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BIG DATA ANALYTICS IN OPERATIONS & SUPPLY CHAIN MANAGEMENT

Data laboratory for supply chain response models during epidemic outbreaks

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Abstract Disasters in developing countries tremendously affect the economy and long-term development. Recent years have seen an increase in epidemic outbreaks in countries like Haiti and in West Africa. However, there seems to be a lack of decision support to address epidemic outbreak challenges in developing countries compared to their developed counterparts. The lack of data to implement such models is a potential reason. This paper presents a data set that will permit to develop data-driven allocation models and policies for an epidemic outbreak in a developing country. The data set is for the cholera epidemic that occurred in the aftermath of the 2010 earthquake in Haiti. The detailed time-series patient data is intended to facilitate the development and evaluation of multi-period supply chain models that support emergency health response, allocate medical resources and staff, and design coordination mechanisms among humanitarian stakeholders. We also provide a simple model to illustrate how the data can be utilized to develop a basic epidemic outbreak response model. The data set will be made available online for researchers interested in developing models in this field.

Keywords Data-driven models · Supply chain · Health care · Time-series data · Epidemic outbreaks · Emergency response

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1 Introduction

The global burden of epidemics has increased tremendously over the past years. The 2008 cholera outbreak in Zimbabwe, the 2010 outbreak in Haiti and the most recent 2014 Ebola outbreak in West Africa saw cases of hundreds and thousands losing their lives. In developing countries, consequences of epidemics are exacerbated due to poor health care infrastructure facilities (Lemonick 2011) and impeded access to treatment facilities (Farmer et al. 2011; McCoy and Johnson 2014). The planning and effective organization of local procurement, warehousing and transport as well as fleet services proved fundamentally important in combatting the Ebola outbreak in West Africa (Goentzel and Heigh 2015). Epidemic outbreaks create a huge blow to developing and least developed economies. The World Bank (2014) asserted that the average loss in GDP to the most affected West African countries due to Ebola is likely to range from \$4.8 billion in 2014 to \$13.4 billion in 2015. The negative impact of epidemics calls for a rapid response and the effective planning of logistical supply chains (Dasaklis et al. 2012).

Various aspects relevant to challenges observed in epidemic outbreaks have been modeled, such as the location of accessible temporary medical facilities (Drezner 2004; Apte et al. 2015; Lee et al. 2009), the requirements of public health personnel for mass prophylexis (Lee et al. 2009), or the allocation and distribution of medical resources in the event of unanticipated epidemic outbreaks (Koyuncu and Erol 2010; Rachaniotis et al. 2012; Aaby et al. 2006). However, these models are constructed for developed regions (i.e., mainly U.S. cities) and do not necessarily capture the additional complications and limitations experienced in developing countries (Rahman and Smith 2000).

Health care delivery challenges in developing countries have started receiving increased attention (see, e.g., Kraiselburd and Yadav 2013; McCoy and Johnson 2014). However, none of the above studies focus on epidemic outbreaks and their inherent challenges. To the best of our knowledge, there is no study addressing the combination of epidemic propagation patterns, medical resource supply chain challenges, and resource allocation decisions in the context of a developing country.

One of the reasons for the lack of decision support models addressing the context of epidemics in developing countries is due to the lack of available data and the difficulty to compile relevant data sets. Green (2012) states that the utilization of data will help take decisions pertaining to capacity of health facilities, the need for dedicated versus flexible resources, design of patient-centered process of care, etc. However, as mentioned by Green (2012), the utilization of data in health care operations management seems to be heavily centered on the U.S. health care system.

Prasad et al. (2016) explain that increased capabilities for and awareness about data collection and retrieval make possible to utilize very effectively big data for humanitarian operations. They argue that in the humanitarian supply chain context different value stream activities (e.g., providing education, basic healthcare, or relief items) demand different data attributes (i.e., data attributes: value, volume, veracity, variety and velocity) depending on their specific nature. One of the misconceptions in utilizing big data for decision-making is the idea that the volume of the data has to be large. However, according to Russom (2011), it is not just the volume of the data that matters, but also their velocity and variety that makes them most useful. In the same vein, Prasad et al. (2016) state that "a relatively small data set generated by various sources in multiple formats and updated frequently is also considered big due to its variety and velocity and would enhance the current capabilities of organizations to capture, store, compute, communicate, and predict it."

