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S.I.: DESIGN AND MANAGEMENT OF HUMANITARIAN SUPPLY CHAINS

Evaluation of field visit planning heuristics during rapid needs assessment in an uncertain post-disaster environment

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Abstract

A Rapid Needs Assessment process is carried out immediately after the onset of a disaster to investigate the disaster's impact on affected communities, usually through field visits. Reviewing practical humanitarian guidelines reveals that there is a great need for decision support for field visit planning in order to utilize resources more efficiently at the time of great need. Furthermore, in practice, there is a tendency to use simple methods, rather than advanced solution methodologies and software; this is due to the lack of available computational tools and resources on the ground, lack of experienced technical staff, and also the chaotic nature of the post-disaster environment. We present simple heuristic algorithms inspired by the general procedure explained in practical humanitarian guidelines for site selection and routing decisions of the assessment teams while planning and executing the field visits. By simple, we mean methods that can be implemented by practitioners in the field using primary resources such as a paper map of the area and accessible software (e.g., Microsoft Excel). We test the performance of proposed heuristic algorithms, within a simulation environment , which

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enables us to incorporate various uncertain aspects of the post-disaster environment in the field, ranging from travel time and community assessment time to accessibility of sites and availability of community groups. We assess the performance of proposed heuristics based on real-world data from the 2011 Van earthquake in Turkey. Our results show that selecting sites based on an approximate knowledge of community groups' existence leads to significantly better results than selecting sites randomly. In addition, updating initial routes while receiving more information also positively affects the performance of the field visit plan and leads to higher coverage of community groups than an alternative strategy where inaccessible sites and unavailable community groups are simply skipped and the initial plan is followed. Uncertainties in travel time and community assessment time adversely affect the community group coverage. In general, the performance of more sophisticated methods requiring more information deteriorates more than the performance of simple methods when the level of uncertainty increases.

Keywords Rapid needs assessment · Simulation · Heuristics · Selective routing · Disaster response

1 Introduction

After occurrence of a sudden-onset disaster, humanitarian aid agencies need to make key decisions on how to respond and how to help affected people. Before making response decisions, humanitarian organizations quickly assess the needs of affected people, which, in humanitarian practices, is called the Rapid Needs Assessment (RNA). (IFRC 2008). The RNA starts immediately after a disaster strikes and has to be completed within a few days to quickly evaluate the disaster impact and population needs (IFRC 2008; Arii 2013). Without a successful needs assessment, humanitarian agencies may fail to satisfy needs effectively, which not only wastes precious resources at a time of great need, but can also lead to a further burden on authorities and affected people (de Goyet et al. 1991; Arii 2013). For instance, in the aftermath of the 1988 Armenian earthquake, a lack of a proper needs assessment has been mentioned as one of the main reasons for the mismatch between demand and supply of medical items sent by international organizations (Hairapetian et al. 1990; Lillibridge et al. 1993).

The RNA process begins with a preliminary review of secondary information which is collected from various sources such as national institutions, NGOs, United Nations agencies, satellite images, aerial photography and media including social media (IFRC 2008; ACAPS 2011b; IASC 2012; ACAPS 2014). After reviewing this secondary information, humanitarian agencies need to plan field visits in order to (i) confirm assumptions, initial impressions and predictions; (ii) receive more information on uncertain issues; and (iii) obtain beneficiary perspectives related to their priority needs (ACAPS 2011b). Rapid assessment via field visits includes interviews with affected community groups and direct observations of affected sites (IFRC 2008; ACAPS 2011b). The assessment is conducted by experts, who are familiar with the local area and have specialties such as public health, epidemiology, nutrition, logistics and shelter (ACAPS 2011b; Arii 2013).

Planning the field visits plays a significant role in achieving a successful assessment. One of the key decisions that influences the quality of this planning is to decide which sites to visit. Site selection processes aim to achieve acceptable coverage of various community groups. Due to time and resource restrictions during the RNA stage, it is normally neither feasible nor desirable to evaluate the entire affected region. Consequently, a sample must be drawn (ACAPS 2011b). Sampling methods are applied in practice to choose a limited number of sites to visit, which will allow assessment teams to observe and compare the post-disaster conditions of different community groups such as displaced persons, host communities, and returnees (IFRC 2008; ACAPS 2011b). Limited time and resources usually do not permit statistically representative sampling at the household or individual level; therefore the sample of sites that represent community level must be drawn (IASC 2012). Selecting which sites to visit may significantly affect the time spent for RNA.

Beside site selection, routing decisions, which involve determining the order of site visits, can also affect the efficiency of the field visit plan. The importance of reducing travel time by planning routes has been emphasized in practical resources (Garfield 2011; Benini 2012). Savings in travel time can improve the quality of assessment by providing the opportunity to spend more time at each site and/or to increase the number of sites to visit (Benini 2012). Despite existing optimization approaches in the academic literature, humanitarian organizations may have difficulties applying these methods in the field (Gralla and Goentzel 2018). Reviewing practical humanitarian resources as well as interviews with practitioners, however, show that, in practice, the tendency is to use simple methods such as greedy heuristics for determining vehicle routes in the field, rather than advanced solution methodologies and software (Gralla and Goentzel 2018). This is mainly due to the lack of available computational tools and resources on the ground, lack of experienced technical staff, and also the chaotic nature of the post-disaster environment.

While advances in technologies such as satellite data and drone images can assist humanitarian organizations in obtaining timely and accurate information about the physical impact of a disaster in the affected region, the availability of these technologies is a matter of concern due to their costs and possible disruptions in IT infrastructure after the disaster strikes (EPRS 2019). Besides, in the RNA stage, it is necessary to conduct interviews with the affected community groups, and usually it is a challenging task for humanitarian agencies to know their exact location. Therefore, both site selection and routing decisions during the RNA stage may be made in a highly uncertain post-disaster environment. Given the difficulties in accessing technological advances, evaluation of the uncertain factors can assist decision-makers in better utilizing these tools. These uncertainties largely stem from; (i) transportation network disruptions including link capacity, reliability and availability; (ii) safety and security concerns in affected regions, and; (iii) ambiguities with respect to the existence or availability of a certain community group in a specific region and their willingness to be interviewed (IFRC 2008; Garfield 2011; ACAPS 2011b; Liberatore et al. 2013; Arii 2013). In this paper, we use the term *inaccessibility* to refer to the cases when a site in the field visit plan turns out to be not accessible for assessment teams for various reasons such as security issues or road blockage. The term *unavailability* refers to the cases when the assumption regarding the existence or availability of a specific community group in a specific site turns out to be inaccurate. This happens when community groups are displaced, or they are unwilling to assist in collecting information (IFRC 2008). While planning the field visits in the RNA stage, "where overall needs are urgent, widespread and unmet, it is justifiable to focus on accessible areas" (IASC 2012, p. 7). However, sometimes information regarding inaccessibility or unavailability is revealed when assessment teams travel through the region (ACAPS 2011b). In fact, while visiting affected sites, the assessment teams may receive updated information regarding inaccessibility and/or unavailability. In such cases, they usually follow a pre-defined set of rules to react appropriately (ACAPS 2011b). That is, they need to decide how to update their original plan in order to obtain better assessment results within the restricted time limit. Therefore, while planning the field visits in the RNA stage, the uncertainties related to accessibility of sites and existence of community groups at the visited sites must be taken into account.

For field visit planning, humanitarian organizations, depending on availability of information and required resources, can use different pre-defined rules in case of inaccessibility/unavailability as well as different methods regarding site selection and routing decisions. Different combinations of methods and pre-defined rules provide a list of options for planning the field visit. We refer to them as a *heuristic*. The term heuristic in our study describes the approach followed to make decisions. That is, each heuristic represents a combined set of methods for making site selection and routing decisions and rules to follow in case of inaccessibility/unavailability. Depending on which methods and pre-defined rules are considered, the heuristics can vary in terms of required resources and information. For instance, regarding the resources, applying a simple routing method, requires easier to access tools and software than an advanced optimization procedure. Likewise, concerning the required information, selecting sites randomly requires less information than selecting sites based on the location of target community groups. This paper investigates the following research question:

RQ1. How do different heuristics, which are developed based on simple rules and methods applied by field visit teams that conduct humanitarian needs assessment, perform in post-disaster settings characterized by uncertainty with respect to travel times, assessment times, site accessibility, and availability of communities?

We provide a list of heuristics, including simple methods and pre-defined rules, that can be applied while planning the field visit in the RNA stage under uncertainty, evaluate their performance and provide an overview for decision-makers to be able to compare them in various scenarios. The terms “easy” or “simple” are both subjective and need to be clarified within the scope of this study. We consider methods as simple or easy when they carry the following two characteristics: first, practitioners should be able to implement them in the field using primary resources such as a paper map of the affected area and accessible software (e.g., Microsoft Excel). Second, these methods should follow the general principles mentioned in practical reports for field visit planning during the RNA stage. When practitioners observe that applying simple algorithms in practice can improve their field visit planning, they may recognize the need for further improvements. We believe that optimization models have a great potential to assist in decision-making processes, provided that practitioners recognize the need for these models and the required computational tools and resources are available at the time of planning. Accordingly, we briefly show in Section 5.3.3 how optimization procedures can further improve the results.

As a testing environment to evaluate the performance of heuristics, we incorporate them into a simulation model. Simulation models in general aim to analyze, evaluate and compare the performance of different options that differ in relation to various parameters (Lund et al. 2017). This is in line with the main objective of this study, which is not to provide one optimal solution but instead help the decision makers to compare the performance of a variety of heuristics in different settings. Moreover, simulation models enable us to incorporate various uncertain factors of the post-disaster environment in a reasonable amount of computational time. We compare the performance of different heuristics based on metrics that generally focus on achieving higher coverage of various community groups within time and resource limitation. We perform a numerical analysis based on a case study of the 2011 Van (Turkey) earthquake. We observe that updating the routes based on pre-defined rules positively affects the performance of the field visit plan and leads to higher coverage of community groups in comparison to an alternative strategy where inaccessible sites and unavailable community groups are simply skipped and the initial plan is followed. In addition, we see that selecting sites based on an approximate knowledge of community groups' location leads to significantly better results than selecting sites randomly. Our results show that uncertainties in travel time and community assessment time adversely affect the heuristics' performance in terms of coverage ratio, no matter which one we use; however, its impact is not the same on all heuristics. The results of more sophisticated heuristics requiring more data deteriorate more when the level of uncertainty increases.

The paper is structured as follows: Sect. 2 provides an overview of related works. Section 3 describes the decision making environment and Sect. 4 presents an overview of heuristics. In Sect. 5, we present computational results. Finally, the conclusion and future research directions are presented in Sect. 6.

2 Related literature

Transportation planning for needs assessment processes has recently attracted attention in the field of optimization. Huang et al. (2013) consider routing of post-disaster assessment teams. They construct routes for assessment teams to visit all communities in the affected regions. This model may be appropriate for the detailed assessment stage where time allows visits to all sites. However, usually in the RNA stage it is only possible to visit a subset of sites. Oruc and Kara (2018) propose a bi-objective optimization model that provides damage assessment of both population centers and road segments with aerial and ground vehicles. Balcik (2017) presents a mixed-integer model for the proposed "Selective Assessment Routing Problem" (SARP) which simultaneously addresses site selection and routing decisions and supports the RNA process that involves the purposive sampling method, a method that only selects those sites that carry certain characteristics. Balcik and Yanıkoğlu (2020) take the study further by considering the travel time as an uncertain parameter in post-disaster networks and present a robust optimization model to address the uncertainty. The objective function in Balcik (2017) is maximizing the minimum coverage ratio achieved across the community groups, where the coverage ratio for a group is calculated by dividing the number of times that the group is covered by the total number of sites in the network with that group. As an alternative objective function, Pamukcu and Balcik (2020) specify coverage targets in advance and the objective is to ensure covering all community groups in minimum duration. Bruni et al. (2020) approach the post-disaster assessment operations from a customer-centric perspective by including a service level constraint that guarantees a given coverage level with the objective of minimizing the total latency. They consider travel time uncertainty and address this uncertainty through a mean-risk approach. Li et al. (2020) propose a bi-objective model addressing both the RNA stage and the detailed needs assessment stage to balance the contradictory objectives of the two stages. The objective of the RNA stage is, similar to Balcik (2017), maximizing the minimum coverage ratio achieved among community groups, and the second objective is minimizing the maximum assessment time of all assessment teams. There is a stream of literature focusing on damage assessment using unmanned aerial vehicles (UAVs), which shows similarities to the needs assessment routing problem (e.g., Zhu et al. 2019, 2020; Glock and Meyer 2020). The main difference is that damage assessment studies focus mainly on settings where UAVs' high-quality pictures can meet the assessment purposes, and there is no possibility or necessity to conduct interviews with the community groups. Both of the literature streams mentioned above belong to the family of Team Orienteering Problems (Chao et al. 1996) as both problems address site selection and vehicle routing decisions.

The goal of both problems is maximizing the benefits collected from the visited nodes and constructing efficient routes.

One of the main criticisms of using optimization models is their limited applicability in practice (Altay and Green III 2006; Galindo and Batta 2013; Anaya-Arenas et al. 2014; Gralla and Goentzel 2018). Difficulties in accessing data, required computing time and resources, lack of contextualization, poor problem definition, complexity of the approach and lack of trust in its conclusions by humanitarian organizations are the main barriers that limit the possibility of using optimization models in practice (de la Torre et al. 2012; IFRC 2013; Kunz et al. 2017; Gralla and Goentzel 2018). Nevertheless, according to Gralla and Goentzel (2018), in order to improve the current dependence on "error-prone" and "by hand" planning methods, there is still a great need for decision support in practice. Developing "easy-to-understand" and "easy-to-apply" heuristics has been mentioned as an effective way to improve transportation planning by building trust between humanitarian logisticians and academic researchers as well as reducing implementation challenges (Gralla and Goentzel 2018). Some researchers have focused on developing simple heuristics that can be easily implemented in practice to support routing decisions in various non-profit settings. For instance, Bartholdi III et al. (1983) present a heuristic vehicle-routing strategy for delivering prepared meals to people who are unable to shop or cook for themselves. Knott (1988) suggests a simple heuristic based on methods used in practice by experienced field officers for scheduling emergency relief management vehicles. In a more recent study, Gralla and Goentzel (2018) develop simple and practice-driven heuristic algorithms for planning and prioritization of vehicles to transport humanitarian aid to affected communities based on their observational study on planning practices currently in use in the humanitarian sector. The authors compare the solutions of heuristics to each other and to those of a mixed-integer linear program to identify the strengths and weaknesses of each approach.

