Designing Valid Humanitarian Logistics Scenario Sets: Application to Recurrent Peruvian Floods and Earthquakes

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Chapter 2
Designing Valid Humanitarian Logistics Scenario Sets:
Application to Recurrent Peruvian Floods and Earthquakes

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ABSTRACT

Literature about humanitarian logistics (HL) has developed a lot of innovative decision support systems during the last decades to support decisions such as location, routing, supply, or inventory management. Most of those contributions are based on quantitative models but, generally, are not used by practitioners who are not confident with. This can be explained by the fact that scenarios and datasets used to design and validate those HL models are often too simple compared to the real situations. In this chapter, a scenario-based approach based on a five-step methodology has been developed to bridge this gap by designing a set of valid scenarios able to assess disaster needs in regions subject to recurrent disasters. The contribution, usable by both scholars and practitioners, demonstrates that defining such valid scenario sets is possible for recurrent disasters. Finally, the proposal is validated on a concrete application case based on Peruvian recurrent flood and earthquake disasters.

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INTRODUCTION

A variety of approaches, ranging from analytical models and theories to case studies, have been considered to manage risks during disaster operations. In the field of Humanitarian Logistics (HL), mathematical programming is the most frequently used research methodology (Galindo and Batta, 2013). While the use of optimization tools and algorithms has been shown to have a great potential to improve disaster management practices, they are rarely used in the field (Laguna Salvadó *et al.*, 2015; Laguna Salvadó *et al.*, 2016). Hence, the lack of an easy-to-use and established approach to risk assessment means that in practice, decision-makers often refer to their experience and intuition, which can lead to a range of biases and loss of performance (Comes, 2016). As demonstrated by (Charles et al., 2016), this statement is mainly due to research works that frequently use fictitious scenarios and data compensating for the lack of information. This approach fails to validate whether decision support systems can be successfully applied in the actual context of disaster relief (Charles et al., 2016). Real cases, or at least realistic ones, with accurate data are necessary to enable practitioners to be confident with the results of scholar and to start to use them concretely in the field. This chapter tackles this issue by suggesting an innovative methodology able to generate valid and realistic scenario sets on future disaster trends as suggested by (Galindo and Batta, 2013; Pedraza-Martinez and Van Wassenhove, 2013). We therefore develop a series of requirements that are designed to support researchers in producing valid and plausible scenarios for their quantitative decision support systems that are tailored to fit the needs and standards of field-based decision-makers. Basically, such systems should be able to support HL decisions such as location-allocation, routing or inventory management for instance.

When referring to disasters, most of us will intuitively refer to mega-disasters such as Indonesia's tsunami in 2004, Haiti's earthquake in 2010, Japan's earthquake / tsunami in 2011 or Nepal's earthquake in 2015. Although all those cases have had dramatic consequences, they are far from typical for disaster response. Ferris *et al.* (2013) define the notion of "recurrent disaster" as "*the repeated occurrence of a unique natural hazard in the same geographical region*". Since 2000, each year, more than 400 disasters have been recorded in the disaster database EM-DAT (http://www.emdat.be). More than 90% of those disasters recur in the same regions: cyclones in the Caribbean, earthquakes in the Pacific Ring of Fire or floods in South-Eastern Asia. In this chapter, we focus on recurrent disasters, which constitute the great majority of disasters.

To conduct empirically grounded work that enables HL practitioners to analyse the implications of their HL decisions (such as planning, routing, allocating…), we suggest using a scenario-based approach. Scenario based reasoning has been advocated for its flexibility and appeal to the user, particularly in complex situations (Comes *et al.*, 2015). Scenarios are understood as a means for exploring eventualities before they occur. They support users to think through a variety of different situations, and as such are well-positioned for HL decisions support. We here propose an approach that avoids some of the most common pitfalls of a too narrow or biased set of scenarios, which reflects opinions of a small number of experts, or is subject to groupthink (Wright *et al.*, 2009; Comes *et al.*, 2012). Our approach guarantees that each individual scenario is sufficiently plausible (i.e. a good assessment of truth (Bosch, 2010)) and relevant for feeding HL decision support systems.

The remainder of this chapter is divided into four parts. The subsequent section will present a literature review and overview of research statements. The third section will describe the proposed scenario method and its associated tools. The fourth section will develop an application case based on real data on HL preparedness for Peruvian recurrent disasters. The final section will then discuss the limitations of the approach and derive implications for research and practice.