Considering the importance and impact of efficiently responding to epidemic outbreaks in developing countries and the benefits of utilizing a variety of data sources, this paper presents a data set that will assist the humanitarian community to develop and test emergency response supply chain models in the immediate aftermath of an epidemic outbreak. It will facilitate taking data-driven decisions pertaining to emergency health facility location, medical staff deployment, and effective patient and medical resource transportation.

While there is a large amount of disaster related data that can be freely accessed, these data have limitations that make them less suitable to directly apply on a decision support model that might be developed using operations research methods. For example, non-governmental organizations, humanitarian organizations and large health organizations provide information about disaster impact and risk, global assessment reports, disaster damage and loss related data (UNISDR 2015); total number of disasters recorded each year, number of persons affected and damage caused in each region of the world (IFRC 2014). All these databases describe the overall disaster impact. They do not offer more granular and disaggregated data that are needed to develop models that address epidemic outbreaks in developing countries. In this paper we present a data set that is at a more granular level and that can be readily used by researchers to implement models relevant to epidemic outbreaks.

The data set can also be used to assess transportation capacity requirements for health delivery supply chains in developing countries, particularly when facing an epidemic outbreak. The "coordination problems across multiple stakeholders with widely divergent objectives has been identified as one of the main drivers of inefficiencies in global health supply chain (Kraiselburd and Yadav 2013). The availability of this set of data could help researchers develop better coordination mechanisms when responding to an epidemic outbreak in a resource-restricted country. Furthermore, attention should be given to antibiotics and vaccine delivery following epidemics, and related coordination issues that may arise in the process (Maskery et al. 2013). The data set could also be used to analyze optimal asset transfer mechanisms and to decide between earmarked and other donation policies used by humanitarian organizations (Bhattacharya et al. 2014) in case of an epidemic.

Simchi-Levi (2014) emphasized the need for more data-driven models, and to analyze data to "identify new models that drive decisions and actions". He also mentions that a prerequisite to undertake such research endeavors will require "an open source data repository that allows scholars to let the data tell a story, be creative, and develop and test models and solution methods". Making the described data set available will permit to develop and validate data-driven epidemic response models and is aligned with Simchi-Levi's call.

The rest of this paper is organized as follows. In Sect. 2 we describe details of the data set presented in this paper. Section 3 presents a simple model as an illustration of how researchers could utilize the data set provided in this paper. Section 4 concludes with a summary of the use of this data set for potential researchers, and describes some imitations and future research directions.

2 Description of the data set

2.1 Introduction

In this paper, we present a detailed data set for the 2010 cholera outbreak in Haiti. We present geographic location details, patient numbers, details of existing health care facilities, and international standards relevant to setting up and operating cholera treatment centers. The availability of such detailed data will enable researchers to understand the landscape of an epidemic outbreak in a developing country and develop suitable decision support models for response. In their literature review of relief distribution networks, Anaya-Arenas et al. (2014) conclude that developing tools that would advance decision-making in location and distribution problems in humanitarian response is crucial to saving more lives. The data set detailed below—and available online (Anparasan and Lejeune 2017)—is intended to serve as a repository for researchers developing tools for epidemics in developing countries.

2.2 Data sources

While disparate sources provide data related to the epidemic outbreak in Haiti, we have focused on and collected the data made public by reliable organizations. Detailed patient data and information relevant to cholera treatment standards and guidelines were collected from the World Health Organization (WHO), the Centers for Disease Control and Prevention (CDC), and the Ministry of Health and Population of Haiti (MSPP). The data are provided online (see Anparasan and Lejeune 2017) and are described next.

2.3 Geographic location data

Haiti has ten administrational departments and these departments are further broken down to 42 arrondissements. The latter are subdivided into 140 communes. Geographic positioning system (GPS) coordinates for the capital city of each commune (i.e., the third administrative division in Haiti) are obtained from Geohack data (Geo Locator 2015). Population numbers based on the most recent consensus prior to the 2010 earthquake in Haiti are included for each commune (Geohive 2015). Table 1 gives a sample of the fields as they appear in the data set (see Anparasan and Lejeune 2017). Each commune is identified with a field ID. The two communes indicated as C1 and C2 in Table 1 are located in the L'Artibonite department and its de Dessalines arrondissement. Table 1 also displays the longitude (X) and latitude (Y) coordinates of the communes and the size of their population.