The general approach in this study is similar to that of Gralla and Goentzel (2018); that is, we also develop simple practice-driven heuristics to support RNA operations and compare their performance to each other and with a modified version of the optimization model presented in Balcik (2017). The modification on the original SARP model is due to the fact that we want to keep assumptions consistent between all heuristics that we test in this paper. The main modification is uncertainty concerning the existence of community groups. In the original SARP, the existence of a community group is known in advance. In the modified SARP, we consider the expected value of visiting the community group. Furthermore, in this study we divide sites into some clusters and add a new constraint to the original SARP to ensure that we visit each community group a certain number of times within each cluster. Note that although we made above changes to the original Balcik (2017), the main focus of this paper is not extending the Balcik (2017) but taking the optimization approach in this work as a basis to compare it with the other heuristic algorithms inspired by practical humanitarian resources. Balcik (2017) was closest to the assumption of our developed heuristic algorithms and required fewer changes. The practice-driven heuristics are inspired by the main assumptions, principles and procedures that are described in practical humanitarian resources and guidelines regarding field visit planning for the RNA stage (e.g., IFRC 2008; ACAPS 2011b; IASC 2012; ACAPS 2013, 2014; USAID 2014). Our study differs from Gralla and Goentzel (2018) in two main aspects; (i), we incorporate different heuristics and an optimization model into a simulation model for decision makers to facilitate evaluating their performance in an uncertain environment, and (ii) we focus on RNA operations rather than delivery of relief items. We elaborate more on these two subjects in the following paragraphs.

Practical studies and guidelines provide general and conceptual principles for the RNA processes which are mostly open to interpretation. Regarding the site selection decisions, available practical reports almost unanimously highlight the importance of using purposive sampling. IASC (2012) emphasizes the fact that in the response phase of a disaster due to time, access and logistics constraints, assessing needs at household or individual levels is often unrealistic and it is more reasonable to collect information at community level. They also emphasize the importance of purposive sampling by mentioning that limited time normally does not permit random or statistically representative sampling. Therefore a sample of sites which represent a cross-section of typical regions and affected populations must be drawn (IASC 2012). IASC (2012) also states that the size of the selected sites is determined by the availability of resources (staff, time and logistics), the geographic spread of the disaster and the heterogeneity/homogeneity of the community groups. Similarly, IFRC (2008) declares that if the affected sites differ significantly, it is beneficial to select a variety of sites reflecting different characteristics (e.g., ethnicity, economics, town/village, etc.). ACAPS (2011b) focuses specifically on the purposive sampling method and provides a case study to guide how to select relevant community groups and identify the most appropriate sites to assess. Routing decisions are the other important decisions which need to be taken during the RNA stage. Although the importance of saving in travel time using routing methods has been highlighted in some practical resources (e.g., Garfield 2011; Benini 2012), the details of applied or suggested methods for routing decisions have not been discussed in detail (IFRC 2008; ACAPS 2011b; IASC 2012; ACAPS 2013, 2014).

As stated in Sect. 1, practical studies mention different uncertain factors which assessment teams might encounter while planning and also during the RNA stage (IASC 2000; Darcy and Hofmann 2003; ACAPS 2011a, b). We use a simulation model to deal with these uncertainties. Simulation models are powerful tools to evaluate a set of predefined options, especially in a situation with a high level of uncertainty (Liberatore et al. 2013; Davidson and Nozick 2018). Furthermore, simulation models often have an excellent capability of providing a graphical user interface that can facilitate applying these models as a decision support tool and improve understanding of the underlying problem settings. There is a growing body of simulation-based decision support tools that focuses on supporting various humanitarian operations (e.g., Yu et al. 2014; Fikar et al. 2016, 2018). Mishra et al. (2019) present a review of simulation models developed as an analytical tool for different stages of disaster relief operations. Within our proposed simulation model, we develop easy-to-apply heuristic algorithms based on practical guidelines for planning field visits during the RNA stage. We also incorporate a modified version of a MIP model presented by Balcik (2017) in our model. We compare the solution of the proposed heuristics to each other and to those of the MIP model to provide an overview for decision-makers to be able to compare them in various scenarios and see the trade-offs.

In summary, we explore evidence from practice and formulate heuristic algorithms motivated by humanitarian reports implemented for field visit planning during the RNA stage. The importance of evidence-based research has been highlighted in humanitarian literature (e.g., de Vries and Van Wassenhove 2017; Besiou and Van Wassenhove 2020). In this regard, we consider a wide range of uncertainties, including the accessibility of sites, availability of community groups, travel time, and assessment time. Our proposed decision-making environment assists humanitarian organizations in investigating the trade-offs between different heuristics and deciding on the most suitable choice.

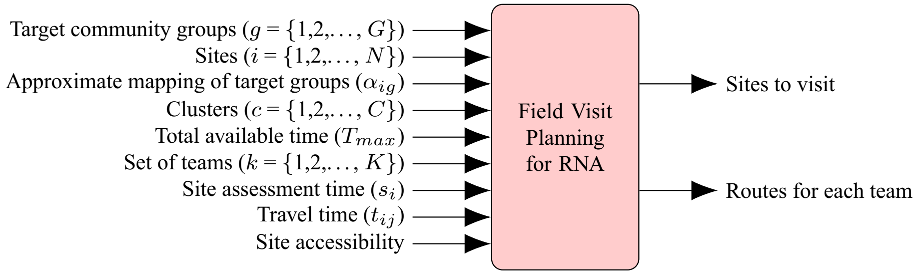

Fig. 1 Inputs and outputs of a field visit planning model for RNA

3 Decision making environment

RNA starts immediately after a disaster strikes and is often completed within a few days. Assessment teams visit a number of sites in the affected areas to evaluate and compare the impact of the disaster on different community groups. The number of sites is limited since assessments must be completed quickly.

Reviewing practical studies shows that, in general, a field visit plan requires input from various information sources. This information is based on secondary data (e.g., sources from governments, NGOs, United Nations agencies, satellite images, aerial photography, and media including social media) and available resources such as logistical, staff, and time (ACAPS 2014). The main information is summarized in Table 1. The better the quality of available information, the higher the quality of the assessment plan. The quality of the assessment plan is higher when the assessment teams can increase the number and diversity of visited community groups within the time and resource limitation. Figure 1 shows the main inputs of field visit planning ranging from transport network, community groups and their possible locations to number of teams and total available time. Below we briefly explain each of the inputs mentioned in Fig. 1:"

Target community groups refer to different groups of the population that have been affected by a disaster in very different ways and have different needs (ACAPS 2011b). These groups of the population could be various sub-groups of the population (e.g., refugees vs. residents), different vulnerable groups (e.g., disabled, food insecure, unemployed) and different demographic groups (e.g., women vs. men or elderly vs. youth) (ACAPS 2011b; IASC 2012). The set of target community groups is denoted by G and indexed by $g \in G$ in this work.

Sites refer to geographical locations where assessment teams can find target community groups. In the RNA stage, sites generally refer to cities, towns, and villages (ACAPS 2011b). Different districts, neighborhoods, or individual houses are considered as sites while doing detailed assessment (Waring et al. 2002). Let N represent the set of sites in the affected region. Each assessment team departs from the origin node {0} and returns to the origin node after completing all site visits. Let $N_0 = N \cup 0$.

Approximate mapping of community groups (availability) points out the fact that humanitarian agencies are not always sure about the existence of a community group within a specific site due to lack of accurate secondary information and breakdown of established information and communication technology infrastructure (ACAPS 2011b). Recent developments in technology can help humanitarian agencies to gather more accurate information in the planning phase. For example, Nagendra et al. (2020) show how a satellite data analytics platform was adopted to identify the locations that needed high-priority rescue support. ACAPS (2011b) uses terms such as "we assume" or "we have good reason to believe" to show the possibility of the existence of a community group in a specific site. In Sect. 4.1, we explain how we can map these verbal terms onto numeric probabilities.

Clusters refer to a group of sites that share the same characteristics. Geographical or disaster impact features can be used as stratification factors for making clusters (ACAPS 2011b). Assessment teams are interested in comparing the situation of community groups among different clusters. For example, they might be interested in evaluating the needs of disabled people (as a community group) in both urban and rural areas (as clusters) or needs of refugee people (as a community group) in directly affected areas with indirectly affected areas (as clusters). The set of clusters is denoted by C and indexed by $c \in C$. It is worth mentioning that clusters may have different priority levels (IFRC 2008; ACAPS 2011b). For instance, in case of an earthquake, humanitarian organizations may define clusters based on the distance from the earthquake's epicenter. In such a case, they may give more priority to clusters that are closer to the epicenter and select a larger portion (or percentage) of sites to visit from these clusters.

Total available time The RNA operations must be completed quickly (e.g., within 3 days based on Arii (2013)). Depending on the severity, extent, and scope of a disaster, decision-makers decide on the total available time, which is denoted by T_{max}.

Number of assessment teams refers to the available number of assessment teams. These teams consist of experts familiar with the local area and specialties such as public health, epidemiology, nutrition, logistics, and shelter (ACAPS 2011b; Arii 2013). The set of teams is denoted by K and indexed by $k \in K$.

Community assessment time By using secondary data and previous experiences of the assessment teams, an estimation of time for assessing one community group at a site, which mainly consists of conducting interviews and direct observation, is determined (Garfield 2011). The time for assessing community groups is an uncertain parameter and can deviate from its nominal value. One reason for increased assessment time is a phenomenon called assessment fatigue, which may happen if different humanitarian agencies assess a community group many times (IFRC 2008). In this situation, people are frustrated and unwilling to answer the interview questions which are mostly similar to the questions that the other agencies have already asked. *Site assessment time* refers to the total time spent at each site for assessing its existing community groups. Estimated site assessment time is represented by s_i, which is calculated by the number of community groups at a site multiplied by the nominal value of assessing one community group.

Travel time Travel time between sites is calculated using the available information on the road conditions and damage to the infrastructure (Garfield 2011). Travel time is another uncertain parameter in the RNA stage and can increase due to reasons such as network and infrastructure disruptions. The nominal value of travel time between nodes is represented by t_{ij}.

We assume travel time and community assessment time both can increase by up to a fraction of their nominal values. We show the level of increase by U. For example, when U (the uncertainty level) is 0.2, travel time and community assessment time can increase by up to 20 percent of their nominal value. In practice, for uncertain parameters little or no data is available. Therefore, to show the probability distribution for both travel time and community assessment, we consider triangular distribution (left triangular since it can only increase) , which is often used when the shape of the distribution is only vaguely known (Stein and Keblis 2009; Fairchild et al. 2016). The parameter for triangular distribution is the lower limit (minimum), best guess (mode) and the upper limit (maximum). In left triangular distribution the value of minimum is equal to the mode.

Site accessibility While planning the field visit using secondary information, assessment teams exclude sites that are not accessible (i.e., those sites of which they have accurate information); however, they may also encounter inaccessibility during their field trip (IASC 2000; IFRC 2008). The assumption in this study is that the assessment teams realize this once they get close enough to the inaccessible site (receiving information from local people, and direct observation). In such situations, the assessment teams usually follow a pre-defined set of rules to update their original plan (ACAPS 2011b). In Sect. 4.3, we introduce two pre-defined rules for updating routes.

The aspects described above characterize the decision-making environment and required information while planning field visits during the RNA stage. To plan a field visit during the RNA stage, two main decisions must be made: (i) site selection: decision regarding which sites to visit and (ii) routing: decision regarding in which order to visit the selected sites and how to update the planned route. The main goal of field visit planning during the RNA stage is to visit different community groups in different clusters as much as possible and in a balanced way, considering the time and resource limits. The main performance measurement in this study is the concept of Coverage Ratio (CR) of community groups. CR is calculated by the number of times one specific community group is visited divided by the total expected number of times this community group exists in the network. For example, if a community group is visited twice and expected to exist in 10 different sites in the whole network, the CR of this community group is 0.2. The higher the rate of CRs for all community groups and, preferably, the closer their values to each other, the better the performance of a heuristic (in Sect. 5.2, we present different KPIs that stem from the concept of CR). Below, we present and explain different heuristics consisting of simple methods inspired by practical reports for both site selection and routing decisions.

4 Overview of heuristics

In this section, we present our proposed heuristics for planning the field visit during the RNA stage. These heuristics include a set of methods for making site selection and routing decisions as well as pre-defined rules to follow in case of site inaccessibility and group unavailability. Figure 2 presents different methods and pre-defined rules considered in this study, and Table 2 shows the list of four heuristics that consist of different combinations of these methods and pre-defined rules. The heuristics are sorted based on the level of simplicity (Heuristic A simplest).

4.1 Site selection methods

Random site selection The main assumption in this method is the fact that assessment teams do not have access to information regarding the location of community groups, or they do not have time to gather and analyze this information using secondary data. Therefore, sites are selected randomly. This method is the simplest approach for selecting sites that we found in practical resources (IFRC 2008). This method is typically used when humanitarian organizations assume sites are similar in terms of existing community groups.

