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Forecasting in humanitarian operations: Literature review and research needs

Nezih Altay [a,*], Arunachalam Narayanan [b]

[a] DePaul University, Driehaus College of Business, 1 E. Jackson Blvd., Suite 7000, Chicago, IL 60604, USA
[b] University of North Texas, G. Brint Ryan College of Business, 1155 Union Circle #311160, Denton, TX 76203-5017, USA

A R T I C L E I N F O

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A B S T R A C T

Forecasting research in the humanitarian context is scarce. In this literature review, our goal is not only to show why forecasting research is important for the humanitarian sector, but also to identify what has been done so far, and where are the needs for further research. We conducted a structured literature search in Scopus, Web of Science, ABI Inform, and Google Scholar resulted in only 38 papers published between 1990 and 2018. Based on our findings we highlight three case studies as exemplary research in forecasting within the humanitarian context and list seven future research streams with specific research needs identified in each stream.

1. Introduction

The COVID-19 pandemic highlighted the need for effective humanitarian assistance as millions of vulnerable people have been kept away from their livelihood and families. Unfortunately, with or without the pandemic there is no shortage of people in need of assistance. Even before the pandemic, an unprecedented 79.5 million people around the world were forcibly displaced (UNHCR, 2020). Extreme poverty was still a problem, as of 2015, 734 million people were living under $1.90 a day or less, and the pandemic is expected to push another 40–60 million more people into extreme poverty (World Bank, 2020). The pandemic also did not stop neither climate change nor natural and man-made disasters. About 143 million people in the world are expected to be forced out of their homes due to crop failure, water scarcity and rise in the sea level (Rigaud et al., 2018), all effects of climate change. In 2019 alone, the world has experienced 396 natural disasters, which took 11,755 lives and affected 94.9 million people (CRED, 2019). These figures and estimates make it very clear that there will be an increasing need for humanitarian aid in the near future. Consequently, efficient and effective procurement, security, storage, allocation, and distribution of humanitarian relief are ever more important. Forecasting lies in the root of these activities.

In the for-profit world, increasing product varieties, shorter product life cycles, ever-growing expectations of consumers, and increasing cost competition due to globalization make forecasting essential to the matching of supply with demand (Boone, Ganeshan, Jain, & Sanders, 2019). Add to these the complexities of armed conflict, the urgency in responding to a disaster, the uncertainty in the timing and location of the next major incident, the limitations induced by donors, and the pressure coming from media, and it becomes very clear how critical forecasting is to the effectiveness of humanitarian operations.

Disasters are events that overwhelm local resources and we generally separate them into two groups: man-made (terror attacks, armed conflict, and industry accidents) and natural (hurricanes, earthquakes, heat waves, floods, etc.) (Altay & Green, 2006). Natural disasters can also be separated into two groups within itself: slow-onset, refers to events that form and move slowly (e.g. hurricanes/cyclones), and rapid-onset, refers to events

* Corresponding author.
E-mail addresses: naltay@depaul.edu (N. Altay), arunachalam.narayanan@unt.edu (A. Narayanan).

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that arise suddenly and their occurrence cannot be predicted in advance (e.g. earthquakes) (Coppola, 2006). Within the humanitarian sector there is a genuine interest in forecasting natural disasters that would trigger a need for response. Within the hard sciences such as climate science, geophysics, and fluid dynamics, there is plenty of research on forecasting natural events (Done, Holland, Bruyère, Leung, & Suzuki-Parker, 2015; Tiampo & Shcherbakov, 2012). For example, in the short-term, climate scientist and meteorologists can simulate the formation and movement of a hurricane or cyclone to forecast its strength, travel path, and expected time and point of landfall. This information is then used by emergency managers to estimate demand for relief items and pre-position these stocks for a fast and effective response. In the long-term, climate scientists forecast the frequency and intensity of hurricanes expected in the next hurricane season, which then allows federal, state, and local emergency management agencies to adjust their budgets and relief funds. The above-mentioned examples illustrate the potential that forecasting has in improving humanitarian operations. However, the connection between the predictions of natural disasters and the planning of relief efforts is not explored in the literature in hard sciences.

Since climate science, geophysics or fluid dynamics is not part of our subject area, in this article, we focus on statistical forecasting of disasters and disaster-related operational issues (i.e. forecasting supply and demand). Fig. 1 presents a diagrammatic view of the scope of this research. The purpose of this article is to be a call to action for the statistical forecasting community to engage in humanitarian operations research.

Similar to the differences between commercial logistics and humanitarian logistics (Holguín-Veras, Jaller, Van Wassenhove, Pérez, & Wachtendorf, 2012a; Kovács & Spens, 2007; Van Wassenhove, 2006), it is natural to expect to see some fundamental differences in the forecasting process between a commercial setting and a humanitarian setting.

Matching supply and demand is the core of supply chain management. In general, companies utilize inventory to balance the differences in supply and demand. Warehouses and distribution centers are used to facilitate the storage and handling of stock. Therefore, any organization can realize significant savings in operational cost (inventory) as well as fixed costs (warehouses) by simply better matching supply and demand. Large humanitarian organizations such as OCHA (United Nations Office for the Coordination of Humanitarian Affairs), World Food Program (WFP), or the International Federation of Red Cross and Red Crescent Societies (IFRC) respond to almost all humanitarian emergencies in the world or have ongoing development programs all over the world. For these organizations, forecasting demand (i.e. humanitarian needs) is relatively easier since they develop aggregate forecasts. Aggregate forecasts allow them to procure supplies such as blankets, tents, read-to-eat meals, and such in bulk. These items are then stored in large warehouses until needed. Therefore, just like in the for-profit world, better forecasting has the potential to lower inventory costs for humanitarian organizations. For smaller, local organizations, however, forecasting could be a challenge since in their case, catastrophic events are intermittent (Nikolopoulos, 2020). Intermittent demand forecasting is difficult due to the zero demand periods in time series. Therefore, context-specific adjustments, such as correlating demand for relief items to other disaster-related indicators, could improve the performance of the forecast and associated processes (Altay, Litteral, & Rudisill, 2012).

Furthermore, since funding systems can limit the scope of humanitarian response, it is also crucial to have reliable forecasts for fundraising pledges and donations (Wakolbinger & Toyasaki, 2011). This is basically the problem of forecasting supply. Pledges do not always convert into donations, and occasionally humanitarian organizations receive more than what they have requested. Both scenarios stress the organization, because in the former they will have a shortage of supplies and the latter force them to spend the money outside of their mission. Better forecasting of donations would improve the planning and execution of their programs on the ground for these organizations. The last fundamental difference is forecast errors. In the commercial sector, errors in demand forecasts translate into lost sales or excess inventory. Regardless, forecast errors cost a company money. However, in the humanitarian sector, forecast errors could translate to human suffering or worse, loss of lives, and therefore have much more meaning than they do in the commercial sector. For example, the head of supply chain planning at a large humanitarian organization told the authors that when it comes to medical supplies, he would rather keep excess inventory and incinerate it when expired, than not have enough stock when needed. This behavior is rarely seen in the commercial sector, if at all. These differences in forecasting between the two sectors make the study of forecasting within the humanitarian context interesting.

Consequently, while working on a talk on this very topic for the 24th International Institute of Forecasters Workshop, Forecasting for Social Good held at Cardiff University in July 2018, we were surprised to find how little research was actually done on forecasting in humanitarian operations. Therefore, the main purpose and contribution of this article is to show what has been done so far in the literature with respect to forecasting research within the humanitarian context and identify the research needs to stimulate future research.

