

Case study design for short-term predictable disasters

Case study
design for
short-term
disasters

Emilia Grass

Imperial College London, London, UK, and

Kathrin Fischer

Hamburg University of Technology, Hamburg, Germany

391

Received 6 November 2019
Revised 7 May 2020
Accepted 16 May 2020

Abstract

Purpose – The purpose of this work is the development of a structured case study design process for developing case studies in humanitarian logistics, in particular for short-term predictable disaster situations like floods and hurricanes. Moreover, useful public sources are presented in order to enable researchers to find relevant data for their case studies more easily.

Design/methodology/approach – A structured framework for case study design is set up, splitting the process into different steps and phases.

Findings – The framework is applied to an illustrative example, where case studies with different numbers and levels of detail of scenarios are designed based on the three-day forecast for hurricane Harvey in 2017. The corresponding solutions demonstrate the relevance of using as much forecast information as possible in case study building, and in particular in scenario design, in order to get useful and appropriate results.

Research limitations/implications – The case study design process is mostly suitable for short-term predictable disasters, but can also be adapted to other types of disasters. The process has been applied to one specific hurricane here which serves as an example.

Practical implications – Also for practitioners, the results of this work are highly relevant, as constructing realistic cases using real data will lead to more useful results. Moreover, it is taken into account in the case study design process that relief agencies are regularly confronted with disasters in certain areas and hence need to define the basic planning situation and parameters “once and for all” and on a long-term basis, whereas disaster specific data from forecasts are only available within a short time frame.

Originality/value – The new design process can be applied by researchers as well as practitioners, and the publicly available data sources will be useful to the community.

Keywords Framework for case study design, Data sources, Predictable disasters, Hurricane, Floods

Paper type Research paper

1. Introduction

Many people around the world suffer from catastrophic impacts of natural disasters like floods, storms and earthquakes every year. As techniques and quality of disaster forecasts continuously improve, aid agencies rely more and more on these predictions to focus on preventive measures. Excessive rainfall and hurricanes can be predicted about 72 h in advance, allowing relief organizations to take appropriate preparatory actions like initiating evacuations or providing temporary shelters. Floods and storms are of special concern here as these types of natural disasters can be predicted at short notice and occur most frequently with devastating consequences for the affected region. Moreover, there are areas where these types of disasters regularly occur, e.g. the Gulf of Mexico or Punjab in India being prone to hurricanes and flooding, respectively, and for which it is hence of particular interest to build a framework which can be used for analyzing such disaster situations once forecasts become available. Therefore, the focus of this work is mainly on short-term predictable disasters, i.e. more strategic problems as, e.g. strategic planning for seasonal hurricane preparation, have to be handled differently.

Despite of high-quality forecasts, the final outcome of a disaster remains unknown so that relief agencies have to make their preparation decisions under uncertainty. Quantitative



Journal of Humanitarian Logistics
and Supply Chain Management
Vol. 10 No. 3, 2020
pp. 391-419

© Emerald Publishing Limited
2042-6747

DOI [10.1108/JHLSCM-11-2019-0077](https://doi.org/10.1108/JHLSCM-11-2019-0077)

We would like to thank two anonymous referees for their many very helpful comments on a first version of this paper.

optimization models proposed in the humanitarian literature are intended to support decision makers in this challenging task. In most cases, scenarios are used to capture uncertainties associated with disasters. In the humanitarian context, a scenario can represent a plausible outcome and impact of a disaster, e.g. in terms of affected locations and destruction levels. The advantages of the proposed models are usually demonstrated by means of numerical examples and case studies. While, according to [Hong *et al.* \(2015\)](#), [Sabbaghtorkan *et al.* \(2020\)](#) and others, high data quality is essential to guarantee the appropriateness and validity of optimization models, the chosen data and scenarios in many cases are either not realistic or the data used are not publicly available, leading to results which are not useful in practice and for other researchers, in particular when also the number of scenarios considered is too small. As a consequence, relief agencies cannot integrate the solutions offered in the literature into their practical working processes. Moreover, when unrealistic data is used, this “jeopardizes the external validity of their (i.e. the researchers) results” ([Besiou *et al.*, \(2018\)](#)).

On the other hand, researchers argue that real data is often not publicly accessible ([Besiou *et al.*, \(2018\)](#) – “Data is the beast”, as [Starr and Van Wassenhove \(2014\)](#) as well as [Van Wassenhove and Pedraza Martinez \(2012\)](#) point out or that realistic and therefore large case studies cannot be solved within a reasonable time frame. As fast solutions are especially required if short-term forecasts are available, more efficient solution methods have to be developed as, e.g. the accelerated L-shaped method suggested by [Grass *et al.* \(2020\)](#); however, this is not the focus of this work. This paper addresses the first-mentioned challenge of gathering realistic data, with the aim of enabling researchers to study real-world problems. This also has the important advantage that results can be validated based on reality which is impossible when artificial or non-realistic data is used. Moreover, it is in line with the requirement formulated by [Besiou *et al.* \(2018\)](#) who state that a community (of researchers) was needed “that opts to work on these real problems instead of inventing hypothetical problems that do not reflect the realities of humanitarian operations nor the problems practitioners have to face.”

The main contributions of this paper are as follows. First, current literature on sudden-onset disasters with short-term forecasts is reviewed to highlight the scarceness of practical examples and realistic scenario selections. Second, a general framework for developing case studies for short-term predictable disasters and humanitarian logistics activities is suggested. Third, publicly available sources are provided where real data for short-term predictable disasters, namely floods and storms, can be found. As some authors state (see, e.g. [Turkeş and Sorensen, \(2019\)](#)) the data on which case studies are built should be shared in the community, but it might be even more useful to share the knowledge on where to find the relevant data. Fourth, possible negative consequences of defining an insufficient set of scenarios covering only a limited excerpt of the current situation due to the use of less detailed data are shown using different case studies based on historical forecasts for hurricane Harvey in 2017. Harvey was unique in its own way and is used as an illustrative example here. Last but not least, the case studies presented below might help in convincing practitioners of the reliability and usefulness of Operations Research (OR) approaches for humanitarian relief activities as short-term preparation is a highly relevant issue for relief agencies.

The paper is organized as follows: The next section reviews the humanitarian OR literature, focusing on flood- and hurricane-related case studies. Here, the widespread use of artificial data and limited numbers of scenarios is highlighted. In [Section 3](#) publicly available sources are listed where accurate input data can be gathered and a framework for case study construction is presented. Based on these sources of information realistic case studies are designed in [Section 4](#) with different numbers of scenarios. Numerical tests are carried out, revealing the significant impact of scenario definitions on solutions that can be achieved by an OR model in humanitarian logistics. Conclusions are given in [Section 5](#).

2. Literature review

In the OR literature on disaster management, often data settings are studied which either do not reflect a real planning situation or which excessively simplify the planning situation. There is only a modest number of case studies using realistic data and scenarios. This is mainly due to the fact that the availability of useful public data on disasters and related information is very limited (“Data is the beast”, [Van Wassenhove and Pedraza Martinez \(2012\)](#)). [Rottkemper \(2016\)](#) found about 20 publications on humanitarian logistics in which scenarios were used within the studied cases, but among those, only five used real data. Similarly, very recently also [Baharmand et al. \(2019\)](#) state that none of the papers they review on location-allocation models for disaster response “use cases or benchmark their results with real operations in the field.” However, recently some papers were published in which real data were used, see, e.g. [Pedraza-Martinez and Van Wassenhove \(2016\)](#) and the contributions in their respective special issue of JOM.

The literature review in the following concentrates on the preparation phase in disaster situations where short-term forecasts and warnings – and hence reactions to these warnings – are possible, as, e.g. floods and hurricanes. Many studies also have been published for hardly predictable disasters like earthquakes, e.g. [Noyan et al. \(2016\)](#), but those are not discussed here, as the preparation process in the case of earthquakes is totally different from the process for hurricanes ([Sabbaghtorkan et al., 2020](#)). The main advantage of using short-term forecasts is the possibility of evaluating optimization models and case study designs from the ex post perspective; moreover, optimized preparation decisions can be particularly useful in these situations, also for practitioners, and bad decisions usually are extremely harmful. Other phases of the disaster life cycle, in particular the post-disaster phase, are not considered here. For the disaster life cycle and extensive reviews of literature concerning the different phases, see [Altay and Green \(2006\)](#) and [Van Wassenhove and Pedraza Martinez \(2012\)](#).

Although the formulation of mathematical optimization models generally depends on the underlying problem, some studies do not consider a specific disaster situation (A similar observation is also made by [Sabbaghtorkan et al. \(2020\)](#) who point out that around 70% of the papers they considered for their literature review study “general” natural disasters, i.e. no specific disaster type). In [Fan and Liu \(2010\)](#), for example, the different scenarios for the destruction of links in a network and their probabilities are artificially generated without any relation to real-data settings or disaster types. [Liu et al. \(2009\)](#) take a similar approach. The same is the case for [Klibi et al. \(2013\)](#) who generate disaster scenarios which are plausible, but not based on real data, by a Monte-Carlo process, and for [Tricoire et al. \(2012\)](#) who also generate scenarios from distributions. [Bozorgi-Amiri et al. \(2012\)](#) generate scenarios randomly as well. For these contributions, a validation with respect to the actual contribution of the proposed model or method in real disaster settings does not take place.

There are some studies of flooding disasters which consider a specific disaster type, but take into account only few scenarios: [Chang et al. \(2007\)](#) use three different scenarios for different amounts of rainfall in their study of a flooding disaster. Similarly, [Wang and Huang \(2013\)](#) consider a hypothetical flood diversion situation and four flooding scenarios, modeling uncertainties by fuzzy sets. [Maqsood and Huang \(2013\)](#) also consider flood management and water diversion. In their case study, they consider seven different flood levels (scenarios), and, as Wang and Huang, three different regions to which water can be diverted. It will be shown below that a small number of simplified scenarios can lead to rather different (and lower quality) results than a larger number of scenarios; hence, such a limitation can mean a loss in usefulness of the respective approaches.

There are also some more realistic case studies to be found on flooding disasters: [Hu et al. \(2015\)](#) study waterlog disasters, in particular in Shanghai, and aim at locating rescue centers and pumps. Their case study is based on historical rainfall data, takes into account 22

districts and uses 17 scenarios, in which different risks are considered. An even larger number of scenarios (40) is constructed by [Alem et al. \(2016\)](#). They consider floods and landslides in Brazil, using realistic data from past incidents. Finally, an interesting new approach is presented by [Li et al. \(2018\)](#) who study the use of data from social media for the identification of areas which require particular rescue measures.

A similar situation regarding the use of scenarios can be observed with respect to publications on hurricanes: [Salmeron and Apte \(2010\)](#) integrate only five scenarios into their hurricane study, while [Davis et al. \(2013\)](#) use six scenarios. [Li et al. \(2011\)](#) limit their hurricane study to the county level and to three types of hurricanes. These authors also mention that more scenarios make the problem intractable, which of course is an important aspect; in order for an approach to be useful, it must be possible to solve the resulting cases within a limited time frame.

[Rawls and Turnquist \(2010, 2011\)](#), in their studies of pre-positioning relief items for hurricanes, take into account a set of 51 scenarios based on only 15 former hurricanes and study the area at the Gulf of Mexico which they structure into 30 nodes. Their case study is also used by [Lodree et al. \(2012\)](#) and by [Noyan \(2012\)](#). As was shown by [Grass et al. \(2020\)](#), a more detailed modeling of the area as well as the scenarios leads to very different – and more appropriate – results than those of [Rawls and Turnquist \(2010\)](#). (Note that, in contrast to [Grass et al. \(2020\)](#), where an efficient solution method is proposed and a strategic pre-positioning problem is considered, the focus in this work is on developing and presenting a framework for case study design, provide a list of data sources and to take concrete preparation measures for a specific hurricane forecast).

[Hong et al. \(2015\)](#) use the same scenarios and data as Rawls and Turnquist to test their approach to hurricane preparedness. In a second step, they further aggregate the data as in [Klibi and Martel \(2012\)](#) and aggregate the network from 30 to 16 nodes. Moreover, they describe a scenario generation process which does not so much rely on past data, but on choosing epicenters for disasters and modeling occurring destruction based on distances from that epicenter, based on GIS data. [Li et al. \(2012\)](#) base their study of hurricanes in North Carolina on a set of 33 real past hurricanes which required mass evacuation; the respective hurricane scenarios are integrated in their study which focuses on shelter location for evacuees.

Note that the input data used in most of the aforementioned studies is either partially or completely hypothetical. Even if a larger number of scenarios is generated, the corresponding data as, e.g. cost rates or demand, is often fictitious, resulting in solutions with limited applicability.