The selection process is shown in Algorithm 1. First, we randomly select f_c number of sites from each cluster. f_c is determined by experts and represents their preferred number of sites to be visited from each cluster. For simplicity, in our algorithm, we set f_c as a fixed percentage of sites from each cluster (e.g., 30 percent). Then, we assign total selected sites

Table 1 Main factors for planning the field visit during the RNA stage

Factors	Source(s)	Description
The number of assessment locations	Garfield (2011), IFRC (2008)	Geographical locations where assessment teams can find target community groups
Sampling plan and the data collection methods	Garfield (2011), IFRC (2008)	Random sampling or purposive sampling
Travel time between assessment locations	Garfield (2011), IFRC (2008)	Driving time based on available information on the road conditions
The number and size of assessment teams	Garfield (2011), IFRC (2008)	Available number of assessment teams composed of experts familiar with the local area and specialties
Assessment time	Garfield (2011), IFRC (2008)	Community groups assessment time for interviews and direct observation
Target groups of interest	ACAPS (2011)	Various groups of the affected population with different needs
Clustered sites	ACAPS (2011)	Group of sites that share the same characteristics
Inaccessibility of sites	ACAPS (2011), IFRC (2008)	Sites that are not accessible for assessment teams due to security issues or road blockage
Unavailability of community groups	ACAPS (2011)	Unavailability of community groups when they are displaced, or unwilling to assist in collecting information
Mapping the existing groups on their location	ACAPS (2011)	Possibility of the existence of a community group in a specific site
Pre-defined rules in case of inaccessibility/unavailability	ACAPS (2011)	Instructions for updating original plan in case of inaccessibility or unavailability
Total available time	Arii (2013), IFRC (2008)	Total RNA operation time depending on the severity, extent, and scope of a disaster

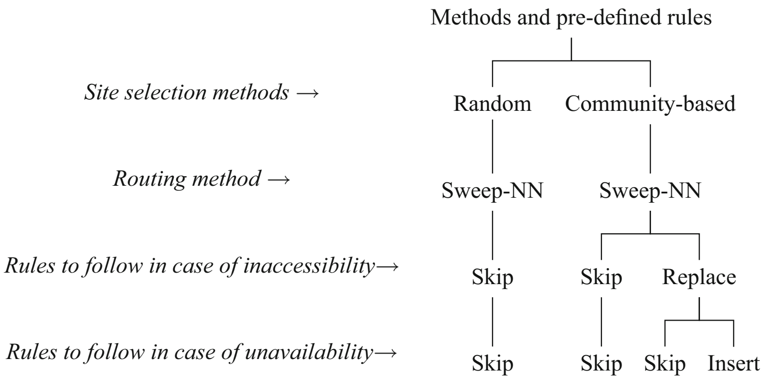

Fig. 2 Methods for site selection and routing and pre-defined rules in case of inaccessibility and unavailability

Table 2 List of heuristics for field visit planning during the RNA stage

	Site selection method	Routing method	Pre-defined rule in case of inaccessibility	Pre-defined rule in case of unavailability	Information requirements per Heuristic
Heuristic A	Random	Sweep-NN	Skip	Skip	Available resources, clusters
Heuristic B	Community-based	Sweep-NN	Skip	Skip	Available resources, clusters, approximate knowledge of the location of community groups
Heuristic C	Community-based	Sweep-NN	Replace	Skip	Available resources, clusters, approximate knowledge of the location of community groups
Heuristic D	Community-based	Sweep-NN	Replace	Insert	Available resources, clusters, approximate knowledge of the location of community groups, planned number of community groups to be visited at each site of the constructed route

to teams using the Sweep-NN algorithm (see Sect. 4.2 for the steps of this algorithm) and construct $|K|$ routes (# of available teams). To consider available resources (total available time), we calculate the travel times and site assessment times required to complete each route. If the time of completing one specific route exceeds the total available time (T_{max}), we start reducing the number of sites from this route (randomly) until we have a feasible route.

Community-based site selection In this method, we assume that while selecting sites, decision-makers have at least an approximate knowledge about where the community groups exist and they make their site selection decision based on this information. This method, which we call community-based site selection, is adopted from the general procedure explained in ACAPS (2011b) and, in general, requires more information compared to the previous one. ACAPS (2011b) places a great emphasis on visiting different community groups and considers the following general factors while selecting sites: i) sample richness (i.e., observing each community group at least once within each cluster is important), ii) collecting adequate

Algorithm 1: Random site selection method

Input:
C: set of clusters;
K: set of teams;
TSS: set of total selected sites $= \emptyset$;
T_{max}: total available time;
CT_k: time of completing route k;
f_c : number of initial selection of sites from cluster c;
M: number of allocated sites to each team = 0;
Step 1. Site selection:
for *each* $c \in C$ **do**
  i. randomly select f_c sites from cluster c;
  ii. add selected sites to TSS;
end
Step 2. Team assignment and routing:
i. $M = \lfloor |TSS|/|K| \rfloor$;
ii. assign M sites to each $k \in K$ using Sweep-NN algorithm (see Algorithm 3);
iii. construct $|K|$ routes (for each $k \in K$) using Nearest Neighbor algorithm (see Algorithm 3);
Step 3. Feasibility check:
for *each route* k **do**
  i. travel time (k)= $\sum_{(i,j)\in k} t_{ij}$;
  ii. site assessment time (k) = $\sum_{i\in k} s_i$;
  iii. CT_k = travel time (k) + site assessment time (k);
  while $CT_k > T_{max}$ **do**
    iv. remove one site from route k randomly ;
    v. update CT_k ;
    vi. update TSS;
  end
end
return TSS;

information (i.e., observing a community group at multiple sites), iii) efficiency (e.g., visiting a site that involves multiple community groups may be beneficial).

Another important factor that is highlighted in ACAPS (2011b) is the uncertainty concerning the existence of a community group in a specific site due to the lack of information. We mentioned in Sect. 3 how humanitarian agencies use verbal terms to show the possibility of the presence of a community group on a particular site. Translation or mapping of these verbal terms onto numeric probabilities in the planning stage is challenging. We assume these verbal terms could be mapped onto numeric probabilities using some suggested methods in literature such as Barnes (2016) or Kent (1964). For example, according to Barnes (2016) we can associate terms such as “almost certain”, “extremely likely” or “highly likely” with the probability of 0.9 or terms such as “very unlikely” or “highly unlikely” with 0.1. After these mappings, we assume that the probability of each group being available in each site is an independent Bernoulli trial with the parameter resulting from verbal terms. We then let α_{ig} represents the probability of visiting community group g in site i. Note that the expected value of a community group g to be in site i is also α_{ig}.

In community-based site selection, we consider the main criteria mentioned in ACAPS (2011b) for site selection. More specifically, we select sites that ensure visiting a minimum target number from each community group within each cluster (l_{gc}) determined by decision-makers. Also, to take efficiency into account, we first try to meet the minimum number by selecting sites that have a higher possibility of visiting community groups to save resources such as time and assessment team (see Algorithm 2).

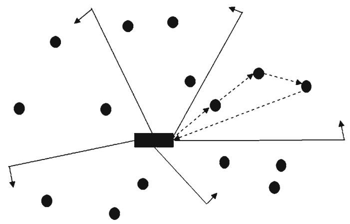

Fig. 3 Sweep clustering and routing

The resource checking process is similar to the one in random site selection. The only difference is that when we have an infeasible route and need to remove one site (or more) from this route, we start removing the site that causes the least decrease in CR of community groups. Using CR helps us to avoid removing a site from the list of selected sites that includes a community group that exists in a limited number of areas.

4.2 Routing method

The routing algorithm we use determines the sequencing of visits to the selected sites, which helps assessment teams utilize limited resources by reducing travel time efficiently. Applying routing methods has been emphasized in practical studies (Garfield 2011; Benini 2012). Nevertheless, due to the limitations mentioned in Sect. 1, in practice, the tendency is to use simpler methods for determining vehicle routes in the field, rather than advanced solution methodologies and software. (Gralla and Goentzel 2018). In the following section, we introduce an easy-to-apply method from literature for generating routes that do not require sophisticated resources.

Sweep-NN algorithm This algorithm is one of the simplest methods for solving the capacitated vehicle routing problem (Gillett and Miller 1974; Nurcahyo et al. 2002). This algorithm consists of two stages: (i) clustering, and (ii) routing. Clustering starts with the unassigned node with the smallest angle with respect to a depot and assigns it to vehicle k. The sweeping for each team continues until M (total selected sites divided by the number of teams) sites are assigned. At the routing stage, a solution to the traveling salesman problem (TSP) is required to construct routes. Following the easy-to-apply approach in this paper, we consider the Nearest Neighbor (NN) algorithm for solving the TSP in each cluster. Algorithm 3 presents the steps of the Sweep-NN method.

4.3 Pre-defined rules in case of site inaccessibility

When the assessment teams start traveling in the field based on their original planned route, they might encounter site inaccessibility and need to update their route accordingly. In our simulation algorithm, we assume that once they finished with the assessment of one site, they realize if the next site in their planned route is accessible or not. After realizing the site is inaccessible, the assessment teams need to decide how to react. Below, we suggest two rules to follow in case of inaccessibility:

Skip In this rule, once the assessment teams realize that the next site on their plan is not accessible, they skip that site and continue with their original plan. That is, they travel to the next node in the original plan. We assume assessment teams can find an alternative route to the next node.

Algorithm 2: Community-based site selection method

Input:
G: set of community groups;
C: set of clusters;
K: set of teams;
TSS: set of total selected sites $= \emptyset$;
SS_c: set of selected sites from cluster $c = \emptyset$;
α_{ig}: expected value of visiting community group g in site i;
l_{gc}: minimum target number of visiting group g within cluster c;
f_c: number of initial selection of sites from cluster c;
T_{max}: total available time;
M: number of allocated sites to each team;
Step 1. Site selection:
for *each* $c \in C$ **do**
  for *each site* $i \in c$ **do**
    i. $\omega_i = \sum_{g \in G} \alpha_{ig}$;
  end
  ii. sort sites in descending order of ω_i;
  iii. $SS_c \leftarrow$ first f_c sites of the sorted list ;
  // gap calculation:
  for *each* $g \in G$ **do**
    for *each site* $j \in SS_c$ **do**
      $Gap(g) += \alpha_{jg} - l_{gc}$;
    end
  end
  if *All* $Gap(g) > 0$ **then**
    iv. add SS_c to the TSS;
    v. continue (go to next cluster);
  end
  else
    for $g \in G$ *with the largest* $Gap(g)$ **do**
      vi. add the site with largest α_{ig} to SS_c;
    end
    vii. go to **iv**;
  end
end
Step 2. Team assignment and routing:
i. $M = \lfloor |TSS|/|K| \rfloor$;
ii. assign M sites to each $k \in K$ using Sweep-NN algorithm (see Algorithm 3);
iii. construct $|K|$ routes (for each $k \in K$) using Nearest Neighbor algorithm (see Algorithm 3);
Step 3. Feasibility check:
for *each route* k **do**
  i. travel time (k)= $\sum_{(i,j)\in k} t_{ij}$;
  ii. site assessment time (k)= $\sum_{i \in k} s_i$;
  iii. CT_k = travel time (k) + site assessment time (k);
  while $CT_k > T_{max}$ **do**
    iv. remove the site from route k that causes the least decrease in CR of community groups;
    v. update CT_k ;
    vi. update TSS;
  end
end
return TSS ;

Replace In this rule, the assessment team replaces the inaccessible site with another site within a specific radius (r). The inaccessible site is replaced by a site that is similar to it. The similarity is calculated by the absolute total difference between the expected value of

Algorithm 3: Sweep-NN method

Input
TSS: set of total selected sites (calculated by Algorithm 1 or 2);
K: set of teams;
RT : set of routes = $\{RT_1, \ldots, RT_{|K|}\} = \emptyset$;
$M = \lfloor |TSS|/|K| \rfloor$: number of allocated sites for each team;
Step 1. Clustering:
i. calculate the polar angle of each site of TSS with respect to depot;
ii. sort sites according to their increasing order of polar angles;
iii. start sweeping the first M sites by increasing polar angle and assign them to the first team;
iv. repeat **iii** for all teams until all sites are assigned;
Step 2. Routing (NN algorithm):
for *allocated sites of team* $k \in K$ **do**
  i. initialize all sites as unvisited;
  ii. select depot as the current site i. Mark i as visited and add it to RT_k ;
  iii. find out the shortest edge connecting the current site i and an unvisited site j;
  iv. set j as the current site. Mark j as visited add it to RT_k;
  if *all the sites are visited* **then**
    terminate.
  end
  else
    go to **iii**;
  end
end
return RT;

visiting each community group (α_{ij}) of the inaccessible site and the sites around it within a r radius. Please see Algorithm 4 for the details of this rule.

Algorithm 4: Replace rule

Input
G: set of community groups;
N: set of total sites;
CS: set of candidate sites $= \emptyset$;
IS: inaccessible site;
r: allowed radius;
CSS: closest similar site $= \emptyset$;
TSS: set of total selected sites (calculated by Algorithm 1 or 2) ;
NSS: set of sites excluding TSS ($N \setminus TSS$) within r radius around IS ;
ω_s: total absolute difference=0;
Step 1. Selection:
i. select sites $\in NSS$ and add them to CS;
if CS *is not empty* **then**
  for $s \in CS$ **do**
    ii. calculate $\omega_s = \sum_{g \in G} |\alpha_{sg} - \alpha_{ISg}|$;
  end
  iii. CSS = the site with the lowest ω_s (total absolute difference) ;
end
return CSS;

4.4 Pre-defined rules in case of group unavailability

Another circumstance based on which the assessment teams can decide whether or not to update their route is the time when they enter the site and realize that their target community group(s) do not exist at that site. Since it is suggested in practical studies that "the assessment teams should respect a pre-defined set of rules to replace communities that turn out to be inaccessible or irrelevant" (ACAPS 2011b, p. 8), we present the following two rules that might be reasonable in case of unavailability of community groups.