The remainder of this article is organized as follows. Section 2 provides an overview of humanitarian operations. Section 3 explains the literature selection process. Section 4 discusses the findings from our literature review. Section 5 constitutes the main part of this article, discusses research gaps, and offers future research directions. Section 6 contains concluding remarks. This article also contains an Appendix where we provide a sample list of data sources as a starting point for scholars interested in entering this research field.

2. Humanitarian operations

In its core, the goal of every humanitarian operation is to alleviate human suffering. What triggers the suffering could be a natural event (e.g. hurricane, earthquake, volcano eruption, and mudslide) or a man-made

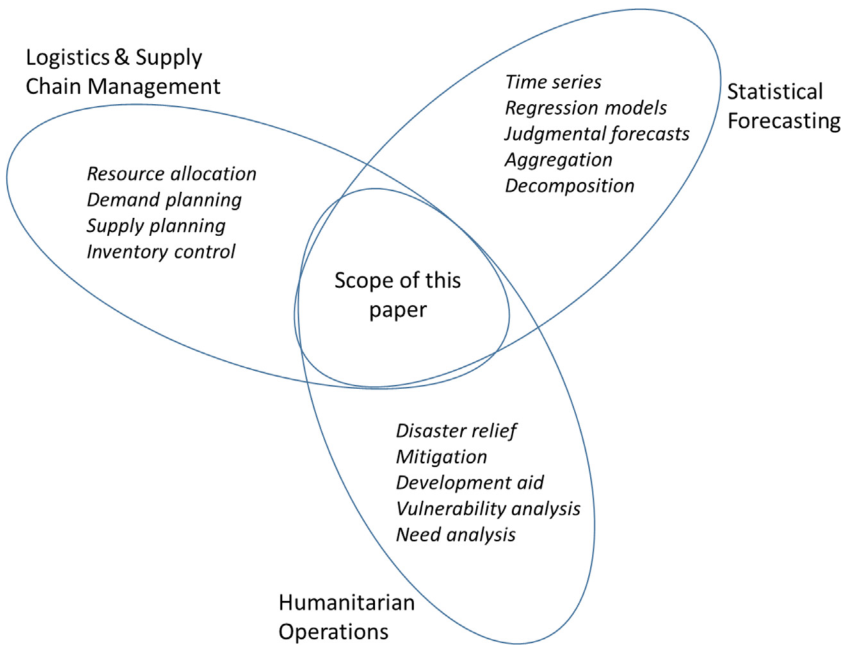

Fig. 1. Scope of this research.

incident (e.g. industrial accidents, terrorism, and war). It could be sudden-onset (e.g. earthquake) or slow-onset (e.g. hurricane) and it could be catastrophic (e.g. earthquake, tsunami) or chronic (e.g. famine). In every case, we are talking about large wicked problems that test the capacity and capability of communities and nations, to prepare for, respond to, and rapidly recover from (Altay & Green, 2006).

The underlying cause of disasters is vulnerability (Kelman, 2011). A good example is populations living on the coastline. According to the 2010 census of the United States, 123.3 Million people, or 39 percent of the US population live on the coastline (NOAA, 2020). When the sea level rises, whether it is temporary due to storm surge or permanent due to climate change, the population living on the coast will be forced to displace. In other words, human settlements in flood zones or at sea level, are vulnerable to the effects of hurricanes and climate change. We do not call a flood, a humanitarian event unless humans are affected by it.

Immediately after a humanitarian event media attention turns to the event location and the viewers see a lot of commotion. What is visible to us is the response phase. However, there are four stages to the disaster management cycle: mitigation, preparedness, response, and recovery (Waugh & Hy, 1990). The four-phase classification is based on the Comprehensive Emergency Management concept introduced in the 1978 report of the National Governors Association Emergency Preparedness Project (Altay & Green, 2006). Mitigation involves steps to reduce vulnerability to disaster impacts. This may include revising land use and zoning laws, introducing compulsory disaster insurance, fortification of public infrastructure. Preparedness includes educating the public about the risks and hazards threatening their livelihood, engaging the business community, prepositioning disaster relief supplies, and other logistical readiness activities. The third stage, response is the most researched phase of the disaster management cycle. It includes search and rescue operations, damage and needs assessment, distribution of relief goods (e.g. food, water, shelter, clothing, and medical relief), safety and security, and debris cleanup. In the last phase, recovery, the immediate goal is to restore the local economy and bring the community some sense of normalcy. It is also the stage where a damaged community has the opportunity to rebuild itself stronger than before, improving their resilience (Coppola, 2006).

There are failures in the response effort almost after every disaster and it is mostly in the same areas, such as coordination. This would mean that there is something amiss with an emergency management system that is virtually the same since 1978. Canton (2019) points out to the need for a modern approach that is supported by social sciences and assessed by new national standards for emergency management. The approach should be a distributed process (rather than centralized) and must be collectively performed by the community, with increased engagement of local officials. This new community-wide approach also alters the general responsibility of the emergency manager. Instead of acting as a technical expert on emergency operations, the person should act as a program manager whose facilitates the development of a community strategy for managing risk and to oversee the implementation of the response strategy (Canton, 2019).

Disasters create shortages of food, water, medical supplies, fuel, money, and other essentials. During normal times, individuals and families enjoy a continuous access to goods and services (e.g. public water or well-stocked supermarkets) and keep their own stocks as well (e.g. kitchen pantry). However, a major catastrophic event not only destroys their homes and stocks but also cuts off the supply of goods and services. Suddenly, demand exceeds supply. Immediate needs arise for water and sanitation, food and kitchen sets, medical assistance, temporary shelter (tents, tarps, and blankets), and fuel for cooking/heating to setup the displaced in temporary living conditions until reconstruction and recovery efforts can start (Smadi, Al Theeb, & Bawa'neh, 2018). In addition to these basic life support needs, the response to a disaster should also ensure the safety and security of survivors, enable communications and information flows, and provide psychological relief to the needy, as many of them would be suffering from post-traumatic stress syndrome (Cohen et al., 2019).

Hopefully, local governments and humanitarian organizations have already forecasted such an event and prepositioned supplies in an alternate location. Need assessment teams immediately hit the ground and count the number of survivors, identify their locations, and collect other situational information such as the conditions of roads and public infrastructure. Prepositioned supplies start flowing into the theater based on the need assessment reports. This means that immediately after a disaster, humanitarian relief supply chains are supply driven (i.e. push system). Once the search and rescue operation ends, survivors settled into their temporary shelters, and their safety is ensured, then information about specific needs start flowing in switching the supply chain from a supply-driven one to a demand-driven one (i.e. pull system). This paragraph may make it sound like in a well-prepared community everything flows smoothly after a disaster. However, according to the interviews that Day, Melnyk, Larson, Davis, and Whybark (2012) conducted with humanitarian workers, there is no accurate way of forecasting resource requirements or estimate the impact of different hazards on a community. Therefore, shortages or misallocations of stock among locations are common problems.