BACKGROUND

Scenario-Based Hazard Prediction

With increasing digitalization and the growing involvement of affected populations and volunteer & technical communities in the response to disasters, there is henceforth no shortage in information about disasters (Van de Walle and Comes, 2015). Disaster databases focus on few core data sets and facilitate analyses across countries, regions or over time. EM-DAT, the most prominent example of such a database, provides data on over 18,000 disasters worldwide from 1900 to present. An open question is how to exploit this wealth of information to provide support to HL decision-makers in practice.

Most authors working on disaster forecasts track past occurrences to characterize recurrent disasters. Predictive methods have been developed for various natural hazards such as floods (Braman *et al.*, 2013; Ndille and Belle, 2014), cyclones (Tatham *et al.*, 2012) or earthquakes (WGCEP, 2008). Most of these models aim to specify the time, location, and magnitude of a future hazard with a probability of occurrence. Historic data enables analyses of trends and developments. In the context of the Climate Change prediction, it is widely expected that there will be more disasters, many of which will be of small or medium scale.

Charles *et al.* (2016) analysed African casualties' patterns (seasonality, location and affected population), and showed that future occurrences, though highly uncertain, *can* be predicted. Vargas *et al.* (2016) confirmed this by studying South

American recurrent disasters. Other researchers (Kovács *et al.*, 2007; Peres *et al.*, 2012) consider that for small and medium disasters, future occurrences will be globally like previous ones.

From Assessing Disaster Risks to Forecasting

Although they are cyclical in nature, individual instances of recurrent disasters are not easily anticipated in terms of their exact time, location, frequency, or magnitude. Driven by an ever more quickly changing socio-economic environment and migrating populations, the disaster needs at local level are even harder to predict (Vitoriano *et al.*, 2013).

In the context of disaster risk reduction, most predictive approaches focus on a combination of hazard (event), exposure (elements at risk) and vulnerability or resilience (Djalante et al., 2011; Merz *et al.*, 2013). The hazard dimension is typically modelled through dedicated meteorological, geological, seismic etc. models, which provide an assessment about the magnitude of specific events that have a given likelihood of occurrence (Karimi and Höllermeier, 2007). The exposure dimension is determined by the topography, demographic and socio-economic structure of a country or region, typically measured in terms of the value of social capital, infrastructure and assets affected by the hazard event (Birkmann *et al.*, 2013).

The vulnerability dimension is defined as "*the characteristics and circumstances of a community, system or asset that make it susceptible to the damaging effects of a hazard*" (UNDP, 2004). While vulnerability is fundamental in explaining disaster impact, it is not sufficient. The importance of resilience as counterpart of vulnerability was highlighted by many authors, as shown by Djalante *et al.* (2011), Peres *et al.* (2012), Vitoriano *et al.* (2013) or Aldunce *et al.* (2014). There is, today, a plethora of resilience definitions, which focus on different systems or aspects of resilience. In this chapter, we follow Peres *et al.* (2012), understanding resilience as the "*capacity to resist and to recover after exposition of a system, community or society, to hazards*".

Based on those elements our ambition is to make the step from disaster impact to needs assessment, and thus close the gap in the sequence of assessing *damage – impact – needs.* Disaster impact is defined by (UNISDR, 2009) as, "*the potential disaster losses, in lives, health status, livelihoods, assets and services, which could occur to a particular community or a society over some specified future time*". While Wisner *et al.* (2004) showed that disaster impact is a function of vulnerability, UNESCAP (2008) indicates that disaster impact is a function of both resilience and vulnerability.

The question of assessing the impact of disasters *a priori* has not yet received sufficient attention in literature. Most work in the disaster-risk domain focuses on modelling the direct impact and damage resulting from a disaster, not on the resulting disaster needs. Recently, a prediction and demand forecasting model was presented for longer term disaster projects of a single organization (van der Laan *et al.*, 2016). However, their forecasts relied on clearly defined project aims that are typical for long-term response to slow-onset disasters or conflicts. Similarly, in a study for the International Federation of Red Cross that has received much attention in disaster practice, (Dieckhaus *et al.*, 2011) present a global framework for assessing demands. This approach enables better sourcing strategies and positioning of warehouses in a context, in which risks can be pooled over longer periods of time or geographical regions.