However, there are also different publications – although none on short-term predictable disasters – which use real data from different sources. An example is [Acimovic and Goentzel \(2016\)](#) who use publicly available UN data in their study of pre-positioning relief items. [Çelik et al. \(2015\)](#) use real data from the HAZUS database in their study on debris clearing after earthquakes, [Duran et al. \(2011\)](#) study pre-positioning and, among other sources, use the international *Emergency Events Database* EM-DAT in order to develop a network for the humanitarian organization CARE international.

However, often the data used is not publicly available. In a study on armed conflicts and their effect on humanitarian operations in Colombia by [Jola-Sanchez et al. \(2016\)](#) the authors use data collected from Colombian hospitals. [Jahre et al. \(2016\)](#) base their study on locating warehouses on (not publicly available) field data from the *United Nations High Commissioner for Refugees* (UNHCR). Field data exclusively collected from the *International Committee of the Red Cross* (ICRC) for the respective study are used by [Pedraza-Martinez and Van Wassenhove \(2013\)](#). [Stauffer et al. \(2016, 2018\)](#) use field data collected from the *International Federation of Red Cross and Red Crescent Societies* (IFRC).

Therefore, in the next chapter it is shown where real and publicly available data can be found in order to enable researchers to formulate and set up useful studies on humanitarian

relief activities without having to collect data in the field. The large relevance of such data is also highlighted by [Starr and Van Wassenhove \(2014\)](#), [Sabbaghtorkan et al. \(2020\)](#) and others. Moreover, a framework for case study construction for short-term predictable disasters is developed.

3. Case study design and data sources

A case study (or test case) in OR is different from case studies in qualitative research, as “test cases in OR are data repositories to replicate, validate and compare models and methods” ([Ferrer et al., 2018](#)); they are not used for theory building as it is the case in qualitative studies. It should be noted that recently [Turkès and Sørensen \(2019\)](#) published some standardized problem instances/case studies for the field of humanitarian logistics which can be used as “benchmark instances”. However, the approach taken in this section is aimed at giving researchers and practitioners the framework and sources of information they need to set up their own, individual case studies, e.g. for a particular planning problem as an approaching hurricane, and to show how this information can be used in case study development.

3.1 Case study design framework

The process diagram in [Figure 1](#) and the following framework is constructed to serve as a guideline for building such case studies for disaster-prone areas where catastrophic events may occur and for situations in which short-term predictions are possible. It may help researchers in building case studies for testing their methods in realistic settings and may also help practitioners in their preparation for actual hurricane or flood situations when short-term forecasts are available.

Framework for case study design

Step 0: Basic Information

In this step the general disaster setting for the case study is determined before a concrete disaster forecast is available.

- (1) Decide on the *disaster situation(s)* for which to derive a case study, e.g. hurricane or flood.
- (2) Decide on the relevant potentially vulnerable *area*, e.g. the US American Gulf region.

Step 1: Deterministic Information

In this step the general problem set up for the case study is defined before a concrete disaster forecast is available.

- (3) Decide on the *level of detail* to be used for
 - (a) The network (number of nodes),
 - (b) Characteristics of facilities,

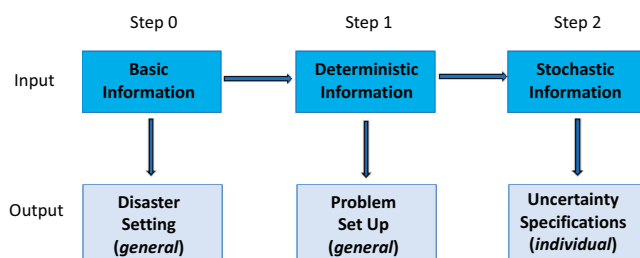


Figure 1.
Case study design
process

(c) Characteristics of relief items.

Note that the level of detail will have a strong influence on results on the one hand and will have to depend on information available, i.e. sources used, on the other.

- (4) Determine the relevant *deterministic information* (see Table 2), using e.g. sources from Table 1.

Step 2: Stochastic Information

In this step uncertain characteristics are specified when short-term forecasts are available for an individual disaster.

- (5) Determine *stochastic information* depending on how uncertainty is modeled, e.g. scenario-based or scenario-free approaches.
- (6) Scenario-free approach:
- (a) Determine information needed for the specific approach, e.g. expected value, chance constraints, distance-damage function.
- (b) Determine distribution function, e.g. normal or log-normal demand, uniform integer inventory.
- (7) Scenario-based approach:
- (a) Determine the number of scenarios to be considered (depending on the range and depth of available information); in the case of short-term predictable disasters, 20–30 scenarios may be sufficient. Take into account that the range of possible developments should be reflected in the scenarios.
- (b) Derive probabilities for the scenarios from available sources.

3.2 Data sources for case study design

One of the main challenges of designing a realistic case study is the collection of real data; Starr and Van Wassenhove (2014) state that “data, data and data” are the three key problems of the field. To support researchers in future case study construction, Table 1 provides a list of

Source	Content
Ahrens (2012)	Damage potential of hurricanes
American Red Cross/FEMA	National shelter system
Census Bureau	Population
Delft-FEWS	Flood prediction and warning system
EM-DAT	Historical disasters worldwide
GFS	Global predictions of temperature, wind, precipitation
HAZUS	Estimations of natural disaster impact
Huizinga et al. (2017b)	Damage potential of floods
HURDAT	Historical hurricanes in the Atlantic and Eastern Pacific Ocean
IBTrACS	Historical hurricanes
IFRC	Relief item catalogue
Mission and Relief Logistics	Container transportation costs
MSF	Relief item catalogue
NHC/NOAA	Hurricane prediction for US
SCEMD	Item specifications
UNHRD	Stockpiles of aid supplies
WPC/NOAA	Flood prediction for US

Table 1.
Data sources

Step	Set and input parameter	Specification	Data source
(0) Basic information			
Disaster setting	Disaster type	Depending on available forecasts	EM-DAT
Network	Set of nodes and arcs	Potentially vulnerable area	Google Maps
(1) Deterministic information			
Facilities	Facility locations Categories	Depending on facility category Shelter, POD, warehouse public building, mobile facility strategic, temporary	FEMA
	Capacities Costs	Concrete or categories Construction, maintenance, rental	FEMA
Relief items	Types Size Weight Costs Required quantities Available quantities	Depending on disaster Purchase, storage, disposal Depending on disaster	MSF, IFRC IFRC, SCEMD IFRC, SCEMD IFRC, SCEMD SCEMD UNHRD
Transportation	Transportation costs	Distance-, item-, mode- dependent	MSF, Mission and Relief Logistics
(2) Stochastic information			
Demand	Quantity of relief items	Depending on disaster type	HAZUS, SCEMD, CB, NOAA Huizinga et al. (2017a)
Network conditions	Number of evacuees Road capacities Facility conditions Transportation times	Depending on disaster type Depending on destruction level Destruction of shelters and stored relief items Depending on destruction level, congestion	HAZUS, CB HAZUS, Huizinga et al. (2017a) HAZUS, Huizinga et al. (2017a) , and Figure 4 HAZUS, Huizinga et al. (2017a)
Scenarios	Number and content	Based on past disasters Based on past forecasts	EM-DAT, IBTrACS, HURDAT NHC, WPC, Delf-FEWS, GFS NHC, WPC
	Probabilities		

Table 2.
Case study design
process for short-term
predictable disasters
with useful data
sources

publicly available sources where researchers can find relevant data for case studies concerning floods and storms. The respective websites are listed in the Reference section.

In the following, it is explained in more detail which data can be found in the different sources listed in [Table 1](#) and how these sources can be used to determine the model specific sets and parameters, see [Table 2](#). In the latter, the case study design process based on the above framework is shown for the preparation phase for short-term predictable disasters. Usually evacuation measures, shelters and storage of relief items play an important role in preparation for disasters. Depending on the underlying planning problem and the planner's goals, different input parameters and data sources are needed. For instance, routing evacuees out of a dangerous zone does generally require information on the network but not necessarily on demand for relief items. [Table 2](#) gives an overview of the most common sets and input parameters used in optimization models in preparation for disasters. The associated sources where relevant data can be found are taken from [Table 1](#).

3.2.1 Basic and deterministic information. In general, basic information on disaster type and potentially vulnerable area has to be gathered in Step 0. A comprehensive database

where all types of disasters and impacts are collected is the international disaster database EM-DAT. After defining the network consisting of nodes and arcs using, e.g. Google Maps, potential locations for opening facilities like warehouses or shelters can be identified in Step 1 in [Table 2](#). The underlying problem determines what type of facility with what kind of characteristics, e.g. capacities and costs, is considered. While pre-positioning models are concerned with facilities for storing relief items, evacuation models focus on shelters that are located in safe areas. The *American Red Cross* in corporation with the *Federal Emergency Management Agency* (FEMA) offers the National Shelter System where, e.g. locations, capacities and accessibility of shelters like public buildings, points-of-distribution (PODs), warehouses, etc. can be found. An Excel sheet with 70,386 locations and the corresponding specifications is constantly updated by [FEMA \(2019\)](#) and is publicly available. Especially for those aid agencies without own facilities this is a valuable source for determining potential sites that are tailored to their needs. Information is solely provided for the United States.

In the case of a natural disaster, different types of relief items are required. An extensive catalog of humanitarian commodities for disaster relief is available on web pages of *Doctors Without Borders* ([MSF, 2013](#)) and ([IFRC, 2016](#)). In the latter case, additional information like purchase price, weight and volume of each item is given. Similar specifications are listed in [SCEMD \(2007\)](#). The *United Nations Humanitarian Response Depot UNHRD (2020)* provides information on available stockpiles in their five globally located hubs. According to [MSF \(2016\)](#), costs for road transport are US\$ 0.50 per kg and km. Current container shipping rates can be obtained on request from the *Mission & Relief Logistics* organization.

Some of the basic and deterministic data is basically fixed and can be used for different hurricane and flooding outcomes, e.g. the disaster-prone area or cost rates for aid supplies or facilities remain the same for different hurricanes. Other input parameters like facility categories are case-dependent, e.g. shelters have to be opened for evacuees and warehouses are needed for storage of relief items. For a specific disaster type, as, e.g. hurricanes, these parameters usually do not change and hence steps 0 and 1 have to be carried out only once and independently of the concrete disaster being considered.

3.2.2 Stochastic information. In Step 2 in [Table 2](#), stochastic data that depends on the individual case and setting has to be collected. Defining demand for aid supplies and estimating the number of affected people has a significant impact on the results of a case study. In this context, FEMA's HAZUS tool offers estimations on shelter needs, displaced households and on the population size affected by natural disasters like floods, hurricanes and earthquakes. This information can be used to specify demand for different aid types and different natural hazards. In addition, HAZUS can forecast economic and infrastructural damage and losses. An advantage of this toolset is its worldwide applicability to multiple types of hazards, and it is therefore valuable for a variety of different case study settings. The *Geographic Information System* ArcGIS and its *Desktop Basic* software are required to run the HAZUS. If licenses for ArcGIS are not available, demand can be estimated based on the population size, provided by the Census Bureau (CB) of the respective country, and required relief items per person. For instance, the *South Carolina Emergency Management Division* ([SCEMD, 2007](#)) states that after a power failure 60% of households without electricity require aid supplies. It is assumed that one household consists of three persons on average and each person needs, e.g. 3 liters of water and two meals per day. Besides this general approach, demand can vary with the type and damage potential of a disaster. Destruction levels of different hurricane categories can be found in [NOAA \(2016\)](#) and [Ahrens \(2012\)](#). [Huizinga et al. \(2017a\)](#) provide coherent damage potentials of floods at the continent level and the authors differentiate between damages to several classes of objects like infrastructure, residential buildings and agriculture. Depending on the destruction level and infrastructure condition like congestion, evacuation and delivery times can be assessed.

As the majority of optimization models proposed in the humanitarian literature applies scenarios to capture the uncertain nature of disasters (Grass and Fischer, 2016), the focus here is exclusively on scenario-based approaches. Past disasters represent a useful source for realistic scenario definitions. The following sources can be used to determine an appropriate number and content of scenarios.