While disaster relief operations are temporary, development aid tends to continue for a long time. In this case, the supply chain tends to be efficient rather than responsive (Fisher, 1997). Forecasting demand is relatively easier and plays a critical role in keeping the supply chain efficient. There is an interaction between development aid and disaster relief. While disasters disrupt development efforts, development aid builds capacity and resilience, thus reducing the risk of future disasters in the community (Day et al., 2012). Therefore, development is embedded within disaster risk reduction. A common notion is that such developmental aid network is only seen in poor and less fortunate locations; however, such networks are very common in developed nations. For example, consider the Feeding America food bank network in the US, they provide food for 46 million individuals through their network of food pantries, soup kitchens, shelters, and other community-based agencies. Forecasting demand or resource requirement in such network is crucial for managing the supply and demand in their operations.

Forecasting plays a role in all four phases of disaster management as well as in development aid operations. Mitigation and preparedness require careful planning and budgeting of procurement where forecasting plays an integral role (da Silva Lamenza, Fontainha, & Leiras, 2019). During a response, the execution of the plan is frequently enhanced with improvisation (Tint, McWaters, & van Driel, 2015), creating a need for "real-time" rather than traditional "near-time" forecasting of demand (Yagci-Sokat, Zhou, Dolinskaya, Smilowitz, & Chan, 2016). Recovery, reconstruction and development will be budget constrained where forecasts would once more play an essential role in the budgeting process. Clearly, forecasting should be in the center of all this planning and preparation. Also, in contrast to the commercial sector, in humanitarian operations forecasting is not just about demand but also upstream supplies. Since, in humanitarian operations, a major portion of the supplies are voluntary contributions, forecasting that is key in their planning process. In addition, these supplies and contributions are intermittent, they are at their peak during a crisis event (more donations arrive at the onset of a crisis), or during the holiday/end of season days (Nelan, Penta, & Wachtendorf, 2019). Hence, exploring how much forecasting research has been done within the humanitarian context is the central theme of this article. In the next sections, we search the relevant literature, review our findings, and identify further research needs in forecasting for humanitarian operations.

3. Literature selection and analysis

We performed a database search for journal articles concerning forecasting in humanitarian operations. The databases searched include SCOPUS, ABI/Inform Collection, Web of Science Core Collection, and Google Scholar. We used the keywords "humanitarian", "disaster*", "catastroph*", "relief", "aid", "nonprofit", and "not for profit", in combination with "forecast*", "demand", and "resource" (the asterisk at the end of the word indicates that we also searched using extensions of that word; e.g. forecast* = forecast, forecasts, forecaster, forecasting, forecasted, etc.). We searched for these keywords in author provided keywords, article title, and abstract for the publication date range 1990–2018. We have excluded work not published in English. In addition, we only focused on peer-reviewed publications such as articles published in academic journals, and excluded conference proceedings, books, and book chapters because we have no way of knowing if they went through a peer-review process. Excluding non-peer-review publications is a common practice in literature review studies (Altay & Green, 2006; Grange, Heaslip, & McMullan, 2019). The search was performed between July and October of 2018. The initial search results are tabulated in Table 1.

Once the raw results of the above searches are gathered, we went over the titles of the articles first. When the relation of an article to forecasting was not clear from its title, we read the abstract of the article. Some of the articles found through Google Scholar could not be verified whether it is written in English or not. This was the case with several Chinese journals, where the title and abstract of the paper were in English but the journal website was in Chinese. Results were refined using Web of

Table 1
Initial search results.

Search keywords	Scopus	Web of science	ABI inform	Google scholar
humanitarian and "demand planning"	1	0	2	1
humanitarian and "resource allocation"	4	1	0	8
humanitarian and forecast*	5	4	1	8
"non profit" and "demand planning"	0	0	0	0
"non profit" and "resource allocation"	2	4	0	5
"non profit" and forecast*	2	1	0	2
"not for profit" and "demand planning"	0	0	0	0
"not for profit" and "resource allocation"	0	0	0	0
"not for profit" and forecast*	5	0	0	0
disaster* AND forecast*	153	34	3	131
catastroph* AND forecast*	45	8	1	14
demand AND disaster*	82	38	2	88

Table 2
Refined search results.

Database	Initial	Filtered	References
SCOPUS	299	9	Davis, Jiang, Morgan, Nuamah, and Terry (2016), Florez, Lauras, Dupont, and Charles (2013), Haghi, Ghomi, and Jolai (2017), Li, Hernandez, Milburn, and Ramirez-Marquez (2018), Lopez et al. (2020), Yu, Yang, Miao and Zhang (2018), Yu, Zhang, Yang and Miao (2018), Tall, Mason, van Aalst, Suarez, Ait-Chellouche, Diallo, and Braman (2012) and Zhan and Liu (2016)
Web of Science	46	22	Braman et al. (2013), Chevuturi and Dimri (2016), de la Poterie et al. (2018), Coughlan de Perez et al. (2016), Coughlan de Perez et al. (2015), Dore (2003), Du, Zhang, Deng, and Li (2014), Han and Tang (1999), Hsieh (2004), Jin, Cheng, and Wei (2008), Kgakatsi (2014), Kim, Kim, and Park (2009), Miao and Ding (2017), Mude, Barrett, McPeak, Kaitho, and Kristjanson (2009), Musa et al. (2018), Noda (2016), Pisarenko and Rodkin (2006), Ramírez and Briones (2017), Shen, Ou, Chen, Zhang, and Tan (2013), van der Laan, van Dalen, Rohrmoser, and Simpson (2016), Wang (2013) and Xu, Qi, and Hua (2010)
ABI Inform	7	3	Guo, Hou, Yang, Du, and Xiao (2015), Sheu (2010) and Song, Chen, and Lei (2018)
Google Scholar	241	4	Basu, Roy, and DasBit (2018), de Silva (2011), Matori and Lawal (2014) and Zhang, Feng, and Wang (2018)

Science as the basis (i.e. articles that appeared in Web of Science and other databases were removed from the other databases and were only associate to Web of Science in Table 2). This refining process resulted in 38 relevant papers listed in Table 2.

Table 2 provides a representative but not exhaustive list of forecasting papers in the humanitarian context. The humanitarian field has seen increased interest from the OR/MS community since the Indian Ocean tsunami (December 2004) and Hurricane Katrina in the US (August 2005) (Leiras, de Brito, Queiroz Peres, Rejane Bertazzo, & Tsugunobu Yoshida Yoshizaki, 2014). A similar trend seems to be happening in forecasting research based on the publication dates of the papers in Table 2. Fig. 2 shows 38 papers by year and depicts the increase in forecasting research within the humanitarian context in the last two decades. Our hope is that the research needs and future research directions we identify in the later sections in this article would fuel this interest even further.

We refrained from focusing on papers that develop methods based on physical sciences to forecast an event. The reason behind this choice is the fact that while most disaster forecasting research comes from physical sciences such as meteorology, geophysics, and hydrology, the audience we are trying to reach with this article includes operations research and management science scholars. Consequently, we only kept the papers that try to forecast an event using statistical approaches rather than physical sciences.

4. Literature review findings

Our literature search results confirmed our initial assumption that forecasting research within the humanitarian context is scarce. Despite the 38 papers listed in Table 2 showing an increasing trend, a closer look to where these papers have been published reveals that very little is actually from the OR/MS community. We were also surprised to see that none of the references in Table 2 were in forecasting journals. Consequently, we searched in Google Scholar for the words "forecasting" and "disaster" anywhere in the article but limited the search to *International Journal of Forecasting* and *Journal of Forecasting*. This search resulted in 11 papers for the former and 7 for the latter. However, after reading the abstracts of these papers we were even more surprised that only three papers in the *International Journal of Forecasting* fit what we looked for, and none in the *Journal of Forecasting.* The results of this quick search confirmed that there is tremendous potential for impactful forecasting research in the humanitarian context. The three papers we found are listed in Table 3.

