 1 \quad \forall j \in T_2 \tag{9}$$

$$\sum_{k \in R} b_{kj} Z_k \leqslant 1 + (r_2 - 1) W_j \quad \forall j \in T_2 \tag{10}$$

$$Z_k \leqslant \sum_{j \in T_2} b_{kj} W_j \quad \forall k \in R \tag{11}$$

$$W_i + W_j \leqslant 3 - \left(b_{ki} + b_{kj}\right) Z_k \quad \forall k \in R,\ i,\ j \in T_2,\ i \neq j \tag{12}$$

$$W_j \in \{0, 1\} \quad \forall j \in T_2 \tag{13}$$

$$Z_k \in \{0, 1\} \quad \forall k \in R \tag{14}$$

The objective function (8) minimizes the weighted sum of the cost of training and deploying a CHWL and the routing costs. Constraints (9) state that each town with a CHW must be on at least one selected route. Further, constraints (10) state that if town j is a base for a CHWL ($W_j = 1$), then town j can be on at most r_2 routes. If town j is not a base for a CHWL ($W_j = 0$), then town j can be on at most one route. Constraints (11) and (12) require that each route is associated with exactly one town with a CHWL. Constraints (11) ensure that if a route is used, at least one town on that route is selected to be a CHWL. Constraints (12) ensure that, given two towns and a route visiting both, only one of those towns can have a CHWL ($W_i + W_j \leqslant 1$ if $b_{ki} + b_{kj} = 2$ for a chosen route $Z_k = 1$).

4.2.2 CHWL model implementation. For Rivercess County, the values of F_j are several orders of magnitude larger than the distance costs; thus, making the minimization of CHWLs the main objective. CHWLs can travel up to three days per week to visit the CHWs within its catchment ($r_2 = 3$ routes per week).

The ability to solve Model (2) depends on the size of the route set R. In many location-routing problems, complex solution approaches are developed to handle instances for which R becomes prohibitively large; see Albareda-Sambola (2015) and Drexl and Schneider (2015). However, in this setting, the knowledge of LMH operations is used to generate a manageable set of routes, which allows Model (2) to be solved with commercial software. For example, a CHWL visit to a CHW typically lasts one to two hours. Adding travel time between towns, it is reasonable to assume that a CHWL cannot visit more than three CHWs in a single day. Feasible routes: have at most V_2 stops (excluding the origin), do not exceed D_2 kilometers, and begin and end at the same origin, allowing the CHWL to return home in a single day. Using Euclidean distances, rather than true distance along a road network, to determine the distance between two towns increases R by assuming routes are shorter than they actually are according to the road network. Thus understanding the context in which models are applied enables a uniquely simplified model that can be easily solved and implemented.

5. Results

This section presents results from three districts in Rivercess County: Jowein, Central C, and Yarnee. Additionally, we highlight the importance of proper assumptions within the problem setting; particularly the use of Euclidean vs road network distances. Lastly, we describe the implications of this collaboration for research, practice, and society as well as the limitations.

5.1 Rivercess results

Table I presents descriptive statistics for each district: number of towns in the district ("towns"), number of households in the district ("HH"), and median number of households per town in the district ("HH/town median"). Additionally, the table presents the average proportion of towns within a set distance of another to provide a different perspective on the relative density of the districts. The three districts vary in terms of the geographic distribution of communities: the average distance between two towns is 49.83 km in Central C, 25.87 km in Jowein, and 27.36 km in Yarnee.

Table II presents solution statistics for the three districts. The table presents the percent of towns in the district that serve as a base for at least one CHW ("% CHW towns"), and the percent of population served by a CHW located in their town ("% pop in town"). For the towns that serve as CHW base locations, the table reports the average ("ave.") and median ("med.") values for CHW per town ("CHW/town"), towns served by each CHW in the town ("towns served"), and households served by each CHW in the town ("HH served").

