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Tactical network planning for food aid distribution in Kenya

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A B S T R A C T

In Sub-Saharan Africa, annual weather patterns cause frequent and regular shocks which make the population more vulnerable to food insecurity. Countries are affected by periodic droughts between two irregular rainy seasons, which have a profound effect on seasonal food crises. This study is rooted in a food aid distribution problem arising in Kenya, but it can also be applied to other developing countries. Our aim is to design an effective last-mile food aid distribution network. We present location models to determine a set of distribution centers, where the food is directly distributed to the beneficiaries, for the region of Garissa in Kenya. Our models take into account the welfare of all stakeholders involved in the response system: the World Food Programme, the Kenya Red Cross, and the beneficiaries. We describe how we have combined need assessment and population data to plan food distribution in Garissa. We also show how we have used GIS data on the road network to establish a set of potential distribution centers. In addition to the results obtained by solving our primary model, we present several comparative analyses and variants of the basic covering model.

1. Introduction

According to the United Nations (UN), hunger and malnutrition pose the largest risks to worldwide health. Some progress has been made toward achieving food security, but eradicating extreme poverty and hunger remains the first of the eight UN Millennium Development Goals [60]. Maintaining food security at the national and household levels is indeed a priority for most developing countries. Relief food aid is generally distributed in situations of war, natural disasters and population displacement, but a number of countries facing some forms of chronic food insecurity have also become permanent recipients of this form of aid [41]. Many developing countries suffer from food shortages, but Sub-Saharan Africa is the only region in the world that is constantly suffering from widespread chronic food insecurity and persistent threats [52]. Seasonalities have always had an important impact on hunger and poverty in Sub-Saharan Africa. The annual patterns of the two dry and the two rainy seasons cause frequent and regular shocks which make people vulnerable to food insecurity and hamper their opportunities to move out of poverty. Relatively little attention has been paid to the implications of seasonalities on food insecurity and rural poverty, despite the fact that they generate short-term hunger and seasonal food crises every year [17]. Because seasonalities are repetitive, rural households and communities have developed coping strategies to buffer their effects, like pastoralist livelihood systems which enable populations to migrate where water and pastures are more abundant [67]. This project aims at providing a methodology for designing and managing a tactical food aid distribution network in such a context.

Food aid is an instrument used to reduce insecurity in poor nations. Although food aid has often been criticized [7,5,13,34], it remains an important component of humanitarian operations. Food aid management entails operations evolving within highly complex supply chains. As stated by Van Wassenhove [62] and Christopher and Tatham [11], logistics is now being recognized to be an integral part of relief operations. In the last decade, humanitarian organizations have started adopting supply chain management methodologies to increase their performance and enhance coordination between the actors involved in assistance operations. For example, the World Food Programme (WFP) has made continuous efforts to expand its logistics capacity and to improve the efficiency of its transportation operations, which has enabled it to acquire an acknowledged expertise in moving large amounts of food commodities, often under difficult circumstances, throughout the developing world [53].

Haddow and Bullock [24] distinguish four phases for disaster management operations of humanitarian organizations: response, recovery, mitigation and preparedness. The preparedness and response phases have a relief purpose whereas the recovery and the mitigation

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phases are more focused on capacity development. These four phases encompass strategic, tactical and operational planning. In disaster management, one typically considers that the shocks (disasters) occur before the response phase. These shocks are often unpredictable and devastating, and they only last a relatively short period of time. Our problem is related to the preparedness phase of continuous relief operations rather than to the disaster relief response (see [30,10], for a distinction between development aid and disaster relief operations). Although food aid is often associated with rapid and short-term disaster relief, there are cases in poor and low rainfall areas where food aid needs are more foreseeable since they result from regular and seasonal food insecurity. For long-term development operations, such as food aid distribution in Sub-Saharan Africa, the shocks grow gradually over time and are more predictable than food shortages arising in natural sudden catastrophes such as earthquakes and tsunamis, even if emergency responses can also occur in sustained food aid distribution operations, as was the case during the 2011 famine in the Horn of Africa. Nevertheless, the four phases of disaster management are still appropriate and applicable to the context of food security, but they overlap with each other over time. Using the framework of Haddow and Bullock [24], food aid distribution planning can be viewed as a tactical relief problem since it involves medium-term decisions reviewed every six months. Like the consequences of sudden-onset disasters, long-term development issues also engender human suffering, often coupled with economic damage or poverty, even if the causes cannot usually be attributed to one specific catastrophe.

In this context, where the welfare of the stakeholders is related to economical or accessibility concerns, the tactical management of food aid supply chains is a complex task. Humanitarian organizations operate with limited resources which depend primarily on donations. It is therefore critical for these organizations to effectively design their supply chain and transportation plans in order to reach as many affected people as possible during crises. Humanitarian logistics shares several characteristics with its industrial counterpart. Indeed, multiple relevant location and transportation problems encountered in the context of food distribution are defined on networks and share a common structure with classical distribution management problems. Tzeng et al. [59] have compared general physical distribution systems for business with relief distribution systems. They have suggested that the points located in non-devastated areas where the commodities are collected act as supply nodes (depots), whereas the devastated areas where relief is provided to victims act as demand nodes (customers).

As mentioned by White et al. [64] operations research can make important contributions to the improvement of decision making in developing countries. Nevertheless, most of the works published in the humanitarian operations literature rely on generated data to solve mathematical models. There are, however, some exceptions, such as Pedraza-Martinez and Van Wassenhove [44], Besiou et al. [6] and McCoy and Lee [37], but these contributions focus on different problems than the one tackled in this paper. Van Wassenhove [62] pinpoints the cross-learning potential for both humanitarian and private sectors in emergency food relief operations and the benefits of potential collaborations. This has motivated us to analyze the food aid distribution problem in developing countries through the use of a mathematical programming based methodology and by collaborating with humanitarian organizations to gather real data, an approach not commonly used in this context. We believe that the results obtained by exploiting

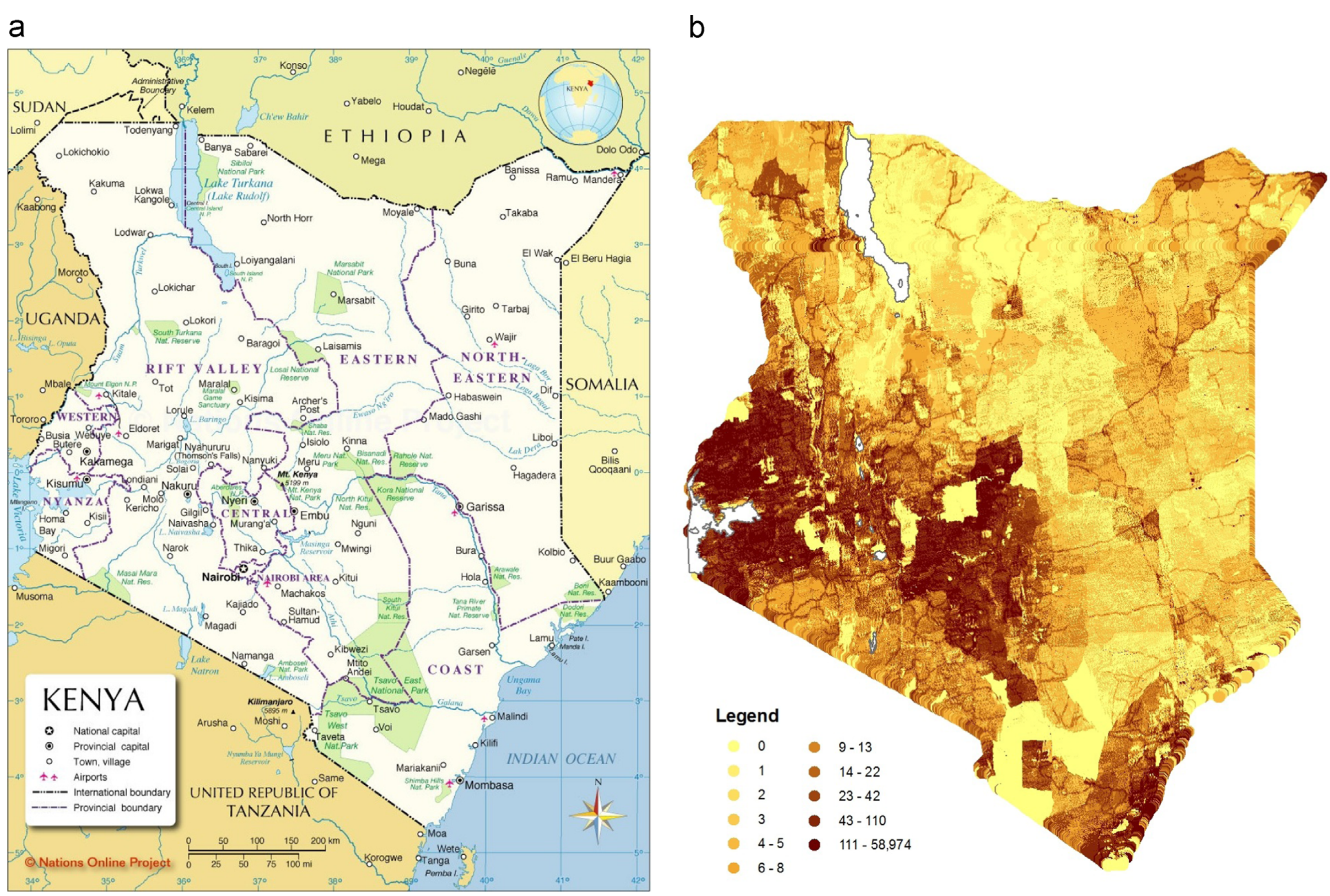

Fig. 1. (a) Map of Kenya [43]. (b) Population data for Kenya [27].

such a methodology can provide a valuable perspective for the decision makers responsible for food relief management.

Our study is motivated by a food aid distribution problem arising in a region of Kenya, the Garissa District and its surroundings, situated in North Eastern Province (Fig. 1a), but our contribution is of general applicability to developing countries that are struggling with food insecurity. To our knowledge, this project constitutes the first attempt to solve location models in such a context using real data to assess different tradeoffs, which could serve as a basis for the development of a decision support tool to design last-mile distribution in food aid supply chains. This final step is borne by the beneficiaries who have to walk to collect their food and carry it home. Its planning makes use of real seasonal need assessment data, geographic information systems, and data related to demographics and road infrastructure. Maxwell and Watkins [35] have argued that it makes sense to invest in the optimization of the distribution network in the context of regular food aid distribution. The Garissa District is one such area and serves as a relevant example for medium-term network optimization in similar contexts.

1.1. Literature review

The surge of natural disasters over the last decade has fueled a growing interest in the humanitarian applications of quantitative research in the field of humanitarian logistics. Van Wassenhove and Pedraza-Martinez [61] show that significant improvements can be achieved by using an operations research methodology to adapt supply chain practices to humanitarian logistics for two applied cases of field vehicle fleet management. Altay and Green [1] and Simpson and Hancock [55] have provided exhaustive surveys of operations research-based projects which have contributed to disaster related research in the last decades. Johnson and Smilowitz [26] have introduced the area of community-based OR, which addresses problems common to humanitarian logistics, such as vulnerable populations, fairness, and sustainability objectives. Ergun et al. [19] have summarized several contributions addressing key problems from the humanitarian and public sectors and have suggested solution approaches.