Besides information on the disaster type, impact and affected area, EM-DAT provides the number of killed, missed, homeless and affected people as well as the economic damage caused by either a natural or technological disaster. Data concerning tropical cyclones, e.g. wind speed, path and width of a specific hurricane, can be gathered via the database *International Best Track Archive for Climate Stewardship* IBTrACS. This database contains all hurricanes which occurred since 1850s, including all hurricanes captured by the *Hurricane Database* HURDAT. Such information is particularly useful for constructing long-term case studies, e.g. for strategic network planning. It can also be reasonable to design case studies based on past forecasts. The US agency *National Oceanic and Atmospheric Administration* (NOAA) saves all predictions on tropical cyclones for the Atlantic, Central and Eastern Pacific regions. Comprehensive information on, e.g. potential paths and wind speeds of past hurricanes can be found in the archive of the *National Hurricane Center* (NHC, 2019) up to five days before the respective landfall. Historical precipitation forecasts and excessive rainfall outlooks for the United States are provided by the *Weather Prediction Center* (WPC, 2019b) where, e.g. six hourly precipitation amounts and probabilities for flooding are given. Flood and storm forecasts not limited to a specific region are available through the *Flood Forecasting System* Delft-FEWS (2019) and the *Global Forecast System* GFS (2019). The former is an open data handling platform where, e.g. different simulations and flood scenarios can be executed. The GFS dataset covers up to 16-days forecasts concerning temperatures, winds, precipitation, soil moisture and atmospheric ozone concentration. Researchers can use all these forecast sources for their scenario definitions and evaluate the solutions of their optimization models based on the actual outcome of the disaster provided by, e.g. EM-DAT.

The main drawback of using scenarios is that the respective probabilities of occurrence have to be determined. In general, such probability distributions are difficult to obtain. However, disaster forecasts often include probability details, facilitating the definitions of scenario likelihoods. For instance, NHC published probability tables for different hurricane categories in the past. As shown in Figure 2, the probability that Katrina would become a category 4 or 5 hurricane in 48 h is 20%. These estimates were published by NHC on August 26, 2005, three days before Katrina's landfall.

Such tables are no longer available for more recent hurricanes. According to Chris Landsea from NOAA, research is ongoing to calculate hurricane category probabilities explicitly at landfall [1]. In the meantime, NHC's advisories contain probabilities for specific areas and wind speeds exceeding 63 km/h (tropical storm), 93 km/h and 119 km/h (hurricane) for five days in advance. In addition, the so-called *discussions* are provided by NHC where maximum wind speeds for upcoming days are given. Similar to the wind speed probabilities, WPC determines the likelihood that rainfall will cause flooding in a specific region. How these pieces of information can be used to design scenarios and the corresponding probabilities will be shown in the following section. Moreover, it is demonstrated that different degrees of detail in the information used for scenario construction can largely influence the results.

4. Realistic case study

The proposed framework and the sources listed in the previous section are used to gather realistic data and to design more realistic case studies than usually presented in the literature (Section 4.1 and Section 4.2). How the choice and number of scenarios and the quality of information used to construct scenarios can influence the results and final decisions are



WIND SPEED FORECAST FOR KATRINA
EXPRESSED AS PROBABILITY
FROM NHC ADVISORY 14
5:00 PM EDT AUG 26 2005



400

Figure 2.
Wind speed
probability table for
hurricane Katrina
(NHC, 2005)

TIME	WIND SPEED INTERVAL IN MPH							
HOURS	DISSIPATED	TROPICAL DEPRESSION < 39	TROPICAL STORM 39 - 73	HURRICANE >= 74	HURRICANE			
					CAT. 1	CAT. 2	CAT. 3	CAT. 4-5
					74 - 95	96 - 110	111 - 130	>= 131
12	<2%	<2%	<2%	>98%	30%	50%	20%	3%
24	<2%	<2%	5%	95%	40%	30%	15%	5%
36	<2%	<2%	<2%	>98%	30%	25%	30%	15%
48	<2%	2%	2%	95%	35%	15%	20%	20%
72	<2%	<2%	2%	97%	15%	25%	25%	30%

shown in [Section 4.3](#). As [Besiou *et al.* \(2018\)](#) state, the “humanitarian research community desperately needs good test cases” and the following sections are aimed at making some progress in this respect.

4.1 Case study design

Quantitative optimization models can support relief organizations to prepare for catastrophic events by determination of shelter locations, routing evacuations or pre-positioning relief items nearby. The latter is most often addressed in the humanitarian literature ([Grass and Fischer, 2016](#)) where the two-stage stochastic model proposed by [Rawls and Turnquist \(2010\)](#) is regarded as the main representative of this class [2]. Their model determines the quantity and type of relief items which are to be pre-positioned before the occurrence of a disaster. In addition, decisions concerning storage size and locations are made. It is assumed that these storage facilities and items pre-positioned there can be damaged by the disaster to some extent. Besides the facilities also roads can be destroyed, preventing the delivery of first aid to those in need. Neither the degree of damage nor the final demand for relief items are known in advance. These uncertainties are captured by the optimization model through the use of scenarios. Input parameters are divided into deterministic and stochastic and are shown in [Table 3](#).

Such pre-positioning measures can significantly accelerate response times shortly after a disaster and therefore improve supply to and treatment of affected people. As relief goods like medicine or food are perishable, pre-positioning decisions are often made for short-term predicted disasters like floods and hurricanes. The case studies constructed below consider the Gulf and Atlantic Coast of the US which is hit by hurricanes every year.

4.1.1 Step 0: Basic Information. As the Gulf and Atlantic Coast of the United States suffers from hurricanes every year, this area is used to define a network consisting of 90 nodes where each node constitutes the center of several neighboring counties (see Figure 3). This high number of nodes, in comparison to 30 nodes used in Rawls and Turnquist (2010) for the same region, allows a much more accurate and precise analysis, as was shown in Grass *et al.* (2020). During a typical Atlantic hurricane season between June and November, several tropical storms and hurricanes can occur, sometimes shortly after each other. It is assumed that a hurricane can hit each of the nodes in Figure 3 causing demand for first aid supplies. Storage facilities can be opened at these nodes to pre-position essential goods before the occurrence of a hurricane. Existing public buildings like schools or gyms can serve as shelters and warehouses in the case of an upcoming hurricane. Relief agencies can use this network as a base map in preparation for individual hurricanes during the entire hurricane season where different hurricanes may hit different areas. For instance, hurricane Harvey hit the western part of the Gulf and Atlantic Coast just shortly before the category 5 hurricane Irma made landfall on Florida affecting the eastern region. Three-day forecasts leave aid agencies not enough time to repeatedly set up new networks tailored to single hurricane forecasts. Therefore, the map in Figure 3 supports humanitarian organizations in the preparation for many different hurricane outcomes with little time for making decisions.

4.1.2 Step 1: Deterministic Information. According to Table 3, the set of deterministic parameters contains cost rates for opening facilities, purchasing relief items, transport of

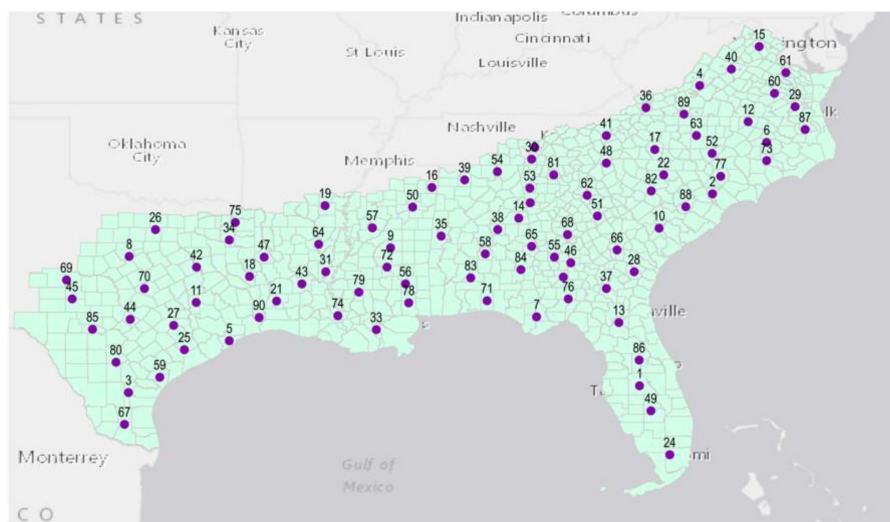


Figure 3.
The American Gulf and
Atlantic Coast with 90
nodes (Grass *et al.*, 2020)

Deterministic

Space and transport requirements
Storage capacity
Transport costs
Costs for opening facilities
Purchasing costs
Penalty costs for unsatisfied demand
Penalty costs for unused items

Stochastic

Demand
Proportion of useable relief items
Road capacities
Probabilities of scenarios

Table 3.
Deterministic and
stochastic input
parameters for Rawls
and Turnquist (2010)

relief items and penalty costs for unsatisfied demand and unused items. In addition, space and transport requirements for relief items and facility capacities have to be set. In general, these parameters can be used for different types of disasters. For instance, drinking water or medical emergency equipment are needed after every natural catastrophe and have to be stored at selected facilities.

Table 4 shows costs and capacities of different types of storage facilities.

The latter is based on average values taken from FEMA (2019).

In order to limit computation times, not more than two item types are generally used in the humanitarian literature. However, this is not sufficient to reflect the actual needs of affected people. For the case study under consideration five types of relief items have to be pre-positioned, namely water, meals ready-to-eat (MREs), tents, medical sets and first-aid-kits (FAKs). Medical sets are necessary to prevent epidemic crises and include, e.g. sets for the purification of drinking water. FAKs contain, e.g. equipment needed for immediate treatment of injuries. Prices as well as weights and volumes of these items are shown in Table 5.

People affected by a disaster need, e.g. water and food for at least two days. During this time frame more detailed information on the hurricane's path and impact becomes available, allowing relief agencies to adapt to the actual situation on site. If necessary, additional orders can be placed in order to satisfy demand over a longer period.

Table 6 summarizes how many relief items have to be pre-positioned such that basic needs can be covered for at least two days. In particular, six liters of water and four meals per person are required for the duration of two days. Up to five people can live in a tent if houses are destroyed and shelters are not accessible. Therefore, one-fifth of a tent is required for one person. Similarly, each box of medical sets and FAKs consists of medical components sufficient for 1,000 and 5 people, respectively. Information regarding population numbers for each node in Figure 3 is gathered from the United States Census Bureau (CB, 2016).

Table 4.

Opening costs and capacities for storage facilities (Rawls and Turnquist, 2010) and (FEMA, 2019)

Size category	Fixed costs (in US\$)	Capacity (in ft ³)
1 Small	19,600	36,392
2 Medium	188,400	295,441
3 Large	300,000	468,185

Table 5.

Purchase price, weight and space requirement of each relief item (based on IFRC (2016) and SCEMD (2007))

Item <i>k</i>	Unit	Purchase price (in US\$/unit)	Weight (in kg/unit)	Space requirement (in ft ³ /unit)
1 Water	One liter	0.68	1.13	0.093
2 MRE	One package	3.36	0.76	0.1029
3 Tent	One piece	310	55	9.9499
4 Medical Set	One box	770	45	6.3566
5 FAK	One box	870	10.5	2.2434

Table 6.

Required relief items per person for two days (SCEMD, 2007)

No	k	Unit	Required items pp (2 days)
1	Water	One liter	6
2	MRE	One package	4
3	Tent	One piece	1/5
4	Medical Set	One box	1/1,000
5	FAK	One box	1/5

Penalty costs for unused items can either be disposal and/or storage costs. The ratio between penalty costs for unused items and unsatisfied demand has decisive influence on the model's outcome (Rawls and Turnquist, 2010). For this case study the relation suggested by Rawls and Turnquist (2010) is adopted. In particular, penalty costs for unused items are 25% of the purchase price, whereas penalty costs for unsatisfied demand are 10 times higher than the purchase price. With this ratio demand satisfaction is prioritized more than avoiding surplus stocks. Note that the specification of penalty costs for unsatisfied demand is treated controversial in the literature and attempts have been made to avoid the quantification of the value of human life (Hong *et al.*, 2015). However, in many cases the use of penalty costs is the most straightforward approach when unfulfilled demand is to be handled and is often used in the literature (other approaches include the minimization of unmet demand), e.g. Rottkemper and Fischer (2013). Sensitivity studies may help to find the appropriate penalty cost rates for a specific problem at hand.

As mentioned in the previous section, costs for road transport are taken from MSF (2016), i.e. US\$ 0.50 per kg and km. Here, the ArcGIS software is used to obtain distances between the respective nodes in the network. Alternatively Google Maps is publicly available and can be used for this purpose.

4.1.3 Step 2: Stochastic Information. The model proposed by Rawls and Turnquist (2010) requires the definition of additional parameters which are dependent on the scenario which occurs. First, demand is strongly influenced by the type and intensity of a disaster. For this case study hurricanes, i.e. storms with wind speed exceeding 118 km/h, are considered. According to Table 7, damage potential does not increase linearly with the hurricane category. For instance, a category 3 hurricane is 50 times worse than a category 1 hurricane whereas a hurricane of category 4 is even 250 times more destructive. Demand depends on this classification and can be represented as the proportion of population which requires first aid. In the case of a category 4 hurricane, 25% of the population under risk have to be provided with relief items.