Skip In this rule, the assessment teams stick to their original planned routes and do not update their route based on the number of community groups that have been successfully visited during their trip.

Insert The assumption in this rule is that the assessment teams keep track of the visited number of each community group during their trip. Then, once in a while (e.g., after visiting every ρ sites), they compare this number with what they expected to visit in their original plan. If the gap between the expected and real number of visits is larger than a threshold (i.e., τ) , they insert a site that has the highest possibility of visiting the community group that has the largest gap. The inserted site will be chosen within a specific radius (r) around the current location. Please see Algorithm 5 for the detailed procedure.

Algorithm 5: Insert rule

```
Input
G: set of community groups;
RT: set of routes ;
ρ: number of sites to visit and check for route update ;
τ: the level of threshold;
r: allowed radius;
Step. Selection:
for each route k ∈ RT do
    After visiting every ρ sites do
    for each group g ∈ G do
        i. Gap(g) = ∑_i α_ig(expected value or what is planned) - ∑_i α_ig(realization);
    end
    if All Gap(g) < τ then
        ii. continue visiting next ρ sites
    end
    else
        iii. select group g with the highest gap as target group;
        iv. go to the site within r radius which has the highest possibility of visiting target group ;
        v. continue visiting next ρ sites ;
    end
end
```

To facilitate investigating the trade-offs between using different heuristics, we incorporate all heuristics into a simulation model. A high-level process overview of the steps performed in the simulation is provided in Fig. 4. Pre-simulation computations refer to the determination of sites and original routes, which then feed into the simulation run where the realization of the uncertain parameters occurs. Then, based on the pre-defined rules, the original routes get updated. Note that the need for simulation (or more specifically the need for updating routes) is due to uncertainties which resolve over the assessment horizon. Otherwise, there would be no need for simulation and updating the initially constructed routes. This is the

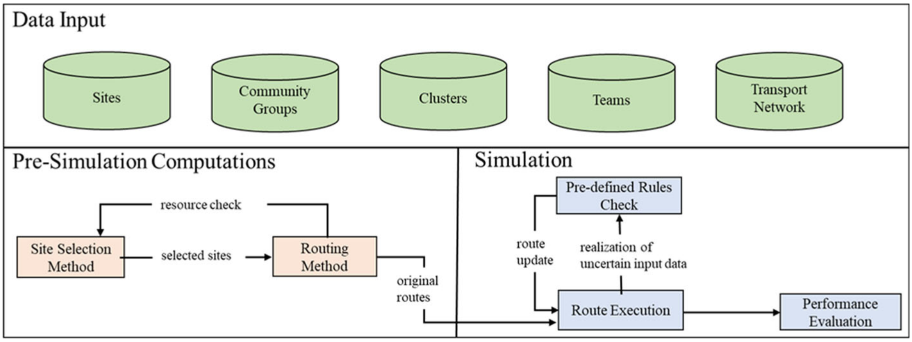

Fig. 4 A high-level evaluation process overview of the steps performed for each heuristic

first study that considers a wide range of uncertainties, including the accessibility of sites, availability of community groups, travel time, and assessment time within a new problem environment capable of comparing different field visit planning methods for site selection and routing decisions, and pre-defined rules for updating routes. This new decision-making environment allows humanitarian organizations, depending on the specific setting of a disaster, to investigate the trade-off between using different heuristics and decide on the most suitable choice.

5 Computational results

We evaluate the performance of the presented heuristics using the case study network in Balcik (2017) that focuses on the affected towns and villages after the 2011 earthquake in Van, Turkey. This last mile network was introduced in Noyan et al. (2016). We vary critical parameters of the problem instance such as number of teams, total available time, level of uncertainty and allowed radius for detour, and analyze the performance of the heuristics across all instances. In Sect. 5.1, we briefly describe the case study and provide parameters and assumptions considered. Key performance indicators and numerical results and analyses are provided in Sects. 5.2 and 5.3.

5.1 Case study

This case study focuses on 93 affected sites after the 2011 earthquake in Van. A case study can be applied to capture the conditions generated by a disaster and evaluate the performance of the disaster management system (Rodríguez-Espíndola et al. 2018). Ketokivi and Choi (2014) states that case studies can be used for theory generation, theory testing or theory elaboration. Based on this categorization, the case study in this paper is defined as theory testing since it aims to test the performance of proposed heuristics for field visit planning during the RNA stage.

This case study is a good example to test our proposed heuristics because of the following reasons. First, in the 2011 Van earthquake, the scale of disaster and number of affected sites were large such that the RNA operations were necessary to be conducted. The Turkish Red Crescent (TRC), teams that immediately arrived in the city from agency offices located in Van were responsible for the assessment operations (AFAD 2020; Kizilay 2021). This is very important because when the number of sites is limited, there is usually no need for site selection (sampling), and the assessment teams are able to visit all sites. Furthermore, the affected area in the 2011 Van earthquake was diverse in terms of geographical aspects (e.g., elevation, proximity to the Van lake), and demographic differences(e.g., population classifications and vulnerable groups). This diversity highlights the importance of purposive sampling, which is applied when the affected sites differ significantly, and it is beneficial to select a variety of sites reflecting different aspects (IFRC 2008).

According to Disaster and Emergency Management Presidency of Turkey (AFAD), this earthquake killed 604, left 200,000 people homeless and in need and caused damage to more than 11,000 buildings in the region, out of which more than 6,000 were found to be uninhabitable (AFAD 2020). The case study in Balcik (2017) provides information regarding transport network, geographical characteristics of the affected sites (e.g., elevation and proximity to the lake), disaster impact (proximity to the epicenter), and demographic information. Note that in this paper the existence of community groups is uncertain and determined after the occurrence of the disaster, which is different from that of Balcik (2017), where the existence of community groups is known in advance. Moreover, the concepts of clustering and inaccessibility of sites are specific to the case study in this paper. Other information regarding the considered community groups and their possible locations, and clustering factors are created for this study, which will be explained below.

Target community groups We consider the following three community groups:

g_1 - *Internally displaced people* Those who were forced to leave their homes due to reasons such as damaged buildings and fear of aftershocks.

g_2 - *Injured people* Those who require medical attention in the immediate aftermath of a disaster.

g_3 - *Disabled people* Those who usually need special attention during disaster relief and it is not easy for them to move.

These community groups are chosen based on reviewing reports and studies that describe the situation right after the Van 2011 earthquake (Zare and Nazmazar 2013; Platt and Drinkwater 2016) as well as practical reports which define most critically (and highly possible) affected groups after the occurrence of an earthquake (ACAPS 2011b).

Mapping of community groups As mentioned earlier, determining the existence of community groups within sites includes uncertainty due to the lack of precise information in the early stages after a disaster strikes. Using secondary data is one of the main sources to approximate the likelihood of finding a specific community group at a specific site. This approximation creates the parameter (i.e., α_{ig}) for the Bernoulli trial, which represents the probability of group i being available at site j. Table 3 represents the generated parameters for the Bernoulli trial (i.e., Bernoulli (α_{ig})). For g_1 and g_2 (displaced and injured people), we assume that the proximity to the epicenter of the earthquake increases the damage to the building and consequently increases the chance of finding more displaced and injured people. For g_3 (disabled people), we use demographical aspects of the region provided by Balcik (2017) which categorizes the population of disabled people into three groups of low, medium and high.

Clusters The affected sites are dispersed through a rural region with a population between 112 and 20,000. Other characteristics of the affected region, such as geographic aspects and disaster impact, can be used as stratification factors for making clusters. Deciding how detailed the stratification must be depends on how different the impact of the disaster is on the region. We consider four clusters based on the available data regarding the geographical characteristics and the disastrous impact of the Van 2011 earthquake. Table 4 shows the

Table 3 Parameters for Bernoulli trial used to represent availability of community groups

Group	Criteria	Category	Likelihood	Parameter (α_{ig})
		<16 km	highly likely	$\sim$ Uniform(.75,1)
g_1 and g_2	proximity to epicenter	16 km< and <30 km	likely/probable	$\sim$ Uniform(.5,.75)
		>30 km	less likely	$\sim$ Uniform(0,.5)
		high	highly likely	$\sim$ Uniform(.75,1)
g_3	demographic statistics	medium	likely/probable	$\sim$ Uniform(.5,.75)
		low	less likely	$\sim$ Uniform(0,.5)

Table 4 Clusters considered for the 2011 earthquake in Van, Turkey

Cluster	Site characteristics	Number of sites
Cluster 1	"high impact "	15
Cluster 2	"low impact" AND "coastal"	15
Cluster 3	"low impact" AND "inland " AND " high elevation"	28
Cluster 4	"low impact" AND "inland "AND " medium or low elevation"	35

factors and number of sites considered for each cluster and Fig. 5 illustrates the case study network.

Community assessment time and travel time As indicated in Sect. 3, travel time and community assessment time are both considered as uncertain parameters and can increase up to a certain fraction of their nominal values (i.e., $(1+U)\times$nominal value). Therefore, when we change the level of uncertainty (i.e., setting different values to U), it only refers to deviation in nominal values of travel time and community assessment time. The nominal values of road travel times for this network are obtained from Noyan et al. (2016). The nominal value to assess each community is considered to be 45 minutes (based on approximated time provided in Garfield (2011)). We consider left triangular distribution to generate the realization of both community assessment time and travel time in our simulation model. The parameters for left triangular distribution are the lower limit (minimum), best guess (mode) and the upper limit (maximum), where the minimum is equal to the mode. Figure 6 represents the components of a left triangular distribution.

Site accessibility We assume the chance of facing inaccessibility increases when the assessment team gets closer to the earthquake epicenter. Therefore the probability of facing inaccessibility is defined similarly to the availability of community groups g_1 and g_2 , i.e., Bernoulli trial with parameters provided in Table 3.

Table 5 provides other parameters considered. In total we obtained 2,520 instances.

5.2 Key performance indicators

As mentioned earlier, the main performance measures in this study are developed based on the CR of community groups. The CR of each community group is calculated using the below

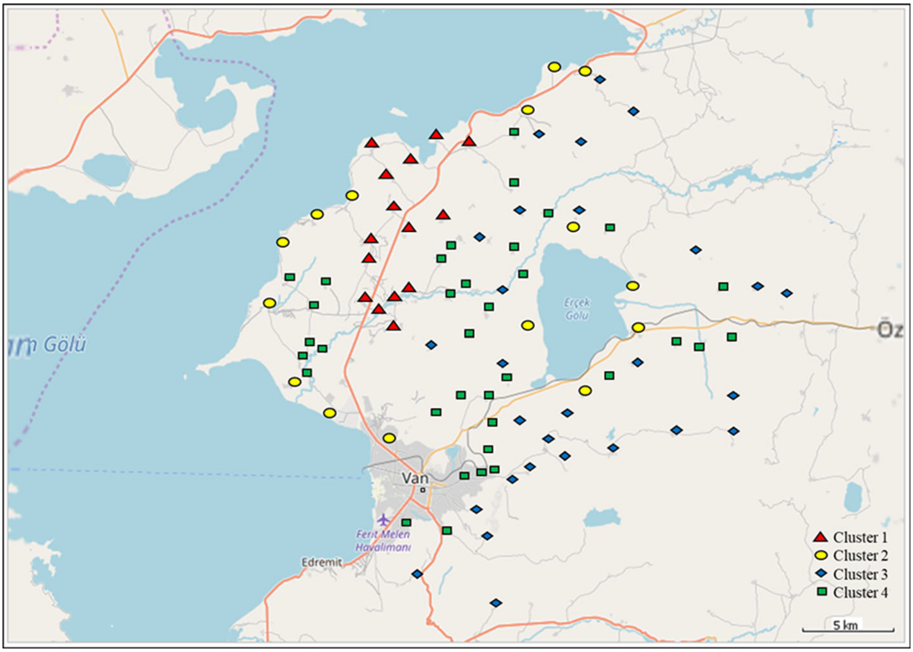

Fig. 5 The case study network representing affected sites and clusters considered for the Van earthquake; adapted from Noyan et al. (2016)

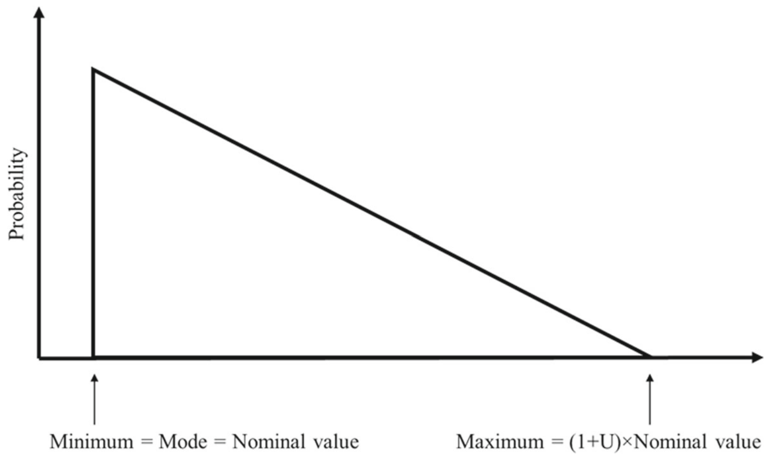

Fig. 6 Components of a left triangular distribution for generating the realization of travel time and community assessment time

formula in one simulation run.

$$CR_g = \frac{number\ of\ times\ group\ g\ is\ visited}{total\ expected\ number\ of\ times\ group\ g\ exists\ in\ the\ network\ (\sum_{i=1}^{N} \alpha_{ig})} \tag{1}$$

Using the concept of CR, we define the following KPIs:

Table 5 Other parameters

Parameter	Description	Value
f_c	initial selection of sites from cluster c	30 percent of sites in cluster c
l_{gc}	minimum target number for each group from each cluster	1 for all clusters and groups
T_{max}	total available time	40 and 50 (in thousands of seconds)
$\|K\|$	number of assessment teams	2, 3 and 4
r	allowed radius for detour	10, 15, …40 kilometers
ρ	number of sites to visit and check for route update	2 and 3
τ	threshold level	1 and 2
U	uncertainty level for travel time and community assessment time	0,0.1,0.2,…1.0

- Average Coverage Ratio (ACR): ACR is the average of coverage ratios of community groups (g_1, g_2, and g_3) in one simulation run.
- Minimum Coverage Ratio (MCR): MCR is the minimum of coverage ratios of community groups (g_1, g_2 and g_3) in one simulation run.
- Coefficient of Variation of Coverage Ratios (CVCR): CVCR is the coefficient of variation of coverage ratios (the ratio of standard deviation to the average of coverage ratios) in one simulation run. See the below formula:

$$CVCR = \frac{SD(CR_{g_1}, CR_{g_2}, CR_{g_3})}{ACR} \tag{2}$$

Note that since the network is divided into different clusters, the CR and correspondingly, other KPIs can be calculated for each cluster separately. We calculate CVCR per cluster, which can be used to show how balanced the CRs are within each cluster.