A number of algorithms have been proposed to deal with location problems related to disaster management issues. Tzeng et al. [59] have used fuzzy multi-objective programming to create an emergency relief distribution model and have proposed a framework for data collection. They have also tested their methodology on a real case study based on earthquake response in Taiwan. Recently, Naji-Azimia et al. [42] have modeled the distribution of survival goods to people in disaster areas as a generalization of the covering tour problem and have proposed a heuristic tested on randomly generated data. Campbell and Jones [9] have studied the problem of prepositioning supplies in the context of preparation for disaster by considering risk and inventory levels. They first solve the problem analytically for one depot and then incorporate their results into a heuristic for a p-median problem. Salmerón and Apte [50], Rawls and Turnquist [48] and Sheu [54] have proposed sophisticated models for disaster response. These approaches were tested on realistic instances generated based on information from public sources about natural disaster threats, but these authors did not use parameters derived from real data or effective contracts. The context of prepositioning assets for disaster response is different from that of food aid distribution, which is less unpredictable and lasts for longer periods.

White et al. [64] provide a broad overview of operations research applications in developing countries and also discuss its relevance for long-term development. We refer the reader to Çelik et al. [10] for a recent comprehensive tutorial on humanitarian logistics, where the authors clearly distinguish papers related with disaster management and long-term development issues. Three projects were conducted in collaboration with the WFP regarding food aid planning. De Angelis et al. [16] have proposed a routing and scheduling for emergency air deliveries of food aid in Angola. Aviles et al. [3] have implemented an inventory management tool and have solved a mathematical model of the WFP country-level supply chain (location of commodity pre-positioning depots). By testing their approaches on historical and simulated data, these authors have shown that increased service levels and decreased costs could be achieved through better inventory management policies and a redesigned supply chain. Alvarenga et al. [2] have created a simulation tool to generate an optimal shipment schedule which takes into account transportation lead times, transportation capacities, land transportation storage and handling costs while considering the current state of the supply chain network. This tool first simulates port operations, and then optimizes the truck shipping routes and schedules for food shipments to the main warehouses of a country. However, to our knowledge, none of the projects presented in this literature review directly applies to food aid network planning at the last-mile distribution level.

The problem considered in this paper is related to medium-term humanitarian operations and consists in designing a tactical network for food aid distribution. This problem is normally reexamined after a need assessment exercise which typically occurs at the end of every rainy season. The problem can be modeled as a modified uncapacitated facility location problem (UFLP), which has been largely studied by location scientists. Mathematical models and classification schemes for location problems have been reviewed by ReVelle et al. [49] and Daskin [15]. Melo et al. [38] have presented applications of facility location models to supply chain network design arising in various industries and have highlighted the current state-of-the-art contributions. Although many sophisticated exact branch-and-bound algorithms have been developed for similar models [20,29], a number of simple heuristics have also been proved to be very successful [31,39].

1.2. Aim, challenges and organization of this paper

The aim of this paper is to model and solve a practical problem arising in planning food aid assistance programs and to analyze the results. The main challenge of the project lies more in modeling the problem, in carrying out data collection and in performing analyses than in algorithmic development. As pointed out by several experts in humanitarian aid (e.g. [62,1,45,46]), in order to generate relevant and impactful methodological developments, it is important to properly understand the humanitarian context. We have performed a careful measure of food distribution costs that apply in the context of this study. Thus, before modeling and solving our problem, the first phase of this project consisted in a field-based research phase to gain a better understanding of food aid distribution management from an operational process perspective.

Fieldwork and objective data collection and processing are fraught with difficulties in developing countries like Kenya. Two problems we have encountered were related to the fact that the road network in Kenya is not fully described in any database, and it is also difficult to gather reliable information on population data and food distribution, partly because the relevant information is dispersed between several stakeholders who often operate in destitute or insecure areas. Data collection for this project was facilitated by the fact that the fourth author runs a consultancy involved in several projects related to food assistance in Kenya, and the first author made a one-month field trip in August 2012 which enabled her to understand the issues at stake and to gather first-hand information.

As a part of the information and data collection process, the first author realized different activities during her one-month field trip: (1) she met with the WFP logistics managers at the national and regional levels in Kenya; (2) she visited facilities such as the WFP Kenyan offices and the warehouse in Garissa; (3) she analyzed documents provided by WFP and the Kenya Red Cross; and (4) she conducted direct observations of food aid distribution operations. The insights derived from these activities allowed us to describe the food aid regional supply chain as well as the relationships and responsibility sharing between the different stakeholders involved in the distribution process. We believe that our fieldwork and collaboration with the practitioners was an essential component of this research project given that it is rooted in a real-life application. Not having spent time in the field would have resulted in a misconception of the problem, and some important realities would not have been identified, like the fact that the beneficiaries pay for a donkey transportation service to bring their food back home. It is also worth mentioning that the dissemination of our research results to various audiences during the execution of this project has helped gather valuable comments and has been instrumental in validating our methodology. In addition, presenting the outcomes of our work to several WFP head logistics managers has led to the gathering of further valuable insights.

The remainder of this paper is organized as follows. Section 2 provides a detailed description of the problem, which is then formulated in Section 3. These two sections contain several descriptions and data gathered in the fieldwork phase of the project. Section 4 presents our computational results, as well as extensive comparative analyses. Conclusions follow in Section 5.

2. Detailed problem description

We now present the context of food aid distribution in Kenya. We first describe the humanitarian operation activities associated with the food distribution supply chain, and we then explain the roles of the main stakeholders involved in the process.

2.1. Seasonalities and assessment

Rainfalls are highly variable in Kenya; there are two rainy seasons separated by two dry seasons. The long rain season lasts from March to June, and is followed by a long dry season from June to October. The second rainy season is shorter and lasts from October to December, followed by another dry period from December to March. All parts of the country are subject to periodic droughts between the rainy seasons, which has a profound effect on settlement patterns and on the Kenyan population affected by nutrition crises. Poor rainy seasons negatively affect agricultural production and can lead to periodic food shortages. The consequences are even worse in the case of successive failures of the rainy seasons (e.g. short rainfalls, or late start and early end of the rain), which can lead to severe famines. The severity of these periodic droughts has a deep influence on the ability of the affected population to recover from food insecurity, which indeed drives the food aid needs for the following periods. The most vulnerable regions of Kenya are the arid and semi-arid regions in which agro-pastoralism and pastoralism are the dominant livelihood systems [8].

To account for the effects of seasonalities, the Kenya Food Security Steering Group (KFSSG) conducts a need assessment for food aid twice a year, after each rainy season. The KFSSG is a joint group of specialists from the Government of Kenya (GoK), the United Nations (UN), non-governmental organizations (NGOs), and district level teams [21]. The assessments consist in determining the number of beneficiaries and the ratio entitlements at the division levels across the country. These values are sometimes determined at the location level for the densely populated areas. Kenya is a rather large country, about 10% smaller than France. At the time of data collection, its administrative division levels were the following, in ascending level order: sub-location, location, division, district and province.

The ratio entitlement corresponds to the percentage of a standard food ration that the beneficiaries are entitled to receive, and is calculated on the basis of their nutritional requirements. A full ratio entitlement, commonly called a food basket, is made up of 400 g of cereal, 60 g of pulses, 25 g of oil (fortified with vitamins A and D), 50 g of fortified blended food (corn soya blend), 15 g of sugar, and 15 g of iodized salt. This ratio depends on the severity of the seasonal food scarcity and on some relevant socio-economic factors. Indeed, in order to determine the number of beneficiaries and the ratio entitlement, the KFSSG analyzes the available information on the food security situation and other indicators, such as price data, field assessment and livelihood economic contexts. The results of the assessment are valid for a six-month period, i.e. until the following assessment plan is implemented.

The pastoralist populations practice seasonal migrations depending on resource availabilities for their livestock. These allow them to exploit more land in order to suit their food production and to survive in arid regions, but the women and the children who remain in pastoralist settlements are often left behind with few resources. Pastoralist households are indeed among the most vulnerable groups in this society. Sanford and Habtu [51] expose the shortcomings of early warning and response systems in the pastoral areas. The need to develop service delivery models that meet the particular demands of the pastoral communities and can respond to the effects of seasonal food scarcity is of critical importance. Managing food aid supply chains in such complex environments is a real challenge for humanitarian organizations. This project aims at providing a decision support tool for planning tactical food aid distribution networks. Our study takes into account the results of the 2012 short rains assessment for the district of Garissa and its surroundings, a district characterized by arid lands and pastoralist populations.

The district of Garissa, which represents about 8% of the area of Kenya, is important for food aid in that country. During each six-month period over the period ranging from September 2004 to August 2011, an average of 83,483 people of this district have received food aid. This corresponds to about 5% of the 1,823,588 people who have received food aid in the whole Kenya, making it the sixth most important district in number of beneficiaries out of the 28 in which aid is distributed, behind Turkana, Wajir, Makueni, Mandera and Kitui. On average, 35% of the district population has been receiving aid. During the most difficult period, this number reached 62%. Only five districts have a higher percentage of the population receiving aid (the district receiving the most aid is Marsabit, where the beneficiaries represent 60% of the population, on average).

Importantly, the district of Garissa has been receiving aid more consistently than the country as a whole. Indeed, the variation in the number of its beneficiaries is lower than it is at the national level: the coefficient of variation in the number of beneficiaries across six-month periods is 0.45 in Garissa, and 0.51 at the country level. Only Turkana, Marsabit, Samburu, Mandera, Wajir, Tana River and Kwale, receive aid more consistently. These are all mostly arid regions prone to drought. As noted by Maxwell and Watkins [35], in Garissa like in these other districts, the relatively stable number of beneficiaries has led to a fixed distribution system which justifies the need for an optimized network.

2.2. Food aid supply chain

Sub-Saharan African in-country food aid supply chains are composed of several main warehouses (MWs) located in strategic regions where primary storage infrastructure is available. The MWs serve mostly as storage facilities and transshipment hubs (Fig. 2a). The food is then transported to distribution centers (DCs)

Fig. 2. Photographs of a (a) main warehouse (MW) and (b) distribution center (DC).

from the MWs, where it is informally stored and directly handed out to the beneficiaries. The DCs are temporary depots such as shelters, schools, and community facilities which are often located in remote regions, depending on the population needs (Fig. 2b). The beneficiaries must walk to one of the DCs in order to receive food assistance. For ongoing aid operations, the MWs are usually fixed warehouse infrastructures located in strategic locations in the country, whereas the DCs are temporary depots whose locations may vary over time. These informal warehouses must be located in places accessible to the population. Each MW is used for supplying a specific region in the country, and each DC is supplied from the MW that serves its region. Determining where to locate the DCs in order to reach the vulnerable populations and planning how much food aid should be delivered to these distribution points is of primary importance for supply chain responsiveness and cost-effectiveness.