The next parameter which is scenario-dependent is the proportion of pre-positioned items that is not destroyed by the disaster and can be used to satisfy demand. In Figure 4 it is shown what damage can be expected for different hurricane categories. For instance, major hurricanes of category 4 or 5 are likely to destroy buildings and therefore also the items stored there. In this case study, the proportion of destroyed items is independent of the aid type as it can be assumed that collapsed roofs or walls can destroy or block access to any kind of goods.

Road capacities are also scenario-dependent and vary with hurricane intensities. As indicated in Figure 4 even minor hurricanes can blow down trees, leaving roads impassable.

In general, often not much more than 30 scenarios are required when short-term forecasts are available. However, this is not the case for strategic preparation planning where a considerably larger variety of disaster outcomes can be expected. For instance, Rawls and Turnquist (2010) use only 15 historical hurricanes to construct 51 scenarios. Based on this set of scenarios the authors suggest to open five facilities of which two are located in vulnerable cities, namely in Brownsville and Tampa. On average, Brownsville is hit by storms and hurricanes every 5 years (Brownsville, 2018) and Tampa holds the fourth place of the most

Hurricane category	Wind speed (km/h)	Damage potential	Percentage of affected population (in %)
1	119–153	1	0.1
2	154–177	10	1
3	178–208	50	5
4	209–251	250	25
5	≥252	500	50

Table 7.
Percentage of
population to be
provided with relief
items depending on the
damage potential of
hurricanes
(NOAA, 2016)

Figure 4.
Saffir–Simpson
hurricane damage-
potential scale
(Ahrens, 2012)

SCALE NUMBER (CATEGORY)	CENTRAL PRESSURE		WINDS		STORM SURGE		DAMAGE
	mb	in.	mi/hr	knots	n	m	
1	≥980*	≥28.94	74–95	64–82	4–5	~1.5	Damage mainly to trees, shrubbery, and unanchored mobile homes
2	965–979	28.50–28.91	96–110	83–95	6–8	~2.0–2.5	Some trees blown down; major damage to exposed mobile homes; some damage to roofs of buildings
3	945–964	27.91–28.41	111–130	96–113	9–12	~2.5–4.0	Foliage removed from trees; large trees blown down; mobile homes destroyed; some structural damage to small buildings
4	920–944	27.17–27.88	131–155	114–135	13–18	~4.0–5.5	All signs blown down; extensive damage to roofs, windows, and doors; complete destruction of mobiles homes; flooding inland as far as 10 km (6mi); major damage to lower floors of structures near shore
5	<920	<27.17	>155	>135	>18	>5.5	Severe damage to windows and doors; extensive damage to roofs of homes and industrial building; small buildings overturned and blown away; major damage to lower floors of all structures less than 4.5cm (15ft) above sea level within 500m of shore

hurricane-vulnerable cities (AccuWeather, 2018). Therefore, many more hurricanes have to be taken into account and more scenarios are needed to develop reasonable and practicable solutions (see Grass *et al.* (2020) for an approach along these lines).

In the following, scenarios and the corresponding probabilities will be defined based on the three-day forecast for hurricane Harvey in 2017. Besides Katrina in 2005, Harvey is the costliest hurricane causing US\$ 125b damage to property.

4.2 Case studies

As pointed out in Section 2, the number of scenarios is often relatively small in the humanitarian literature. This is either because real data is missing or computation times would otherwise become too long. However, scenario numbers and scenario content can be decisive for the solution quality of an optimization model as will be shown below. In order to do so, three case studies are designed based on forecasts with varying degrees of detail, highlighting the effects of the use of more detailed data and information and a larger number of scenarios on the location and pre-positioning results.

4.2.1 Case study with 4 scenarios. In the first case study, four scenarios are constructed that are solely based on basic information from NHC, i.e. from the visual forecast in Figure 5. On August 23, 2017, NHC predicted that Harvey would hit the coast as a tropical cyclone with wind speeds between 62 km/h and 117 km/h, denoted by “S” in Figure 5. However, the pink area indicates that a hurricane watch was issued for almost the entire Texas coast. This means that even though a tropical cyclone is predicted it could strengthen to a hurricane with wind speed of more than 119 km/h (74 mp/h) (NHC, 2017a). Therefore, for this case study it is assumed that Harvey will make landfall as a category 1 hurricane.

The first scenario in Table 8 covers the fact that weather conditions may change in such a way that Harvey will dissipate sparing the entire region. However this is very unlikely and therefore the corresponding probability is very low, see “Probability Hur”. The remaining scenarios are based on the most likely track of Harvey, indicated by the black line in Figure 5, where different counties along the coast can be hit. As shown in Figure 5, node 3, 25 or 59 (see Figure 3) could be affected by Harvey. Therefore, scenarios 2–4 are defined in Table 8 where each of these nodes has the same probability of being hit, i.e. node 3 is at the same risk as node 25 or 59, namely 1/3. Note that the hurricane probabilities are scaled in Table 8, ensuring that

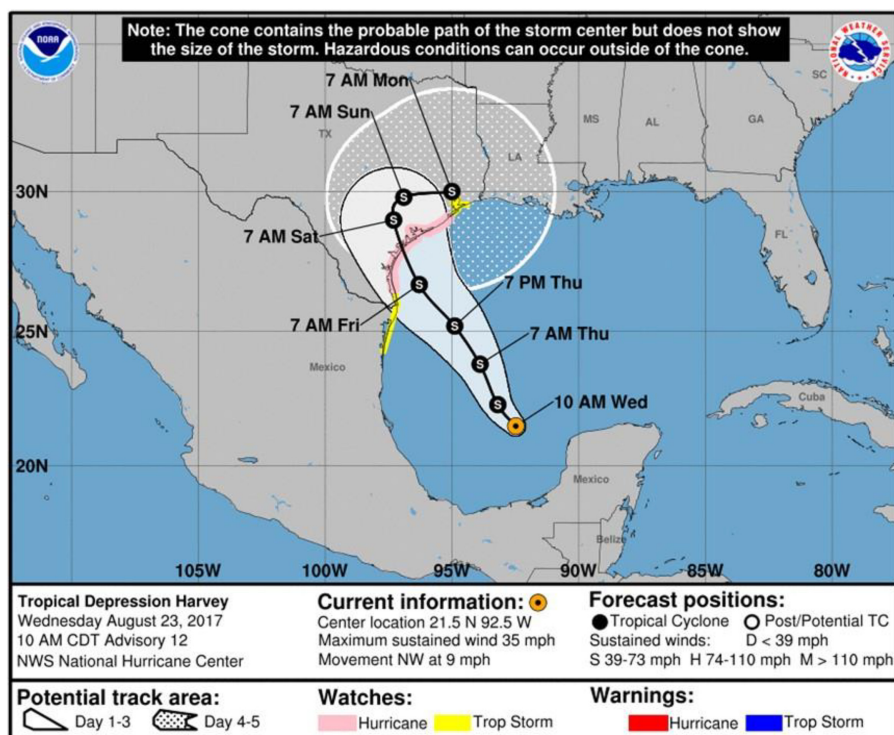


Figure 5.
Potential pathway of
hurricane Harvey three
days before landfall
(NHC, 2017a)

Scenario No	Probability Hur	Scenario	Affected Node	Hur Cat	Water	MRE	Demand Tents	Medical sets	FAKs
1	0.001	0.0082	—	—	0	0	0	0	0
2	1/3	0.3306	3	1	4300.86	2867.24	143.36	0.72	143.36
3	1/3	0.3306	25	1	5564.97	3709.98	185.50	0.93	185.50
4	1/3	0.3306	59	1	735.97	490.65	24.53	0.12	24.53

Table 8.
Scenario specifications
for the illustrative
Harvey case study with
4 scenarios

the sum of probabilities for all scenarios is 1 (see column “Scenario Probability”). As it is highly unlikely that Harvey’s width will reach such a dimension that two nodes are affected simultaneously, each scenario contains only one vulnerable node.

According to Table 7, 0.1% of the population of node 3, 25 or 59 have to be supplied with relief items. In addition, these proportions have to be multiplied by the factor for each relief item given in Table 6, resulting in the final demand presented in columns “Demand” in Table 8.

As it is unlikely for category 1 hurricanes to lead to major destructions, it is assumed that pre-positioned items and roads remain unaffected. Therefore, all items stored in advance are supposed to be completely available and can be transported to any region in the aftermath of the hurricane. In order not to limit road capacities in this case capacities are set to 100,000 kg.

4.2.2 Case study with 7 scenarios. Besides visual forecasts in form of Figure 5, NHC provides advisories where more detailed information can be found. An extract of such an advisory on wind speed probabilities for different locations and time periods is given in Figure 6 [3]. For

ECZC MIAPRSAT4 ALL TTAA00 KNHC D0H9M									
TROPICAL DEPRESSION HARVEY WIND SPEED PROBABILITIES NUMBER 12 NWS NATIONAL HURRICANE CENTER MIAMI FL AL092017 1500 UTC WED AUG 23 2017									
AT 1500Z THE CENTER OF TROPICAL DEPRESSION HARVEY WAS LOCATED NEAR LATITUDE 21.5 NORTH...LONGITUDE 92.5 WEST WITH MAXIMUM SUSTAINED WINDS NEAR 30 KTS...35 MPH...55 KM/H.									
Z INDICATES COORDINATED UNIVERSAL TIME (GREENWICH) ATLANTIC STANDARD TIME (AST)...SUBTRACT 4 HOURS FROM Z TIME EASTERN DAYLIGHT TIME (EDT)...SUBTRACT 4 HOURS FROM Z TIME CENTRAL DAYLIGHT TIME (CDT)...SUBTRACT 5 HOURS FROM Z TIME									
WIND SPEED PROBABILITY TABLE FOR SPECIFIC LOCATIONS									
CHANCES OF SUSTAINED (1-MINUTE AVERAGE) WIND SPEEDS OF AT LEAST ...34 KT (39 MPH... 63 KM/H)... ...50 KT (58 MPH... 93 KM/H)... ...64 KT (74 MPH...119 KM/H)...									
FOR LOCATIONS AND TIME PERIODS DURING THE NEXT 5 DAYS									
PROBABILITIES FOR LOCATIONS ARE GIVEN AS OP(CP) WHERE OP IS THE PROBABILITY OF THE EVENT BEGINNING DURING AN INDIVIDUAL TIME PERIOD (ONSET PROBABILITY) (CP) IS THE PROBABILITY OF THE EVENT OCCURRING BETWEEN 12Z WED AND THE FORECAST HOUR (CUMULATIVE PROBABILITY)									
PROBABILITIES ARE GIVEN IN PERCENT X INDICATES PROBABILITIES LESS THAN 1 PERCENT PROBABILITIES FOR 34 KT AND 50 KT ARE SHOWN AT A GIVEN LOCATION WHEN THE 5-DAY CUMULATIVE PROBABILITY IS AT LEAST 3 PERCENT. PROBABILITIES FOR 34...50...64 KT SHOWN WHEN THE 5-DAY 64-KT CUMULATIVE PROBABILITY IS AT LEAST 1 PERCENT.									
- - - - WIND SPEED PROBABILITIES FOR SELECTED LOCATIONS - - - -									
TIME	FROM	FROM	FROM	FROM	FROM	FROM	FROM		
PERIODS	12Z WED	00Z THU	12Z THU	00Z FRI	12Z FRI	12Z SAT	12Z SUN		
	TO	TO	TO	TO	TO	TO	TO		
	00Z THU	12Z THU	00Z FRI	12Z FRI	12Z SAT	12Z SUN	12Z MON		
FORECAST HOUR	(12)	(24)	(36)	(48)	(72)	(96)	(120)		
- - - -									
LOCATION	KT								
PORT O CONNOR	34	X	X(X)	4(4)	30(34)	20(54)	3(57)	2(59)	
PORT O CONNOR	50	X	X(X)	X(X)	5(5)	15(20)	1(21)	2(23)	
PORT O CONNOR	64	X	X(X)	X(X)	1(1)	4(5)	1(6)	1(7)	
ROCKPORT TX	34	X	X(X)	4(4)	31(35)	21(56)	2(58)	3(61)	
ROCKPORT TX	50	X	X(X)	X(X)	6(6)	14(20)	2(22)	1(23)	
ROCKPORT TX	64	X	X(X)	X(X)	1(1)	4(5)	1(6)	1(7)	
CORPUS CHRISTI	34	X	X(X)	4(4)	26(30)	20(50)	3(53)	2(55)	
CORPUS CHRISTI	50	X	X(X)	X(X)	5(5)	11(16)	1(17)	1(18)	
CORPUS CHRISTI	64	X	X(X)	X(X)	1(1)	3(4)	X(4)	1(5)	
GPFX 270N 960W	34	X	1(1)	17(18)	44(62)	9(71)	1(72)	2(74)	
GPFX 270N 960W	50	X	X(X)	1(1)	21(22)	8(30)	1(31)	1(32)	
GPFX 270N 960W	64	X	X(X)	X(X)	6(6)	3(9)	1(10)	X(10)	
MCALLEN TX	34	X	X(X)	4(4)	19(23)	8(31)	3(34)	1(35)	
MCALLEN TX	50	X	X(X)	X(X)	2(2)	3(5)	X(5)	X(5)	
MCALLEN TX	64	X	X(X)	X(X)	X(X)	1(1)	X(1)	X(1)	
HARLINGEN TX	34	X	1(1)	6(7)	27(34)	8(42)	3(45)	2(47)	
HARLINGEN TX	50	X	X(X)	X(X)	7(7)	4(11)	1(12)	X(12)	
HARLINGEN TX	64	X	X(X)	X(X)	1(1)	2(3)	X(3)	X(3)	
BROWNSVILLE TX	34	X	1(1)	9(10)	27(37)	7(44)	2(46)	2(48)	
BROWNSVILLE TX	50	X	X(X)	X(X)	9(9)	3(12)	X(12)	1(13)	
BROWNSVILLE TX	64	X	X(X)	X(X)	2(2)	1(3)	X(3)	X(3)	
GPFX 250N 960W	34	X	3(3)	35(38)	13(51)	2(53)	1(54)	2(56)	
GPFX 250N 960W	50	X	X(X)	7(7)	10(17)	X(17)	1(18)	X(18)	
GPFX 250N 960W	64	X	X(X)	1(1)	3(4)	1(5)	X(5)	X(5)	