The GPS coordinates of hospitals, health centers with beds, and field hospitals in operation prior to the 2010 earthquake are given for each Haitian department. This data item is very important, as the pre-existing health facility locations serve as prospective sites for adding emergency health facilities in the immediate aftermath of an epidemic outbreak. Moreover, it was recently revealed that the effective utilization of existing health facilities played a crucial role in combatting the 2014 Ebola outbreak in West Africa (Goentzel and Heigh 2015). Table 2 lists a sample of health facilities (and their coordinates) in the Artibonite department.

Table 1 Sample population numbers and GPS coordinates

Commune ID	Department/arrondissement/commune	Population (2009 estimate)	Coordinates	
			X	Y
	Departement de L'Artibonite	1,571,020		
	Arrondissement de Dessalines	375,499		
C1	Commune de Dessalines	165,424	−72.50	19.28
C2	Commune de Grande Saline	21,131	−72.78	19.25

Table 2 Sample GPS coordinates for health facility locations in Haiti

Health facility ID	Department	Category	Name	Coordinates	
				X	Y
H1	Artibonite	Hospital	Terre Neuve Hospital Terreneuve	−72.78	19.60
H2	Artibonite	Hospital	St Michel Att Hospital	−72.33	19.36
H3	Artibonite	Hospital	St Marc Hospital Pierre Payen	−72.70	19.12

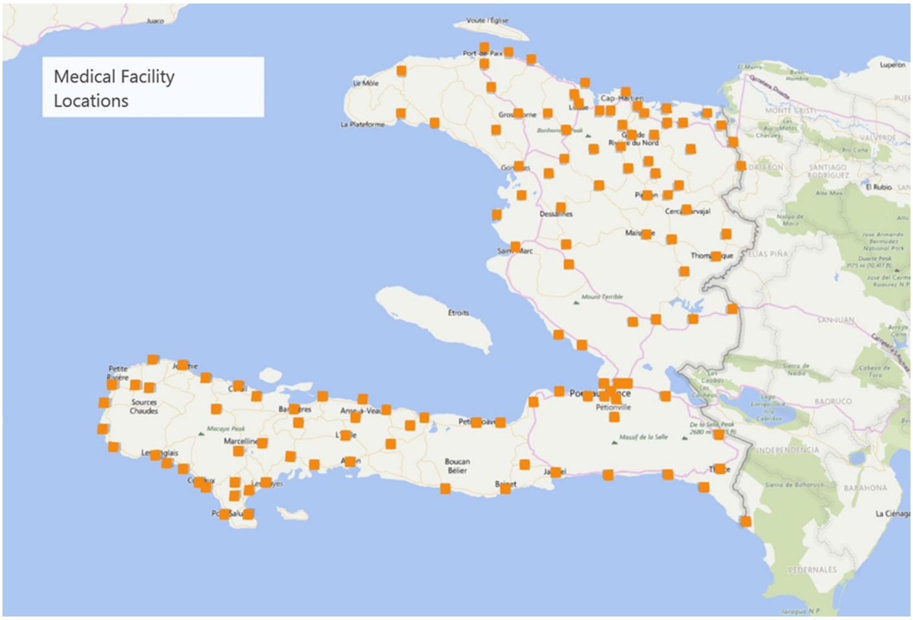

Fig. 1 Sample mapping of health facility locations in Haiti

The category item defines the type of health facility. There are 530 prospective health facility locations in this data set. Figure 1 maps the health facility locations in Haiti.

2.4 Travel time data

Table 3 provides a sample of driving and walking times between a health facility and the capital city of a commune as calculated with the Google distance matrix API (Google 2015). Even though driving and walking times between locations can seem easy to obtain, it is worth to note that detailed data about actual road distances and conditions are not readily available to researchers. For this data set, we compute the driving and walking times between 125 communes and 530 prospective health facility locations (i.e., 132,500 travel times). Approximately two computational hours per day over a 4-week period were required to obtain accurate travel time data using a script specifically developed to calculate Google travel times. The data permit to locate facilities within a pre-specified maximal distance and/or travel time from patient locations.