Each instance is run with 300 replications and average results of ACR, MCR, and CVCR are reported. Simulation algorithms were implemented with AnyLogic 7.2.0 and all the test runs were run on an Intel Core i5-5300U CPU, 12.0 GB RAM, with MS-Windows 10. The optimization model (Appendix A) is coded in Java and CPLEX 12.6.1 is used to solve instances.

5.3 Results

We divide the computation results into three sections. In Sect. 5.3.1, we analyze the effect of the site selection methods by comparing the performance of Heuristics A and B, which apply different site selection methods but do not update routes. To analyze the impact of different route update rules in case of inaccessibility and unavailability, in Sect. 5.3.2, we compare Heuristics C and D, which implement the same site selection method but different rules for updating the routes. In Sect. 5.3.3, we compare the performance of our best heuristic with the solution obtained by an exact optimization procedure.

5.3.1 Heuristic A vs Heuristic B (random vs community-based site selection)

In random site selection (Heuristic A), the assumption is that decision-makers do not have enough time to gather information or do not have access to data regarding the location of community groups. In community-based site selection (Heuristic B), decision-makers spend some time before starting the assessment to analyze secondary data. This leads to approximate information about the location of community groups. Based on this information they decide where to go, to cover more community groups. Table 6 shows that Heuristic B shows a better performance in terms of ACR (on average 32 percent improvement) and MCR (on average 38 percent improvement) than Heuristic A, which means they can visit a higher number of community groups with the same amount of resources. Nevertheless, as Fig. 7 shows, this improvement in the solution decreases when the level of uncertainty (U) with respect to travel time and community assessment time increases. That is, while planning the field visit, where time is of vital importance, even if the assessment teams spend time to gather more information regarding the existence of community groups, other uncertainties such as road situation can deteriorate the expected results.

Moreover, in addition to having higher coverage ratios, Heuristic B has a lower CVCR in comparison to Heuristic A. That means if we assume community groups have the same priority for the assessment teams, Heuristic B provides more balanced results than Heuristic A, both within the whole network and every cluster.

5.3.2 Heuristic C vs Heuristic D (Replace-Skip vs Replace-Insert)

In Heuristics C and D, the assessment teams update their pre-planned routes. In Heuristic C, the assessment teams react to site inaccessibility (see Algorithm 4 for the procedure), i.e., where possible, an inaccessible site is replaced with another if it falls within a specified radius (r) from the inaccessible site. In Heuristic D, in addition to inaccessibility, the assessment teams react to community group unavailability such that they insert suitable site(s) in their original plan (see Algorithm 5 for the procedure).

Table 7 presents the solutions of both Heuristic C and D. The first observation is that in general, these two heuristics achieve better coverage than the previously discussed two heuristics, which shows that updating the routes has improved the results. This stems from the fact that when assessment teams face inaccessibility and unavailability and do not replace or insert sites, their field visit plan, in many cases, finishes before the total available time period (i.e., T_{max}). Heuristics C and D utilize this extra time.

Moreover, as observed in Table 7, in lower uncertainty levels (less than 0.2), Heuristic D shows a better performance in terms of ACR and MCR than Heuristic C. CVCRs are also slightly lower in Heuristic D. That means updating planned routes based on the number of visited community groups, in lower uncertainty levels, has a positive effect on coverage ratios. Please note that when we increase the threshold level (i.e., $\tau = 2$ or more), there is no significant difference between Heuristics C and D since it is rare for teams to be so far behind the original plan.

In higher uncertainty levels, we see a similar impact to that discussed in Sect. 5.3.1, i.e., the better performance of Heuristic D over Heuristic C decreases when the uncertainty level increases (see Fig. 8). In other words, considering more complex methods does not lead to a significant improvement in the results in higher uncertainty levels.

Another observation is about the effect of allowed radius for a detour (i.e., r) on ACR and MCR. Increasing r expands the options to choose when the assessment teams need to find a replacement, but further causes more deviation from the original planned route. The outcome of these two opposing effects is presented in Table 7. We see that increasing r, which continuously increases the total distance traveled, does not necessarily improve ACR and MCR and in some cases even leads to lower values. For example, in Heuristic D, for instances with $U = 0$, $|K| = 3$, $T_{max} = 40$, $\tau = 1$ and $\rho = 2$ when r varies from 10 to 40 km,

Table 6 Evaluation of the performance of Heuristics A and B

Heuristic	U	K	T_{max}	CR_{g_1}	CR_{g_2}	CR_{g_3}	ACR	MCR	$CVCR$	$CVCR$ per cluster			
										cluster 1	cluster 2	cluster 3	cluster 4
A	0.0	2	40	0.118	0.118	0.126	0.121	0.092	0.212	0.40	0.68	0.58	0.41
B	0.0	2	40	0.142	0.139	0.132	0.138	0.112	0.164	0.28	0.49	0.41	0.24
A	0.0	2	50	0.151	0.149	0.153	0.151	0.118	0.189	0.32	0.60	0.51	0.35
B	0.0	2	50	0.180	0.179	0.171	0.177	0.147	0.142	0.28	0.40	0.37	0.23
A	0.0	3	40	0.169	0.169	0.169	0.169	0.137	0.166	0.29	0.55	0.49	0.31
B	0.0	3	40	0.228	0.226	0.185	0.213	0.176	0.147	0.22	0.37	0.46	0.23
A	0.0	3	50	0.177	0.177	0.177	0.177	0.143	0.169	0.28	0.51	0.47	0.31
B	0.0	3	50	0.270	0.273	0.218	0.254	0.210	0.148	0.21	0.36	0.38	0.21
A	0.0	4	40	0.172	0.173	0.173	0.173	0.141	0.160	0.30	0.54	0.46	0.31
B	0.0	4	40	0.280	0.281	0.231	0.264	0.223	0.133	0.21	0.35	0.32	0.21
A	0.0	4	50	0.176	0.174	0.173	0.174	0.141	0.165	0.29	0.56	0.47	0.30
B	0.0	4	50	0.287	0.288	0.234	0.270	0.225	0.138	0.21	0.34	0.32	0.22
A	0.3	2	40	0.113	0.115	0.121	0.116	0.088	0.211	0.40	0.72	0.58	0.40
B	0.3	2	40	0.138	0.133	0.131	0.134	0.108	0.166	0.29	0.46	0.40	0.24
A	0.3	2	50	0.144	0.147	0.152	0.148	0.116	0.182	0.34	0.59	0.50	0.34
B	0.3	2	50	0.171	0.173	0.163	0.169	0.140	0.147	0.29	0.42	0.37	0.23
A	0.3	3	40	0.165	0.164	0.164	0.165	0.133	0.169	0.30	0.55	0.49	0.32
B	0.3	3	40	0.216	0.214	0.180	0.203	0.170	0.144	0.22	0.38	0.47	0.24
A	0.3	3	50	0.178	0.174	0.176	0.176	0.142	0.169	0.29	0.55	0.47	0.31
B	0.3	3	50	0.260	0.265	0.210	0.245	0.204	0.142	0.21	0.35	0.39	0.21
A	0.3	4	40	0.168	0.170	0.171	0.170	0.137	0.167	0.29	0.57	0.49	0.30
B	0.3	4	40	0.273	0.272	0.228	0.257	0.218	0.132	0.23	0.34	0.32	0.22
A	0.3	4	50	0.178	0.177	0.175	0.177	0.140	0.162	0.28	0.52	0.48	0.30
B	0.3	4	50	0.285	0.285	0.234	0.268	0.224	0.135	0.22	0.34	0.32	0.22
A	0.6	2	40	0.109	0.113	0.117	0.113	0.086	0.212	0.43	0.69	0.65	0.43
B	0.6	2	40	0.129	0.126	0.122	0.126	0.101	0.170	0.32	0.47	0.42	0.25
A	0.6	2	50	0.140	0.137	0.144	0.141	0.110	0.189	0.36	0.64	0.57	0.35
B	0.6	2	50	0.161	0.161	0.154	0.159	0.132	0.145	0.29	0.46	0.37	0.23
A	0.6	3	40	0.157	0.158	0.160	0.158	0.127	0.173	0.31	0.58	0.50	0.33
B	0.6	3	40	0.204	0.202	0.173	0.193	0.161	0.141	0.21	0.41	0.45	0.24
A	0.6	3	50	0.171	0.176	0.174	0.174	0.141	0.165	0.28	0.54	0.48	0.31
B	0.6	3	50	0.252	0.248	0.205	0.235	0.195	0.145	0.21	0.34	0.41	0.22
A	0.6	4	40	0.167	0.164	0.168	0.166	0.133	0.172	0.31	0.53	0.49	0.32
B	0.6	4	40	0.259	0.262	0.221	0.247	0.210	0.131	0.22	0.36	0.33	0.22
A	0.6	4	50	0.173	0.178	0.173	0.175	0.139	0.160	0.29	0.52	0.46	0.30
B	0.6	4	50	0.284	0.289	0.236	0.270	0.220	0.133	0.22	0.34	0.33	0.21

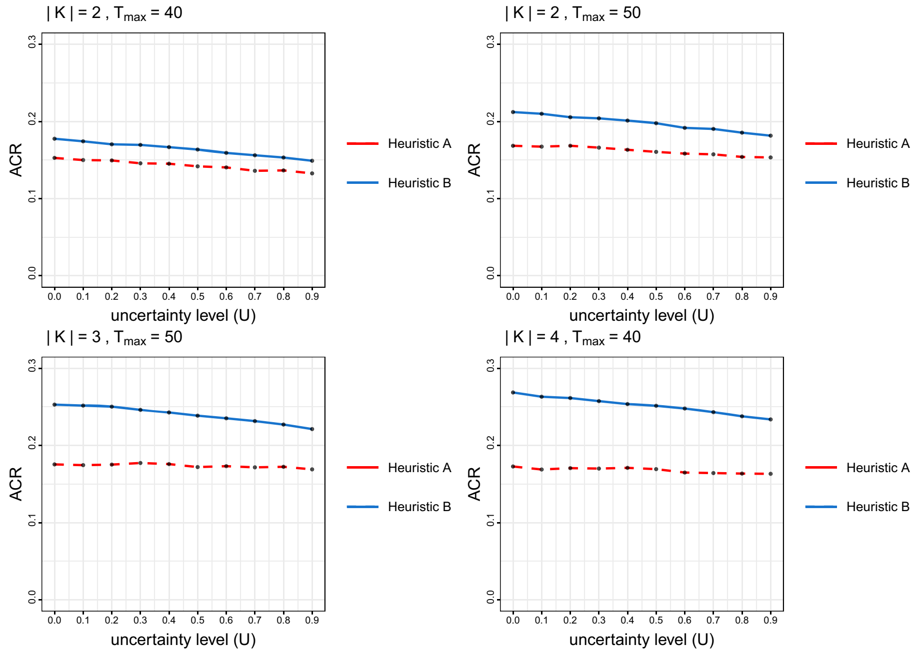

Fig. 7 Impact of uncertainty level on ACR on Heuristics A and B

the total distance traveled increases from 479 to 559 km, but the ACR decreases from 0.241 to 0.231 and MCR from 0.203 to 0.197.

5.3.3 Improvement in pre-simulation computations

In this section, we investigate how we can further improve the results, provided that more sophisticated computational tools and resources are available to select sites and determine routes in the initial planning phase. In Fig. 4, we showed that site selection and routing decisions are calculated separately in pre-simulation computations using proposed heuristics. For a similar problem, Balcik (2017) proposed a MIP model called the Selective Assessment Routing Problem (SARP), in which the site selection and routing decisions are made in an integrated manner. The SARP considers a coverage type objective to ensure balanced coverage of the community groups. This balanced coverage is ensured by defining an objective that maximizes the minimum coverage ratio across the community groups. The main constraints of SARP are limiting the number of routes by the available number of assessment teams and ensure that each route is completed within the allowed duration.

We use a modified version of the original SARP and feed the results of the modified SARP into our simulation model and compare the results with our best heuristic (i.e., Heuristic D). We call the new heuristic Heuristic D*. The modification on the original SARP model is due to sticking to the same assumptions with other heuristics. The main modifications are as follows (see Appendix A for the modified SARP formulation):

- uncertainty with respect to the existence of community groups: In the original SARP the existence of community groups is known in advance. Therefore, the α_{ig} is either 0 or 1.