Figure 6.
Extract of the wind
speed probability table
for hurricane Harvey
(NHC, 2017c)

instance, the probability that Port O'Connor will be hit by a storm with wind speed of 34 kt/h (63 km/h) in exactly 120 h is 2%, which is referred to as the onset probability. In contrast, the cumulative probability of 59% indicates how likely Port O'Connor will be affected by a storm *within* the next 120 h.

For this case study only locations are relevant for which there exists a cumulative probability that a hurricane, i.e. wind speed reaches more than 64 kt/h (119 km/h), will occur within the next 72 h. Based on the probabilities given in Figure 6, certain locations are at risk, see Table 9. For instance, the probability that node 5, consisting of Galveston, Freeport and High Island, will be hit by a hurricane within the next three days is 2%. That is, the maximum probability of the cities belonging to the same node is chosen as the onset probability, to avoid an underestimation of probabilities.

According to Table 9, six nodes on the Texas coast could be affected by hurricane Harvey, resulting in seven scenarios summarized in Table 10 where the first scenario illustrates again a no-hurricane case. The respective hurricane and scaled scenario probabilities are shown in column "Probability Hur" and "Probability Scenario", respectively. As, in general, hurricanes quickly weaken over land, it can be assumed that nodes located more inland, e.g. 11, 44 and 70, are not at risk of being hit by Harvey as a hurricane and are therefore not considered in Table 10.

The remaining parameter values are set in the same way as for the case study with four scenarios. For instance, neither pre-positioned items nor roads are affected by the category 1 hurricane.

4.2.3 Case study with 23 scenarios. For the next case study additional information from NHC is used to define more realistic scenarios. In particular, NHC's advisories contain discussions where a warning was issued on 23rd of August that Harvey could strengthen after 48 h and may be accompanied by heavy rainfall (NHC, 2017b). Therefore, the three-day precipitation forecasts from WPC are consulted. In Figure 7 probabilities for exceeding the

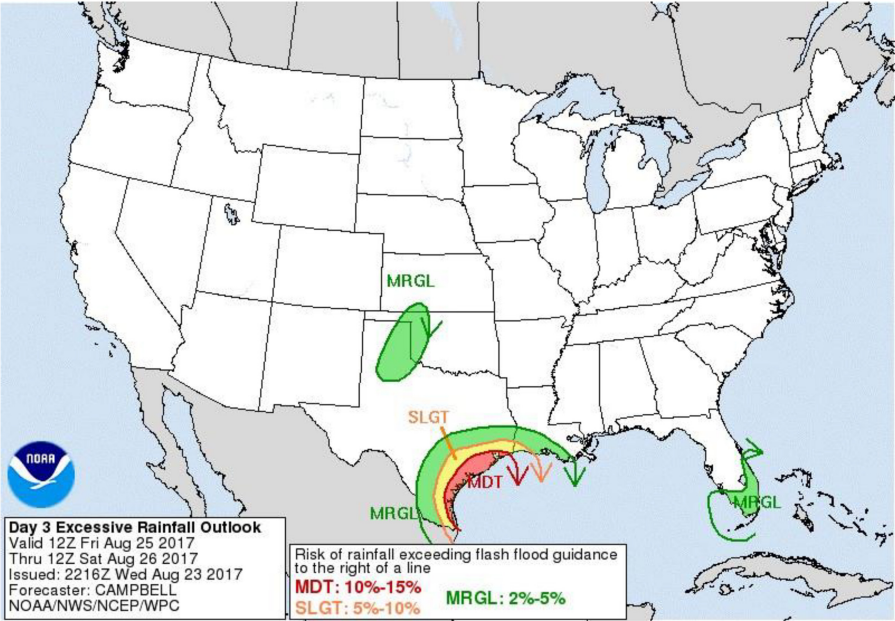
Table 9.
Probabilities for
specific locations to be
hit by a hurricane
within the next 72 h
(NHC, 2017c)

Location	Node	Probability (in %)
Galveston	5	1
Houston	27	1
Freeport	5	2
High Island	5	1
Matagorda	25	4
Port O'Conner	59	5
Rockport	59	5
Corpus Christi	3	4
Harlingen	67	3
Brownsville	67	3

Table 10.
Scenario specifications
for the illustrative
Harvey case study with
7 scenarios

No	Hur	Scenario	Node	Cat	Water	MRE	Tents	Medical sets	FAKs
1	0.001	0.01	–	–	0	0	0	0	0
2	0.04	0.21	3	1	4300.86	2867.24	143.36	0.72	143.36
3	0.02	0.10	5	1	4341.15	2894.10	144.71	0.72	144.71
4	0.04	0.21	25	1	5564.97	3709.98	185.50	0.93	185.50
5	0.01	0.05	27	1	29348.99	19565.99	978.30	4.89	978.30
6	0.05	0.26	59	1	735.97	490.65	24.53	0.12	24.53
7	0.03	0.16	67	1	8310.14	5540.09	277.00	1.39	277.00

Figure 7.
Excessive rainfall
outlook for hurricane
Harvey three days in
advance (WPC, 2017b)



Flash Flood Guidance (FFG) are indicated. This guidance represents a threshold where precipitation causes minor flooding. In the case of Harvey, flooding can occur at the coast with a moderate (MDT) probability of 10%–15% (red area in Figure 7) [4]. The risk of flooding decreases inland, namely to slight risk (SLGT) of 5–10% (yellow area) and marginal risk (MRGL) of 2–5% (green area).

Figure 7 shows the probability for flooding but not its extent. More detailed information on the rainfall amount is provided by the 72-h Quantitative Precipitation Forecast (QPF) in Figure 8. Here, the amount of 8.78 inch (223 mm) rain is estimated to fall on a 20 × 20 km area in 24 h for the next three days. Even if major destructions through wind forces are not expected three days before Harvey’s landfall, heavy rainfall can cause tremendous damage to the entire Texas coast. Note that hurricanes typically carry a lot of water so that flood damages are already indirectly covered by the Saffir–Simpson scale in Figure 4. However, in the case of Harvey the rainfall forecast is significantly higher than the predicted hurricane category and therefore, potential damage from flooding has to be explicitly included in the scenario definitions. In Table 11 flood categories and the corresponding damage potentials are given.

The QPFs in Table 11 indicate how much rain is expected to fall on average per day, see Figure 8, resulting in an estimated flood depth after three days. For instance, at coastal regions 177 mm (7 inch) of rain is expected within the next 24 h, leading to a total rain amount of 531 mm within the next 72 h, see “Flood Depth” in Table 11. According to Huizinga *et al.* (2017a), flood depth of 0.5 m can destroy 44% of residential buildings [5], i.e. 44% of the population is expected to be affected by flooding.

Based on the described hurricane and rainfall forecasts, 23 scenarios are defined and listed in Table 12. The first seven scenarios are as in the previous case study whereas the remaining scenarios take additional information into account. As discussed above, NHC predicted the strengthening of Harvey without providing exact probability details. In scenarios 8–13 it is

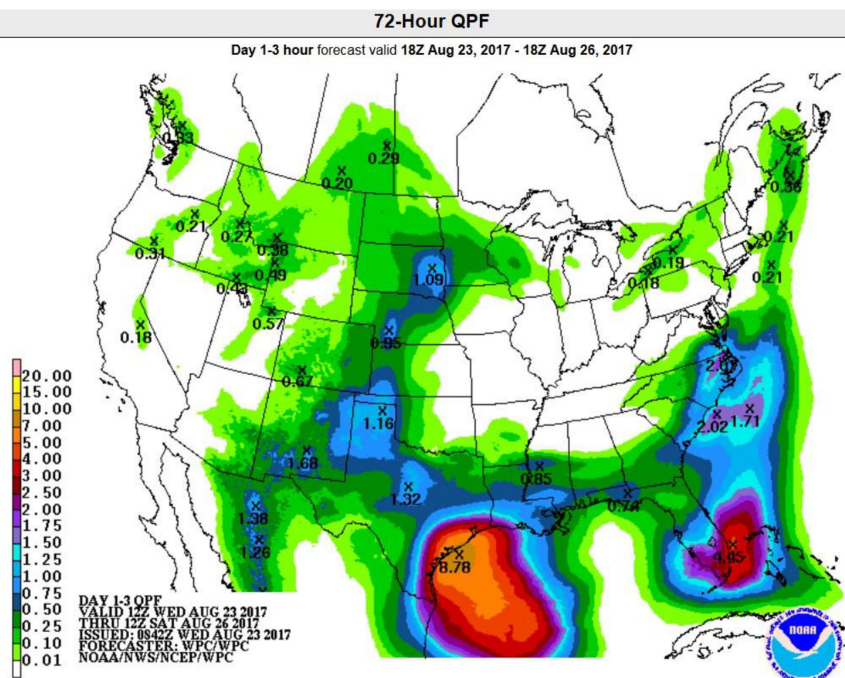


Figure 8.
Quantitative
precipitation forecast
(QPF) for hurricane
Harvey three days in
advance (WPC, 2017a)

Flood category	QPF (in mm)	Flood depth (in m)	Damage potential	Percentage of affected population (in %)
1	19	0.057	0	0
2	25	0.075	0.001	0.1
3	38	0.114	0.05	5
4	63	0.189	0.1	10
5	76	0.228	0.15	15
6	127	0.381	0.2	20
7	177	0.531	0.44	44

Table 11.
Percentage of
population to be
provided with relief
items depending on the
damage potential of
floods (Huizinga *et al.*,
2017a; WPC, 2017a)

assumed that Harvey will hit the same nodes as in the previous case study but as a category 3 hurricane. Due to the fact that a strengthening of Harvey is not considered to be highly likely, but as exact probability specifications are missing, the respective probabilities are assumed to be half as big as those for a category 1 hurricane. For instance, Harvey will hit node 3 as a category 3 hurricane with a probability of 2% whereas it is twice as likely that it will hit node 3 as a category 1 hurricane, namely 4%.