In contrast, in the context of the national or local response to sudden onset disasters most authors assume that "*urgent needs related to sudden and unpredictable disasters with shifting demand*" (Balcik *et al.*, 2015) need to be met. Many authors therefore circumvent the planning problem and focus on responsiveness of supply chains (Balcik *et al.*, 2015), or their agility (Charles and Lauras, 2011; Charles *et al.*, 2010; Oloruntoba and Gray, 2006). Some further research has also been done on the assessment of needs *a posteriori* (Xu *et al.*, 2010; Zhang *et al.*, 2012), but there are no studies that forecast disaster needs in recurrent sudden-onset disasters that provide an overview of the disaster needs across clusters or organizations before a disaster occurs.

Designing Relevant and Valid Scenarios

Scenarios used in scientific approaches can perform two fundamentally different representational functions (Frigg and Hartmann, 2012): a scenario can be a representation of a selected part of the world (model of data) or a scenario can simulate the consequences of implementing the theory, policy or decision (model of theory). Since our objective is creating valid scenario sets to feed HL quantitative models, we understand scenarios here as "models of data".

Numerous such models of data have been developed over the last decades, many of them in the context of stochastic programming and Monte-Carlo simulations (Dupačová *et al.*, 2000; Di Domenica *et al.*, 2007; Klibi and Martel, 2012). More recently, researchers adapted scenarios for use in HL models, particularly in the context of disaster aid (Peres *et al.*, 2012; Galindo and Batta, 2013). Although those models are interesting from a mathematical programming standpoint, they are usually not implemented through a valid model of real data. Consequently, these proposals need to be reconsidered as they are not meeting the requirements of plausibility.

HL Scenario Definition

Respecting previous comments and scenario requirements (Comes *et al.*, 2015), we define a HL scenario by:

- A trigger event (disaster characteristics) and its probability of occurrence.
- A period: time horizon (overall duration) and frequency (intervals).
- A set of geographical regions potentially affected.
- A set of sourcing capacities: inventory of sourcing options that exist or might exist in the network. Each potential source should be defined through its existing or expected capabilities (types of products that can be delivered) and capacities (volume of products that can be delivered).
- A set of disaster needs (demand): expected number of victims per region affected and per period. Disaster practitioners can then translate this into product needs by considering international standards (e.g. http://www.SphereProject.org) or internal rules and practices.
- A set of HL capacities: assessment of required capacities (HL facilities, transportation infrastructures, etc.). These losses of capacities can be defined as percentages of the normal ones (i.e. 100% means that the HL capacity is fully available while 50% means that the available capacity is only half of the usual one). Those should be expressed per region and per period.

Such a scenario represents a *minimal set* of data and information that is required to inform properly HL decision-makers.

HL Scenario Creation

There is a wealth of methods that has been used in practice and research to create scenarios (Carter *et al.*, 2004; Comes *et al.*, 2014). But none of those methods completely meets the requirements of field-based practitioners in terms of content (see above), computation time, scope, granularity, update frequency and transparency / ease of understanding. Lacking a suitable formal method that is quick and easy to use, disasters will most often rely on their own expertise or experience (Mendonca *et al.*, 2006) – leading to inefficiencies and misallocations.

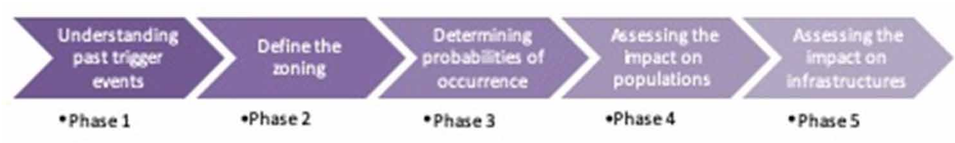
A suitable scenario creation technique for the HL context thus requires the definition of plausible scenarios and to assign them reliable probabilities. For operational decision-making, a relatively small number of scenarios needs to be identified as a basis for reasoning. As resources are typically short in the heat of a disaster requirement, the run-time needs to be minimized of both the scenario creation and the mathematical model. Based on (Tietje, 2005; Comes *et al.*, 2015), we conclude that the creation of valid scenario sets should include two complementary steps:

- The generation of a large set of accurate and representative scenarios;
- The selection of a covering sub-set able to answer the question asked.

Proposal

Our research objective is to generate a covering set of valid scenarios for improving HL performance. To reach this goal, we have defined a five-step methodology, as described in Figure 1:

Figure 1. Five-step methodology to define valid scenario sets



Phase 1. Understanding past trigger events.