We understand and accept that to forecast humanitarian needs we do need to rely on event forecasts. Since we removed papers using physical sciences to forecast catastrophic events from our final list of papers presented in Table 2, we decided to use Google Scholar to scan for papers from the OR/MS literature which cited the papers we removed. As a result we found nine papers relevant to

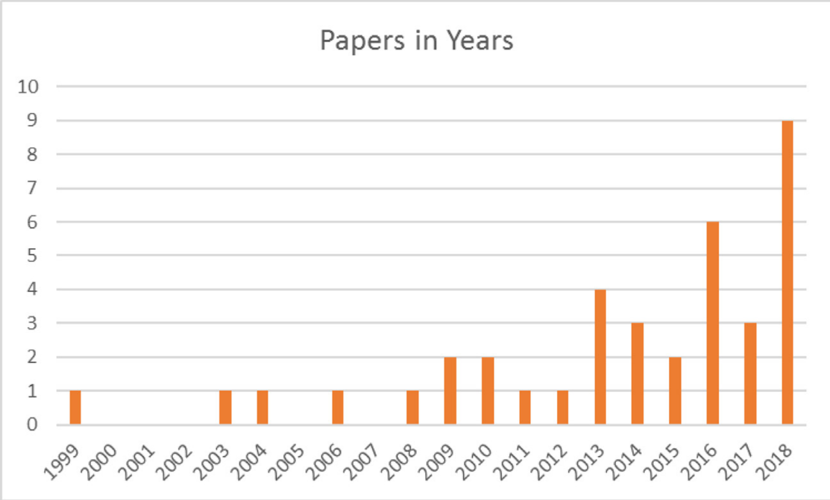

Fig. 2. Papers on forecasting in humanitarian operations in years.

Table 3
Papers in forecasting journals.

Authors	Year	Title	Journal
Vere-Jones	1995	Forecasting earthquakes and earthquake risk	IJF
Wright and Goodwin	2009	Decision-making and planning under low levels of predictability: Enhancing the scenario method	IJF
Taleb	2009	Errors, robustness, and the fourth quadrant	IJF

this study and presented them in Table 4. In these interdisciplinary works the authors do not develop forecasting techniques but rather utilize techniques and/or forecast data from physical sciences to solve a humanitarian problem. All of the nine papers make use of climate models or meteorological forecasts. Six of the papers deal with hurricanes and three with floods. Collectively, these papers touch all four phases of disaster management, but the majority of the papers (six of nine) tackle inventory/resource issues in preparedness. Five of the papers fulfill a huge need in practice: they use forecasts to make inventory decisions. Humanitarian inventories are social inventories serving broad social objectives (Whybark, 2007) and stock-outs have a different meaning for the suffering. It is our hope that the OR/MS community would seek more collaborations with colleagues from physical sciences to solve humanitarian problems such as these.

Perhaps the biggest finding of our literature review are these three papers: Davis et al. (2016), Holguín-Veras and Jaller (2011) and van der Laan et al. (2016) perfectly fit the mold we were looking for in this literature search. Holguín-Veras and Jaller (2011) extracts data on commodities needed immediately after Hurricane Katrina from the Federal Emergency Management Agency's (FEMA) action request forms. They analyze the statistical patterns in the data and how demand evolves in time and found that demand data were non-stationary. Hence, they develop ARIMA models to forecast demand. An interesting observation they found is that the demand estimates before landfall and the requests afterwards were not correlated at all (they reported a correlation coefficient of 0.02). This means that FEMA's short-term forecasts were poor.

Davis et al. (2016) focus on development work rather than disaster relief. They analyze food donation behavior for the food bank of Central and Eastern North Carolina. They first approach the six years of data they received from the foodbank with descriptive methods to understand donation behavior at the network, branch and donor level. Then they apply data aggregation techniques and utilize EWMA and ARIMA models to forecast donations. Forecast accuracy was measured by mean absolute percentage error (MAPE). They found that donations were seasonal and at the aggregate level carried a negative trend. However, the trends for individual branches were different (some negative, some positive). Expectedly, they found that aggregate data is easier to forecast but at the branch level average MAPEs ranged between 9.5 and 28 per cent. Davis et al. (2016) show that demand prediction models could also be applied to forecast supply for humanitarian operations (in this case food donations).

The third paper, van der Laan et al. (2016) investigates the demand planning process for Médecins Sans Frontières (MSF), also known as Doctors Without Borders. It is an excellent study delving into the processes involved in forecasting, demand planning, and ordering within a humanitarian organization. The MSF data consists of two order cycles worth of consumption and forecast data on 2223 medical items from 19 projects in eight countries. First, the authors explain the forecasting process within MSF and how they are linked to safety stock and reordering. Since the data contain consumption as well as forecast data, the authors start with calculating forecast accuracy for MSF. One of the difficulties they found is that the consumption of about 40% of the medical items

Table 4
Papers making use of forecasts from physical sciences.

Event	Method	Reference	Forecast	Stage
Hurricane	Climate	Taskin and Lodree (2010)	Resources	Preparedness
Hurricane	Climate	Taskin and Lodree (2011)	Inventory	Preparedness
Hurricane	Time series	Holguín-Veras and Jaller (2011)	Resources	Response
Hurricane	Climate	Davis, Samanlioglu, Qu, and Root (2013)	Inventory	Preparedness
Hurricane	Climate	Galindo Pacheco and Batta (2016)	Inventory	Preparedness
Hurricane	Hazus	Lorca, Çelik, Ergun, and Keskinocak (2017)	Debris	Recovery
Flood	Climate	Braman et al. (2013)	Inventory	Preparedness
Flood	Fuzzy Delphi	Chan, Wey, and Chang (2014)	Resilience	Mitigation
Flood	Near real-time	Jongman, Wagemaker, Romero, and de Perez (2015)	Inventory	Preparedness

is intermittent, and therefore, traditional error measures such as MAPE do not work when the actual demand at any point is zero. To remedy this, the authors propose using the symmetric mean absolute percentage error (sMAPE) to measure forecast performance. van der Laan et al. (2016) find that at MSF the majority of the medical items are over-forecasted (about 70% of items). This interesting find clearly shows the forecaster's bias in the humanitarian sector. As shortages lead to lost sales in the commercial sector, they lead to lost lives or prolonged suffering in the humanitarian sector. However, when aggregate demand is concerned they show that about 20% of the products suffer from aggregate demand being higher than aggregate forecasts, creating shortages at higher levels or planning. This study also shows that the humanitarian situation of the organization in operating affects forecast accuracy. They find that forecast accuracy suffers in areas with ongoing internal conflict, while forecast performance is much better in post-conflict areas since there is less uncertainty.

These three case studies shed light into the intricacies of forecasting within the humanitarian sector. Although collectively they cover response to a hurricane, development aid, and medical response in armed conflict, they do not cover the whole disaster management cycle. There is still a lot to be learned about forecasting in humanitarian organizations. In the next section, we identify the research needs in forecasting for humanitarian operations.

5. Research needs and discussion

Our literature review shows that forecasting research within the humanitarian context is scarce. The literature is dominated by research on predicting the disaster or the event that causes the response. However, an important piece that is missing is forecasting the resources needed to mitigate or recover from a disaster. The three case studies summarized in the previous section are simply not enough. Therefore, in this section, we identify research needs and suggest some future research directions to OR/MS and forecasting scholars who are interested in the humanitarian sector.