From the table, one sees that Central C and Jowein tend to have more CHWs serving a single town, whereas the low-population density in Yarnee results in greater coverage for the CHWs in that district. Further, the shorter distance between towns in Yarnee allows greater geographic coverage. When towns are close, a CHW can serve more towns while still respecting the distance constraint. Elsewhere in the county,

Table I.
CHW summary statistics: input statistics

				Percent of towns within set distance of another town						
District	Towns	HH	HH/town median	2.5 km	5 km	10 km	15 km	20 km	25 km	50 km
Central C	78	2,408	15.5	3	5	8	13	20	26	58
Jowein	34	1,328	18	7	10	20	30	38	50	92
Yarnee	59	1,587	10	6	12	25	37	49	61	89
Total	171	5,323	15							

Table II.
CHW summary statistics: CHW town statistics

			CHW/town		Towns served		HH served	
District	% CHW town	% Pop. in town	Ave.	Med.	Ave.	Med.	Ave.	Med.
Central C	63	90	1.5	1	1.5	1	28.7	29
Jowein	68	89	1.7	1	1.5	1	29.8	31
Yarnee	46	85	1.6	1	2.1	2	32.0	33
Total	58	88	1.6	1	1.7	1	29.7	31

geographically dispersed towns with low-population density cannot share CHW resources in this way. Thus the models provide insight for LMH about the optimal way to efficiently provide access to CHWs to everyone in the region.

Given the set of CHW towns, T_2, and the set of feasible routes, R, the results are obtained for the three districts. Table III presents a summary of CHWL coverage throughout Jowein, Central C, and Yarnee in the Rivercess County. For each CHWL, daily route statistics are presented, in terms of both route length and number of CHW towns visited. Finally, the number of households served by the CHWs supervised by each CHWL is presented.

Throughout the three districts there is a large variation in both the distance traveled by CHWLs and the population served. The number of routes per week varies from one to three and the length of the routes varies from 3.5 to 39 km. Two of the CHWLs serve remote locations on single-town routes that exceed the distance limit, one from Barte and one from Zammi. In assigning specific workers to roles, this information is useful in aligning individuals' skillsets with their assignment. Recent work in the routing literature has attempted to balance workload (e.g. Jozefowiez *et al.*, 2007; Levy and Bodin, 1989). This is an interesting area of future research, as the results in Table III suggest that balancing CHWL workload is likely difficult to achieve given geographic constraints.

5.2 Comparison with Euclidean distances

As reviewed in Shahid *et al.* (2009), road distance measures are the most accurate distance metric. In order to assess the value of capitalizing on proper road network

Table III. Road network CHWL summary statistics

	Daily route length			Towns visited			
CHWL	Day 1	Day 2	Day 3	Day 1	Day 2	Day 3	HH Served
Central C							
Barte	39.0	23.0	16.1	1	1	3	321
Sand Beach Gold Camp	20.3	17.3	13.9	2	2	1	470
Make Sure	15.1			2			135
Neezuin	24.2	23.5	22.4	3	3	2	491
Pokpaye Town	24.3			3			122
Bolozah	23.8	22.1	11.5	1	1	1	274
Teekpah	8.0			1			72
Zammi	34.4	19.0	17.4	1	2	2	335
Kpageeyah	21.8	16.6	8.8	2	1	1	137
Wapee	25.0	22.1		2	1		125
Dupa Camp	6.4			1			97
Jowein							
Budoin Town	22.8	19.9		3	2		550
Cooperative Town	17.0	14.1		1	1		92
Kpotoll Town	22.5			3			355
Kahn Town	11.2			2			55
Larkpazee	24.3	13.6	8.6	2	2	1	261
Yarnee							
Klagba	24.9	15.7	3.5	3	3	1	297
Neegbah	21.6	10.5		3	1		757
Kai Town	23.4	22.1	19.3	3	2	2	208
Glanyah	22.0	20.5		2	2		169

assumptions within the problem setting in Rivercess County, results are compared with those obtained with Euclidean distances. It is determined that the CHW Model (1) results are identical regardless of distance matrix used; many CHWs serve only the town at which they are based. However, in other cases, the distance limit of 2.5 km is small enough such that the choice of distance matrix is inconsequential.