This first phase consists in analysing past disaster characteristics through a review of past disasters. Dedicated databases provide a lot of information on past events: date; localization; phenomenon typology; geomorphology; intensity; impacts on different areas and duration of the phenomenon. In our study, we assume that the quality and the exhaustiveness of the databases are sufficiently rich for data-based analyses and forecasting.

Since we study recurrent disasters, the time frame needs to be sufficiently large to be representative. Data needed can be provided by specific national or topical databases or by generic ones such as the OFDA/CRED International Disaster Database (EM-DAT, http://www.emdat.be/database).

Phase 2. Defining the zoning

This phase consists in proposing a geographical grid of the territory concerned. This division should be coherent with the natural phenomena, but also with the administrative and organizational boundaries. To reach this goal, socio-demographic, geomorphological, climatological or administrative information is used. Experts (on floods, earthquakes, landslides or local politics for instance) should be solicited.

In addition to zoning, this phase must allow the characterization of how spreads a hazard. The analysis of data gathered during step 1 should allow an understanding of the cause-effects relationships that exist between the different zones. In simple cases, a correlation matrix between each zone will be defined. In more complex cases, specific functions should be established with dedicated experts. Usually, those experts / institutions can establish the sensitivity that exists between two regions regarding such or such a phenomenon and formulate the propagation function of this sensitivity. As an example, for an earthquake, the border region between two regions could be considered as a Sensitive Zone (SZ) if the seismic wave will propagate strongly into it, or a Non-Sensitive Zone (NSZ) if a geological barrier, such as a mountain or sea, will alleviate the intensity of the seismic wave.

Phase 3. Determining probabilities of occurrence

The aim of this phase is to build a set of scenarios, with an estimation of their probabilities of occurrence. For this purpose, we assume that there is a quasi-periodical value for disasters per fixed time. This assumption is only valid because we are working on “recurrent disasters”. In practice, we use here the data gathered in phase 1. To determine the region where the epicentre of the disaster is located, we calculate the percentage of past disasters in each region determined in phase 2.

A disaster event is defined by both its occurrence and its intensity. Consequently, a scenario must include a probability of occurrence of a given intensity. For instance, it could indicate that 45% of the earthquakes of a given region (see Phase #2) have a magnitude between 6 and 7 on the Richter scale. To reach this goal, we decided to consider intensity through intervals. In the case of earthquakes for instance, a scenario might be defined through 5 classes of intensity (magnitude below 5.5; between 5.5 and 6; between 6 and 7; between 7 and 8, and above 8). Then, based on data gathered in Phase #1, we calculate the percentage of earthquakes belonging to each class. As we focus on “recurrent” disasters, extreme events are excluded from our statistics.

Finally, the number of scenarios generated can vary from 0 to n, in which n is the number of intervals of intensity. The phenomenon-oriented zoning (Phase #2) associated to the impact-oriented definition of scenarios (phase 3) allow defining a set of scenarios that is representative and manageable as the number of intervals is necessarily limited. Since extreme events are discarded, in some cases less than 100% of the gathered data during phase 1 will be kept. We suggest verifying that at least 75% of the whole data recorded in phase 1 is represented. If it is less than 75%, it means that the region is not mainly affected by recurrent phenomena but by chaotic ones. In that case, we do not respect our assumptions. It is obvious that this threshold is not absolute and can be discussed for each case.

Phase 4. Assessing the impact on populations

In this research, in accordance with the background discussed in previous sections, we assumed that the disaster-occurrence forecasts are like the previous recorded disasters. Consequently, disaster-demand forecasts will depend only on the future-disaster impact assessment. Based on these hypotheses, we propose the following approach to assess future disaster demand.

The first step consists in identifying the influencing factors that allow us qualifying the vulnerability and resilience of a potentially affected area. A literature review based on (Weichselgartner, 2001; UNDP, 2004; Alinovi *et al.*, 2009; Tveiten *et al.*, 2012; Aldunce *et al.*, 2014) allows us identifying 81 generic factors that could characterize the vulnerability and the resilience of impacted areas (see Tables 1 and 2).

Table 1. Influencing factors that can explain vulnerability in a territory.