Table 7 Evaluation of the performance of Heuristics C and D

Heuristic	U	$\|K\|$	T_{max}	r	τ	ρ	CR_{g_1}	CR_{g_2}	CR_{g_3}	ACR	MCR	$CVCR$	Traveled Distance (km)	$CVCR$ per cluster			
														cluster 1	cluster 2	cluster 3	cluster 4
C	0	3	40	10	_	_	0.246	0.240	0.198	0.228	0.189	0.143	470	0.202	0.366	0.461	0.226
D	0	3	40		1	2	0.255	0.251	0.216	0.241	0.203	0.129	479	0.182	0.341	0.424	0.211
	0	3	40			3	0.253	0.254	0.207	0.238	0.199	0.137	477	0.189	0.338	0.449	0.217
	0	3	40		2	2	0.249	0.245	0.206	0.233	0.195	0.135	471	0.194	0.360	0.432	0.219
	0	3	40			3	0.248	0.246	0.204	0.233	0.195	0.130	471	0.204	0.365	0.433	0.212
C	0	3	40	15	_	_	0.248	0.244	0.200	0.231	0.191	0.148	474	0.205	0.368	0.446	0.236
D	0	3	40		1	2	0.256	0.251	0.214	0.240	0.204	0.111	491	0.188	0.359	0.425	0.226
	0	3	40			3	0.257	0.253	0.210	0.240	0.202	0.118	483	0.188	0.338	0.435	0.221
	0	3	40		2	2	0.249	0.245	0.203	0.233	0.195	0.127	479	0.194	0.363	0.397	0.222
	0	3	40			3	0.245	0.246	0.205	0.232	0.195	0.122	479	0.197	0.361	0.409	0.217
C	0	3	40	20	_	_	0.246	0.240	0.202	0.229	0.194	0.136	477	0.204	0.356	0.432	0.227
D	0	3	40		1	2	0.255	0.254	0.211	0.240	0.203	0.121	507	0.178	0.327	0.428	0.204
	0	3	40			3	0.256	0.253	0.209	0.240	0.202	0.130	487	0.181	0.328	0.416	0.207
	0	3	40		2	2	0.245	0.248	0.205	0.233	0.196	0.125	481	0.203	0.350	0.416	0.208
	0	3	40			3	0.250	0.242	0.203	0.232	0.196	0.138	482	0.194	0.351	0.420	0.227

Table 7 continued

Heuristic	U	$\|K\|$	T_{max}	r	τ	ρ	CR_{g_1}	CR_{g_2}	CR_{g_3}	ACR	MCR	$CVCR$	Traveled Distance (km)	$CVCR$ per cluster			
														cluster 1	cluster 2	cluster 3	cluster 4
C	0	3	40	25	_	_	0.243	0.241	0.200	0.228	0.191	0.138	483	0.196	0.361	0.501	0.254
D	0	3	40		1	2	0.256	0.255	0.204	0.238	0.200	0.123	526	0.165	0.354	0.447	0.234
	0	3	40			3	0.257	0.250	0.206	0.238	0.199	0.129	502	0.188	0.355	0.421	0.235
	0	3	40		2	2	0.248	0.245	0.201	0.231	0.194	0.124	495	0.189	0.355	0.459	0.223
	0	3	40			3	0.247	0.245	0.203	0.232	0.196	0.123	488	0.191	0.358	0.462	0.214
C	0	3	40	40	_	_	0.245	0.243	0.197	0.228	0.188	0.147	508	0.194	0.384	0.459	0.221
D	0	3	40		1	2	0.245	0.246	0.203	0.231	0.197	0.126	559	0.168	0.417	0.432	0.216
	0	3	40			3	0.243	0.242	0.204	0.230	0.196	0.123	544	0.181	0.386	0.388	0.219
	0	3	40		2	2	0.245	0.248	0.201	0.231	0.193	0.132	518	0.193	0.383	0.457	0.220
	0	3	40			3	0.244	0.242	0.204	0.230	0.194	0.126	514	0.198	0.361	0.440	0.224
C	0	3	50	10	_	_	0.290	0.299	0.234	0.274	0.227	0.146	542	0.208	0.344	0.381	0.217
D	0	3	50		1	2	0.318	0.314	0.261	0.298	0.252	0.117	544	0.173	0.305	0.357	0.203
	0	3	50			3	0.315	0.315	0.251	0.293	0.244	0.128	549	0.172	0.315	0.370	0.213
	0	3	50		2	2	0.298	0.300	0.240	0.279	0.231	0.137	544	0.201	0.318	0.399	0.216
	0	3	50			3	0.305	0.296	0.238	0.280	0.229	0.137	542	0.194	0.328	0.370	0.204
C	0	3	50	15	_	_	0.297	0.295	0.237	0.276	0.229	0.143	552	0.206	0.336	0.391	0.214
D	0	3	50		1	2	0.320	0.322	0.256	0.300	0.254	0.135	564	0.165	0.316	0.376	0.206
	0	3	50			3	0.321	0.319	0.250	0.297	0.246	0.136	563	0.177	0.332	0.380	0.212
	0	3	50		2	2	0.300	0.306	0.243	0.283	0.235	0.136	561	0.195	0.338	0.393	0.209
	0	3	50			3	0.304	0.303	0.239	0.282	0.233	0.135	557	0.208	0.337	0.391	0.203
C	0	3	50	20	_	_	0.297	0.303	0.238	0.279	0.231	0.145	557	0.198	0.339	0.363	0.206
D	0	3	50		1	2	0.324	0.321	0.250	0.298	0.255	0.129	585	0.163	0.322	0.340	0.203
	0	3	50			3	0.324	0.320	0.247	0.297	0.247	0.135	573	0.158	0.323	0.360	0.201
	0	3	50		2	2	0.302	0.310	0.240	0.284	0.235	0.126	567	0.184	0.332	0.368	0.201
	0	3	50			3	0.302	0.308	0.240	0.283	0.235	0.126	562	0.190	0.331	0.360	0.201

Table 7 continued

Heuristic	U	$\|K\|$	T_{max}	r	τ	ρ	CR_{g_1}	CR_{g_2}	CR_{g_3}	ACR	MCR	$CVCR$	Traveled Distance (km)	$CVCR$ per cluster			
														cluster 1	cluster 2	cluster 3	cluster 4
C	0	3	50	25	_	_	0.293	0.297	0.237	0.275	0.231	0.145	568	0.197	0.345	0.431	0.224
D	0	3	50		1	2	0.315	0.320	0.248	0.295	0.255	0.134	611	0.161	0.344	0.422	0.209
	0	3	50			3	0.317	0.320	0.247	0.295	0.248	0.142	589	0.160	0.340	0.429	0.195
	0	3	50		2	2	0.299	0.307	0.241	0.282	0.236	0.135	578	0.190	0.338	0.395	0.196
	0	3	50			3	0.300	0.305	0.241	0.282	0.234	0.145	572	0.199	0.330	0.408	0.211
C	0	3	50	40	_	_	0.295	0.295	0.238	0.276	0.230	0.143	593	0.201	0.340	0.391	0.214
D	0	3	50		1	2	0.312	0.306	0.244	0.287	0.241	0.122	669	0.147	0.332	0.355	0.203
	0	3	50			3	0.311	0.311	0.243	0.288	0.239	0.133	643	0.159	0.334	0.353	0.207
	0	3	50		2	2	0.295	0.306	0.241	0.281	0.234	0.128	613	0.193	0.334	0.394	0.210
	0	3	50			3	0.298	0.303	0.241	0.281	0.232	0.125	606	0.191	0.320	0.376	0.197
C	0	4	40	10	_	_	0.308	0.309	0.256	0.291	0.243	0.134	674	0.206	0.349	0.339	0.214
D	0	4	40		1	2	0.344	0.328	0.274	0.316	0.266	0.130	678	0.174	0.323	0.324	0.204
	0	4	40			3	0.324	0.322	0.267	0.304	0.258	0.125	683	0.193	0.329	0.300	0.208
	0	4	40		2	2	0.316	0.314	0.257	0.296	0.249	0.135	677	0.194	0.337	0.312	0.204
	0	4	40			3	0.308	0.313	0.254	0.292	0.245	0.134	676	0.197	0.343	0.328	0.210

Table 7 continued

Heuristic	U	$\|K\|$	T_{max}	r	τ	ρ	CR_{g_1}	CR_{g_2}	CR_{g_3}	ACR	MCR	$CVCR$	Traveled Distance (km)	$CVCR$ per cluster			
														cluster 1	cluster 2	cluster 3	cluster 4
C	0	4	40	15	_	_	0.311	0.309	0.251	0.290	0.244	0.136	681	0.192	0.337	0.326	0.217
D	0	4	40		1	2	0.337	0.336	0.277	0.317	0.269	0.114	687	0.179	0.322	0.312	0.194
	0	4	40			3	0.325	0.323	0.268	0.305	0.259	0.112	690	0.177	0.316	0.300	0.210
	0	4	40		2	2	0.308	0.312	0.260	0.293	0.250	0.112	683	0.197	0.321	0.308	0.193
	0	4	40			3	0.307	0.309	0.255	0.290	0.247	0.110	681	0.195	0.325	0.306	0.200
C	0	4	40	20	_	_	0.309	0.312	0.253	0.292	0.245	0.135	687	0.202	0.320	0.336	0.215
D	0	4	40		1	2	0.337	0.339	0.268	0.315	0.269	0.136	709	0.157	0.313	0.327	0.200
	0	4	40			3	0.328	0.324	0.265	0.306	0.257	0.128	701	0.183	0.327	0.325	0.193
	0	4	40		2	2	0.314	0.313	0.257	0.295	0.248	0.129	691	0.204	0.328	0.331	0.195
	0	4	40			3	0.311	0.318	0.254	0.294	0.247	0.132	692	0.207	0.325	0.319	0.217
C	0	4	40	25	_	_	0.307	0.313	0.254	0.291	0.246	0.133	695	0.203	0.379	0.347	0.227
D	0	4	40		1	2	0.333	0.337	0.267	0.312	0.263	0.117	729	0.168	0.364	0.333	0.196
	0	4	40			3	0.322	0.331	0.261	0.305	0.255	0.119	714	0.186	0.339	0.329	0.202
	0	4	40		2	2	0.312	0.315	0.256	0.294	0.249	0.116	699	0.186	0.347	0.318	0.195
	0	4	40			3	0.308	0.313	0.257	0.293	0.247	0.115	700	0.198	0.337	0.328	0.207
C	0	4	40	40	_	_	0.309	0.308	0.256	0.291	0.243	0.127	725	0.208	0.340	0.336	0.236
D	0	4	40		1	2	0.332	0.327	0.263	0.307	0.258	0.134	787	0.152	0.327	0.329	0.208
	0	4	40			3	0.317	0.319	0.263	0.299	0.254	0.126	769	0.173	0.333	0.321	0.201
	0	4	40		2	2	0.308	0.315	0.257	0.293	0.247	0.128	726	0.207	0.340	0.321	0.202
	0	4	40			3	0.312	0.312	0.255	0.293	0.249	0.122	731	0.211	0.336	0.304	0.200

Table 7 continued

Heuristic	U	$\|K\|$	T_{max}	r	τ	ρ	CR_{g_1}	CR_{g_2}	CR_{g_3}	ACR	MCR	$CVCR$	Traveled Distance (km)	$CVCR$ per cluster cluster 1	cluster 2	cluster 3	cluster 4
C	0	4	50	10	_	_	0.315	0.315	0.259	0.296	0.243	0.138	679	0.218	0.345	0.322	0.220
D	0	4	50		1	2	0.361	0.359	0.291	0.337	0.284	0.113	700	0.167	0.305	0.303	0.200
	0	4	50			3	0.334	0.328	0.275	0.312	0.265	0.117	693	0.196	0.298	0.314	0.198
	0	4	50		2	2	0.318	0.318	0.260	0.298	0.253	0.113	681	0.195	0.329	0.320	0.213
	0	4	50			3	0.313	0.313	0.259	0.295	0.249	0.112	684	0.202	0.332	0.304	0.199
C	0	4	50	15	_	_	0.311	0.311	0.255	0.292	0.245	0.136	686	0.206	0.335	0.347	0.219
D	0	4	50		1	2	0.363	0.370	0.289	0.341	0.285	0.127	713	0.172	0.317	0.328	0.194
	0	4	50			3	0.339	0.338	0.279	0.319	0.271	0.126	704	0.189	0.328	0.324	0.193
	0	4	50		2	2	0.321	0.317	0.261	0.299	0.253	0.127	689	0.205	0.324	0.325	0.207
	0	4	50			3	0.317	0.317	0.260	0.298	0.251	0.134	687	0.187	0.330	0.313	0.208
C	0	4	50	20	_	_	0.320	0.316	0.255	0.297	0.248	0.137	692	0.206	0.336	0.350	0.214
D	0	4	50		1	2	0.358	0.370	0.285	0.338	0.286	0.127	735	0.155	0.318	0.317	0.202
	0	4	50			3	0.342	0.344	0.275	0.320	0.272	0.123	721	0.174	0.315	0.313	0.200
	0	4	50		2	2	0.327	0.323	0.261	0.304	0.255	0.120	701	0.184	0.325	0.320	0.209
	0	4	50			3	0.324	0.320	0.260	0.301	0.254	0.123	700	0.199	0.315	0.331	0.206
C	0	4	50	25	_	_	0.313	0.318	0.259	0.297	0.252	0.127	707	0.195	0.360	0.331	0.220
D	0	4	50		1	2	0.366	0.366	0.287	0.340	0.284	0.129	752	0.160	0.305	0.330	0.196
	0	4	50			3	0.342	0.344	0.272	0.319	0.268	0.130	736	0.171	0.352	0.322	0.190
	0	4	50		2	2	0.322	0.324	0.260	0.302	0.253	0.135	706	0.192	0.353	0.310	0.210
	0	4	50			3	0.319	0.322	0.260	0.300	0.252	0.128	706	0.196	0.328	0.315	0.208
C	0	4	50	40	_	_	0.314	0.318	0.261	0.297	0.249	0.135	729	0.197	0.357	0.329	0.205
D	0	4	50		1	2	0.360	0.362	0.281	0.334	0.278	0.122	830	0.147	0.352	0.324	0.203
	0	4	50			3	0.334	0.341	0.274	0.316	0.269	0.111	797	0.175	0.322	0.329	0.202
	0	4	50		2	2	0.327	0.324	0.258	0.303	0.252	0.122	736	0.198	0.335	0.310	0.202
	0	4	50			3	0.314	0.321	0.262	0.299	0.253	0.123	746	0.209	0.321	0.325	0.210