2.3. *Stakeholders' responsibilities*

Here we explain who are the different stakeholders involved in the supply chain (WFP, Kenya Red Cross Society, Community Relief Committee, and beneficiaries) and what their responsibilities are. We will focus on the supply chain activities at the regional level, i.e. on the logistics operations engaged once the food is stored at the regional MW. There also exist several ethical, social, and economic implications associated with food aid distribution which are neither analyzed nor discussed in this paper since they lie beyond the scope of this project. Indeed, food aid interventions in developing countries can sometimes be political [12,4,33], but we believe that such concerns are less relevant when managing supply chains at the regional level.

2.3.1. *The World Food Programme*

WFP is a major player in food aid. This organization handles more than 95% of multilateral food aid [32,65], usually in partnership with NGOs and government institutions, which are in charge of food distribution in recipient countries. In Kenya, WFP is in full charge of the international transportation movements, the transportation of food aid from the port of Mombassa to the MWs, and the transshipments between the MWs. Once the food supplies arrive at an MW, the cooperating lead partner agency manages the remaining logistics activities up to the beneficiaries. WFP usually contracts with trucking companies to move cargo across the network rather than rely on a private fleet, and such secondary transport operations are generally very costly [47]. While not taking the lead for contracting with transporters, WFP fixes the transportation rates and reimburses the cooperating lead partner agency for its transportation costs. WFP is also engaged in offering guidance on logistics activities, such as storage and handling of commodities, as well as providing training on food aid distribution practices, reporting and warehousing when necessary.

2.3.2. *The Kenya Red Cross Society*

In the humanitarian sector, several organizations are typically involved in relief service delivery at the regional level. For example, several local NGOs may take part in school feeding programs. Each NGO may focus on different schools or on special projects designed for girls, while other international NGOs, UN or governmental agencies can be involved in other programs, such as labor-based work programs [63,25] or complementary feeding programs for children [18]. The regional lead partner agency is usually a major humanitarian organization (e.g. World Vision, Care, Save the Children, Red Cross or UNICEF) which has developed expertise and capacity for food security programs in that specific region.

In the district of Garissa and its surroundings, the Kenya Red Cross Society (KRCS) acts as the cooperating lead partner for food assistance, which implies that it is responsible for the reception and storage of food at the MW. The KRCS is also mandated to organize secondary transport operations and to distribute commodities provided by the WFP or the GoK to the beneficiaries. The KRCS must maintain records and facilitate monitoring for all commodities received at the MW and distributed through the DCs. The KRCS must also take reasonable measures to ensure that food assistance reaches the beneficiaries within a reasonable delay and in the condition in which it has been received. In order to be qualified for conducting food aid distribution, the KRCS staff receives some training on the community based food aid targeting and distribution system [66]. The KRCS acts as facilitator and monitor to ensure that the principles established for food aid distribution in Kenya are properly followed during the settlement process following the assessment, and during the monthly food distribution operations. The organization thus continuously assists the community during the different phases of the food aid distribution.

2.3.3. *Community Relief Committee*

The community members of each DC elect a Community Relief Committee (CRC) comprised of 7–17 members. After being trained by the KRCS, the CRC becomes mainly in charge of the beneficiary registration and of the food aid distribution. The CRC is thus responsible for the targeting of the beneficiaries, record keeping, as well as setting arrangements to call the beneficiaries during the monthly distribution activities, and dealing with absences and complaints. The CRC must make arrangements to provide accessible temporary storage, to receive and handle the food, and to ensure security at the DC. The purpose of the relief committee is to give more responsibilities to the community and enhance information transparency. The CRC acts as a link between the KRCS and the community, including the beneficiaries. This system aims to provide a better understanding of the food distribution mechanisms for the people receiving assistance and to help the beneficiaries make decisions for themselves rather than being controlled by agencies remote from their environment. An important policy aimed at ensuring better access to information is the participation of women within the relief committee since humanitarian organizations strive to encourage the presence of the women in assistance projects [66]. The committee's role is to ensure that the community is well served. It shares the same interests as the beneficiaries since its activities are carried out for their benefit on a voluntary basis and without remuneration. Its objective is the same as that of the beneficiaries and, therefore, not directly considered in the optimization problem.

2.3.4. Beneficiaries

The beneficiaries are the people within the communities who receive food assistance through different aid programs. Ideally, they should be targeted because they are the most vulnerable people in the community. They must travel and collect their food at their assigned DC on the day of the distribution. To a feasible extent, the organizations hand out food aid to women. For the food distribution to be successful, the community should get involved in the process and should participate in the meetings organized by the KRCS and the CRC.

3. Problem formulation

We propose a mathematical programming based methodology to determine where to locate the DCs, how much food to deliver to them and which populations they should serve. The regional food aid distribution network can be formulated on a directed graph $G=(V,A)$, where V is a set of nodes and A is a set of arcs. The set V can be partitioned into $\{\{0\},V_1,V_2\}$, where 0 is an MW supplying a specific affected region, V_1 is a set of population points, and V_2 is a set of potential locations for DCs. The quantity of food, expressed in tonne (t), required by the population located at node i during the planning horizon is equal to q_i. We define $W_i(r) \subseteq V_2$ as the set of potential DCs located within a coverage radius of r km from i, i.e. $W_i(r)=\{j \in V_2 | d^g_{ij} \le r\}$, where d^g_{ij} is the geographical distance from i to j. We also define a set $V_1(r)=\{i \in V_1 | \exists j \in V_2 \text{ with } d^g_{ij} \le r\}$ of population points with at least one potential DC located within r km. Our models do not consider remote population points i for which $W_i(r)=\varnothing$ for a given r, as is often the case in the location of emergency services such as fire stations in rural areas. Nevertheless, these people can still register to a DC and walk there to collect their food ration when distribution takes place. There does not seem to exist a well defined standard for what the value of r should be. However, the standards set in a study conducted by a consortium of humanitarian agencies, the Sphere Project [56], state that supplementary feeding programs should have enough distribution sites to ensure that more than 90% of the target population can reach treatment within one day's return walk for dry rations. In our study, we do not use a preset walking time. Instead, we let the value of r vary in our computational experiments and we conduct several sensitivity analyses. The route taken by a transporter to go from 0 to j is represented by an arc $(0,j)$, and the path taken by the population point located at i to walk from i to j, is represented by an arc (i,j).

3.1. Mathematical model based on social welfare costs

The model must take into account the anticipated food assistance needs and must optimize the social welfare of all the stakeholders involved in the food distribution. For a given coverage radius r, we define the following variables:

x_{ij}: the food aid proportion of population at i needing a hand-out from a DC at j, with $i \in V_1(r)$, and $j \in W_i(r)$;
y_j: a binary variable equal to 1 if and only if DC at j is in operation during the planning horizon, with $j \in V_2$.

For a given coverage radius r, the tactical food aid network design problem that considers all stakeholder costs and the corresponding covered population is formulated as follows:
*Model*1

$$\text{minimize} \quad \sum_{i \in V_1(r)} \sum_{j \in W_i(r)} \alpha_{ij} x_{ij} + \sum_{i \in V_1(r)} \sum_{j \in W_i(r)} \beta_j q_i x_{ij} + \sum_{j \in V_2} \gamma_j y_j$$

subject to

$$\sum_{j \in W_i(r)} x_{ij} = 1, \quad i \in V_1(r) \tag{1}$$

$$x_{ij} \le y_j, \quad i \in V_1(r), \quad j \in W_i(r) \tag{2}$$

$$x_{ij} \ge 0, \quad i \in V_1(r), \quad j \in W_i(r) \tag{3}$$

$$y_j \in \{0,1\}, \quad j \in V_2. \tag{4}$$

The objective is to minimize the total welfare cost of all the stakeholders involved in the food distribution process at the regional level. The first term of the objective function is the total access cost for the beneficiaries to travel and collect their food at the DCs, the second term is the supply cost paid by WFP for transporting the food from the MW to the DCs, and the last term accounts for the DC management and hand-out costs which are under the KRCS responsibility. The coefficient α_{ij} represents the cost borne by the population at i needing a hand-out from a DC located at j; the coefficient β_j represents the cost per tonne borne by WFP to transport food destined to the DC located at j; the coefficient γ_j represents the fixed cost of locating a DC at j. Since all costs are expressed in the same monetary units, it makes sense to use an additive objective, as opposed to a multicriteria objective. The determination of these coefficients is described in Section 3.2.2. Constraints (1) ensure that the demand of each population is satisfied, while constraints (2) stipulate that the population points can only be served from open DCs. Constraints (3) and (4) are standard non-negativity and integrality constraints. Note that since the DCs are uncapacitated, there always exist an optimal solution in which each population point is assigned to a single DC. The integrality constraints for the population assignment variables x_{ij} are therefore relaxed in Model 1 (see e.g. [14]).

Model 1 is a hybrid model between an UFLP and a location-covering problem, which considers the tradeoffs between the fixed DCs' operating costs and the distribution costs [28]. The distribution cost between a population point i and a DC j is equal to $\alpha_{ij}+q_i \beta_j$, which is the sum of the opportunity cost of a beneficiary i allocated to DC j and of the transportation cost to DC j of the quantity of food required by i. By considering $W_i(r)$ as the only set of potential DC locations available to a population point i for a given r, we effectively embed covering constraints within the UFLP.

3.2. The case of Garissa and its surrounding

We now explain how the graph G was constructed for the region of Garissa and its surroundings. We first describe how the different parameters associated to the graph were determined through the use of geographic information system data. We then explain how the parameters in the objective function were determined, which entails the evaluation of all the corresponding stakeholder welfare costs.

3.2.1. Network description

To construct the graph G for the region of Garissa and its surroundings, we used the gridded population proxies based on satellite data proposed by Jordan et al. [27]. Fig. 1b illustrates this discretized population data on a map of Kenya, where the population points $i \in V_1$ correspond to the centroids of delimited landscape areas of one square kilometer. The potential geographical grid points for the potential DC locations, which constitute the set V_2, are those points of V_1 close enough to a road (within a distance of at most 200 m) and which are also sufficiently populated to constitute a CRC (their population must be at least 20 people per square km). Indeed, the DCs must be close to the road in order to be accessible by truck, and they must be sufficiently populated so that the security of the DC can be ensured by the surrounding community. We have also ensured that these potential DC locations included different points of interests, such as schools, community centers, and health facilities. This information was retrieved from government data publicly available online and can be manipulated through a GIS [22].