From scenario 14 on, probabilities for excessive rainfall and the corresponding flood categories are included (see column “Probability FFG” and “Flood Cat” in Table 12). In particular, scenarios 14–22 cover situations where several nodes could be affected by wind and flood destructions. As mentioned above, it is unlikely that Harvey can hit more than one node at the same time. However, flooding can occur on a much broader area, deluging many counties. Therefore, the probability of Harvey hitting one of the nodes within one scenario is calculated as the sum of the individual probabilities. For instance, the probability that Harvey

Table 12.
Scenario specifications
for the illustrative
Harvey case study with
23 scenarios

Scenario No	Probability hurricane	Probability FFG	Joint probability	Scenario probability	Affected nodes	Hurr Cat	Flood Cat
1	0.001	0.000	0.001	0.0006	–	–	–
2	0.040	0.000	0.040	0.0244	3	1	–
3	0.020	0.000	0.020	0.0122	5	1	–
4	0.040	0.000	0.040	0.0244	25	1	–
5	0.010	0.000	0.010	0.0061	27	1	–
6	0.050	0.000	0.050	0.0306	59	1	–
7	0.030	0.000	0.030	0.0183	67	1	–
8	0.020	0.000	0.020	0.0122	3	3	–
9	0.010	0.000	0.010	0.0061	5	3	–
10	0.020	0.000	0.020	0.0122	25	3	–
11	0.005	0.000	0.005	0.0031	27	3	–
12	0.025	0.000	0.025	0.0153	59	3	–
13	0.015	0.000	0.015	0.0092	67	3	–
14	0.110	0.150	0.150	0.0917	5,25,59	1	7,6,6
15	0.050	0.150	0.150	0.0917	11,25,27	1	3,6,4
16	0.120	0.150	0.150	0.0917	5,11,25,27,59	1	7,3,6,4,6
17	0.110	0.150	0.150	0.0917	5,25,59,90	1	7,6,6,4
18	0.020	0.150	0.150	0.0917	5,21,90	1	7,3,4
19	0.020	0.150	0.150	0.0917	5,21,74,90	1	7,3,2,4
20	0.000	0.100	0.100	0.0611	21,74,90	0	3,2,4
21	0.120	0.150	0.150	0.0917	3,59,67	1	3,6,3
22	0.120	0.150	0.150	0.0917	3,59,67,80	1	3,6,3,1,1
23	0.000	0.050	0.050	0.0306	24	0	5

will hit either node 5, 25 or 59 in scenario 14 as a category 1 hurricane is the sum of the probability that Harvey will hit node 5 (scenario 3), node 25 (scenario 4) and node 59 (scenario 6), i.e. $0.02 + 0.04 + 0.05 = 0.11$, see column “Probability hurricane” in Table 12. The sum calculation is reasonable as the individual events are mutually exclusive, i.e. the probability of node 5, 25 and 59 being simultaneously hit by a hurricane is assumed to be 0.

The flooding situation is different as all nodes in the respective scenario can be affected. According to Figure 7, coastal nodes 5, 25 and 59 are especially prone to flooding, i.e. with a probability of 15% FFG will be exceeded there. Expected flood categories at these nodes are determined based on Figure 8 and Table 11. For instance, 7 inch (177 mm) of rain is predicted at node 5 and 5 inch (127 mm) at node 25 and 59, respectively, within the next 24 h, i.e. node 5 may experience a category 7 flooding and nodes 25 and 59 a category six flooding, see scenario 14 in Table 12. Flood categories for the remaining scenarios are assigned in an analogous manner. The FFG probability for each of the scenarios 14–22 is set to the maximum probability of one of the nodes included in the scenario to experience flooding in order to avoid underestimation. See scenario 21 as an example, where flooding may occur at node 59 with a 15% probability and at node 3 and 67 with a probability of 5% each, leading to a final FFG probability of 15%. The rational behind is the widespread occurrence of floods so that neighboring nodes are also highly at risk, i.e. often more than one node is hit at the same time.

By Joint probability in Table 12 the probability is meant that at least one of the nodes included in the scenario is hit by flooding or the hurricane (or both). This is the maximum of the respective hurricane and FFG probabilities. This definition is made because two possible outcomes are conceivable for scenarios 14–22: The hurricane hits a specific node and is accompanied by flooding, or the hurricane dissipates but due to it carrying huge amounts of rainfall it can still cause flooding. In other words, flooding can occur with or without the appearance of a hurricane at a specific node. To avoid underestimation of probabilities, the maximum probability is used which is the FFG probability for scenarios 14–22. Finally,

the joint probabilities have to be scaled, similarly to the previous case studies, in order to obtain the “Scenario Probability” in [Table 12](#).

The affected nodes in scenarios 14–23 are chosen according to Harvey’s predicted trajectory and rainfall forecast, see [Figures 5–8](#). Harvey can hit Texas’ central coast (scenarios 14–17) or it takes a rather eastward direction (scenarios 18–20) or a westward path (scenarios 21–22). The last scenario meets the forecast in [Figure 7](#) where Harvey can cause flooding at node 24 without hitting it directly.

It is assumed that pre-positioned items and roads are not damaged by a hurricane of category 1 and if no flooding is considered. This holds for the first seven scenarios. In the case where Harvey will become a category 3 hurricane, fallen trees can partially block roads such that the road capacity is reduced from 100,000 to 50,000, i.e. only a limited quantity of items can be transported. According to [Figure 4](#), a category 3 hurricane is likely to damage smaller buildings, leading to the assumption that only half of the stored relief items are still useable if a node with the respective facility is hit. As soon as flooding is taken into consideration, i.e. for scenarios 14–23, roads are expected to become impassable, resulting in a road capacity of 0. Similarly, access to warehouses can be blocked and it is very likely that water-damage can render pre-positioned items unusable. Therefore, all relief items stored at an affected node are considered to be lost.

Demand for scenarios 2–13 is determined by the same rules as before, i.e. the population size is either multiplied by 0.001 in case of a category 1 hurricane or by 0.05 in case of a category 3 hurricane, see [Table 7](#). Similarly, demand caused by flooding is again the product of the percentage of affected population given for different flood categories in [Table 11](#) and the required number of aid supplies from [Table 6](#). The final demand in scenarios 14–22 depends on the percentage of affected population. If flooding causes more damage than the hurricane at a specific node then the final demand results from the population affected by the flood. For instance, a category 1 hurricane can affect 0.1% of the population, according to [Table 7](#), whereas the percentage is 5% in the case of a category 3 flood, see [Table 11](#). Therefore, 5% rather than 0.1% of the population have to be supplied with relief items. The rationale behind this is that those who are affected by the hurricane are most likely to be also affected by flooding and hence, do not need the double amount of relief items.

In the following section it is highlighted how the model solutions are influenced by the number and content of scenarios.

4.3 Evaluation of case study results

The two-stage stochastic model proposed by [Rawls and Turnquist \(2010\)](#) was solved for the three case studies by the accelerated L-Shaped method described in [Grass et al. \(2020\)](#) on a dual 2.60 GHz Intel Core i7 laptop with 8 GB memory. Solutions concerning the pre-positioning locations for the three cases are shown in [Figure 9](#). In all cases only one small facility is chosen, namely at node 25 for the case study with 4 scenarios, at node 59 for the second and at node 18 for the last case study.

In order to evaluate the location decisions, Harvey’s actual path and destruction level is illustrated in [Figure 10](#). According to this figure and [NWS \(2017\)](#) Harvey hit the area near Port Aransas as a category 4 hurricane, turned around almost reaching San Antonio and made final landfall in Lake Charles as a storm. In contrast to other hurricanes Harvey strengthened unexpectedly fast to a major hurricane shortly before the coastline. It hit San Jose Island with wind speed of about 233 km/h (145 mp/h). Even areas 48 km away from Harvey’s eye felt its impact, e.g. through fallen trees and power failures. According to FEMA’s damage assessment, more than 60,000 buildings in Texas were damaged of which one-quarter suffered severe or total destruction. About 240 shelters were opened for housing more than 35,000 people.

Besides extreme wind forces Texas experienced historical storm surge and flooding with tide levels of up to 3.7 m above ground level. The main reason was Harvey’s slow movement.

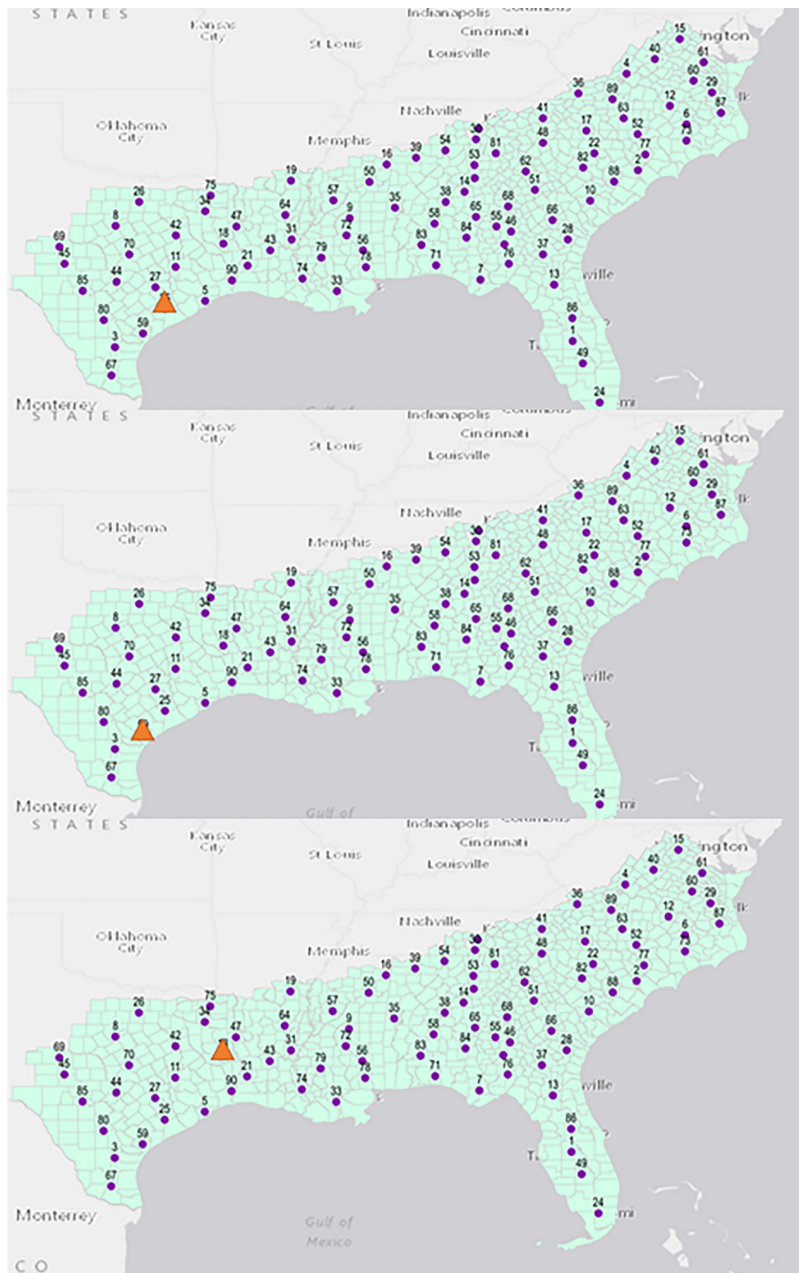


Figure 9. Location solution for case study with 4 scenarios (top), 7 scenarios (center) and 23 scenarios (bottom)

Heavy rainfall lasted for several days causing rivers to burst their banks and breaking North America's rainfall record. In particular, a precipitation amount exceeding 100 cm (40 inch) was measured within a period of just two days. While obviously Harvey developed rather differently from what had been predicted, it is still interesting to study the effect the three

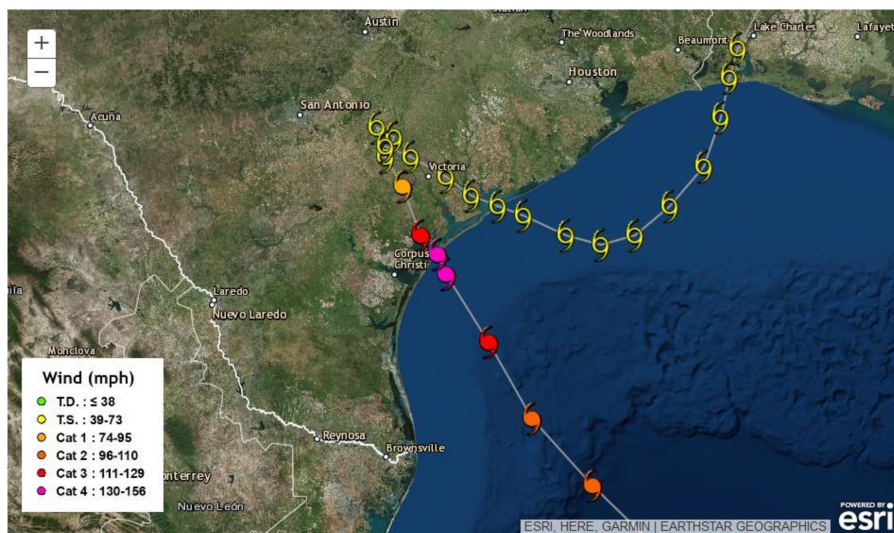


Figure 10.
Actual track of
Hurricane Harvey on
August 25–29, 2017
(NWS, 2017)

different case study results have, in order to illustrate the consequences of different degrees of detail considered and number of scenarios built.