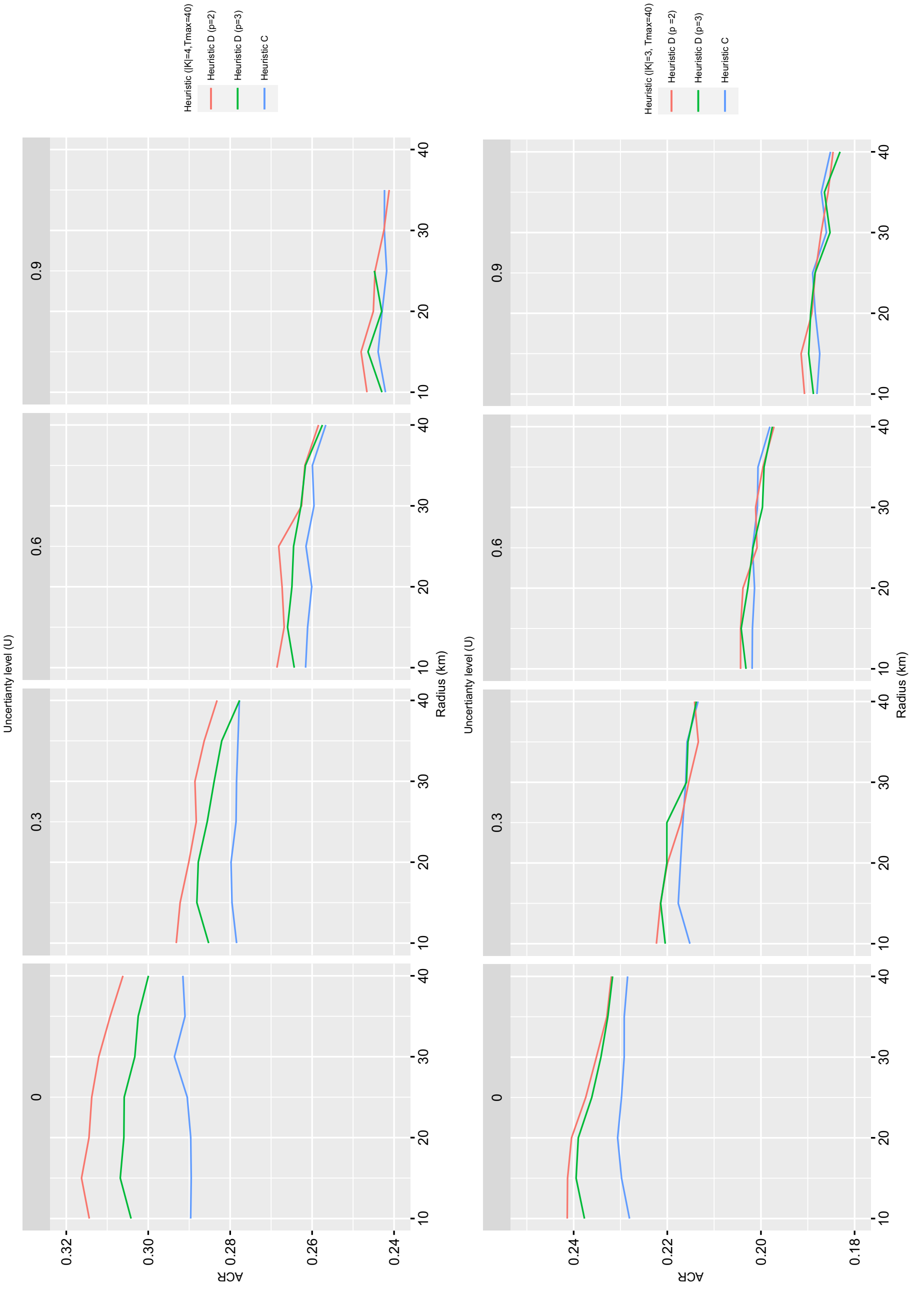

Fig. 8 Impact of uncertainty and radius on ACR in Heuristics C and D

Table 8 Evaluation of the performance of Heuristics D and D*

U	$\|K\|$	T_{max}	r	τ	ρ	Heuristic	CR_{g_1}	CR_{g_2}	CR_{g_3}	ACR	MCR	$CVCR$
0	3	40	10	1	2	D	0.453	0.475	0.479	0.469	0.397	0.128
0	3	40				D*	0.581	0.606	0.567	0.585	0.507	0.110
0	3	40			3	D	0.448	0.454	0.463	0.455	0.390	0.127
0	3	40				D*	0.582	0.615	0.572	0.590	0.505	0.120
0	3	40		2	2	D	0.430	0.441	0.474	0.448	0.383	0.126
0	3	40				D*	0.577	0.586	0.567	0.577	0.504	0.107
0	3	40			3	D	0.423	0.432	0.452	0.436	0.377	0.120
0	3	40				D*	0.578	0.599	0.579	0.585	0.515	0.104
0	3	40	20	1	2	D	0.495	0.511	0.522	0.509	0.443	0.112
0	3	40				D*	0.615	0.635	0.598	0.616	0.541	0.104
0	3	40			3	D	0.461	0.479	0.486	0.475	0.404	0.127
0	3	40				D*	0.619	0.630	0.605	0.618	0.547	0.098
0	3	40		2	2	D	0.444	0.449	0.474	0.456	0.392	0.120
0	3	40				D*	0.596	0.612	0.604	0.604	0.530	0.105
0	3	40			3	D	0.438	0.450	0.481	0.456	0.389	0.128
0	3	40				D*	0.591	0.612	0.600	0.601	0.531	0.100
0	2	50	10	1	2	D	0.462	0.474	0.477	0.471	0.396	0.134
0	2	50				D*	0.527	0.544	0.482	0.518	0.441	0.125
0	2	50			3	D	0.445	0.465	0.473	0.461	0.392	0.129
0	2	50				D*	0.538	0.538	0.497	0.524	0.454	0.111
0	2	50		2	2	D	0.430	0.447	0.465	0.447	0.380	0.131
0	2	50				D*	0.528	0.533	0.500	0.520	0.452	0.112
0	2	50			3	D	0.433	0.447	0.472	0.450	0.384	0.129
0	2	50				D*	0.521	0.528	0.499	0.516	0.447	0.111
0	2	50	20	1	2	D	0.486	0.498	0.508	0.497	0.433	0.112
0	2	50				D*	0.549	0.572	0.500	0.540	0.469	0.109
0	2	50			3	D	0.477	0.489	0.495	0.487	0.421	0.115
0	2	50				D*	0.538	0.557	0.513	0.536	0.469	0.107
0	2	50		2	2	D	0.442	0.452	0.488	0.461	0.395	0.123
0	2	50				D*	0.541	0.538	0.520	0.533	0.464	0.108
0	2	50			3	D	0.441	0.455	0.489	0.462	0.391	0.131
0	2	50				D*	0.545	0.537	0.520	0.534	0.465	0.108
0.3	3	40	10	1	2	D	0.455	0.464	0.467	0.462	0.394	0.125
0.3	3	40				D*	0.558	0.555	0.520	0.545	0.470	0.112
0.3	3	40			3	D	0.438	0.434	0.443	0.439	0.393	0.125
0.3	3	40				D*	0.568	0.587	0.536	0.564	0.487	0.115
0.3	3	40		2	2	D	0.430	0.441	0.458	0.443	0.378	0.128

Table 8 continued

U	$\|K\|$	T_{max}	r	τ	ρ	Heuristic	CR_{g_1}	CR_{g_2}	CR_{g_3}	ACR	MCR	$CVCR$
0.3	3	40				D*	0.555	0.575	0.523	0.551	0.471	0.119
0.3	3	40			3	D	0.427	0.433	0.461	0.440	0.377	0.126
0.3	3	40				D*	0.555	0.576	0.550	0.560	0.486	0.114
0.3	3	40	20	1	2	D	0.487	0.506	0.519	0.504	0.435	0.120
0.3	3	40				D*	0.573	0.592	0.548	0.571	0.496	0.110
0.3	3	40			3	D	0.455	0.466	0.486	0.469	0.399	0.127
0.3	3	40				D*	0.568	0.593	0.554	0.572	0.496	0.112
0.3	3	40		2	2	D	0.440	0.449	0.488	0.459	0.388	0.135
0.3	3	40				D*	0.568	0.584	0.557	0.570	0.499	0.107
0.3	3	40			3	D	0.443	0.450	0.465	0.453	0.388	0.122
0.3	3	40				D*	0.568	0.583	0.557	0.569	0.494	0.112
0.3	2	50	10	1	2	D	0.441	0.456	0.471	0.456	0.393	0.122
0.3	2	50				D*	0.499	0.512	0.440	0.484	0.412	0.121
0.3	2	50			3	D	0.446	0.460	0.472	0.459	0.397	0.121
0.3	2	50				D*	0.497	0.511	0.442	0.483	0.413	0.124
0.3	2	50		2	2	D	0.428	0.438	0.464	0.444	0.380	0.127
0.3	2	50				D*	0.495	0.497	0.468	0.487	0.425	0.105
0.3	2	50			3	D	0.424	0.434	0.454	0.437	0.374	0.128
0.3	2	50				D*	0.496	0.497	0.452	0.482	0.414	0.117
0.3	2	50	20	1	2	D	0.467	0.479	0.479	0.475	0.410	0.117
0.3	2	50				D*	0.513	0.532	0.449	0.498	0.424	0.123
0.3	2	50			3	D	0.456	0.467	0.494	0.472	0.407	0.122
0.3	2	50				D*	0.503	0.521	0.456	0.493	0.425	0.117
0.3	2	50		2	2	D	0.433	0.443	0.481	0.452	0.388	0.124
0.3	2	50				D*	0.507	0.520	0.457	0.495	0.424	0.119
0.3	2	50			3	D	0.434	0.449	0.474	0.452	0.387	0.127
0.3	2	50				D*	0.506	0.521	0.451	0.493	0.416	0.128
0.6	3	40	10	1	2	D	0.443	0.452	0.470	0.455	0.391	0.125
0.6	3	40				D*	0.506	0.548	0.485	0.513	0.440	0.122
0.6	3	40			3	D	0.436	0.454	0.470	0.453	0.387	0.128
0.6	3	40				D*	0.533	0.556	0.497	0.528	0.450	0.123
0.6	3	40		2	2	D	0.421	0.430	0.463	0.438	0.369	0.136
0.6	3	40				D*	0.529	0.554	0.493	0.526	0.452	0.115
0.6	3	40			3	D	0.427	0.425	0.458	0.437	0.376	0.121
0.6	3	40				D*	0.531	0.557	0.493	0.527	0.448	0.124
0.6	3	40	20	1	2	D	0.476	0.494	0.506	0.492	0.422	0.121
0.6	3	40				D*	0.538	0.562	0.484	0.528	0.449	0.123
0.6	3	40			3	D	0.460	0.464	0.492	0.472	0.401	0.127
0.6	3	40				D*	0.532	0.561	0.499	0.531	0.460	0.113

Table 8 continued

U	$\|K\|$	T_{max}	r	τ	ρ	Heuristic	CR_{g_1}	CR_{g_2}	CR_{g_3}	ACR	MCR	$CVCR$
0.6	3	40		2	2	D	0.445	0.451	0.489	0.461	0.392	0.133
0.6	3	40				D*	0.535	0.565	0.502	0.534	0.459	0.118
0.6	3	40			3	D	0.434	0.443	0.482	0.453	0.388	0.127
0.6	3	40				D*	0.537	0.562	0.506	0.535	0.462	0.113
0.6	2	50	10	1	2	D	0.422	0.429	0.448	0.433	0.371	0.125
0.6	2	50				D*	0.473	0.486	0.402	0.454	0.380	0.134
0.6	2	50			3	D	0.424	0.427	0.463	0.438	0.371	0.130
0.6	2	50				D*	0.471	0.485	0.414	0.457	0.387	0.124
0.6	2	50		2	2	D	0.412	0.417	0.440	0.423	0.362	0.125
0.6	2	50				D*	0.466	0.480	0.415	0.454	0.383	0.128
0.6	2	50			3	D	0.416	0.421	0.443	0.427	0.363	0.126
0.6	2	50				D*	0.464	0.476	0.422	0.454	0.384	0.128
0.6	2	50	20	1	2	D	0.439	0.445	0.448	0.444	0.380	0.124
0.6	2	50				D*	0.484	0.496	0.411	0.464	0.389	0.131
0.6	2	50			3	D	0.434	0.441	0.456	0.444	0.383	0.117
0.6	2	50				D*	0.479	0.481	0.416	0.459	0.387	0.126
0.6	2	50		2	2	D	0.427	0.425	0.460	0.437	0.373	0.126
0.6	2	50				D*	0.479	0.490	0.409	0.459	0.387	0.128
0.6	2	50			3	D	0.414	0.428	0.467	0.436	0.373	0.128
0.6	2	50				D*	0.473	0.483	0.411	0.456	0.383	0.134

In the modified SARP, α_{ig} represents the expected value of visiting community group g in site i.

- minimum target number of visiting each community group within each cluster: We add a new constraint to the original SARP to ensure that we visit each community group a certain number of times (l_{gc}) within each cluster.

This comparison helps decision-makers see, in cases of providing more advanced computational resources, to what extent they can improve their plan. Table 8 presents the comparison of Heuristic D with Heuristic D*. We observe that in lower uncertainty levels, Heuristic D* shows a better performance than Heuristic D. However, the better performance of Heuristic D* decreases when the level of uncertainty increases. In other words, the results of Heuristic D* deteriorate faster by increasing the uncertainty level. This deterioration can be seen in Fig. 9. We also see that, the average values of ACR and MCR of Heuristic D* (0.527 and 0.454, respectively), are relatively close to average values of ACR and MCR of Heuristic D (0.456 and 0.391,respectively). Note that in this section we only consider a network of 30 nodes (clusters 1 and 2). The reason to select the subset of affected sites is the limitation we have in solving the MIP optimally.