5.1. Forecasting disasters

As mentioned in Section 1 of this paper, there is plenty of research on forecasting hazardous events within physical sciences. However, the forecasting community grossly neglected this area. Forecasting the demand of relief items starts with the event itself. If we can forecast when and how intensely a hurricane will struck a community then we can budget for, purchase, and stock relief supplies. Similar comments can be made for floods, wildfires, heat/cold waves, etc. Clearly, it would be unwise to disregard all the research that has been done within the physical sciences community. Therefore, we believe the research direction that needs to be followed includes inter-disciplinary research, where inputs from physical sciences are utilized in statistical methods to strengthen the predictive power of such forecasts. An interesting research question is how climate change is affecting the seasonal nature of meteorological events such as monsoons, cyclones, droughts, etc. Significant shifts in seasonality may have devastating effects on crop yields and livestock productivity. Understanding the seasonality of these events would lead to improved preparedness and response.

5.2. Forecasting supply

We believe one of the biggest differences between the commercial sector and the humanitarian sector is the uncertainty in supply. There is considerable literature dealing with supplier selection and supply management issues in the commercial sector. To a great extent, commercial firms have control over their supply processes. However, for humanitarian organizations supply could be fairly uncertain. In the humanitarian context, supply includes cash and material donations, volunteers, and unsolicited gifts-in-kind. Cash donations are seasonal, prone to have sudden spikes that correspond to occurrences of events and their associated media coverage, and may come with certain conditions that limit where the cash could be spent (these are called earmarked funds), making forecasting of expected cash donations challenging. Outside of these event-specific instantaneous donations, the nonprofit sector also spends a lot of money on fundraising. Research on yield of fundraising efforts would help humanitarian organizations with their budgeting efforts, while understanding different causal factors in donor behavior could be used in regression models to help secure sustainable funding (Kaufmann, Miller, & Cheyne, 2011).

Material donations is an umbrella term for all kinds of commodities, tools, equipment, and even heavy machinery. These donations may be fast moving (i.e. frequent and in high quantities) like cereal, grains, and other food items, or intermittent in the case of equipment and heavy machinery. But almost never they show up unannounced or unplanned. Donations to food banks, for example, require diverse resources to come together, from marketing and administrative staff times, to advertising budget, to transportation and material handling equipment (Ahire & Pekgün, 2018). Another issue, specific to the humanitarian sector, is that multiple donations need to come together to make up a single resource. For example, a forklift donated by the manufacturer is useless without an operator. Therefore, the donated forklift can only become useful if a forklift operator volunteers his/her time to move the vehicle, which leads us to another difficult issue in the humanitarian sector, namely, volunteer management. Forecasting how many volunteers should be expected to what type of event to cover which types of capabilities would be a tremendous help to humanitarians.

Not all material donations are welcome. After a catastrophic event, people from all around the world want to help the survivors by sending whatever they think or imagine is needed to the disaster location. Since these donations are unsolicited, most of the times they prove to be useless and end up clogging the supply chain. Humanitarians call this "the second disaster" (Holguín-Veras, Jaller, Van Wassenhove, Pérez, & Wachtendorf, 2012b). There has been no attempt to forecast unsolicited donations to help prevent the second disaster. We believe the forecasting community could help alleviate this problem.

5.3. Forecasting demand

Demand in the humanitarian context refers to needs. This is another fundamental difference between the humanitarian sector and the commercial sector. Demand and need are not the same thing. The commercial sector can create and stimulate demand through advertising and other marketing strategies like creating artificial shortages/hypes. For example, no one "needs" a gaming console but gamers want it and would buy it if they can afford it. Therefore, there is a fundamental difference between demand forecasting and need forecasting that, to the best of our knowledge, has not been investigated. For example, Mohan, Gopalakrishnan, and Mizzi (2013) looking at food aid differentiates "need" as a macro-level concept, which depends on economic factors like poverty, cost of living, unemployment, and migration. The day-to-day demand however is highly variable and depends on location-specific factors such as how many people show up to a food pantry or soup kitchen at a given day. This leads us to think that aggregate needs are useful for procurement while local demand is important for inventory planning and prepositioning of supplies. Forecasting would help at both levels but the research need is on understanding and developing effective aggregation/disaggregation procedures.

Park, Kazaz, and Webster (2018) brings on another layer of differentiation to humanitarian demand: slow-onset vs rapid-onset demand. They claim that slow-onset demand is more predictable because the forecast could be enhanced using external factors that are leading into the arrival of an event such as hurricane. Here, collaborations with climate scientists, for example, would prove beneficial. Rapid-onset demand, however, is highly variable and therefore hard to predict. Future forecasting research could improve how we deal with rapid-onset disasters, while interdisciplinary research on the interface of forecasting and inventory management would improve operations for slow-onset events. In this article, we already provide some examples for the latter case in Table 4, but there is certainly room for more research in this area.

5.4. Forecasting errors in the humanitarian context

Do the standard error measures such as the mean absolute deviation (MAD) or MAPE allow planners to account for variation in inventory management decisions within the humanitarian context? This question alone is worthy of investigating due to the special nature of humanitarian operations. Development of context-specific error measures is not new. For example, new or adapted error measures have been developed for intermittent demand series (Boylan & Syntetos, 2006; Hyndman, 2006). Other research questions with regard to forecast errors in the humanitarian context include whether we need unbiased forecasting methods for humanitarian response operations, or should we include a positive bias so that we always overestimate needs for relief items? Do we need novel error measures for humanitarian forecasting? What are the operational, financial, and ethical tradeoffs in choosing a particular forecasting error metric? What are the consequences of errors in humanitarian forecasting? These are a small set of research questions and challenges we are proposing to the forecasting community.

5.5. Forecasting in the disaster management cycle

As mentioned before in this article, most humanitarian operations and logistics research focus on the response phase of disaster management. This could be because response is the most "visible" phase. In addition, it is also the phase where the impact of one's research is immediate. However, we also know that investment in preparedness and mitigation actually saves money in response operations because there would be less people affected if the mitigation and preparedness efforts were effective (Perry & Lindell, 2003). Hence, more research is needed on mitigation and preparedness. In these two phases, forecasting and budgeting are closely related. Therefore, research on the interface of forecasting and budgeting would be most welcome to practitioners. Similarly, the recovery phase interacts with development aid operations. Predicting the resilience level of a community before and after development/recovery efforts could impact resource allocation decisions. Forecasting research on the interface of recovery and development could help us understand the problems that policy makers, practitioners, and communities face in planning, budgeting, and execution.

5.6. Forecasting process

Forecasting for many humanitarian organizations (especially smaller ones) is not simply a statistical but mostly an organizational challenge. Many humanitarian organizations do not possess the capabilities and skill set required to do forecasting and operational planning. The MSF case summarized towards the end of Section 4 is an exception not the rule. Therefore, more research on the forecasting process within the humanitarian context is needed. We need to understand the issues and challenges humanitarian organizations are facing with respect to forecasting and demand planning, so that we can develop better solutions for them. This includes not only the technical but also the organizational (i.e. personnel behavior, management, and leadership) issues and challenges.