Income and Food Access: Average per person daily income (local currency/person/day); Average per person daily expenditure (local currency / person/day); Household food insecurity access score; Dietary diversity and food frequency score, Dietary energy consumption (Kcal/person/day).
Access to Basic Services: Physical access to health services; Quality score of health services; Quality of educational system; Perception of security; Mobility and transport constraints; Water, electricity and phone networks.
Social Safety Nets: Amount of cash and in-kind assistance (local currency/person/day); Quality evaluation of assistance; Job assistance; Frequency of assistance (number of times assistance received last 6 months); Overall opinion of targeting.
Assets: Housing (number of rooms owned); Housing equipment index (TV, Car, etc.); Tropical livestock unit (TLU) equivalent to 25 K; Land owned (in hectares).
Adaptive Capacity: Diversity of incomes sources; Educational level (household average); Employment ratio (ratio, number of employed divided by household size); Available coping strategies; Food consumption ratio (by expenditure).
Stability: Number of household members that have lost their job; Income change; Expenditure change; Capacity to maintain stability in the future; Net safety dependency (share of transfers on the total income); Education system stability, the Human de Development Index (IDH).

The second step consists in selecting a subset of significant independent variables among influencing factors identified in step one. To support this step, we propose to use a Principal Component Analysis (PCA) (Jolliffe, 2002) to identify the discriminating variables associated with a given type of disaster. The objective consists in reducing the size of the problem and finding the discriminating variables that will be used in step three. In the following stage, only the discriminating variables will be used.

Table 2. Influencing factors that can explain resilience in a territory.

Exposure of resources: Zoning by seismic exposition, also inundation zones due to tsunami hazards.
Access to resources: Accessibility of resources in emergency situation.
Functional and vulnerability structures: Structural vulnerability, major bridges, interchanges; Structural function & vulnerability key health facilities.
Access to resources and vulnerability of the population: Access to resources (rate resource / population); Population by age; Population by access to services; Population without access to any services; Average population by households by room; Population without potable water; Population without drainage system; Population without electricity; Households with average people per room; Population living with dirt floors; Population settlements resulting from land's invasion; % Population that are newcomers to the district; % Population with low education; Accessibility due to urban design; Exposure to Hazards.
Vulnerability humanitarian response: Governance humanitarian response system; Quality of system, processes, services and tasks; Maturity and expertise humanitarian institutions; Decision and intervention centers available; Water supply hubs available; Food supply available; Health care available; Energy supply available; Transport, roads and accessibility available; Telecommunications available; Shelters area available; Waste dumps disposable areas available; Economic and finance support; Keep permanent measure system population vulnerability updated; Keep measure system hazard seismic updated; Keep measure system tsunami threat updated; Keep a database robustness and updated base

The third step consists in modelling the correlation formula that allows the future demand to be assessed, using a multivariate regression analysis (Hair *et al.*, 2006). For the occurrence of any given disaster, two different areas would not record the same impact due to their own vulnerability and resilience characteristics. Considering the previous frame, we define for each region impacted in the past, the following association:

$$\text{Past Disaster Impact} = f(V_1, V_2, \ldots, V_m; R_1, R_2, \ldots, R_n) \tag{1}$$

In which:

{V1, …, Vm} are the vulnerability discriminating variables identified during the PCA analysis.

{R1, …, Rn} are the resilience discriminating variables identified during the PCA analysis.

Based on these equations, we estimate, for a potential impacted localization and for a given period *t*, an expected gravity using a multivariate regression model. Following Sopipan *et al.* (2012), if explanatory independent variables have multi-collinearity, the forecasting calculation can be defined as:

$$\text{Future Disaster impact} = f_{(t=1,\ldots,T)}(X_1,\ldots,X_k,\ldots,X_{mxn}) \quad (2)$$

In which:

X_k is an independent variable composed of *{m x n}* values recorded in each period *t,* from a database which carries a total of *T* periods.

The fourth step consists in validating the relevance of the proposed regression models. To support this step, we propose carrying out a comparative analysis to measure the deviation between the forecast calculated by the model and the real needs that have been recorded in the field. This is defined as Ratio. We should note that the objective is to obtain a valid forecast that constitutes a rough estimate and not necessarily a very accurate estimate. The following deviation ratio criteria are proposed:

- If Ratio < 50% then the model is considered as "good";
- If Ratio < 100% then the model is considered as "admissible";
- If Ratio > 100% then the model is considered as "irrelevant".

Of course, those thresholds might appear quite high compared with commercial supply chain context, in which a Ratio of more than 80% is generally considered as irrelevant. But the standards of forecast accuracy differ from one sector to another. Due to the high level of uncertainty in disaster world, new thresholds must be defined. Of course, those ratios can be adapted for each case study in function of the targeted precision level.