In our case, the demand of the system corresponds to the food aid needs. Each population point $i \in V_1$ has p_i inhabitants and has a food aid need q_i to be satisfied over a six-month planning horizon, which is the result of a specific need assessment. We have computed the need of each population point as a proportion of the need for the entire population in the area of interest corresponding to the smallest given administrative level (division or location). The beneficiary population count and the ratio entitlement were obtained from the short rain assessment of 2012, while the beneficiary population count for each population point was obtained from the gridded population proxies for the area of interest. We have also used population and Kenyan road network shapefile information to determine the following distances:

- for all $i \in V_1$, the geographical distance d_i^{r*} from a grid population point i to its closest road (obtained by means of PostGIS);
- for all $i \in V_1$ and $j \in V_2$, the geographical distance d_{ij}^g from a population grid points i to a potential DC located at j (obtained by means of PostGIS);
- for all $j \in V_2$, the road distance d_{0j}^r from the Garissa MW to a potential DC located at j (obtained by means of Google API).

We have used the geographical distances between the population points and the potential DCs rather than the road distances for two reasons. First, we have assumed that the beneficiaries walk directly to the DCs through a shortest path since Garissa and its surroundings is characterized by flat arid lands. This would not have been a valid assumption for a hilly or a vegetation-rich region. Second, the current available shapefiles for the Kenyan roads were incomplete, with disconnected underlying road networks, which prevents using applications that can compute road distances because the graphs are disconnected.

3.2.2. Objective function

In the context of food aid distribution, several costs affect both the beneficiaries and the humanitarian organizations. In our study, the humanitarian organizations involved in the regional supply chain of Garissa and its surroundings are the WFP and the KRCS. These stakeholders, the beneficiaries, the WFP and the KRCS, have their own responsibilities in the supply chain, which translate into different objectives. In order to determine a global social welfare function, we have evaluated the values of all these responsibilities in Kenya shillings (KSh). For the humanitarian organizations, these are management, transportation, and hand-out costs; for the beneficiaries, these are access costs.

3.2.2.1. Beneficiary access costs. The beneficiary access costs are opportunity costs measured by evaluating the productive activities sacrificed for collecting food assistance. The access cost is thus a value associated with the time taken by a beneficiary to walk from her location to her assigned DC and back. We have assumed that the beneficiaries use a least duration path to walk from i to j at an off-road pace of 4 km/h. The walking time from i to j is thus equal to 0.25 h/km times twice the geographical distance. To evaluate the value of walking time, we have used the minimum wage rate for unskilled labor [40]. This corresponds to 178 KSh/day (22.25 KSh/h) at the time of data collection, which was about two US dollars per day. Moreover, the beneficiaries must pay for transportation to bring their food ration back home, which is usually done by paying an individual who operates a trailer attached to a donkey (Fig. 3a). Using statistics presented in monitoring reports from WFP, we have determined that the cost of donkey transportation can be approximated by the linear function 20 KSh + 2.5 KSh/km × *distance*. The total access cost α_{ij} per km of a beneficiary located at node i and collecting her food ration entitlement q_i at the DC located at j is obtained by adding up her opportunity costs and the donkey transportation cost.

3.2.2.2. WFP supply costs. WFP contracts with trucking companies to transport food aid across the network (Fig. 3b). For transportation operations between the MW to the DCs, WFP sets a fixed price per tonne, which depends on the distance between

Fig. 3. Photographs of some stakeholder activities. (a) Donkey transportation. (b) Ground transportation. (c) Monitoring activities.

Table 1
Summary of the food aid distribution network.

Description	Parameter	Mean	Std. dev.	Median	Min.	Max.
Population nodes ($\|V_1\| = 24,453$)	V_1					
Number of people	p_i	17.36	221.15	5	3	13,793
Six-month food need per beneficiary (t)	q_i	0.02438	0.02442	0.01136	0.0396	0.11534
Geographical distance to closest route (km)	$d_i^{r^*}$	11.03	9.34	8.49	0	50.34
Geographical distance to closest potential DC (km)	$d_{ij^*}^{g}$	11.85	10.91	8.71	0	54.48
Potential DC nodes ($\|V_2\| = 1460$)	V_2					
Road distance to MW (km)	d_{0j}^r	106.32	71.41	107.16	0.05	268.93

the MW and the delivery location. The WFP offers a constant price c_0 per tonne for the DCs located within a short distance of the MW. For the locations that are further from the MW, the WFP sets constant prices c_1 and c_2 per km-t, depending on the distance to the MW. The total cost of transporting food to a DC located at j will thus depend on the required quantity of food $\sum_{i \in V_1} q_i x_{ij}$ to deliver to this DC and to its road distance d_{0j}^r from the MW. For confidentiality reasons, we are not allowed to reveal the current cost function, but only a generic one with $\overline{d_0}$ and $\overline{d_1}$ being the distance bounds delimiting the constant prices per tonne. The long-haul transportation costs in KSh per tonne to serve DC located at j from Garissa MW located at 0 can be represented by the following step function:

$$\beta_j = \begin{cases} c_0 & \text{if } d_{0j}^r \in [0, \overline{d_0}] \\ c_1\, d_{0j}^r & \text{if } d_{0j}^r \in (\overline{d_0}, \overline{d_1}] \\ c_2\, d_{0j}^r & \text{if } d_{0j}^r > \overline{d_1}. \end{cases}$$

3.2.2.3. KRCS location and hand-out costs. The KRCS must mobilize staff to ensure that food distribution proceeds according to the established practices of the WFP and the GoK [66]. The CRC training and the beneficiary registration validation require about two days of work for the KRCS facilitators at each DC, which should be considered as a fixed cost for the six-month planning horizon. There are also monthly costs for the food distribution monitoring functions, such as advertising, dispatch and distribution supervision, which require two days of work per month per DC. The KRCS location and hand-out cost at each DC located at j are thus the cost of labor γ_j for ensuring that food distribution is carried out properly during the planning horizon (Fig. 3c).

3.3. Descriptive statistics

We now provide an overview of the data through descriptive statistics. Table 1 summarizes the relevant information on the food aid distribution network in Garissa and its surroundings. It shows that for the region of interest, there are 24,453 population grid points (V_1) with at least three inhabitants (Fig. 4a). The average population per square km is 17.36, and most of the population grid points are scarcely populated (the standard deviation is 221.15 and the median is equal to five). The average distance from the population centroids to their closest routes is 11.03 km and the median is 8.49 km. The largest distance between a population point and its closest potential DC is 54.48 km, which implies that some population points are located in very remote areas impossible to cover within small coverage radii. The average estimated food aid allocation per beneficiary in these population points is equal to 24.38 kg for the six-month period (Fig. 4b).

The set V_2 of potential DCs, which consists of the population grid points close to a route and densely populated ($V_2 = \{i \in V_1 | d_i^{r^*} \le 0.2$ km and $p_i \ge 20\}$), where $d_i^{r^*}$ is the geographical distance of population i to its closest road and p_i is its number of inhabitants, contains 1,460 elements. The average travel distance from Garissa MW to these potential DC is 106.32 km. The average distance from the population points to their closest potential DC j^* is 11.85 km and the median is 8.71 km, which indicates that there is at least one potential DC located close to most of the population points.

3.4. Classical location-covering models

The problem can also be viewed as a location-covering problem. Modeling it by means of a set covering formulation would allow us to determine the proportion of the population covered by a DC by fixing the number of DCs to a given value $\overline{w}$, or to compute how many DCs would be required to cover all the beneficiaries within a given coverage radius r. The outputs of such models can be used to assess the current network comprised of 156 DCs as well as to compute tradeoffs between the minimum number of operating DCs and the beneficiary opportunity costs. We thus define the following variables:

y_j: a binary variable equal to 1 if and only if DC located at j is in operation during the planning horizon, with $j \in V_2$;
z_i: a binary variable equal to 1 if and only if population point i, where the food aid need is of q_i tonne, is covered by at least one DC during the planning horizon, with $i \in V_1$.

A first problem is to maximize the need coverage for a given coverage radius r and with a given number $\overline{w}$ of operating DCs:

Model 2

$$\text{maximize} \quad \sum_{i \in V_1(r)} q_i z_i$$

subject to

$$z_i \le \sum_{j \in W_i(r)} y_j, \quad i \in V_1(r) \tag{5}$$

$$\sum_{j \in V_2} y_j = \overline{w} \tag{6}$$

$$0 \le z_i \le 1, \quad i \in V_1(r) \tag{7}$$

$$y_j \in \{0, 1\}, \quad j \in V_2. \tag{8}$$

A second problem of interest is to minimize the number w of DCs to cover all the beneficiaries within a coverage radius r:

Model 3

$$\text{minimize} \quad w$$

subject to

$$\sum_{j \in W_i(r)} y_j \ge 1, \quad i \in V_1(r) \tag{9}$$

$$\sum_{j \in V_2} y_j = w \tag{10}$$

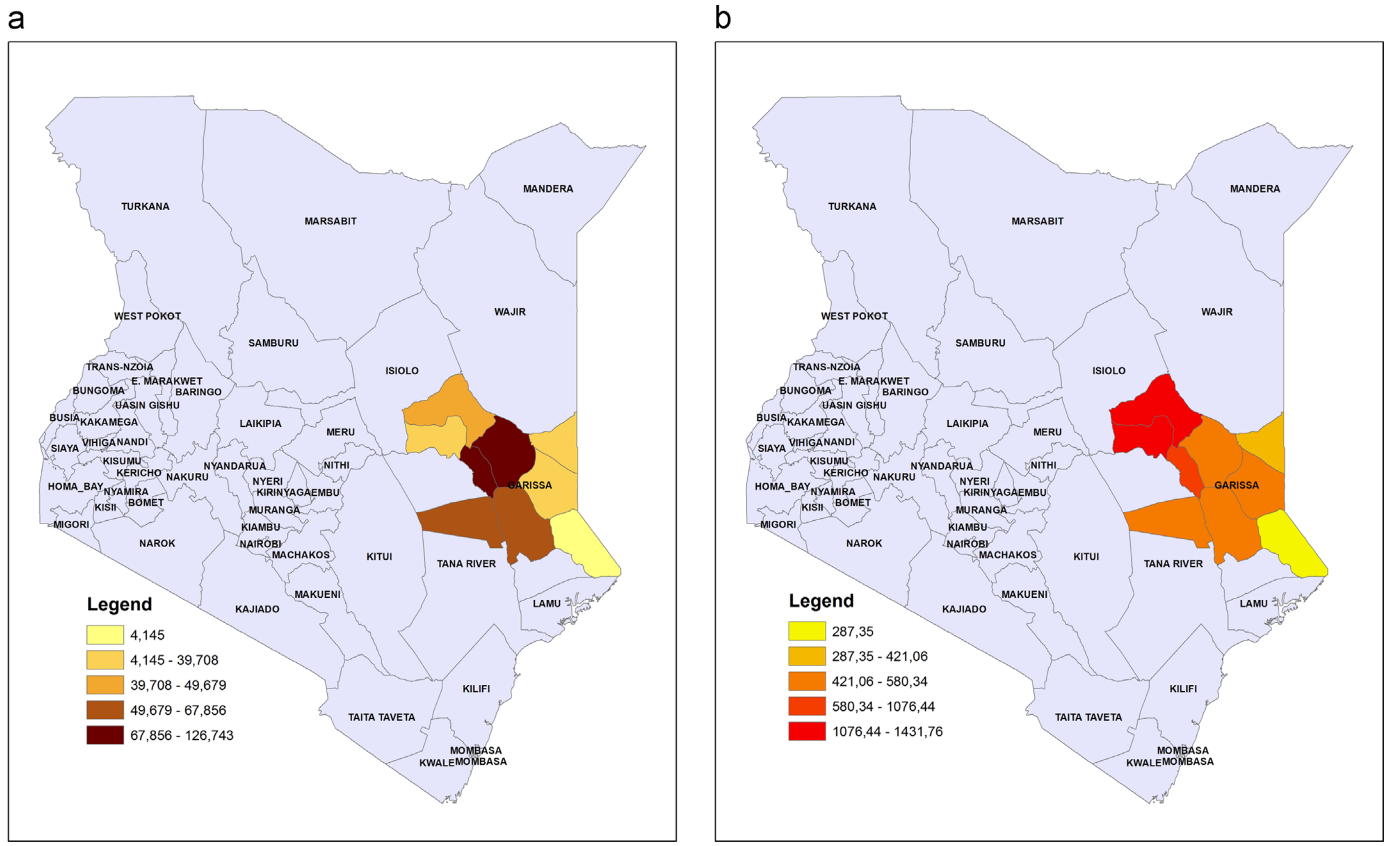

Fig. 4. Population (a) and food aid allocation (b) maps for each division of Garissa District and its surroundings.