Gralla and Goentzel (2018) recommend that practice-driven heuristics can be used as a planning approach when optimization is not feasible. Our results also support this idea. As it is based on a practice-driven methods and rules, Heuristic D provides reasonable results compared to Heuristic D* while it is easier to be implemented in practice. However, our practice-driven heuristics' main challenges are their greedy natures, which do not usually

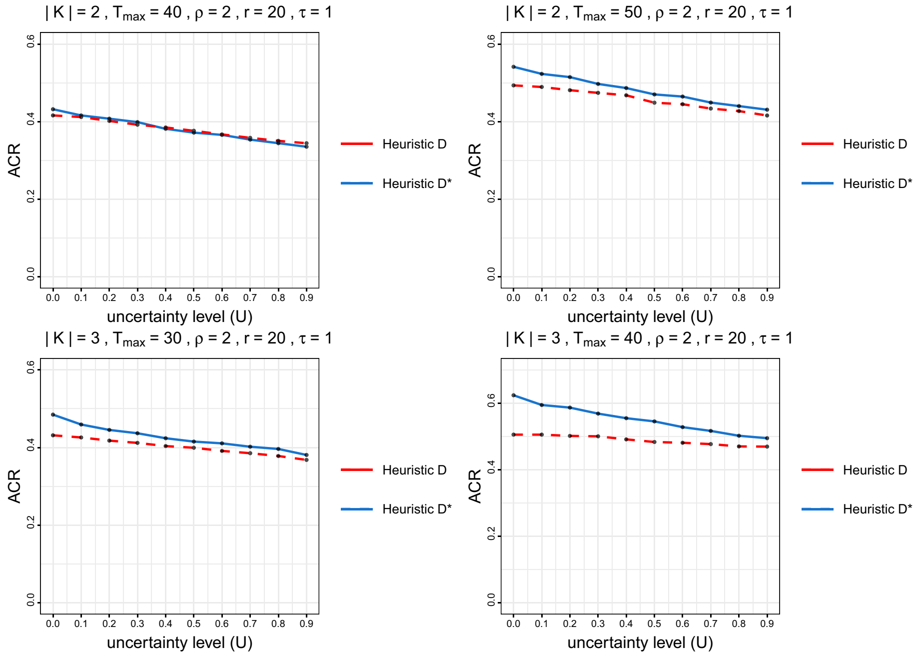

Fig. 9 Impact of uncertainty level on ACR on Heuristics D and D*

produce an optimal solution but may find solutions that approximate a globally optimal solution in a reasonable amount of time.

6 Conclusion

In this study, we provide methods and pre-defined rules to assist and improve the decision-making process in the field visit planning of the RNA stage of humanitarian relief, where assessment teams aim to choose and visit sites that involve different community groups. Reviewing practical reports shows that time and resources are limited, which hampers using sophisticated decision-making methods. For this purpose, we developed different heuristic algorithms inspired by practical humanitarian reports that are easily implementable in practice. Each combination of methods and rules for site selection and routing decisions was named as a heuristic. We evaluated the performance of these heuristics by changing the critical parameters and enhanced our best heuristic by using an optimization approach. Considering the inherent uncertainty in various input data such as travel time, community assessment time, inaccessibility of sites, and unavailability of community groups is an important and yet challenging factor while planning the field visit. We incorporated these uncertain parameters within a simulation model, which enabled us to analyze our results under different levels of uncertainties and in a reasonable amount of computational time. Our work consists of two central parts:

First, there is a great need for decision support in practice, given the current situation of using a less systematic procedure in the field. In this situation, even applying simple methods, which can be implemented using accessible software (e.g., Microsoft Excel) and a paper map of the field, can improve the assessment plan significantly by increasing the accuracy of the plan and efficiency of the available resources. Using these methods in practice and observing their performance by practitioners pave the way for decision-makers to trust more complex optimization-based approaches.

Second, we incorporated all the heuristics in a simulation model. Designing this model was in line with the primary approach of this paper, which was to show the trade-off between using different methods and having different levels of resources such as time and number of assessment teams. We investigated the impact of various uncertain factors ranging from accessibility of sites and availability of community groups to travel time and assessment time. We showed how much these uncertainties can deteriorate the results in terms of community coverage ratios.

6.1 Managerial implications

As indicated by the results of the computational experiments, choosing which heuristic to follow for field visit planning has a substantial impact on achieving higher community group coverage. Selecting sites based on the approximate knowledge of the existence of community groups leads to significantly better results in comparison with selecting sites randomly. This, of course, comes at the cost of gathering more information related to the location of community groups. Further, updating the original routes in case of inaccessibility and unavailability also improves the performance of the field visit plan. While updating the routes, it is important to take the allowed radius into account. Increasing the radius expands the total distance traveled, but this extra distance traveled after a certain limit does not necessarily increase coverage ratios and, in some cases, even decreases them.

Another important factor is uncertainties in travel time and community assessment time. These uncertainties adversely affect the results, no matter which heuristic is applied. However, the effects of these uncertainties are not the same on all heuristics. We see that, in general, the result of more sophisticated heuristics or, in other words, those requiring more information for planning the field visit, deteriorates more when the level of uncertainty increases. This factor becomes more important when the trade-off is to use a more advanced heuristic instead of a simpler heuristic in a highly uncertain environment, which in the end will not provide significantly different results.

6.2 Social implications

The number of natural disasters due to the increase in extreme weather events such as storms and floods is growing (Hoeppe 2016). Furthermore, the negative impacts of geophysical events such as earthquakes and tsunamis have been increasing due to socio-economic/demographic factors such as population growth and urbanization (Hoeppe 2016). Considering this devastating impact of disasters, enhancing the performance of humanitarian operations is becoming increasingly important. After the occurrence of a disaster, humanitarian agencies conduct various operations to assist the affected people. While there exists a large body of literature on last mile distribution problems, needs assessment operations have received little attention (Pamukcu and Balcik 2020). In fact, most studies focusing on relief distribution assume that the needs of different affected people are already known or can be estimated, and needs assessment operations are not specifically addressed (de la Torre et al. 2012). Providing timely and accurate information at the RNA stage is of vital importance for the success of disaster response by matching needs with the available resources effectively.

Having a successful needs assessment also leads to saving precious resources at a time of great need. This paper improves the disaster response by analyzing the performance of existing methods in literature to assist decision-makers in selecting the most suitable heuristic at the RNA stage. Improving disaster response contributes to using the limited financial resources more efficiently and effectively; therefore help can be provided to more people.

6.3 Research implications

Disasters are hard to anticipate with respect to their occurrence and consequences. Thus, humanitarian organizations often have to make decisions and plan for their operations in a highly uncertain environment (Liberatore et al. 2013). The RNA stage, which should be carried out immediately after the onset of a disaster to investigate the disaster's impact on affected communities, also includes various uncertain factors. In this paper, we evaluated the impact of various uncertain factors of the RNA stage within a simulation environment. These factors were accessibility of sites, availability of community groups, travel time, and assessment time. The proposed evaluation environment showed that these uncertainties significantly impact the field visit plan, i.e., site selection and routing decisions. We see that most of the studies addressing the RNA stage consider a deterministic environment for this stage. To the best of our knowledge, Balcik and Yanıkoğlu (2020) is the only study in the RNA literature which considers travel time as a single uncertain factor. Our numerical results reveal that optimization models do have the potential to improve decision-making, but they very much depend on the quality of the input data. We showed that adopting a deterministic model such as modified SARP cannot effectively address the highly uncertain environment. The humanitarian context has unique characteristics, and it is not easy to adopt a model to its condition; also, the adopted model should be carefully evaluated. On the one hand, there is criticism that current models are too complicated for practitioners. On the other hand, the current models need to consider important real world assumptions such as a wide range of uncertain factors.

6.4 Limitations

One of the main limitations of this study is that we evaluate the proposed methods' performance based on one case study specific to an earthquake setting. Also, in the present case study, we assume the likelihood of finding displaced and injured people is correlated with the location of the earthquake's epicenter, i.e., these groups are more available in sites closer to the epicenter. However, this assumption might be different in other settings. Furthermore, in our simulation algorithm, we assume once the assessment teams finalize the assessment of one site, they realize whether the following site in their planned route is accessible or not. This assumption is based on a pessimistic approach, where the communication infrastructure is impacted by the disaster, and the assessment teams receive updated information when they get closer to the affected area, observe the situation, and talk to local people. However, the assessment teams may receive updated information at other times of the assessment, e.g., either at the beginning of planning or traveling in the field.

6.5 Future research

Needs assessment operations have not been studied extensively in the humanitarian logistics field. This study was an initial step toward providing an evaluation of various methods for decision-makers. There are certain avenues for future research. First, in this paper we assumed assessment is done by a single organization. Future research can consider this issue by considering a cooperative multi-sector assessment with other agencies, in which agencies are able to share the resources and information. Furthermore, the heuristics we developed are based on and limited to the general principles of reports available from humanitarian agencies. Therefore, future studies depending on the availability of the information can formulate other heuristics and compare the results with each other. This can also go in the direction of considering other disaster settings. For instance, needs assessment for a flood might be different from the one for an earthquake. Finally, we showed that deterministic models cannot address the inherent uncertainties well and models that can consider these circumstances need to be developed. Balcik and Yanıkoğlu (2020) is a good first step toward addressing uncertainty by considering the travel time as an uncertain parameter in post-disaster networks and present a robust optimization model to tackle the uncertainty. Nevertheless, other uncertain factors such as inaccessibility of sites and unavailability of community groups need to be investigated further.

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Appendix A Integrated site selection and routing: Modified SARP Model

Balcik (2017) proposed the Selective Assessment Routing Problem (SARP), a mathematical formulation for purposive sampling strategy. The SARP determines site selection and vehicle routing decisions simultaneously. The SARP considers a coverage type objective in order to ensure balanced coverage of the selected community groups. This balanced coverage is ensured by defining an objective that maximizes the minimum coverage ratio of community groups. The purpose of this objective is to ensure that each community group is observed at least once, and further, if total available time permits, one community group can be observed multiple times. See Balcik (2017) for detailed information.

Below, we present a modified version of SARP. The main difference of the modified SARP with the original is twofold. First, in a modified version, the existence of community groups (α_{ig}) is assumed to be uncertain. Second, the network in the modified SARP is divided into a number of clusters , and we need to make sure that each community group is visited at least l_{gc} times in each cluster. Therefore to ensure this, we add another constraint to the original one, i.e., constraint (8).

The following notation is used to formulate the modified SARP Model:

Sets/indices

N = set of sites in the affected sites indexed by $i, j \in N_0$
$N_0 = N \cup \{0\}$ where $\{0\}$ is the depot
K = set of assessment teams indexed by $k \in K$
G = set of community groups indexed by $g \in G$
C = set of clusters indexed by $c \in C$

Parameters

α_{ig} = expected value of visiting group g when we visit node i
τ_g = sum of the expected values of visiting group g in the whole network
l_{gc} = target number of visiting community group g within cluster c
β_{ic} = 1 if node i belongs to the cluster c, and 0 otherwise
t_{ij} = travel time between nodes i and j
s_i = estimated assessment time at site i
T_{max} = total available time for each team

The decisions to be made are represented by the following sets of variables:

Decision Variables

x_{ijk} = 1 if team k visits site j after site i , and 0 otherwise
y_{ik} = 1 if team k visits site i , and 0 otherwise
u_i = sequence in which site i is visited
Z = minimum expected coverage ratio

Mathematical formulation

$$\text{maximize} \quad Z, \tag{3}$$

$$\text{s.t.} \quad Z \leq \sum_{i \in N} \sum_{k \in K} \alpha_{ig} y_{ik} / \tau_g \qquad \forall g \in G, \tag{4}$$

$$\sum_{j \in N_0} x_{ijk} = y_{ik} \qquad \forall i \in N_0, \forall k \in K, \tag{5}$$

$$\sum_{j \in N_0} x_{jik} = y_{ik} \qquad \forall i \in N_0, \forall k \in K, \tag{6}$$

$$\sum_{k \in K} y_{ik} \leq 1 \qquad \forall i \in N, \tag{7}$$

$$\sum_{k \in K} y_{0k} \leq K, \tag{8}$$

$$\sum_{i \in N_0} \sum_{j \in N_0} (t_{ij} + s_i) x_{ij} \leq T_{max} \qquad \forall k \in K, \tag{9}$$

$$\sum_{i \in N} \sum_{k \in K} \alpha_{ig} \beta_{ic} y_{ik} \geq l_{gc} \qquad \forall c \in C, \forall g \in G, \tag{10}$$

$$u_i - u_j + N x_{ijk} \leq N - 1 \qquad \forall i \in N, \forall j \in N (i \neq j), \forall k \in K, \tag{11}$$

$$Z \geq 0, \tag{12}$$

$$u_i \geq 0 \qquad \forall i \in N, \tag{13}$$

$$x_{ijk} \in \{0, 1\} \qquad \forall i \in N_0, \forall j \in N_0, \forall k \in K, \tag{14}$$

$$y_{ik} \in \{0, 1\} \qquad \forall i \in N_0, \forall k \in K. \tag{15}$$

The objective function (1) maximizes the minimum coverage ratio, which is defined by constraint (2). Constraints (3) and (4) ensure that an arc enters and leaves the depot and each selected site. Constraint (5) guaranties that each site is visited once at most. Constraint (6) limits the number of routes by the available number of assessment teams. Constraint (7) ensures that each route is completed within the allowed duration. Constraint(8) ensures that the number of selected sites to be visited within each cluster must be at least equal to the minimum expected target number. Constraint (9) is for eliminating subtours. Constraints (10)- (13) define the domains of the variables.

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