Phase 5. Assessing the impact on infrastructures

To help those who need assistance after the disaster, disaster workers use available HL resources. Local infrastructures may have suffered from the disaster. An estimation of available capacity, together with an estimation of the impacts of the disaster on local infrastructures is therefore needed to evaluate the potential difficulty of aid delivery.

This phase starts with a review of the information on available infrastructures. This step must be based on HL database in which all the existing resources are identified. All these resources must be characterized through their capacities.

The second step of this phase consists in assessing the potential impact of a disaster on HL infrastructures in terms of transportation and warehousing capability limitations. Practically, we suggest building a propagation tree that describes all the cause-effect links that could exist between the regions. Let us consider an earthquake with a magnitude of 7.5 in region R1. This region is geographically connected with regions R2 and R3 represented by 2 branches of the propagation tree. R2 is a sensitive zone regarding earthquakes (big impact expected) whereas R3 is a non-sensitive zone (low impact expected). Based on geological and territorial expertise, we can estimate the potential impact on HL infrastructure in R2 and R3 in case of an earthquake of 7.5-magnitude earthquake in R1. This could be for instance that the warehousing capabilities could be reduced by 40% in region R2 and 10% in R3. Of course, this estimate is not deterministic and is subject to a high level of uncertainty. However, it provides an indication to decision-makers where to expect and prepare for damage to infrastructure.

At the end of these five phases, a plausible set of scenarios is defined. This set provides figures on the number of expected affected families and capacities of HL resources. The defined set of scenarios can be used to feed any kind of HL decision support systems. To illustrate benefits and limits of this proposal, an application on the recurrent impact of floods and earthquakes in Peru is provided in the following section.

Designing Post-Disaster Scenarios for HL in Peru

Peru is a country prone to natural hazards, including earthquakes, flooding, landslides and climatic shifts. In the following example, we applied the proposed methodology to define a set of valid scenarios that will, in future works, provide accurate and relevant information to feed HL decision-support systems dedicated to this context. The recurrent disasters considered in this study are only floods and earthquakes.

Phase 1: Gathering data on past disasters in Peru

The database used to generate plausible scenarios was built from Geophysical Institute of Peru (IGP) database. This database is considered as the most complete and reliable in the opinion of local experts. For earthquakes, more than 2500 events recorded in this database have been used for this study, with a period of data collection from 1970 to 2012. Regarding flooding events, National Institute of Civil Defence of Peru (INDECI) statistical reports were used on a ten-years period (2002 – 2012) to gather data. All information on localization, time, nature and intensity of past events has been recorded and analysed over those periods for both floods and earthquake disasters.

Phase 2: Defining the zoning of Peru

To define which area may suffer from the recurrent disasters given in the list of scenarios, specialized cartographies from IGP and INDECI were analysed respectively related to seismic and flooding zones. Based on this knowledge, it was possible to consider 24 regions as significant in terms of the natural phenomena studied (earthquakes and floods).

It is important to fully understand the topology of the territory because geographic and geological factors can influence the propagation of the wave of the disaster and can have a great incidence on HL. For example, an earthquake striking Lima will also affect the Ancash and Ica regions, because the seismic fault line follows the coast. However, it will not affect the Pasco and Junin regions though, as they are protected by the Andes Mountains. In this way, regarding an earthquake with its epicentre in Lima region, the Ancash and Ica regions will be considered as Sensitive Zones (SZ) whereas Pasco and Junin will be considered as Non-Sensitive Zones (NSZ).

Phase 3. Defining occurrences of recurrent disasters in Peru

The key parameters, such as magnitude, peak intensity, epicentre, time duration, and occurrence period can be correlated by means of simple functions (Corbi, 2013). For each region, we use past disaster occurrences to evaluate the probability of occurrence of a new disaster in the future, and its magnitude. For example, in the region around Lima, the probability of the occurrence of an earthquake is $p=0.1$ and If a disaster occurs, its magnitude is either low ($p=0.96$ of having a disaster with a magnitude $M<6$) or very high ($p=0.04$ of having an earthquake with a magnitude above 8 in this region). Table 3 provides the probabilities of occurrence for earthquakes and their intensity for each region, as defined in the previous phase.