Based on our own experience with humanitarian organizations, judgmental forecasting seems to be common in this sector. There is already significant research in the literature on combining judgment with statistical forecasts. But the challenges of translating that research into the humanitarian context are not clear. The MSF case also hints about that. For example, doctors responding to injuries within a conflict zone would expectedly over-forecast the needs. The question is how would they respond to the proposal of combining their judgment with an unbiased statistical forecast to reduce over-forecasting?

Finally, the humanitarian sector suffers from data issues. Since their main focus is saving lives and the work is in high stress environments, collecting, cleaning, organizing, and storing relevant data are not priorities. Therefore, forecasting needs to be performed frequently with small datasets, if at all. While the commercial sector is mostly interested in big data these days, the humanitarian sector is coming from behind in that area. However, there are some new developments in big data in relation to humanitarian operations. One example is the use of Twitter and Facebook feeds to understand needs immediately after a disaster. Such crowd-sourcing of needs data comes with its own issues such as bias, coverage, and timing. This leads us to think that there is a need for research on near-real-time forecasting.

5.7. Humanitarian trends and forecasting

Here, we are referring to the forecasting and prediction of long-term events with tremendous impact on the human population. We are specifically referring to the impact of climate change and the ongoing refugee crisis. When these two crises are combined with the current rate of increase in earth's population, it is expected that we will have major food and water shortages in the future. Macro-level forecasting research on these crises and trends is needed to help humanitarian organizations plan their operations more effectively and in the correct geographies. Even though we are currently experiencing an unprecedented refugee crisis in the world, it is expected that climate change and the associated food and water issues would create even more refugees. This would lead to changing political climates and reallocation of national resources. Forecasting research can help understand these trends and their consequences.

6. Conclusion

Forecasting research in the humanitarian context is scarce. This fact is surprising given the amount of forecasting literature one could find for commercial cases. Maybe the thought behind it was that forecasting is forecasting and the basic idea does not change between for-profit and nonprofit sectors. However, our literature review already shows signs that there are fundamental differences between forecasting practices of the two sectors. Furthermore, the impact of forecasting research on human lives could be drastic. For example, Komrska, Kopczak, and Swaminathan (2013) claim that a shortage of ready-to-use therapeutic food in Ethiopia, Kenya, and Somalia partially due to poor forecasting caused 8.4 million people to suffer.

In this literature review, our goal is not only to show why forecasting research is important for the humanitarian sector, but also identify what has been done so far, and where are the needs for further research. Our search in four prominent databases of scholarship resulted in only 38 papers published between 1990 and 2018. Based on our findings we highlighted three case studies as exemplary research in forecasting within the humanitarian context and listed five future research streams with specific research needs identified in each stream. Furthermore, for the interested forecasting scholars, we provide several web links to relevant datasets in the Appendix of this article.

Appendix. Sample data sources

Data sources in the United States:

- FEMA's Hazus Sofware
  GIS-based software model, which produces loss estimates for earthquakes, floods, hurricanes, and tsunamis: https://www.fema.gov/summary-databases-hazus-multi-hazard
- OpenFEMA
  Mission data open to the public in machine-readable formats: https://www.fema.gov/openfema
- US Small Business Administration
  Disaster loan data: https://www.sba.gov/offices/headquarters/oda/resources/1407821

International Data Sources

- EM-DAT
  Most comprehensive international disaster database: https://www.emdat.be/
- UN Office of Disaster Risk Reduction (UNISDR)
  Disaster Statistics: https://www.unisdr.org/we/inform/disaster-statistics
- UN OCHA
  Financial tracking service: https://fts.unocha.org/
  The Humanitarian Data Exchange: https://data.humdata.org/

References

Ahire, S. L., & Pekgün, P. (2018). Harvest hope food bank optimizes its promotional strategy to raise donations using integer programming. *Interfaces*, *48*(4), 291–306.

Altay, N., & Green, W. G., III (2006). OR/MS research in disaster operations management. *European Journal of Operational Research*, *175*(1), 475–493.

Altay, N., Litteral, L. A., & Rudisill, F. (2012). Effects of correlation on intermittent demand forecasting and stock control. *International Journal of Production Economics*, *135*(1), 275–283.

Basu, S., Roy, S., & DasBit, S. (2018). A post-disaster demand forecasting system using principal component regression analysis and case-based reasoning over smartphone-based DTN. *IEEE Transactions on Engineering Management*, Early Access. http://dx.doi.org/10.1109/TEM.2018.2794146.

Boone, T., Ganeshan, R., Jain, A., & Sanders, N. R. (2019). Forecasting sales in the supply chain: Consumer analytics in the big data era. *International Journal of Forecasting*, *35*, 170–180.

Boylan, J. E., & Syntetos, A. A. (2006). Accuracy and accuracy-implication metrics for intermittent demand. *Foresight: The International Journal of Applied Forecasting*, *4*, 39–42.

Braman, L. M., van Aalst, M. K., Mason, S. J., Suarez, P., Ait-Chellouche, Y., & Tall, A. (2013). Climate forecasts in disaster management: Red cross flood operations in West Africa, 2008. *Disasters*, *37*(1), 144–164.

Canton, L. G. (2019). *Emergency management: Concepts and strategies for effective programs*. John Wiley & Sons.

Chan, S. L., Wey, W. M., & Chang, P. H. (2014). Establishing disaster resilience indicators for Tan-sui river basin in Taiwan. *Social Indicators Research*, *115*(1), 387–418.

Chevuturi, A., & Dimri, A. P. (2016). Investigation of uttarakhand (India) disaster-2013 using weather research and forecasting model. *Natural Hazards*, *82*(3), 1703–1726.

Cohen, G. H., Tamrakar, S., Lowe, S., Sampson, L., Ettman, C., Kilpatrick, D., ... Galea, S. (2019). Improved social services and the burden of post-traumatic stress disorder among economically vulnerable people after a natural disaster: a modelling study. *The Lancet Planetary Health*, *3*(2), e93–e101.

Coppola, D. P. (2006). *Introduction to international disaster management*. Burlington, MA: Elsevier.

Coughlan de Perez, E., Hurk, B. V. D., Aalst, M. K. V., Amuron, I., Bamanya, D., Hauser, T., ... Pappenberger, F. (2016). Action-based flood forecasting for triggering humanitarian action. *Hydrology and Earth System Sciences*, *20*(9), 3549–3560.

Coughlan de Perez, E., van den Hurk, B. J. J. M., Van Aalst, M. K., Jongman, B., Klose, T., & Suarez, P. (2015). Forecast-based financing: an approach for catalyzing humanitarian action based on extreme weather and climate forecasts. *Natural Hazards and Earth System Sciences*, *15*(4), 895–904.

CRED (2019). *Natural disasters, Centre for research on the epidemiology of disasters report*. Retrieved from https://reliefweb.int/sites/reliefweb.int/files/resources/ND19.pdf. (Accessed 6 August 2020).

da Silva Lamenza, A. A., Fontainha, T. C., & Leiras, A. (2019). Purchasing strategies for relief items in humanitarian operations. *Journal of Humanitarian Logistics and Supply Chain Management*, *9*(2), 151–171.

Davis, L. B., Jiang, S. X., Morgan, S. D., Nuamah, I. A., & Terry, J. R. (2016). Analysis and prediction of food donation behavior for a domestic hunger relief organization. *International Journal of Production Economics*, *182*, 26–37.

Davis, L. B., Samanlioglu, F., Qu, X., & Root, S. (2013). Inventory planning and coordination in disaster relief efforts. *International Journal of Production Economics*, *141*(2), 561–573.