Table 3 Sample distances from communes to health facility locations

From (commune ID)	To (health facility ID)	Driving time	Walking time
C1	H1	1 h 12 min	6 h 35 min
C1	H2	35 min	3 h 12 min
C1	H3	43 min	3 h 45 min
C1	H4	43 min	3 h 55 min

Table 4 Patient data for each department in Haiti

Day	Department	Number of hospitalized patients	Number of patients discharged	Number of deaths in treatment facilities	Number of deaths in community
11th Nov	Artibonite	570	560	10	14
11th Nov	Centre	15	15	0	0
11th Nov	Nord Ouest	212	212	0	2

2.5 Data on patient numbers

The daily patient reports published by MSPP in PDF format (MSPP 2011) were collected for 120 consecutive days (i.e., 11th November 2010–10th March 2011) in the aftermath of the cholera outbreak. A web-based online file converter was utilized to convert the PDF files to excel format in order to retrieve the detailed patient data. The data include the number of hospitalized patients, the number of patients discharged from hospitals, the number of deaths in health care facilities, and the number of deaths in communities during this initial phase of the outbreak. Even though complete data are available from November 11, 2010, we also report the number of hospitalized patients, the number of deaths in health facilities, and the number of deaths in community from November 4, 2010. Table 4 gives an example of patient data for three departments for the first week.

Figure 2 provides a visual display of the distribution of patients across the main departments in Haiti. The height of the columns indicate the number of hospitalized patients. The North, North West, and Port au Prince areas have very large patient numbers relative to other regions.

2.6 Data on health care standards and guidelines

The data set also gives researchers information about the standards and guidelines set by health care organizations, which can help the validation of their models. Medical staffing and medicine requirement guidelines (WHO 2004; MSPP and CDC 2011) for cholera treatment centers are given in Tables 5 and 6. This enables researchers to make informed analyses and comparisons based on more than one set of standards and guidelines. While MSPP and CDC (2011) guidelines primarily focus on small bed capacity Cholera Treatment Centers (CTC) and Cholera Treatment Units (CTU), WHO (2004) guidelines focus on larger treatment facilities that treat a larger number of incoming patients.

The health care guidelines in Table 5 will help assess the supply chain capabilities for medical staffing as well as medicine and special equipment needed to combat an epidemic

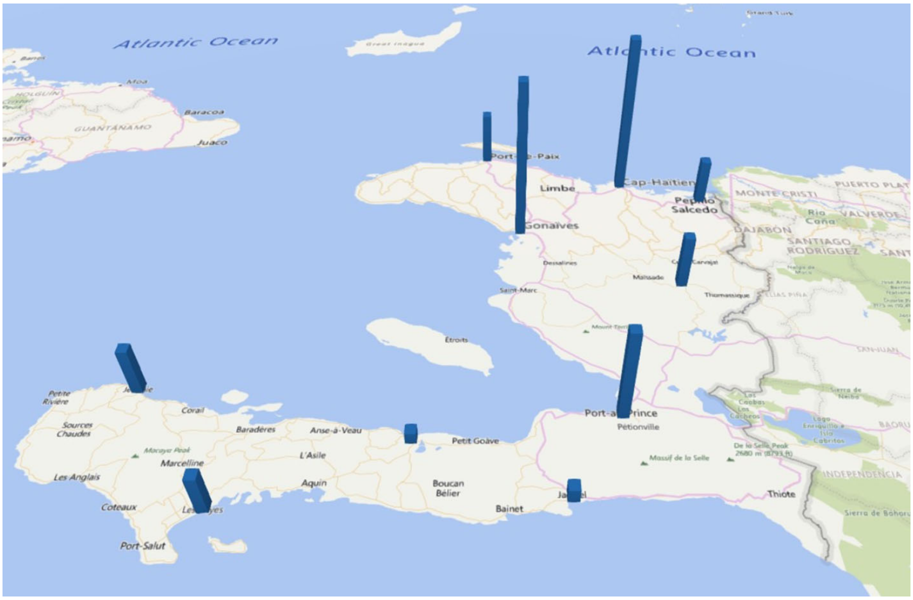

Fig. 2 Case numbers for each department in Haiti

Table 5 Cholera treatment facilities: bed capacities and staffing requirements

Type of treatment center	No. of beds	No. of doctors	No. of nurses	No. of medical assistants	Other support staff
Source: *MSPP and Centers for Disease Control and Prevention (CDC)* (2011)					
CTC[a]	50	3	15	15	17–20
CTC[b]	50	4	20	20	20–30
CTU	20	0	3	3	8–10
Source: *UN MINUSTAH (Peace Keeping Mission of the UN)–WHO* (2004)					
CTC	50	4	12	–	12
CTC	100	6	24	–	40
CTC	200	9	45	–	80

[a] 100% inpatient care; [b] 50 more patients can be treated as outpatients; "Other support staff" includes administrational staff, cleaners, storekeeper, drivers etc

outbreak in a resource-restricted country. Goentzel and Heigh (2015) note that assessing such requirements for each emergency health care facility was critical in combatting the recent Ebola outbreak in Liberia.