Contrary to the CHW model, the choice of distance matrix has a significant impact in the CHWL model. The route set R which is input to the CHWL Model (2) increases dramatically in size, from 446 potential routes from the road network distance matrix to 1,406 potential routes from the Euclidean transportation network. As a result, computational complexity increases significantly. The Model (2) is run with a time limit of one hour, resulting in an optimality gap of 13.4 percent. Summary statistics for the best integer solution found within the one hour time limit are presented in Table IV. Equally important, many of the routes are not feasible when converted to road network distances because they exceed the 25 km daily limit. In fact, only 8.3 percent of routes are feasible, with an average route length difference of 41.2 km between the Euclidean and road network distances.

In summary, using the Euclidean distances as a proxy for true road networks greatly increases the computational time to solve the CHWL model and the resulting solutions are often infeasible. Using the true distances is not only more accurate but also more efficient for it decreases computational time because significantly fewer feasible routes are considered. For the CHW model, in which distances are far shorter, the choice of distance matrix has no impact. Thus again, working within the context of the given problem enables the use of proper assumptions to provide implementable results and reduce complexity.

5.3 Implications

The collaborative effort between Northwestern University and LMH demonstrates that bringing together field practitioners and modelers can create solutions for specific

Table IV.
Euclidean CHWL summary statistics

CHWL	Total CHWL route lengths Euclidean	Total CHWL route lengths Road network	Towns visited	HH served
Central C				
Yarkpah	51.1	95.3	8	333
Sand Beach Gold Camp	35.8	72.2	6	510
Kpageeyah	49.0	116.1	8	208
Forest Venger	48.6	111.2	6	298
Sayee	55.1	223.3	4	265
Karr Camp	29.1	108.4	4	461
Gbokon Camp	40.9	769.8	6	286
Porkor	31.1	46.1	5	160
Jowein				
Kahn Town	27.5	40.8	4	147
Gargar Town	55.9	195.1	8	583
Bahn Town	34.3	48.5	5	435
Yarnee				
Gleekloh	43.5	105.3	8	307
Gbagbo Town	45.0	82.4	8	882
Acfi Mission	32.2	48.4	5	172

contexts while also advancing operations research. Reversing the solution process, beginning with the available data, allows for models that can truly be applied to the setting of interest. Here, the models reflect the specific aims and values of actors in Liberia. Understanding the embedded assumptions surrounding Euclidean vs road network distances both increases the feasibility of implementing the specific solutions and reduces computational complexity. Therefore, the models are computationally simple but maintain an accurate account of the operational model that LMH and its partners have been implementing. This reduction in computational complexity is important for organizations, such as LMH, with limited resources and without access to more advanced solution techniques. Grounded in the problem setting, the models have direct impact in practice.

The scientific methods used to find solutions in Rivercess are replicable in other regions. As a result, LMH and its partners are working toward the scale up of the CHW program with a transferable, informative model. The Rivercess County case presents valuable strategies and tools for saving lives across Liberia.

Additionally, we demonstrate how a close collaboration benefits OR research. We present the application of a special case location-routing model where the routes are enumerated a priori. This special case may be of particular interest to other applications and settings with a limited road network or feasible routes. We also demonstrate the impact of using Euclidean vs road network distances. Using Euclidean distances for the CHWL model increases the number of routes by adding a large number of practically infeasible routes. Euclidean distances also increase computational time. A comparison between the Euclidean approximations and the true distance solutions highlights the importance of using an accurate representation of a given geography to solve routing problems.

Limitations to this research include the use of deterministic travel time. The models are currently generalized to travel time, allowing for the incorporation of multiple modes of transportation such as motor bike and walking. However, a deterministic approach limits the ability to vary the type of transportation mode within the model. Additionally, it limits the ability to include variation in road conditions, such as the consideration of the rainy vs dry season. Improving the model to be robust to these scenarios would further improve the applicability of the model and could be a possible extension to the current research. LMH is currently collecting data to enable this extension, a result of the close collaboration. This again shows how academic-practitioner relationships and knowledge of the problem setting can directly improve the applicability of the models developed.

6. Conclusions

This paper presents a case study partnership between LMH and Northwestern University demonstrating how to bridge the gap between theory and practice. Because LMH's implementation efforts are ongoing, the methods in this paper will continue to be refined. Future mapping efforts will include data collection on the variability of road conditions and an expansion of the mapping scope to ensure all communities are mapped. Furthermore, sensitivity and trade-off analyses will be conducted. In particular, relaxations of the distance constraints both for CHWs and CHWLs can provide greater flexibility. For example, routes may be expanded to allow a CHWL to travel overnight to visit CHWs. Additionally, the impact of moving the constraint of 250 people per CHW closer to the governmental standard of 350 people per CHW will be explored. Overall, these extensions represent approaches to present more robust solutions for last mile communities.