Day, J. M., Melnyk, S. A., Larson, P. D., Davis, E. W., & Whybark, D. C. (2012). Humanitarian and disaster relief supply chains: a matter of life and death. *Journal of Supply Chain Management*, *48*(2), 21–36.

de la Poterie, A. S. T., Jjemba, W. E., Singh, R., de Perez, E. C., Costella, C. V., & Arrighi, J. (2018). Understanding the use of 2015–2016 El Niño forecasts in shaping early humanitarian action in Eastern and Southern Africa. *International Journal of Disaster Risk Reduction*, *30*(A), 81–94.

de Silva, L. (2011). Forecasting of cost escalations in post disaster construction with special reference to Tsunami reconstruction in Sri Lanka. *Built-Environment Sri Lanka*, *9*(1–2), 56–63.

Done, J. M., Holland, . G. J., Bruyère, C. L., Leung, L. R., & Suzuki-Parker, A. (2015). Modeling high-impact weather and climate: lessons from a tropical cyclone perspective. *Climatic Change*, *129*(3–4), 381–395.

Dore, M. H. (2003). Forecasting the conditional probabilities of natural disasters in Canada as a guide for disaster preparedness. *Natural Hazards*, *28*(2–3), 249–269.

Du, S., Zhang, J., Deng, Z., & Li, J. (2014). A new approach of geological disasters forecasting using meteorological factors based on genetic algorithm optimized BP neural network. *Elektronika ir Elektrotechnika*, *20*(4), 57–62.

Fisher, M. L. (1997). What is the right supply chain for your product?. *Harvard Business Review*, *75*, 105–117.

Florez, J. V., Lauras, M., Dupont, L., & Charles, A. (2013). Towards a demand forecast methodology for recurrent disasters. *WIT Transactions on the Built Environment*, *133*, 99–110.

Galindo Pacheco, G., & Batta, R. (2016). Forecast-driven model for prepositioning supplies in preparation for a foreseen hurricane. *Journal of the Operational Research Society*, *67*(1), 98–113.

Grange, R., Heaslip, G., & McMullan, C. (2019). Coordination to choreography: the evolution of humanitarian supply chains. *Journal of Humanitarian Logistics and Supply Chain Management*, Article in print. http://dx.doi.org/10.1108/JHLSCM-12-2018-0077.

Guo, H., Hou, Y., Yang, B., Du, H., & Xiao, W. (2015). Natural disaster forecast on the base of townships collaborative emergency: Take fangshan district as an example. *Grey Systems: Theory and Application*, *5*(3), 392–409.

Haghi, M., Ghomi, S. M. T. F., & Jolai, F. (2017). Developing a robust multi-objective model for pre/post disaster times under uncertainty in demand and resource. *Journal of Cleaner Production*, *154*, 188–202.

Han, Z. Z., & Tang, Y. H. (1999). Fuzzy forecast of flood disaster caused by solar proton flares. *Applied Mathematics and Computation*, *98*(1), 83–89.

Holguín-Veras, J., & Jaller, M. (2011). Immediate resource requirements after hurricane Katrina. *Natural Hazards Review*, *13*(2), 117–131.

Holguín-Veras, J., Jaller, M., Van Wassenhove, L. N., Pérez, N., & Wachtendorf, T. (2012a). On the unique features of post-disaster humanitarian logistics. *Journal of Operations Management*, *30*(7–8), 494–506.

Holguín-Veras, J., Jaller, M., Van Wassenhove, L. N., Pérez, N., & Wachtendorf, T. (2012b). Material convergence: Important and understudied disaster phenomenon. *Natural Hazards Review*, *15*(1), 1–12.

Hsieh, P. H. (2004). A data-analytic method for forecasting next record catastrophe loss. *Journal of Risk and Insurance*, *71*(2), 309–322.

Hyndman, R. J. (2006). Another look at forecast-accuracy metrics for intermittent demand. *Foresight: The International Journal of Applied Forecasting*, *4*(4), 43–46.

Jin, J. L., Cheng, J., & Wei, Y. M. (2008). Forecasting flood disasters using an accelerated genetic algorithm: Examples of two case studies for China. *Natural hazards*, *44*(1), 85–92.

Jongman, B., Wagemaker, J., Romero, B. R., & de Perez, E. C. (2015). Early flood detection for rapid humanitarian response: harnessing near real-time satellite and Twitter signals. *ISPRS International Journal of Geo-Information*, *4*(4), 2246–2266.

Kaufmann, J. R., Miller, R., & Cheyne, J. (2011). Vaccine supply chains need to be better funded and strengthened, or lives will be at risk. *Health Affairs*, *30*(6), 1113–1121.

Kelman, I. (2011). Understanding vulnerability to understand disasters. In *Canadian disaster management textbook*. Canada: Canadian Risk and Hazards Network, (cap. 7).

Kgakatsi, I. B. (2014). The contribution of seasonal climate forecasts to the management of agricultural disaster-risk in South Africa. *International Journal of Disaster Risk Reduction*, *8*, 100–113.

Kim, S., Kim, J. H., & Park, K. B. (2009). Neural networks models for the flood forecasting and disaster prevention system in the small catchment. *Disaster Advances*, *2*(3), 51–63.

Komrska, J., Kopczak, L. R., & Swaminathan, J. M. (2013). When supply chains save lives. *Supply Chain Management Review*, *17*(1), 42–49.

Kovács, G., & Spens, K. M. (2007). Humanitarian logistics in disaster relief operations. *International Journal of Physical Distribution and Logistics Management*, *37*(2), 99–114.

Leiras, A., de Brito, I., Jr., Queiroz Peres, E., Rejane Bertazzo, T., & Tsugunobu Yoshida Yoshizaki, H. (2014). Literature review of humanitarian logistics research: trends and challenges. *Journal of Humanitarian Logistics and Supply Chain Management*, *4*(1), 95–130.

Li, B., Hernandez, I., Milburn, A. B., & Ramirez-Marquez, J. E. (2018). Integrating uncertain user-generated demand data when locating facilities for disaster response commodity distribution. *Socio-Economic Planning Sciences*, *62*, 84–103.

Lopez, A., de Perez, E. C., Bazo, J., Suarez, P., van den Hurk, B., & van Aalst, M. (2020). Bridging forecast verification and humanitarian decisions: A valuation approach for setting up action-oriented early warnings. *Weather and Climate Extremes*, *27*, Article 100167.

Lorca, Á., Çelik, M., Ergun, Ö., & Keskinocak, P. (2017). An optimization-based decision-support tool for post-disaster debris operations. *Production and Operations Management*, *26*(6), 1076–1091.

Matori, A. N., & Lawal, D. U. (2014). Flood disaster forecasting: A GIS-based group analytic hierarchy process approach. *Applied Mechanics & Materials*, *567*, 717–723.

Miao, C., & Ding, M. (2017). Analysis of influence of natural disaster on the economy and prediction of recovery time based on grey forecasting–difference comparison model: a case study in the upper min river. *Natural Hazards*, *85*(2), 1135–1150.

Mohan, S., Gopalakrishnan, M., & Mizzi, P. J. (2013). Improving the efficiency of a non-profit supply chain for the food insecure. *International Journal of Production Economics*, *143*(2), 248–255.