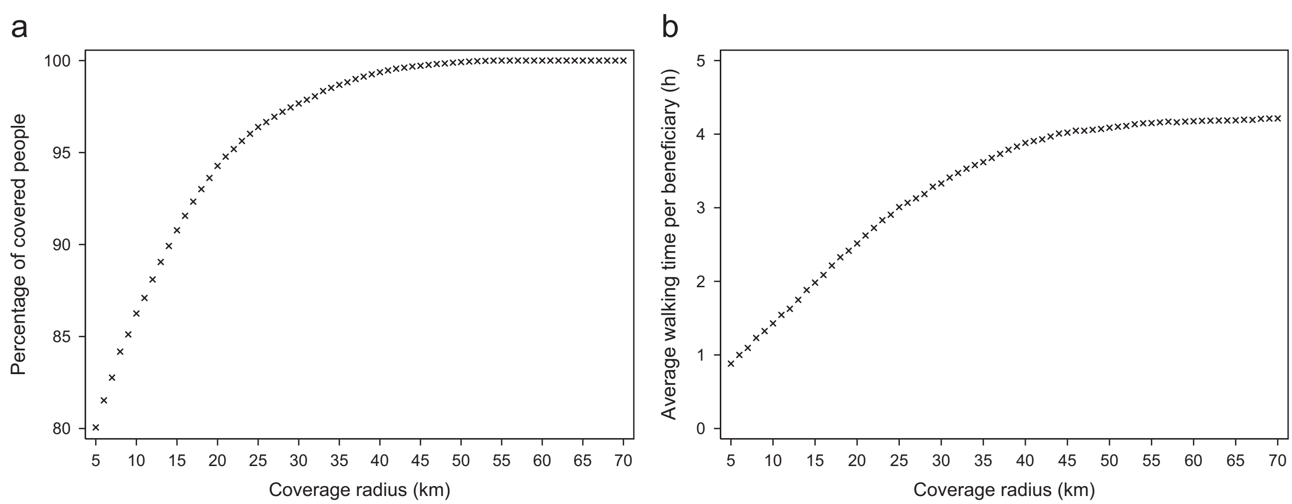

Fig. 5. Percentage of the covered population (a) and average walking time per beneficiary (b) as a function of the coverage radius.

$$w \geq 0 \tag{11}$$

$$y_j \in \{0, 1\}, \quad j \in V_2. \tag{12}$$

4. Computational results

We now describe the computational results obtained by solving different optimization problems for the case of Garissa and its surroundings. We first provide results and depict optimal response systems before presenting some comparative analyses. The models were solved by means of CPLEX 12.5 and by setting the optimality gap to 0.1%. Preliminary tests were carried out and a gap of 0.1% was found to provide solutions within a reasonable time, i.e. about 15 min on average.

4.1. Presentation of the results

We have first assessed the impact of the coverage radius on the percentage of people covered by the response system. In Model 1,

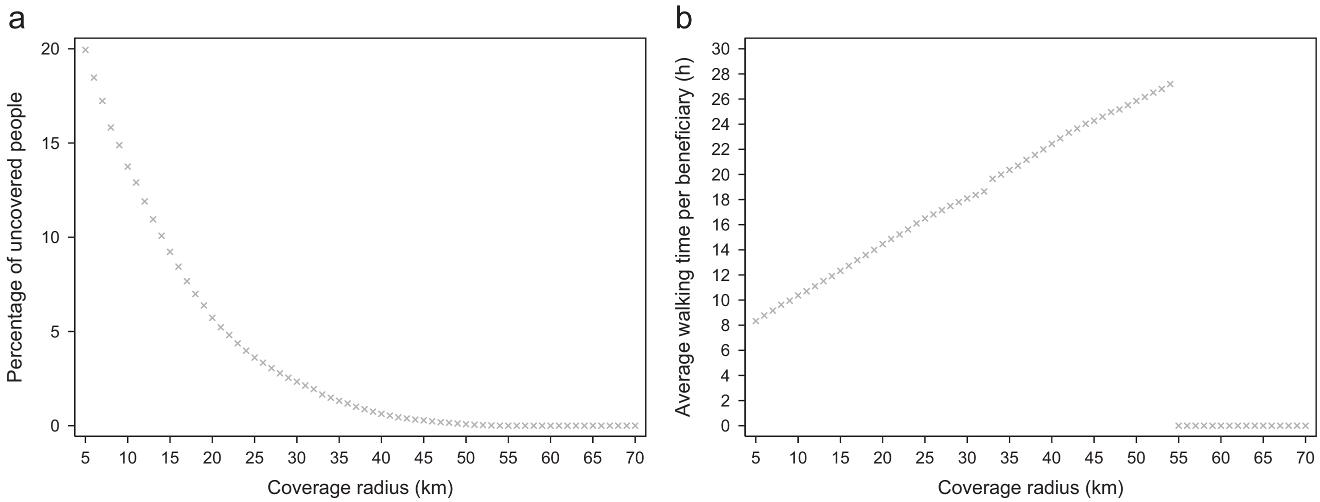

Fig. 6. Percentage of the uncovered population (a) and average walking time per beneficiary (b) as a function of the coverage radius.

we assume that a population without any DC within a distance r is not taken into account in the optimization problem, which implies that this population is not considered as covered by the response system. Whereas the response network is not designed considering such population points, uncovered people may still register at a DC. We have thus assessed the results on the average walking time per covered and uncovered person to ensure that the solution did not result in having beneficiaries walking too far when the coverage radius was fixed at a large value. We have computed the walking times and related costs of the uncovered people as if they were assigned to the closest open DC in the optimal solution obtained by solving Model 1. Fig. 5 shows the results for the covered populations and different values of r, from 5 km to 70 km. We note from Fig. 5a that in order to cover all the population, the coverage radius must be set to at least 55 km. Nevertheless, according to the results shown in Fig. 5b, the average time per beneficiary of walking to their assigned DC and back home remains below 4.5 h even when the coverage radius becomes larger. This value is consistent with a one-day return walk as suggested in the Sphere Project [56]. The increase in average walking time tends to stabilize when it becomes larger than 35 km. This means that even if the coverage radius is large, the optimal solution assigns the covered populations to one of their closest potential DCs. Similarly, Fig. 6 shows the results for the uncovered population points. It shows that small coverage radii are also beneficial for the uncovered people although fewer people are considered when designing the response network. Indeed, the average walking time per beneficiary increases as the coverage radius increases. This is due to the fact that more DCs have to be open to serve the covered population points with small coverage radii since the problem is more constrained, which increases the likelihood to have an open DC closer to uncovered people as well.

Fig. 7a shows the values of the objective function as well as the values of its different terms obtained by solving Model 1 and varying the coverage radius from 5 km to 70 km. For each $r \in \{5, 6, \ldots, 70\}$, the black dots correspond to the value of the objective function (total welfare cost), the grey diamonds correspond to the WFP supply cost, the grey squares correspond to the beneficiary opportunity cost, and the grey triangles correspond to the KRCS hand-out cost. As shown in Fig. 7a, the solution that minimizes the total welfare cost is obtained with $r=12$. When considering the costs per beneficiary depicted in Fig. 7b, we observe that the stakeholder costs decrease as the coverage radius increases. However, the marginal costs tend to be close to zero when the coverage radius is larger than 17 km. We therefore conclude that using coverage radii ranging from 10 to 17 km yields the most efficient solutions.

We observed that the most important part of the total cost is borne by WFP for transporting the food from the MW to the DCs (supply cost). The beneficiary opportunity costs are also important compared with the KRCS hand-out costs, which constitute the smallest component of the total cost. These results show the importance of supply costs in the response system, even when the beneficiary opportunity cost is taken into account. In fact, the transportation cost represents on average 73% of the total cost, whereas the beneficiary opportunity costs and the hand-out costs account on average for 22% and 5% of the total cost, respectively. This finding is consistent with that of [58] who observed that approximately 80% of disaster relief efforts relate to logistics activities. It implies that WFP has an interest in being actively involved in the DC selection process, and should thus collaborate more with the lead partner agency in the design of the food aid distribution network. We also note that the reduction in supply cost becomes less significant when the coverage radius is larger than 30 km and, considering that the minimum radius needed to cover all the population is 55 km, there is no benefit in solving the problem with a larger covering radius.

We now describe some optimal solutions obtained by solving Model 1. Table 2 provides the values of the different attributes of six solutions obtained with $r = 5, 10, 12, 17, 25$ and 55 km. Fig. 8 illustrates the two extreme case solutions on a map of Garissa and its surroundings, where the white dots correspond to potential DC locations (V_2) and the diamonds are the selected ones obtained by solving Model 1 with $r=5$ km and $r=55$ km. We clearly see that the potential DCs are located along the roads and how the selected ones are dispersed on the map for these two coverage radius, with 264 open DCs for $r=5$ km and 64 open DCs for $r=55$ km, as shown in Table 2.

4.2. Comparative analyses

The objective of this section is to better understand the impact of the response system structure on the stakeholder welfare. To this end, we have conducted several comparative analyses by varying some parameters in Model 1 and by solving the covering problems formulated in Section 3.