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Corresponding author
Paige VonAchen can be contacted at: paigevonachen2014@u.northwestern.edu

(The Appendix follows overleaf.)

Appendix

In the network creation process, three common data issues we encountered: town-road disconnects, road-road disconnects, and repeated attributes. This section discusses these issues in detail and the steps taken to address data limitations. For Rivercess County, these issues are manually corrected and verified with the LMH GIS specialist. This feedback on the data collection process has also been used to improve LMH's standard operating procedure for data collection.

Town-road disconnect

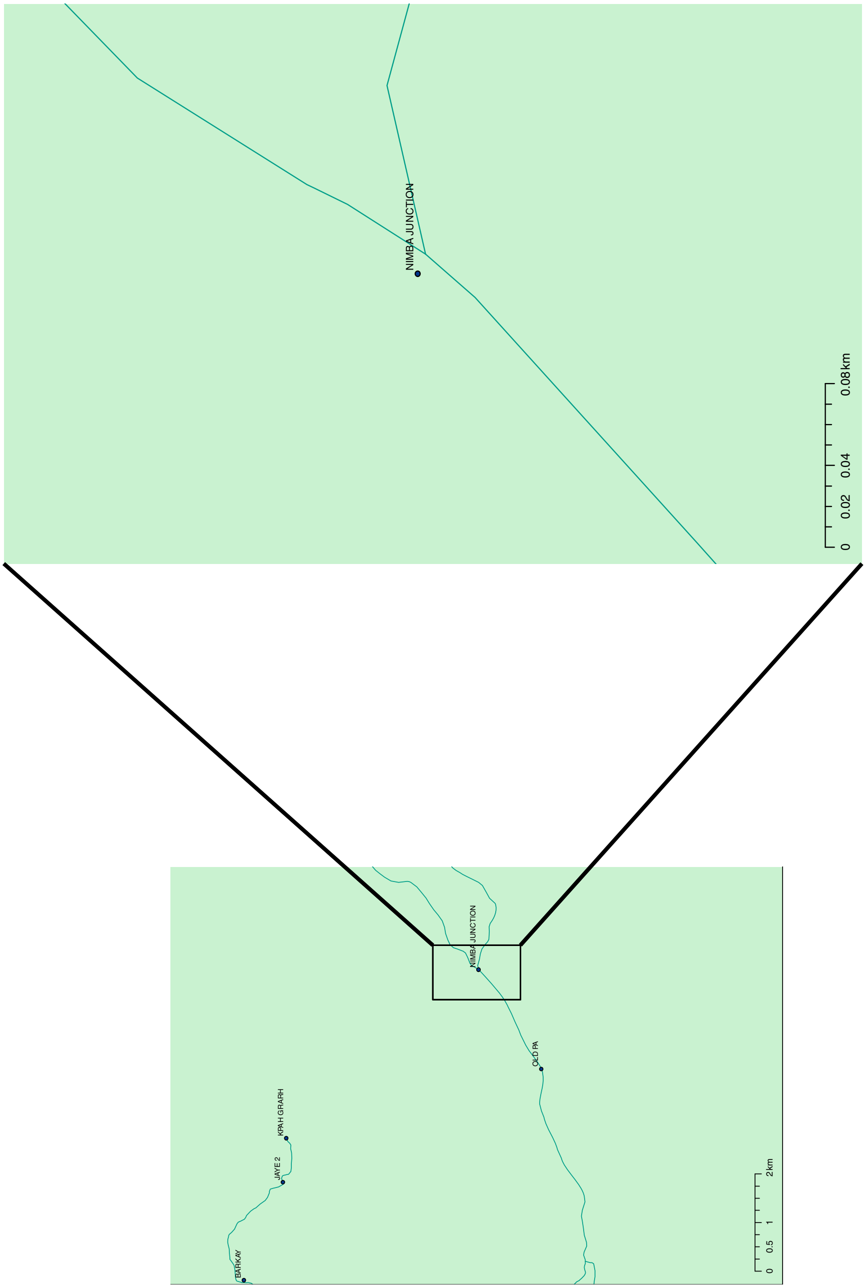
If a town is recorded by an enumerator at a location that does not align with a road, then the town will not be connected in the network created by ArcGIS. The enumerator may be standing at a house or a footpath that is slightly off from the main road. Often, the town is recorded less than one meter from the road as seen in Figure A1. To connect the town to the road network, coordinates for the town are adjusted to align with the nearest road in ArcGIS and verified with the LMH GIS specialist.