To define a consistent list of scenarios, we select the most representative earthquakes. Every earthquake with a magnitude below 5.5 is discarded, because values below this range are related to seismic movements without an important disaster impact (such as Moquegua and Puno regions into as shown in Table 3). A new scenario is built for each non-empty class (value >0% in the last four column of the database). At the end of this phase, a list of 27 potential valid scenarios including “intensity” and “probability of occurrence” is built (see grey cells on Table 3). At this stage, the scenarios should be completed with an assessment of the quantity of victims, which is the main cause of uncertainty and discrepancy between researchers and practitioners. That is the purpose of the next phase.

Phase 4. Estimation of the amount of post-disaster victims

According to the methodology developed in the previous section, we applied a Principal Component Analysis (PCA) on the value of the Peru influencing factors for

Table 3. Probability of earthquakes' occurrences by Peruvian region.

No	Regions	M mean	M max	M critical	%	<5,5	5,5 - 6,0	6,0 - 7,0	7,0 - 8,0	8,0 - 9,0
1	Amazonas	4,8	4,8	7,3	1,3%	50%	0%	0%	50%	0%
2	Ancash	5,2	5,2	8,2	10,0%	75%	0%	0%	0%	25%
3	Apurimac	3,9	6,1	6,0	1,3%	86%	0%	14%	0%	0%
4	Arequipa	4,5	5,9	8,0	10,0%	93%	0%	0%	0%	7%
5	Ayacucho	5,6	5,9	6,7	1,3%	67%	0%	33%	0%	0%
6	Cajamarca	4,3	4,3	7,0	1,3%	88%	0%	0%	12%	0%
7	Cusco	4,6	6,3	7,2	1,3%	93%	0%	0%	7%	0%
8	Huancavelica	3,8	6,0	6,0	1,3%	89%	0%	11%	0%	0%
9	Huanuco	5,7	5,9	5,9	1,3%	60%	40%	0%	0%	0%
10	Ica	4,5	5,7	8,4	10,0%	86%	0%	0%	0%	14%
11	Junin	4,7	5,8	7,5	1,3%	82%	0%	0%	18%	0%
12	La Libertad	4,8	6,1	7,8	10,0%	86%	0%	0%	14%	0%
13	Lambayeque	4,5	6,3	6,3	1,3%	83%	0%	17%	0%	0%
14	Lima	4,2	6,3	8,4	10,0%	0%	96%	0%	0%	4%
15	Loreto	6,0	6,0	7,0	1,3%	0%	0%	75%	25%	0%
16	Madre de Dios	5,8	5,8	6,4	1,3%	0%	50%	50%	0%	0%
17	Moquegua	4,7	4,7	4,7	10,0%	100%	0%	0%	0%	0%
18	Pasco	5,5	5,6	5,6	1,3%	60%	40%	0%	0%	0%
19	Piura	4,5	7,1	6,7	1,3%	0%	0%	80%	20%	0%
20	Puno	4,8	4,8	4,8	1,3%	100%	0%	0%	0%	0%
21	San Martin	5,3	7,5	7,0	1,3%	0%	0%	80%	20%	0%
22	Tacna	5,4	5,4	8,6	10,0%	80%	0%	0%	0%	20%
23	Tumbes	5,0	5,0	7,7	10,0%	66%	0%	0%	34%	0%
24	Ucayali	5,2	5,2	6,7	1,3%	66%	0%	34%	0%	0%
					100,0%					

the years 1993 to 2007. Concerning our problem, it appears that three of them were particularly discriminating (more than 85% of the variance): Human Development Index (IDH), Precariousness of Buildings (or Vulnerability Construction to Seism: VCS), and Insecurity (or Number of Crimes and Delinquency: NCD). Of course, this result is only valid for this country and cannot be generalized for other territories.

Based on this result, and on the historical data on the number of victims associated with past disasters since 1993, we established the equations of regression for each one of the 24 regions (see Table 4). These equations explain the relationships that exist between the number of victims per year and per region and the values of the three discriminating influence factors. The overall significant dependencies between variables were tested and validated through the Fischer test. The numerical

Table 4. Multivariate regression models for each one of the 24 Peruvian regions.