As specified by MSPP and CDC (2011), one unit of interagency cholera medicine kit comprises 4 components: basic, oral rehydration solution, infusion and support. Such a unit helps support a certain number of patients of each type listed in Table 6. This gives researchers a baseline standard in order to study inventory requirements and distribution challenges during a cholera epidemic outbreak.

Table 6 Number of patients treatable per cholera medicine kit (MSPP and CDC 2011)

Unit size of treatment package	Treatment capability (no. of patients)			Inventory to be maintained per health facility
	Severe cholera cases	Moderate cholera cases	Other diarrheal infections	
1 Unit	100	400	100 adults + 100 kids	3–14 days supply

Table 7 Public funds for Haitian earthquake and cholera response (2010–2012)

Disaster	Contribution for humanitarian relief (in USD millions)		
	Pledged	Committed	Disbursed
Earthquake	2368.10	66.2	2227.50
Cholera	204	8.1	191.9

2.7 Humanitarian funding data

Table 7 gives an aggregate view of the humanitarian financing data by the public sector that was disbursed to Haiti since the 2010 earthquake (UNDP 2015). Table 7 compares the funds allocated for the earthquake and for the cholera response efforts, and will help researchers to accurately predict budget requirements. In Table 7, committed funds are those for which projects have been approved or agreements/contracts have been signed or in the process of being transferred/disbursed. Committed funds are not included in the disbursed funds. More details regarding individual allocation of funds to different agencies are provided in the data set available online (Anparasan and Lejeune 2017).

The above data will be useful to research the funding aspects of the humanitarian response to an epidemic or disaster (Bhattacharya et al. 2014; Natarajan and Swaminathan 2014).

3 Provision of medical care: an illustration

In this section, we formulate a basic integer linear programming problem to illustrate the possible usage of how the data accompanying this paper can be utilized. The purpose of this simplified model is to show how the data set provided by this study could be used to develop models and data-driven support systems for responding to an epidemic outbreak.

The objective of the basic model is to provide effective and timely medical care to patients. Table 8 provides a list of the notations used.

The objective of the model is to maximize the number of patients transported in a timely fashion to a medical treatment facility.

$$Max\ Z = \sum_{i \in I} \sum_{j \in J_i} \sum_{k \in K} \sum_{t \in T} s_{ijkt} \tag{1}$$

We describe now the essential constraints of the model. Additional constraints, objectives, and considerations could be included in the model using the data set available online (Anparasan and Lejeune 2017).

The constraints (2) stipulate that the number of patients transported from a triage location to any treatment facility at a period t cannot exceed the total number p_{it} of patients at a triage location i at time t:

Table 8 Notation

Sets	
I	Set of patient triage locations
J	Set of treatment locations
J_i	Set of treatment locations within specified travel time from triage location i
I_j	Set of triage locations within specified travel time from facility location j
L	Set of treatment facility types
K	Set of transportation modes *{driving, walking}*
R	Set of medical staff types {*doctors, nurses*}
T	Set of time periods
Parameters	
p_{it}	Number of severely ill people at triage location i at time period t
c_l	Maximum capacity of treatment facility of type l
u_r	Number of patients that one medical staff person of type r can treat daily
e_l	Stock of medicine available (units) per treatment facility type l
Decision variables	
s_{ijkt}	Number of severely ill patients transported from triage location i to facility location $j$that is within drivable distance using mode $k$at time t
x_{jl}	Binary variable, 1 if facility type l is located at location j, and 0 otherwise
z_{jr}	Number of medical personnel of type r assigned to facility location j

$$\sum_{j\in J_i}\sum_{k\in K} s_{ijkt} \le p_{it} \qquad \forall i \in I, t \in T \tag{2}$$

The set of constraints (3) specifies that the number of ill patients treated in a facility location j is limited by the medical personnel $\sum_{r\in R} z_{jr}$ available at this location.

$$\sum_{i\in I_j}\sum_{k\in K}\sum_{t\in T} s_{ijkt} \quad \le \sum_{r\in R} z_{jr} * u_r \qquad \forall j \in J \tag{3}$$

The constraints (4) ensure that the number of patients admitted to each treatment facility does not exceed the capacity of the facility:

$$\sum_{i\in I_j}\sum_{k\in K}\sum_{t\in T} s_{ijkt} \quad \le \sum_{l\in L} x_{il} * c_l \qquad \forall j \in J \tag{4}$$