Hence, based on the information given above, location results for all three case studies, shown in Figure 9, are assessed in terms of demand satisfaction. Table 13 compares and summarizes the characteristics and the solutions of all three case studies. Note that a comparison with the case study results of Rawls and Turnquist (2010) is not reasonable as they consider a long-term pre-positioning planning problem using historical hurricane records, whereas here short-term pre-positioning decisions are made based on Harvey's three-day forecast. A justified and fair comparison can be found in Grass *et al.* (2020).

Considering location solutions for the first and second case study in Figure 9 it becomes apparent that the opened facilities lie either directly on Harvey's path and/or are affected by

Case study	1	2	3
No of scenarios	4	7	23
Affected nodes	Based on visual interpretation of Figure 5	Based on NHC advisories in Figure 6	Based on Figure 6, 7 and 8
Disaster type	Hurricane Category 1	Hurricane Category 1	Hurricane Category 1 and 3
Destruction level	No Flooding No damage to pre-positioned items and roads	No Flooding No damage to pre-positioned items and roads	Flooding Partial or complete destructions
<i>Solution</i>			
Facility location	25	59	18
Facility category	Small	Small	Small
Pre-positioned items	9,647	38,757	77,544
Satisfied demand	0%	0%	24%
Computation times	28 s	132 s	829 s

Table 13.
Comparison of the
three case studies

flooding. It can be assumed that Harvey would have destroyed the facility at node 59 on its way so that all relief items stored there would have been lost and could not be used to meet the needs of the affected population. As the entire region suffered from flooding, relief items stored at node 25 were likely to be destroyed and/or not accessible as well. Also in this case, demand for aid supplies cannot be satisfied at all. These results show clearly the drawback of constructing a very small set of scenarios and not using all available data. A further problem results from relying mostly on visual inspection, i.e. the vagueness of the information used.

Only for the last case study intactness of the chosen facility after the landfall of Harvey can be assumed, as the facility is located at node 18 in [Figure 9](#) (bottom). As Harvey moved offshore before reaching San Antonio, the hurricane spared nodes located more inland. Therefore, all relief items stored at node 18 would have been available in the aftermath of Harvey and could have been transported to the people in need. A further advantage of this location solution is the close proximity to the affected area, allowing a timely and rapid delivery.

Although the entire quantity of pre-positioned items is still useable in node 18, in contrast to the two previous case studies, the amount is not large enough to cover all needs raised by the highly destructive hurricane Harvey. The main reason is that NHC did not expect Harvey to become a category 4 hurricane three days in advance. Opening a small facility would have been sufficient for a category 1, but not for a category 4 hurricane. If Harvey had been forecast to become a category 4 hurricane by any of the available sources, the demand could have been estimated more realistically (compared to the demand that actually occurred) and this would have influenced the scenarios accordingly, leading to more and larger facilities and larger numbers of pre-positioned items. In particular, for a category 4 hurricane relief agencies would have to deliver humanitarian assistance to 25% of the population, see [Table 7](#), resulting in a demand of 318,952. The amount of items pre-positioned in node 18 based on the NHC forecast would be sufficient for only about 24% of this demand, see row “Satisfied demand” in [Table 13](#). This underlines the need for forecast improvements on the one hand and for flexibility of aid agencies on the other hand, but the results also show that even in such rather extreme case a more detailed modeling approach with more realistic scenarios leads to strongly improved results. The pre-positioned aid items in node 18 can be used to satisfy the most crucial demand while waiting for new supplies, whereas the other case studies lead to solutions which leave the whole area completely without supply.

The computational times of the different cases are given in [Table 13](#): The first case study was solved after 28 s, the second case study after 132 s and the last case study required 829 s (13 min). As to be expected, computational times increase with an increasing number of scenarios, but even the largest case study is still solvable in acceptable time.

It should be emphasized that the main reason why the last case study led to relatively better location and pre-positioning solutions is its more realistic scenario design which results from including more information, e.g. regarding the possibility and consequences of floods. In particular, determining possible demand for relief items and possible destruction levels of roads and facilities based on forecast information which is as detailed and precise as possible is crucial in obtaining good solutions. As a consequence, a larger number of scenarios is particularly useful if in these scenarios also more information regarding possible developments of the disaster is taken into account. If, on the other hand, important sources of information and hence possible developments are ignored, no useful and meaningful results might be obtained.

5. Conclusion

Most case studies in the humanitarian OR literature are artificially constructed and are far from realistic disaster settings. In particular, input parameters are often set to fictitious values and only few possible outcomes of a disaster (scenarios) are considered. Moreover, disasters and the corresponding consequences are often greatly simplified, leading to

unrealistic and/or too few scenarios and hence to no practically useful solutions. For instance, flooding is often neglected in a hurricane setting.

Due to climate change, extreme weather conditions occur with increasing frequency and hence, the number and intensity of natural disasters increase continuously. Therefore, scenario development has to adapt to these developments, as solutions of practical relevance become even more important. In this paper a first step has been made to collect sources where real-world data, in particular for short-term predictable disasters as floods and storms, can be accessed. This list has to be extended in the future in order to additionally cover disasters which are either less predictable, e.g. earthquakes, or are based on intentional acts like terrorist attacks. Moreover, a framework for case study design has been developed which can be used to construct case studies for different disaster situations. The framework is mainly suitable for short-term predictable disasters, but can also be adapted (with modifications) to other situations, e.g. for strategic pre-positioning; of course, different information (e.g. information on former hurricanes) has to be used for the development of scenarios in Step 2 in that case. The proposed framework has been applied to design three case studies of varying detail in preparation for hurricane Harvey in 2017. The corresponding results highlight that realistic scenario definitions based on detailed short-term forecast information is key for gaining practically relevant and good solutions in short-term predictable disaster situations.

If more complicated models than that of [Rawls and Turnquist \(2010\)](#) are used, e.g. multi-echelon or multi-period models, solution times can become huge even for fewer scenarios. Fast solutions are especially needed when short-term forecasts for disasters are available and preparation measures have to be initiated immediately. Therefore, developing efficient solution methods presents another important challenge for researchers. Moreover, there are further limitations to this study, as currently some simplifying assumptions are made in the case studies presented, e.g. each node is assumed to be a potential facility location and unit transportation costs are constant. However, these assumptions can rather easily be modified, as long as the relevant data is available, and hence do not affect the general applicability of the framework presented in this work. Adding more aspects – e.g. different transportation modes – to the framework and including more data sources, also regarding other disaster types and other areas (not only the US) in the presented lists would be other interesting directions of future research which can help researchers in the field to build cases for many different disaster situations.

Notes

1. In [Figure 2](#) probabilities are shown for different time periods. It may happen that a category 4 hurricane would make landfall in 60 h but after 72 h it would rapidly lose its strength over land to the first category. As the probability is given for a time-horizon of 72 h, the landfall probability for the fourth hurricane category cannot be deduced from this table.
2. The reader is referred to [Rawls and Turnquist \(2010\)](#) for the mathematical model formulation.
3. The complete list of wind speed probabilities can be found in [NHC \(2017c\)](#).
4. Note that higher probabilities, i.e. more than 50%, for exceeding FFG can only be predicted two days in advance ([WPC, 2019a](#)).
5. The Excel file provided by [Huizinga et al. \(2017a\)](#) shows damage potentials of flooding depending on the region and building type. For this case study, flood damage potentials for residential buildings in North America are used.

References

- AccuWeather (2018), “Here are the 5 most vulnerable cities during hurricane season”, available at <https://abc7ny.com/weather/5-most-hurricane-vulnerable-cities/1492381/> (accessed 28 03 2019).

- Acimovic, J. and Goentzel, J. (2016), "Models and metrics to assess humanitarian response capacity", *Journal of Operations Management*, Vol. 45, pp. 11-29.
- Ahrens, C.D. (2012), *Meteorology Today: An Introduction to Weather, Climate, and the Environment*, Cengage Learning, Belmont.
- Alem, D., Clark, A. and Moreno, A. (2016), "Stochastic network models for logistics planning in disaster relief", *European Journal of Operational Research*, Vol. 255 No. 1, pp. 187-206, doi: [10.1016/j.ejor.2016.04.041](https://doi.org/10.1016/j.ejor.2016.04.041).
- Altay, N. and Green, W.G. (2006), "OR/MS research in disaster operations management", *European Journal of Operational Research*, Vol. 175 No. 1, pp. 475-493.
- Baharmand, H., Comes, T. and Luras, M. (2019), "Bi-objective multi-layer location– allocation model for the immediate aftermath of sudden-onset disasters", *Transportation Research Part E: Logistics and Transportation Review*, Vol. 127, pp. 86-110.
- Besiou, M., Pedraza-Martinez, A.J. and Wassenhove, L.N.V. (2018), "OR applied to humanitarian operations", *European Journal of Operational Research*, Vol. 269 No. 2, pp. 397-405, doi: [10.1016/j.ejor.2018.02.046](https://doi.org/10.1016/j.ejor.2018.02.046).
- Bozorgi-Amiri, A., Jabalameli, M.S., Alinaghian, M. and Heydari, M. (2012), "A modified particle swarm optimization for disaster relief logistics under uncertain environment", *International Journal of Advanced Manufacturing Technology*, Vol. 60 No. 1, pp. 357-371, doi: [10.1007/s00170-011-3596-8](https://doi.org/10.1007/s00170-011-3596-8).
- Brownsville (2018), "Brownsville's history with tropical systems", available at: <http://www.hurricanecity.com/city/brownsville.htm> (accessed 28 March 2019).
- Çelik, M., Ergun, O. and Keskinocak, P. (2015), "The post-disaster debris clearance problem under incomplete information", *Operations Research*, Vol. 63 No. 1, pp. 65-85.
- CB (2016), "United States Census Bureau", available at: <https://www.census.gov/data/tables/2016/demo/popest/counties-total.html> (accessed 22 June 2017).
- Chang, M., Tseng, Y. and Chen, J. (2007), "A scenario planning approach for the flood emergency logistics preparation problem under uncertainty", *Transportation Research Part E: Logistics and Transportation Review*, Vol. 43 No. 6, pp. 737-754.
- Davis, L.B., Samanlioglu, F., Qu, X. and Root, S. (2013), "Inventory planning and coordination in disaster relief efforts", *International Journal of Production Economics*, Vol. 141 No. 2, pp. 561-573, doi: [10.1016/j.ijpe.2012.09.012](https://doi.org/10.1016/j.ijpe.2012.09.012).
- Delft-FEWS (2019), "The deltares open archive", available at: <https://publicwiki.deltares.nl/display/FEWSDOC/The+Deltares+Open+Archive> (accessed 11 March 2019).
- Duran, S., Gutierrez, M.A. and Keskinocak, P. (2011), "Pre-positioning of emergency items for care international", *Interfaces*, Vol. 41 No. 3, pp. 223-237.
- Fan, Y. and Liu, C. (2010), "Solving stochastic transportation network protection problems using the progressive hedging-based method", *Networks and Spatial Economics*, Vol. 10 No. 2, pp. 193-208, doi: [10.1007/s11067-008-9062-y](https://doi.org/10.1007/s11067-008-9062-y).
- FEMA (2019), "The FEMA national shelter System database-entire excel spreadsheet", available at <http://www.theblackvault.com/documentarchive/fema-national-shelter-system-database-complete-list-70386-locations/#> (accessed 13 March 2019).
- Ferrer, J.M., Martin-Campo, F.J., Ortuno, M.T., Pedraza-Martinez, A.J., Tirado, G. and Vitoriano, B. (2018), "Multi-criteria optimization for last mile distribution of disaster relief aid: test cases and applications", *European Journal of Operational Research*, Vol. 269 No. 2, pp. 501-515.
- GFS (2019), "National centers for environmental information: model data", available at https://www.ncdc.noaa.gov/data-access/model-data#hires_weather_datasets (accessed 11 March 2019).
- Grass, E. and Fischer, K. (2016), "Prepositioning of relief items under uncertainty: a classification of modeling and solution approaches for disaster management", in Mattfeld, D., Spengler, T., Brinkmann, J. and Grunewald, M. (Eds.), *Logistics Management: Contributions of the Section*