Road-road disconnect

When combining data from multiple enumerators, it is possible that coordinates of adjacent road segments do not align. Likely, enumerators begin traveling the roads from the same junction but not the exact same location within the junction. Often, they are located less than one meter from each other. To fix this issue, road coordinates are adjusted manually in ArcGIS to ensure connectivity (Figure A2).

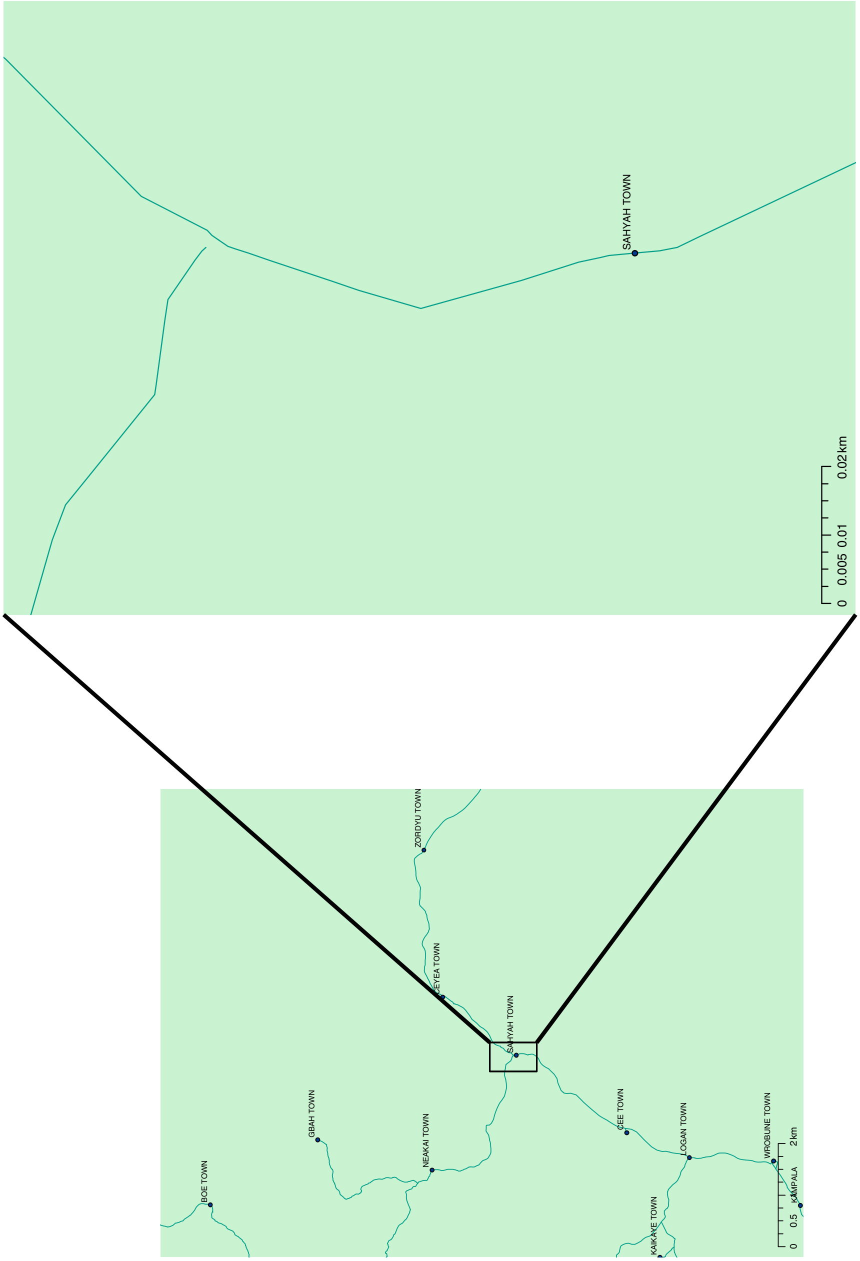
Repeated attributes

This error arises when enumerators repeat a section of a road, as seen in Figure A3. This leads