In Model 1, the objective function is the sum of the three stakeholder objectives evaluated in local currency. In order to determine the behavior of each term, we have solved the problem by minimizing each objective separately, thus yielding three cases:

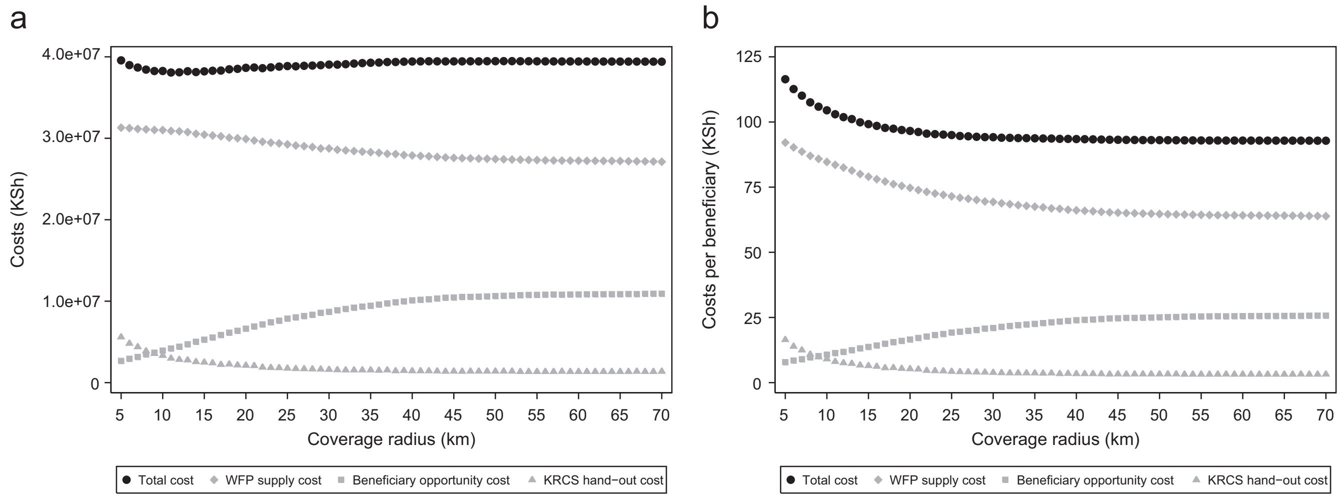

Fig. 7. Costs of solutions obtained with Model 1. (a) Total and stakeholder costs as a function of the coverage radius. (b) Cost per covered person as a function of the coverage radius.

Table 2
Characteristics of six representative optimal solutions.

Solution, r (km)	Costs				DCs #	Covered people, average walk time (h)	Uncovered people		CPLEX, CPU time (s)
	Total (KSh)	Beneficiary (KSh)	Supply (KSh)	Hand-out (KSh)			Proportion (%)	Average walk time (h)	
5	39,564,680	2,659,196	31,299,708	5,605,776	264	0.88	19.94	8.33	4312.3
10	38,260,488	3,921,704.3	31,005,046	3,333,738	157	1.43	13.75	10.37	80.9
12	38,099,196	4,401,085	30,852,754	2,845,356	134	1.63	11.90	11.11	338.36
17	38,314,480	5,842,935	30,241,976	2,229,570	105	2.21	7.67	13.18	203.41
25	38,863,984	7,853,155	29,248,408	1,762,422	83	3.01	3.62	16.50	173.75
55	39,449,296	10,767,909	27,322,410	1,358,976	64	4.15	0	0	1228.85

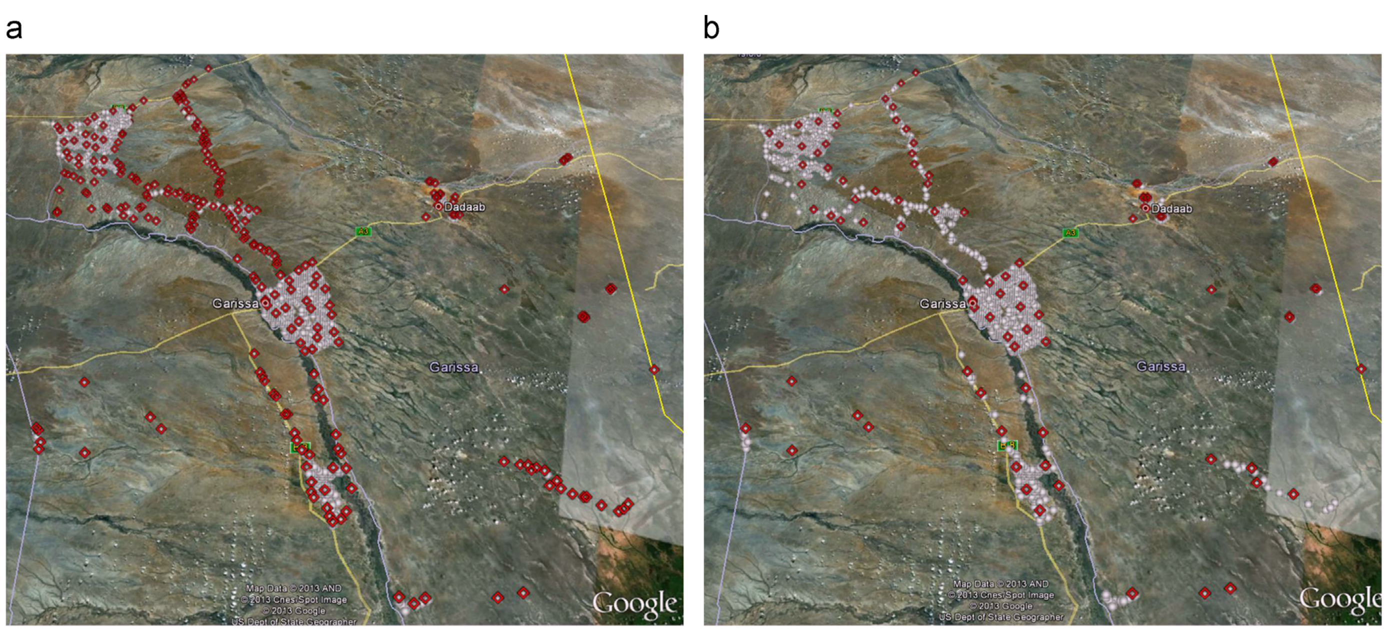

Fig. 8. Optimal solutions with $r=5$ km (a) and $r=55$ km (b).

(1) $\alpha_{ij}=0$ and $\gamma_j=0$ (Fig. 9a–d); (2) $\alpha_{ij}=0$ and $\beta_j=0$ (Fig. 10a–d); and (3) $\beta_{ij}=0$ and $\gamma_j=0$ (Fig. 11a–d). Case 2 is equivalent to solving Model 3, i.e. minimizing the number w of open DCs to cover the population with a coverage radius r. We note that CPLEX could not solve Case 2 for $r=35, 42, 43, \ldots, 55$ within a reasonable time because of excessive branching.

Comparing Figs. 9a, 10c and 11c, we note that optimizing the total welfare cost, as opposed to a single-objective function, yields larger percentages of increase for the WFP supply cost, the KRCS hand-out cost (proportional to the number of open DCs) and the beneficiary opportunity cost as the coverage radius increases. However, Cases 1 and 2 yield solutions that make the beneficiaries

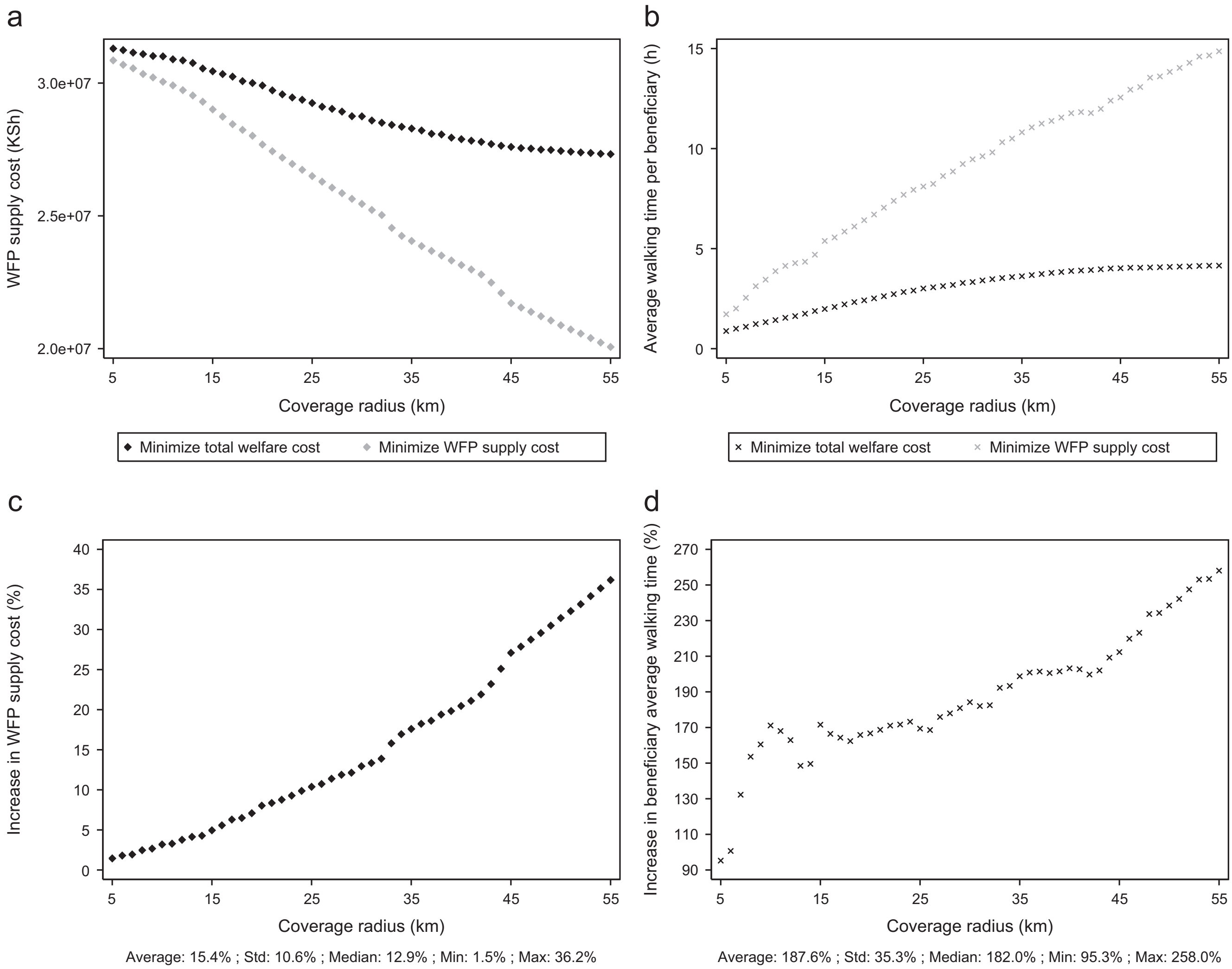

Fig. 9. Comparing the results of multi-objective and single objective optimizations (Case 1). (a) WFP supply costs as a function of the coverage radius. (b) Average walking time per beneficiary as a function of the coverage radius. (c) Percentage increase in the WFP supply cost when minimizing total welfare cost (Model 1) as opposed to a single-objective function (Case 1), as a function of the coverage radius. (d) Percentage increase in the average beneficiary walking time when minimizing a single-objective function (Case 1) as opposed to the total welfare cost (Model 1), as a function of the coverage radius.

walk significantly more to collect their food, as shown in Figs. 9d and 10d. The average walking time per beneficiary exceeds 5 h when the covering radius exceeds 15 km, as shown in Figs. 9b and 10b. Note that the percentage increase in WFP supply cost remains less than 10% for covering radii smaller than 20 km. By computing the tradeoffs between the beneficiary and WFP costs, we observe that a small increase in WFP supply costs can yield a large reduction in beneficiary opportunity costs while the opposite is not true. Indeed, minimizing the beneficiary opportunity costs (Case 3) leads to a 37% decrease in average walking time per beneficiary and to a 14% increase in WFP supply costs, whereas minimizing the WFP supply costs (Case 1) leads to a 15% decrease in WFP costs and to 188% of increase in average walking time per beneficiary.