- Logistics of the German Academic Association for Business Research*, 2015, Springer International Publishing, Cham, Braunschweig, pp. 189-202, doi: [10.1007/978-3-319-20863-314](https://doi.org/10.1007/978-3-319-20863-314).
- Grass, E., Fischer, K. and Rams, A. (2020), "An accelerated L-shaped method for solving two-stage stochastic programs in disaster management", *Annals of Operations Research*, Vol. 284 No. 2, pp. 557-582.
- Hong, X., Lejeune, M.A. and Noyan, N. (2015), "Stochastic network design for disaster preparedness", *IIE Transactions*, Vol. 47 No. 4, pp. 329-357, doi: [10.1080/0740817X.2014.919044](https://doi.org/10.1080/0740817X.2014.919044).
- Hu, S.L., Han, C.F. and Meng, L.P. (2015), "A scenario planning approach for propositioning rescue centers for urban waterlog disasters", *Computers and Industrial Engineering*, Vol. 87, pp. 425-435, doi: [10.1016/j.cie.2015.05.036](https://doi.org/10.1016/j.cie.2015.05.036).
- Huizinga, J., de Moel, H. and Szweczyk, W. (2017a), "Global flood depth-damage functions. Methodology and the database with guidelines", available at http://publications.jrc.ec.europa.eu/repository/bitstream/JRC105688/global_flood_depth-damage_functions_10042017.pdf (accessed 08 03 2019).
- Huizinga, J., de Moel, H. and Szweczyk, W. (2017b), "Global flood depth damage functions: methodology and the database with guidelines, excel file", available at: <https://publications.jrc.ec.europa.eu/repository/handle/JRC105688> (accessed 29 January 2020).
- IFRC (2016), "International Federation of Red Cross and Red Crescent Societies items catalogue", available at <https://itemscatalogue.redcross.int/index.aspx> (accessed 9 March 2019).
- Jahre, M., Kembro, J., Rezvanian, T., Ergun, O., Hapnes, S.J. and Berling, P. (2016), "Integrating supply chains for emergencies and ongoing operations in UNHCR", *Journal of Operations Management*, Vol. 45, pp. 57-72.
- Jola-Sanchez, A.F., Pedraza-Martinez, A.J., Bretthauer, K.M. and Britto, R.A. (2016), "Effect of armed conflicts on humanitarian operations: total factor productivity and efficiency of rural hospitals", *Journal of Operations Management*, Vol. 45, pp. 73-85.
- Klibi, W. and Martel, A. (2012), "Scenario-based supply chain network risk modeling", *European Journal of Operational Research*, Vol. 223 No. 3, pp. 644-658.
- Klibi, W., Ichoua, S. and Martel, A. (2013), "Prepositioning emergency supplies to support disaster relief: a stochastic programming approach", *CIRRELT Montreal*, Vol. 19, pp. 1-35.
- Li, L., Jin, M. and Zhang, L. (2011), "Sheltering network planning and management with a case in the Gulf Coast region", *International Journal of Production Economics*, Vol. 131 No. 2, pp. 431-440, doi: [10.1016/j.ijpe.2010.12.013](https://doi.org/10.1016/j.ijpe.2010.12.013).
- Li, A.C., Nozick, L., Xu, N. and Davidson, R. (2012), "Shelter location and transportation planning under hurricane conditions", *Transportation Research Part E: Logistics and Transportation Review*, Vol. 48 No. 4, pp. 715-729, doi: [10.1016/j.tre.2011.12.004](https://doi.org/10.1016/j.tre.2011.12.004).
- Li, Z., Wang, C., Emrich, C.T. and Guo, D. (2018), "A novel approach to leveraging social media for rapid flood mapping: a case study of the 2015 South Carolina floods", *Cartography and Geographic Information Science*, Vol. 45 No. 2, pp. 97-110.
- Liu, C., Fan, Y. and Ordóñez, F. (2009), "A two-stage stochastic programming model for transportation network protection", *Computers and Operations Research*, Vol. 36 No. 5, pp. 1582-1590, doi: [10.1016/j.cor.2008.03.001](https://doi.org/10.1016/j.cor.2008.03.001).
- Lodree, E.J.J., Ballard, K.N. and Song, C.H. (2012), "Pre-positioning hurricane supplies in a commercial supply chain", *Socio-Economic Planning Sciences*, Vol. 46 No. 4, pp. 291-305, doi: [10.1016/j.seps.2012.03.003](https://doi.org/10.1016/j.seps.2012.03.003).
- Maqsood, I. and Huang, G.H. (2013), "A dual two-stage stochastic model for flood management with inexact-integer analysis under multiple uncertainties", *Stochastic Environmental Research and Risk Assessment*, Vol. 27 No. 3, pp. 643-657, doi: [10.1007/s00477-012-0629-2](https://doi.org/10.1007/s00477-012-0629-2).
- MSF (2013), "Doctors without Borders: item catalog", available at: https://webcache.googleusercontent.com/search?q=cache:ogTgSwXNF64J:https://www.artsenzondergrenzen.nl/documents/32/Green_List_July_2013_for_APU_website.pdf+&cd=1&hl=de&ct=clnk&gl=de (accessed 9 March 2019).

- MSF (2016), *Aerzte ohne Grenzen*, e.V.-Private Communication, Hamburg.
- NHC (2005), "National Hurricane Center", available at: http://www.nhc.noaa.gov/archive/2005/KATRINA_graphics.shtml (accessed 22 June 2017).
- NHC (2017a), "Harvey graphics archive: 5-day forecast track and watch/warning graphic", available at: https://www.nhc.noaa.gov/archive/2017/HARVEY_graphics.php?product=5day_cone_with_line (accessed 12 March 2019).
- NHC (2017b), "Hurricane Harvey advisory archive: discussions", available at: <https://www.nhc.noaa.gov/archive/2017/al09/al092017.discus.014.shtml?> (accessed 12 March 2019).
- NHC (2017c), "Hurricane Harvey advisory archive: wind speed probabilities", available at: <https://www.nhc.noaa.gov/archive/2017/al09/al092017.wndprb.012.shtml?> (accessed 12 March 2019).
- NHC (2019), "NHC data archive", available at: <https://www.nhc.noaa.gov/data/> (accessed 9 March 2019).
- NOAA (2016), "National oceanic and atmospheric administration/Atlantic oceanographic and meteorological laboratory", available at: <http://www.aoml.noaa.gov/hrd/tcfaq/D5.html> (accessed 3 February 2020).
- Noyan, N. (2012), "Risk-averse two-stage stochastic programming with an application to disaster management", *Computers and Operations Research*, Vol. 39 No. 3, pp. 541-559, doi: [10.1016/j.cor.2011.03.017](https://doi.org/10.1016/j.cor.2011.03.017).
- Noyan, N., Balcik, B. and Atakan, S. (2016), "A stochastic optimization model for designing last mile relief networks", *Transportation Science*, Vol. 50 No. 3, pp. 1092-1113, doi: [10.1287/trsc.2015.0621](https://doi.org/10.1287/trsc.2015.0621).
- NWS (2017), "National weather service: major hurricane Harvey August 25-29, 2017", available at https://www.weather.gov/crp/hurricane_harvey (accessed 12 03 2019).
- Pedraza-Martinez, A.J. and Van Wassenhove, L.N. (2013), "Vehicle replacement in the international committee of the red cross", *Production and Operations Management*, Vol. 22 No. 2, pp. 365-376, doi: [10.1111/j.1937-5956.2011.01316.x](https://doi.org/10.1111/j.1937-5956.2011.01316.x).
- Pedraza-Martinez, A.J. and Van Wassenhove, L.N. (2016), "Empirically grounded research in humanitarian operations management: the way forward", *Journal of Operations Management*, Vol. 45 No. 1, pp. 1-10, doi: [10.1016/j.jom.2016.06.003](https://doi.org/10.1016/j.jom.2016.06.003).
- Rawls, C.G. and Turnquist, M.A. (2010), "Pre-positioning of emergency supplies for disaster response", *Transportation Research Part B: Methodological*, Vol. 44 No. 4, pp. 521-534, doi: [10.1016/j.trb.2009.08.003](https://doi.org/10.1016/j.trb.2009.08.003).
- Rawls, C.G. and Turnquist, M.A. (2011), "Pre-positioning planning for emergency response with service quality constraints", *OR Spectrum*, Vol. 33 No. 3, pp. 481-498, doi: [10.1007/s00291-011-0248-1](https://doi.org/10.1007/s00291-011-0248-1).
- Rottkemper, B. (2016), *Entscheidungsfindung in der humanitären Logistik-Ein multikriterielles Transshipmentmodell zur Allokation von Hilfsgütern in laufenden Hilfsaktionen*, PhD thesis, Hamburg University of Technology.
- Rottkemper, B. and Fischer, K. (2013), "Decision making in humanitarian logistics-a multi-objective optimization model for relocating relief goods during disaster recovery operations", in Comes, T., Friedrich, F., Fortier, S., Geldermann, J. and Mueller, T. (Eds.), *ISCRAM, 10th International Conference on Information Systems for Crisis Response and Management*, Baden-Baden, Hamburg, pp. 647-657.
- Sabbaghtorkan, M., Batta, R. and He, Q. (2020), "Prepositioning of assets and supplies in disaster operations management: review and research gap identification", *European Journal of Operational Research*, Vol. 284 No. 1, pp. 1-19.
- Salmeron, J. and Apte, A. (2010), "Stochastic optimization for natural disaster asset prepositioning", *Production and Operations Management*, Vol. 19 No. 5, pp. 561-574, doi: [10.1111/j.1937-5956.2009.01119.x](https://doi.org/10.1111/j.1937-5956.2009.01119.x).
- SCEMD (2007), "South Carolina emergency management division-South Carolina logistical operations plan: appendix 7", available at: <http://dc.statelibrary.sc.gov/handle/10827/20614> (accessed 3 February 2020).

- Starr, M.K. and Van Wassenhove, L.N. (2014), "Introduction to the special issue on humanitarian operations and crisis management", *Production and Operations Management*, Vol. 23 No. 6, pp. 925-937.
- Stauffer, J.M., Pedraza-Martinez, A.J. and Van Wassenhove, L.N. (2016), "Temporary hubs for the global vehicle supply chain in humanitarian operations", *Production and Operations Management*, Vol. 25 No. 2, pp. 192-209.
- Stauffer, J.M., Pedraza-Martinez, A.J., Yan, L.L. and Van Wassenhove, L.N. (2018), "Asset supply networks in humanitarian operations: a combined empirical simulation approach", *Journal of Operations Management*, Vol. 63, pp. 44-58.
- Tricoire, F., Graf, A. and Gutjahr, W.J. (2012), "The bi-objective stochastic covering tour problem", *Computers and Operations Research*, Vol. 39 No. 7, pp. 1582-1592, doi: [10.1016/j.cor.2011.09.009](https://doi.org/10.1016/j.cor.2011.09.009).
- Türkş, R. and Sørensen, K. (2019), "Instances for the problem of pre-positioning emergency supplies", *Journal of Humanitarian Logistics and Supply Chain Management*.
- UNHRD (2020), "United Nations Humanitarian Response Depot", available at: <http://www.wfp.org/unhrd> (accessed 10 April 2020).
- Van Wassenhove, L.N. and Pedraza Martinez, A.J. (2012), "Using or to adapt supply chain management best practices to humanitarian logistics", *International Transactions in Operational Research*, Vol. 19 Nos. 1-2, pp. 307-322.
- Wang, S. and Huang, G. (2013), "A two-stage mixed-integer fuzzy programming with interval-valued membership functions approach for flood diversion planning", *Journal of Environmental Management*, Vol. 117, pp. 208-218, doi: [10.1016/j.jenvman.2012.12.037](https://doi.org/10.1016/j.jenvman.2012.12.037).
- WPC (2017a), "WPC QPF Archive for products issued 12Z August 26, 2017", https://www.wpc.ncep.noaa.gov/archives/qpf/display_maps.php?prodtype=issued&proddate=08/26/2017&prodtime=12&allsent=yes&imagetype=color&actualprods=92e,93e,9ee,9fe,9ge,9he,9ie,9je,9ke,9le,9oe,9ne,day1_pd1_f012,day1_pd2_f018,day1_pd3_f024,day2_pd1_f030,day2_pd2_f036,day2_pd3_f042,day2_pd4_f048,day3_pd1_f054,day3_pd2_f060,day3_pd3_f066,day3_pd4_f072,94q,98q,99q,d12,d45,d67,d13,d15,d17#top (accessed 12 March 2019).
- WPC (2017b), "WPC's excessive rainfall outlook archive", available at: https://www.wpc.ncep.noaa.gov/archives/web_pages/ero/ero.shtml?cpMonth=8&cpYear=2019&inputdate=aug+31+2017 (accessed 12 March 2019).
- WPC (2019a), "Product information", available at: <https://www.wpc.ncep.noaa.gov/html/fam2.shtml> (accessed 16 March 2019).
- WPC (2019b), "WPC's excessive rainfall outlook archive", available at: https://www.wpc.ncep.noaa.gov/archives/web_pages/ero/ero.shtml (accessed 9 March 2019).

Corresponding author

Emilia Grass can be contacted at: egrass@ic.ac.uk

For instructions on how to order reprints of this article, please visit our website:

www.emeraldgrouppublishing.com/licensing/reprints.htm

Or contact us for further details: permissions@emeraldinsight.com