Mude, A. G., Barrett, C. B., McPeak, J. G., Kaitho, R., & Kristjanson, P. (2009). Empirical forecasting of slow-onset disasters for improved emergency response: An application to Kenya's arid north. *Food Policy*, *34*(4), 329–339.

Musa, A., Watanabe, O., Matsuoka, H., Hokari, H., Inoue, T., Murashima, Y., ... Kobayashi, H. (2018). Real-time tsunami inundation forecast system for tsunami disaster prevention and mitigation. *The Journal of Supercomputing*, *74*(7), 3093–3113.

Nelan, M. M., Penta, S., & Wachtendorf, T. (2019). Paved with good intentions: A social construction approach to alignment in disaster donations. *International Journal of Mass Emergencies & Disasters*, *37*(2).

Nikolopoulos, K. (2020). We need to talk about intermittent demand forecasting. *European Journal of Operational Research*, (in press). http://dx.doi.org/10.1016/j.ejor.2019.12.046.

NOAA (2020). What percentage of the American population lives near the coast?. Retrieved from https://oceanservice.noaa.gov/facts/population.html. (Accessed 3 February 2020).

Noda, M. (2016). Does affective forecasting change motivation for disaster preparedness? Motivation one month after a hypothetical earthquake. *Revista de Psicología Social*, *31*(1), 109–136.

Park, J. H., Kazaz, B., & Webster, S. (2018). Surface vs. Air shipment of humanitarian goods under demand uncertainty. *Production and Operations Management*, *27*(5), 928–948.

Perry, R. W., & Lindell, M. K. (2003). Preparedness for emergency response: guidelines for the emergency planning process. *Disasters*, *27*(4), 336–350.

Pisarenko, V. F., & Rodkin, M. V. (2006). Natural disasters: Statistics and forecasts. *Herald of the Russian Academy of Sciences*, *76*(6), 542–548.

Ramírez, I. J., & Briones, F. (2017). Understanding the El Niño costero of 2017: The definition problem and challenges of climate forecasting and disaster responses. *International Journal of Disaster Risk Science*, *8*(4), 489–492.

Rigaud, K. K., de Sherbinin, A., Jones, B., Bergmann, J., Clement, V., Ober, K., ... Midgley, A. (2018). Groundswell: Preparing for internal climate migration. World Bank. Retrieved from https://openknowledge.worldbank.org/bitstream/handle/10986/29461/WBG_ClimateChange_Final.pdf.

Shen, X., Ou, L., Chen, X., Zhang, X., & Tan, X. (2013). The application of the grey disaster model to forecast epidemic peaks of typhoid and paratyphoid fever in China. *PloS one*, *8*(4), Article e60601.

Sheu, J. B. (2010). Dynamic relief-demand management for emergency logistics operations under large-scale disasters. *Transportation Research Part E: Logistics and Transportation Review*, *46*(1), 1–17.

Smadi, H., Al Theeb, N., & Bawa'neh, H. (2018). Logistics system for drinking water distribution in post disaster humanitarian relief, Al-Za'atari camp. *Journal of Humanitarian Logistics and Supply Chain Management*, *8*(4), 477–496.

Song, J. M., Chen, W., & Lei, L. (2018). Supply chain flexibility and operations optimisation under demand uncertainty: a case in disaster relief. *International Journal of Productions Research*, 1–15.

Taleb, N. N. (2009). Errors, robustness, and the fourth quadrant. *International Journal of Forecasting*, *25*(4), 744–759.

Tall, A., Mason, S. J., van Aalst, M., Suarez, P., Ait-Chellouche, Y., Diallo, A. A., & Braman, L. (2012). Using seasonal climate forecasts to guide disaster management: the Red Cross experience during the 2008 West Africa floods. *International Journal of Geophysics*, *2012*.

Taskin, S., & Lodree, E. J., Jr. (2010). Inventory decisions for emergency supplies based on hurricane count predictions. *International Journal of Production Economics*, *126*(1), 66–75.

Taskin, S., & Lodree, E. J., Jr. (2011). A Bayesian decision model with hurricane forecast updates for emergency supplies inventory management. *Journal of the Operational Research Society*, *62*(6), 1098–1108.

Tiampo, K. F., & Shcherbakov, R. (2012). Seismicity-based earthquake forecasting techniques: Ten years of progress. *Tectonophysics*, *522*, 89–121.

Tint, B. S., McWaters, V., & van Driel, R. (2015). Applied improvisation training for disaster readiness and response: Preparing humanitarian workers and communities for the unexpected. *Journal of Humanitarian Logistics and Supply Chain Management*, *5*(1), 73–94.

UNHCR (2020). *Figures at a glance, United nations higher council for refugees report*, Retrieved from https://www.unhcr.org/figures-at-a-glance.html. (Accessed 6 August 2020).

van der Laan, E., van Dalen, J., Rohrmoser, M., & Simpson, R. (2016). Demand forecasting and order planning for humanitarian logistics: An empirical assessment. *Journal of Operations Management*, *45*, 114–122.

Van Wassenhove, L. N. (2006). Humanitarian aid logistics: supply chain management in high gear. *Journal of the Operational Research Society*, *57*(5), 475–489.

Vere-Jones, D. (1995). Forecasting earthquakes and earthquake risk. *International Journal of Forecasting*, *11*(4), 503–538.

Wakolbinger, T., & Toyasaki, F. (2011). Impacts of funding systems on humanitarian operations. In M. Christopher, & P. Tatham (Eds.), *Humanitarian logistics: Meeting the challenge of preparing for and responding to disasters* (pp. 33–46). London: Kogan Page Limited.

Wang, Z. X. (2013). A genetic algorithm-based grey method for forecasting food demand after snow disasters: an empirical study. *Natural hazards*, *68*(2), 675–686.

Waugh, W. L., & Hy, R. J. (Eds.), (1990). *Handbook of emergency management: Programs and policies dealing with major hazards and disasters*. Greenwood Publishing Group.

Whybark, D. C. (2007). Issues in managing disaster relief inventories. *International Journal of Production Economics*, *108*(1–2), 228–235.

World Bank (2020). Understanding poverty. Retrieved from https://www.worldbank.org/en/topic/poverty/overview. (Accessed 5 August 2020).

Wright, G., & Goodwin, P. (2009). Decision making and planning under low levels of predictability: Enhancing the scenario method. *International Journal of Forecasting*, *25*(4), 813–825.

Xu, X., Qi, Y., & Hua, Z. (2010). Forecasting demand of commodities after natural disasters. *Expert Systems with Applications*, *37*(6), 4313–4317.

Yagci-Sokat, K., Zhou, R., Dolinskaya, I. S., Smilowitz, K., & Chan, J. (2016). Capturing real-time data in disaster response logistics. *Journal of Operations and Supply Chain Management*, *9*(1), 23–54.

Yu, L., Yang, H., Miao, L., & Zhang, C. (2018). Rollout algorithms for resource allocation in humanitarian logistics. *IISE Transactions*, 1–23.

Yu, L., Zhang, C., Yang, H., & Miao, L. (2018). Novel methods for resource allocation in humanitarian logistics considering human suffering. *Computers & Industrial Engineering*, *119*, 1–20.

Zhan, S. L., & Liu, N. (2016). Determining the optimal decision time of relief allocation in response to disaster via relief demand updates. *International Journal of Systems Science*, *47*(3), 509–520.

Zhang, J., Feng, M., & Wang, Y. (2018). Intelligent flood disaster forecasting based on improved neural network algorithm. *NeuroQuantology*, *16*(6).