Constraint (5) ensures that there can be at most one treatment facility opened at each candidate location. Constraint (6) makes sure that the number of patients that can be treated at a treatment facility j is limited by the available stock of medicine. The integrality restrictions are given by (7).

$$\sum_{l\in L} x_{jl} \le 1 \qquad \forall j \in J \tag{5}$$

$$\sum_{i\in I_j}\sum_{k\in K}\sum_{t\in T} s_{ijkt} \le \sum_{l\in L} x_{jl}{}^{*} e_l \qquad \forall j \in J \tag{6}$$

$$s_{ijkt}, z_{jr} \in \mathbb{Z}^{+} \quad \forall i \in I, j \in J_i, k \in K, r \in R \tag{7}$$

We consider a sample of the weekly data available online (Anparasan and Lejeune 2017) in the above model. 20% of the severely ill patients are assumed to be cholera patients who are transported to medical facilities by ambulances departing from triage locations. We consider a sample of weeks for the analysis; the average number of severely ill cholera patients for the sample weeks is 443. The optimal solution of the integer problem permits to treat slightly more than 60% (i.e., 266) of the patients severely sick with cholera. Nineteen medical facilities are utilized across Haiti and employ 45 physicians and 45 nurses and 81 for treating patients with cholera.

4 Conclusions

We present in this paper a detailed data set for the cholera epidemic that occurred in the aftermath of the 2010 earthquake in Haiti. The data comprise population data and GPS coordinates for each commune in Haiti, GPS coordinates for pre-earthquake health facilities, driving and walking times from each commune to each health facility, detailed patient data for each department for more than 120 consecutive days, medical staff allocation and medical goods allocation guidelines and cholera related public funding data.

To the best of our knowledge, such granular data that cover patient and hospital location information, transportation times, patient data, medical standards and funding are not currently available to researchers in a centralized fashion. Lack of such detailed data inhibits the development of robust supply chain models for emergency response during epidemic outbreaks, especially in developing countries. With this paper we intend to partially fulfill this gap and provide a set of valuable data for constructing robust data-driven supply chain models for emergency response to an epidemic outbreak. We also provide a simple optimization model as an illustration, to clarify the use of this set of data.

This study will promote the development of descriptive and prescriptive models considering the uncertainties of an epidemic outbreak in a developing economy. There is a lack of data for constructing robust supply chain models for emergency medical response in the aftermath of an epidemic outbreak. For example, it will enable the development of deterministic as well as robust and stochastic models to assess health care triage requirements and capabilities, transportation needs, and requirements for medical personnel. Even though small compared to typical big data applications, the data set presented in this paper is rich in variety (Prasad et al. 2016; Russom 2011) and will facilitate the development and evaluation of models (Hazen et al. 2016) that require time-series data to support emergency health response, allocation of medical resources, designing of coordination mechanisms among humanitarian stakeholders, and use donations for epidemics in a resource-restricted country. In Sect. 3 we present a simple deterministic model to describe the use of this data set. The model, determines where to locate cholera facilities, the allocation of limited human resources such as nurses and doctors and the number of patients that will be transported from triage locations to the constructed health facilities.

The online and public availability of the data set will permit the health care and humanitarian operations management community to conduct further data-driven research (Simchi-Levi 2014) that can support and enhance decision-making for similar scenarios of epidemic outbreaks in developing countries.

4.1 Limitations

This study provides a comprehensive, yet not exhaustive, set of data to develop and test data-driven epidemic response models. Additional information could be needed to address specific model requirements. For example, assumptions would have to be made to characterize the probability distribution of patients in each triage location when using the patient and population data (Tables 4, 5). Similarly, if a researcher wants to consider prioritizing patient care based on deteriorating health conditions (see, e.g., Xiang and Zhuang 2016), assumptions about the proportions of severely ill, moderately ill and least ill patients would also be needed. One of the limitations to the data is that we cannot comment on the validity or authenticity of the data. However, given the lack of established practices for data collection in developing countries, we did our best to stick to government sources (MSPP), WHO and CDC to minimize the effect of unauthentic data.

4.2 Future research

Future research directions for a data paper of this nature are manifold. However, the most important would be the publication of time series data on affected population numbers for multiple epidemic scenarios in various developing countries. While the case of one country provides the ability for researchers to model various dynamics relevant to an epidemic outbreak that is similar in nature, the accessibility of multiple data sets in ready-to-use formats will of greater benefit. It is the authors' hope that this paper will create greater benefit for more researchers in the area of humanitarian relief logistics modeling and that the publication of such data papers becomes relevant in the community.

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