to a distance matrix showing multiple paths between towns, when in fact only a single path exists. To fix this, repeated attributes are manually deleted.



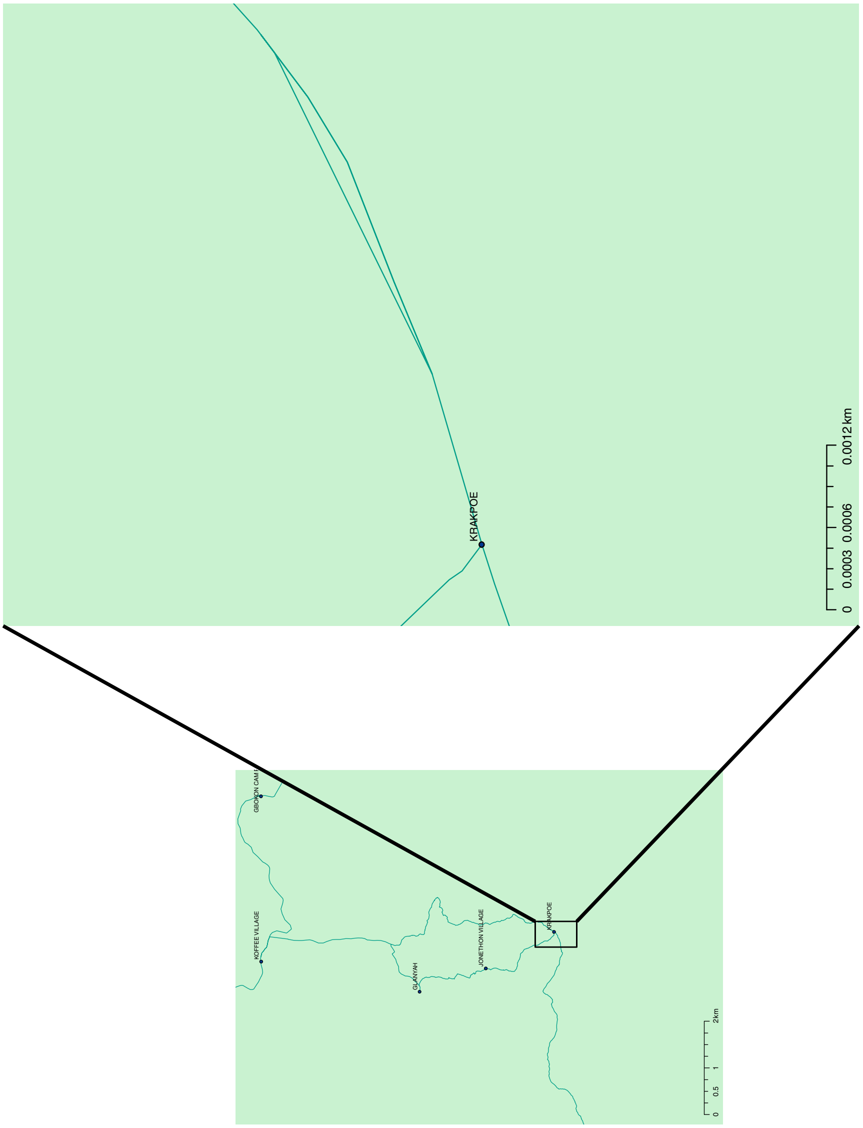
Note: In this example, Nimba Junction is not mapped to a road in the original shape file

Figure A1.
Town-road disconnect



Note: In this example, two intersecting roads are not connected in the original shape file

Figure A2.
Road-road
disconnect



Note: In this example, a road from Krakpoe is represented as two separate roads in the original shape file

Figure A3.
Repeated attributes