These results show that including the beneficiaries' opportunity costs into the network optimization impacts the financial costs incurred by the agencies, but increases accessibility in a larger proportion. Currently, the opportunity cost of beneficiaries is not sufficiently considered in the academic literature and in the WFP emergency costing models. This seems to conflict with the humanitarian principles (humanity, neutrality and impartiality – see [57]) which aim to emphasize beneficiary welfare as opposed to cost minimization [23].

Moreover, in order to ensure that the beneficiaries' time is not underestimated in the parameterization of the mathematical model, we have solved Model 1 with various values of the hourly wage rate. In the initial parameterization, we have estimated the beneficiaries' opportunity costs by valuing their time proportionally to the minimum wage rate for unskilled labor ($wage = 22.25$ KSh/h). We have thus solved Model 1 for each $wage \in \{20, 21, \ldots, 40\}$ to evaluate the impact of the value given to the beneficiaries' time on the response system. The results yielded by this experiment are illustrated in Fig. 12, where we compare these solutions with those obtained by solving Model 1 with $wage = 22.25$ KSh/h. We note from Fig. 12a that the total cost of the response systems is mostly due to the increase in beneficiary opportunity costs, which is in turn mostly explained by the increase of α_{ij}, since the supply costs do not increase significantly when *wage* increases and since the hand-out costs are the least important component of the total welfare costs. Fig. 12b also shows that the average walking time by the beneficiaries does not drop considerably with *wage*. This validates the adoption of the minimum wage rate for unskilled labor as the value for the beneficiary opportunity cost, which has also been confirmed by the WFP.

There are currently 156 DCs in Garissa District and its surroundings. We therefore consider that the solutions obtained by

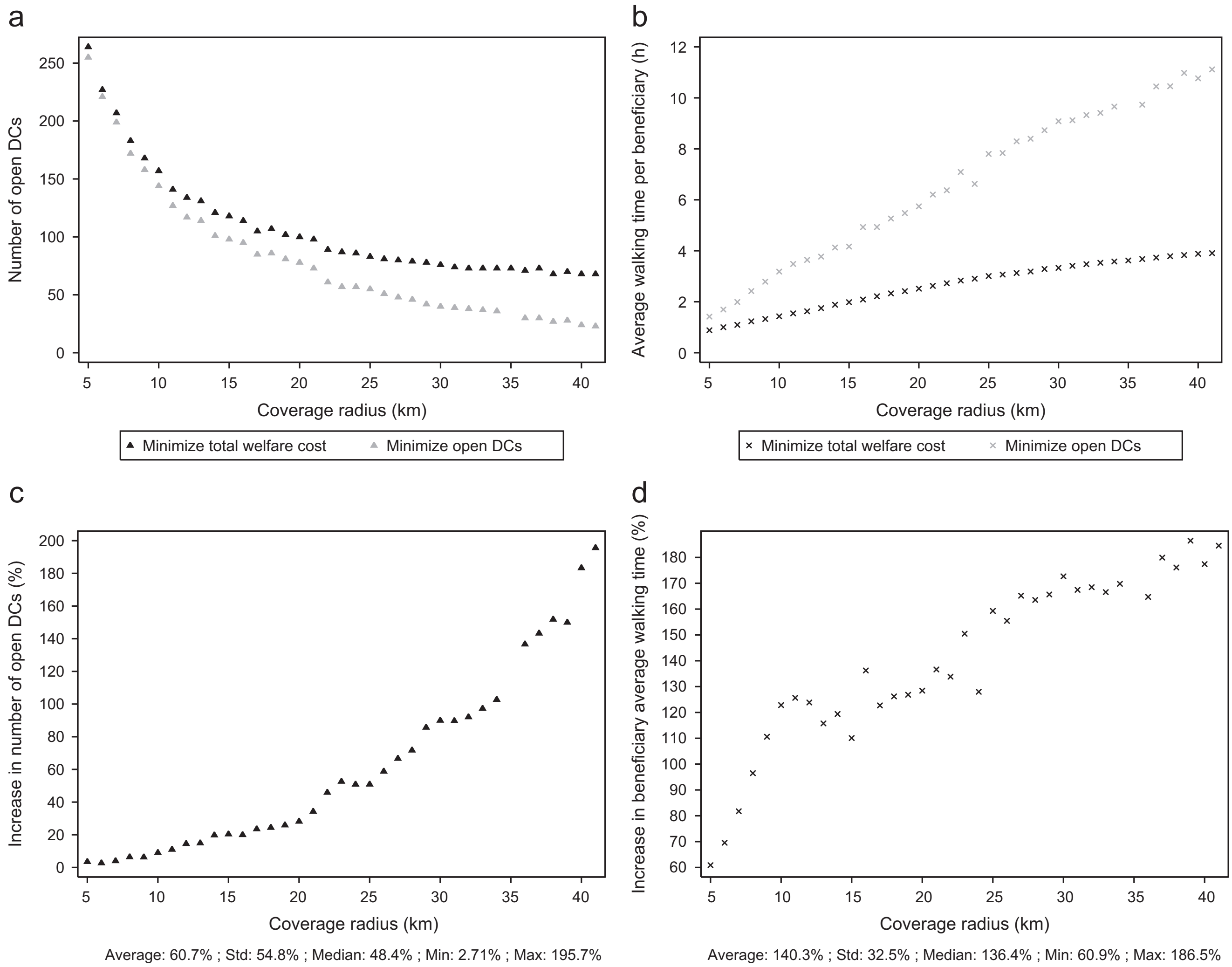

Fig. 10. Comparing the results of multi-objective and single objective optimizations (Case 2). (a) Number of open DCs as a function of the coverage radius. (b) Average walking time per beneficiary as a function of the coverage radius. (c) Percentage increase in the KRCS hand-out cost when minimizing total welfare cost (Model 1) as opposed to a single-objective function (Case 2), as a function of the coverage radius. (d) Percentage increase in the average beneficiary walking time when minimizing a single-objective function (Case 2) as opposed to the total welfare cost (Model 1), as a function of the coverage radius.

solving Model 2 with 156 open DCs adequately represent the current network. In order to assess this current response system and compare it with the solutions obtained with Model 1, we have solved Model 2 with $\overline{w}=156$ and $r \in \{5,6,\dots,55\}$. We have computed the maximum number of people who can be covered with 156 DCs and the resulting average walking times per beneficiary. Fig. 13a and b shows the percentage difference in covered population and average walking times per beneficiary obtained by solving Model 1 as opposed to solving Model 2. Similarly, Fig. 14b shows the difference in the number of open DCs. When maximizing need coverage with 156 open DCs, fewer people are covered than when solving Model 1, and people have to walk more on average to go and collect their ration. Note that, as shown in Fig. 10a, the minimum number of open DCs obtained with Model 3 is 158 for $r=9$ and 145 for $r=10$, which implies that 156 open DCs do not provide a full coverage of the population living within a radius of at most 9 km from a DC.

Fig. 14a shows the percentage decrease in stakeholders costs obtained by solving Model 1 as opposed to solving Model 2 with $\overline{w}=156$, as in the current network. It shows that, for all coverage radii, solving Model 1 is more advantageous for the beneficiaries and for the WFP since Model 2 yields larger beneficiary opportunity and supply costs. These differences tend to become larger as the coverage radius increases. For a coverage radius equal to 10 km, all stakeholder costs are similar when solving the two models. However, these costs are larger for solutions obtained by solving Model 2 with coverage radii larger than 10 km. We therefore believe that the current condition could be improved by considering the total welfare cost in the network design, as we did in Model 1, especially since the DC costs are the least important part of the total welfare cost.

From the results of our experiments, we believe that solving a model that takes into account the welfare of all stakeholders involved in food aid distribution (Model 1) and using a coverage radius ranging from 10 to 17 km generates cost-efficient and fair solutions complying with the Sphere standards [56,36]. Indeed, these solutions are the least costly and yield acceptable walking times for the beneficiaries, i.e. at most a one-day return walk. The number of required DCs is slightly smaller than the current one without negatively affecting the quality of service offered by the response network. We do not claim that these solutions are those that should necessarily be implemented since it is up to the decision maker to assess the impact of various parameters on the design of the food distribution network while taking into account the interest of the various stakeholders. We believe, however, that an objective such as the one we have used helps generate good quality solutions from which the decision maker can choose. This represents an improvement over the current practice where most decisions are made without a strong analytical support.

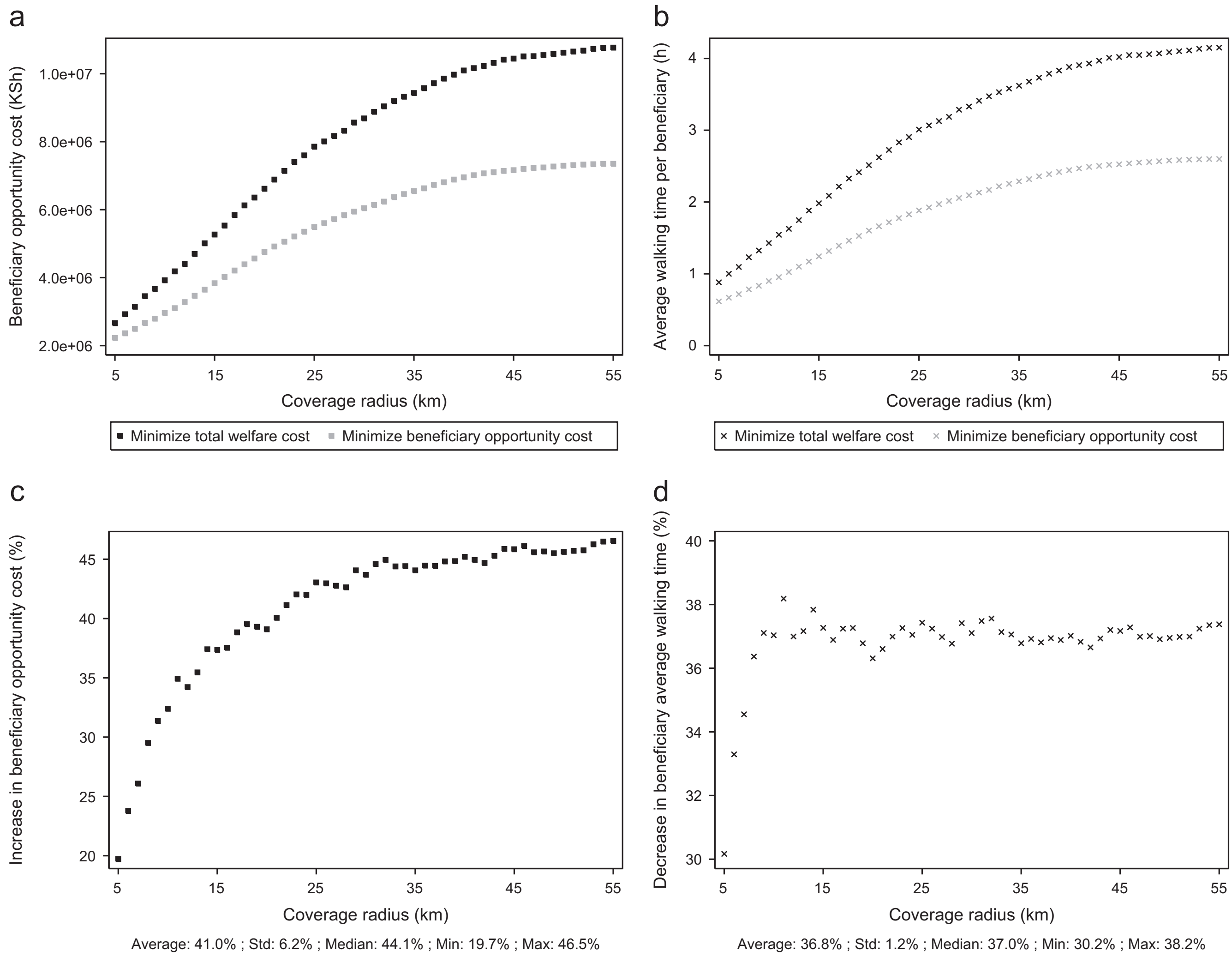

Fig. 11. Comparing the results of multi-objective and single objective optimizations (Case 3). (a) Beneficiary opportunity cost as a function of the coverage radius. (b) Average walking time per beneficiary as a function of the coverage radius. (c) Percentage increase in beneficiary opportunity costs when minimizing total welfare cost (Model 1) as opposed to a single-objective function (Case 3), as a function of the coverage radius. (d) Percentage decrease in the average beneficiary walking time when minimizing a single-objective function (Case 3) as opposed to the total welfare cost (Model 1), as a function of the coverage radius.

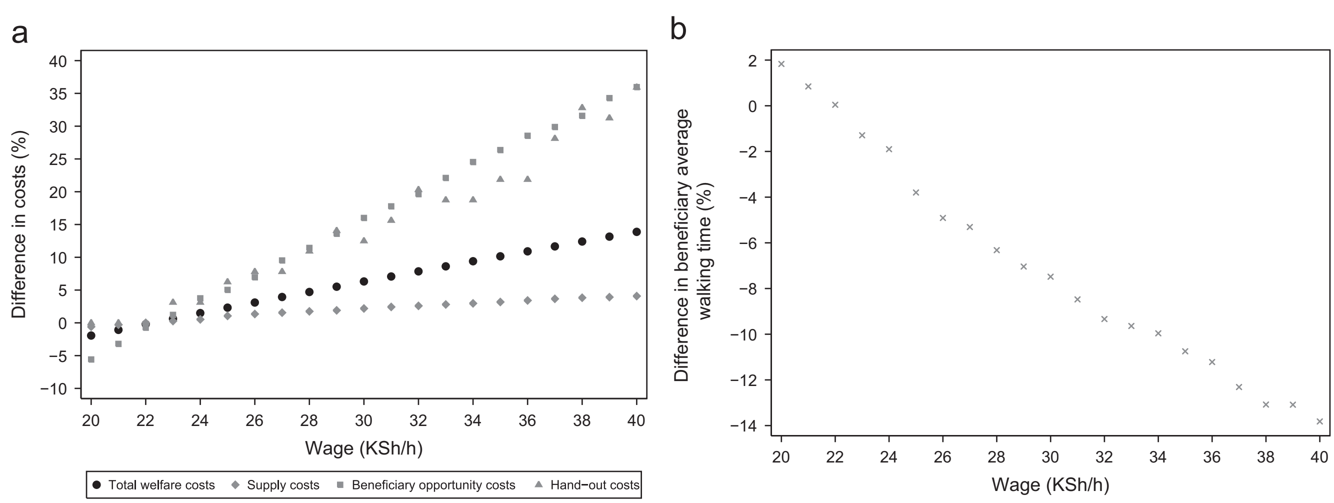

Fig. 12. Impact of beneficiary time value on the response system ($r = 55$ km). (a) Percentage difference in stakeholder costs when solving Model 1 with different values of *wage* as opposed to 22.24 KhS/h, as a function of wage. (b) Percentage difference in beneficiary average walking time when solving Model 1 with different values of *wage* as opposed to 22.24 KhS/h, as a function of wage.

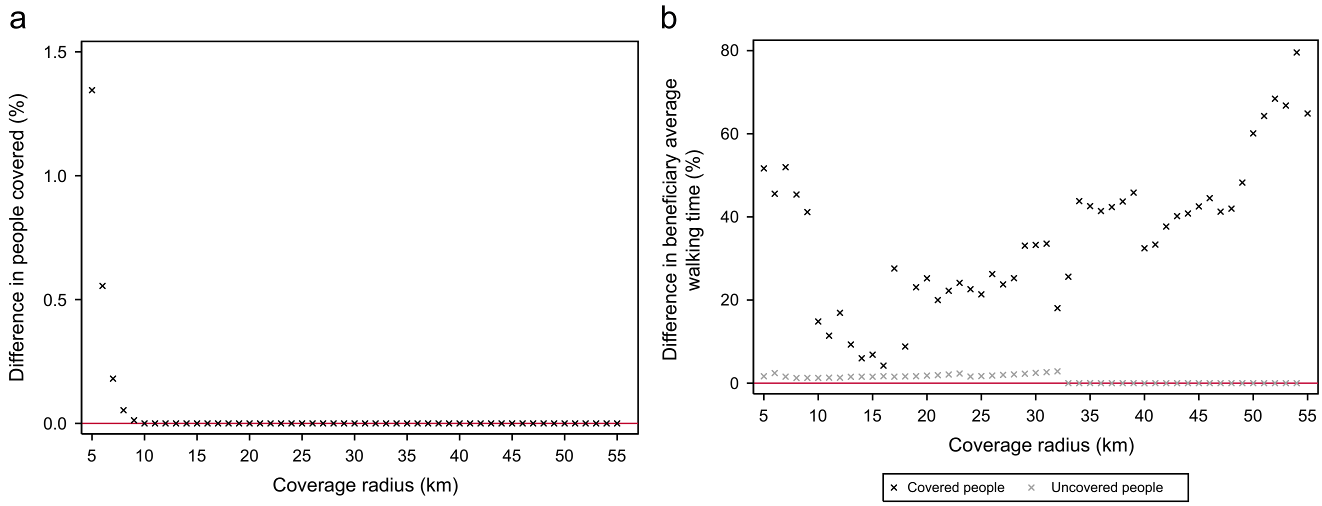

Fig. 13. Comparisons between the coverage and average walking time per beneficiary obtained by solving Model 1 as opposed to solving Model 2 with $\overline{w} = 156$, the current number of DC. (a) Percentage difference in covered population as a function of the coverage radius. (b) Percentage increase in beneficiary average walking time as a function of the coverage radius.

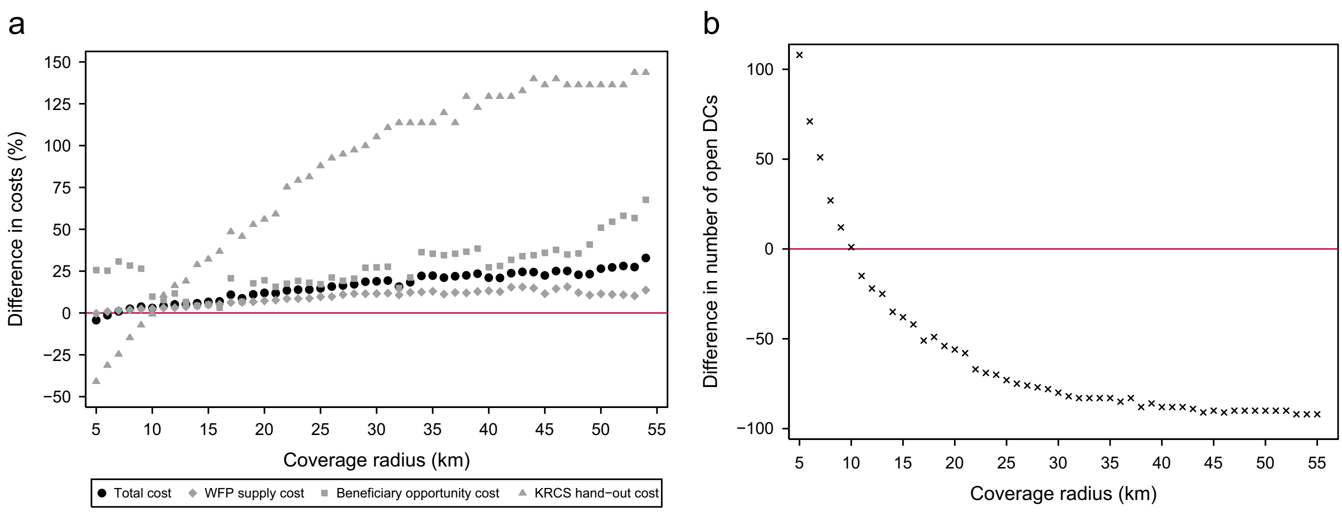

Fig. 14. Comparisons between the stakeholder costs and the number of open DCs obtained by solving Model 1 as opposed to solving Model 2 with $\overline{w} = 156$, the current number of DCs. (a) Percentage decrease in stakeholder costs as a function of the coverage radius. (b) Difference in number of open DCs as a function of the coverage radius.

5. Conclusions

We have solved a location problem arising in the context of food aid distribution in Kenya. The problem was modeled and solved by means of a mathematical programming methodology. Several analyses were conducted to validate the results provided by the model and to study the effects of various parameters on the solutions. We have shown how mathematical programming can be used to design last-mile food aid distribution network using real data for the case of Garissa District in Kenya. Our results show that the most important part of the total cost is related to transporting the food from the district warehouse to the distribution centers. We have also shown the importance of valuing the beneficiary time, which is by itself a new contribution.

This paper bridges part of the gap between theory and practice in the development of humanitarian logistics support decision tools. Solving this problem and quantifying the tradeoffs between costs borne by the different stakeholders contributes to a better understanding of the impacts of food aid supply chain in the country. It can also help decision makers handle simultaneously the objectives of several decision makers and select a suitable solution among those that are generated. This approach should be welcomed in the context of recurrent food aid distribution in other developing countries such as Kenya.

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