No	Regions	Multivariate Equations
1	Amazonas	+38035,515*IDH+0,857*NCD+30227,91*VCS-40410,026
2	Ancash	+16826,995*IDH+0,686*NCD-2581,551*VCS-11168,97
3	Apurímac	+34299,477*IDH-5,995*NCD+91063,601*VCS-91550,67
4	Arequipa	+348649*IDH-10,623*NCD+814492,233*VCS-240522,978
5	Ayacucho	+621533,227*IDH+0,597*NCD+258270,109*VCS-479974,519
6	Cajamarca	-882137,69*IDH-0,699*NCD-1311377,424*VCS+1600535,042
7	Cusco	+220593,116*IDH +1,856*NCD-13987,094*VCS-112461,426
8	Huancavelica	+289253,681*IDH-8,676*NCD+570179,879*VCS-646952,953
9	Huánuco	-43062,933*IDH+0,893*NCD-64148,197*VCS+66515,424
10	Ica	+161046,558*IDH-13,451*NCD-895759,802*VCS+580042,954
11	Junín	+4118,794*IDH-0,022*NCD-12083,176*VCS+6633,609
12	La Libertad	+203718,006 *IDH+2,687*NCD-38391,946*VDC-128032,081
13	Lambayeque	+51480,326*IDH +1,779*NCD-7484,189*VCS-42826,641
14	Lima-Callao	+174323,153*IDH+0,44*QNCD-1450525,446*VCS+23054,334
15	Loreto	-8188822,64*IDH-14,17*NCD-6864768,675*VCS+4943835,767
16	Madre de Dios	+58615,818*IDH+0,022*NCD+103031,332*VCS-37854,745
17	Moquegua	+47548,176*IDH+0,026*NCD+8636,842*VCS-33671,117
18	Pasco	+43953,669*IDH-0,217*NCD+36170,662*VCS-42454,652
19	Piura	+21014,559*IDH-0,134*NCD+16910,62*VCS-18383,037
20	Puno	+75221,765*IDH+0,089*NCD+27714,244*VCS-57515,927
21	San Martin	-3418533,812*IDH-55,448*NCD-445324,247*VCS+2248853,148
22	Tacna	-38427,373*IDH+0,268*NCD+26868,258*VCS+21099,831
23	Tumbes	+11223,028*IDH+0,071*NCD+6190,019*VCS-10253,339
24	Ucayali	+39359,878*IDH+1,838*NCD+102590,051*VCS-28361,224

results indicate that only 12 regions out of 24 meet the assumptions of recurrence (Amazonas, Ancash, Cajamarca, Huanuco, Junin, Madre de Dios, Pasco, Piura, Puno, San Martin, Tacna and Tumbes). The other regions are more chaotic with many years without any significant disasters and some years with major events (Moquegua for instance). Consequently, we focused the next steps only on these 12 regions. In this way, it will be possible to forecast the impact that a new recurrent disaster will have if it occurs in a given region. In Table 5, we can see the results obtained for the year 2012 by means of multivariate regression models and the real number of victims recorded for this year for the regions in which recurrent disasters occur. The results show that:

- 25% of the results (3 regions: Ancash, Huanuco and Junin) can be judged as very reliable with a deviation ratio lower than 50%;
- 33% of the results (4 regions: Amazonas, Piura, Puno, Tacna) can be judged as admissible with a deviation ratio lower than 100%.
- 41% of the results (5 regions: Cajamarca, Madre de Dios, San Martin, Pasco and Tumbes) can be judged as doubtful with a deviation ratio higher than 100%. Among these, two regions were hit by major events in 2012 (San Martin and Madre de Dios). Our models are not able to forecast these exceptional events. If we do not take into consideration the number of victims due to these events, the model becomes reliable. For the three other regions, the problem is because the disaster occurrences are not yearly but have a frequency of several years. The current models are consequently not relevant for these regions. It is important to remark that our approach could be applied successfully to these three regions, and potentially to the twelve regions that did not meet the recurrence assumptions, by changing the periodicity and the time horizon (respectively ten years and one century for instance).

Table 5. Gap analysis between regression-model results and real observations for the year 2012.

No	Regions	Model validation		
		2012 Forecast	2012 Observation	Valid?
1	Amazonas	4138	1 364	Admisible
2	Ancash	2566	2 193	Reliable
6	Cajamarca	12870	745	Doubtfull
9	Huánuco	5013	5 284	Reliable
11	Junín	3909	2 790	Reliable
16	Madre de Dios	-	231 827	Doubtfull
18	Pasco	64	2 051	Doubtfull
19	Piura	1627	649	Admisible
20	Puno	6491	12 453	Admisible
21	San Martin	-	26 011	Doubtfull
22	Tacna	411	1 701	Admisible
23	Tumbes	155	4 655	Doubtfull

Phase 5. Impact on local HL capabilities

After important disruptive events, such as an earthquake, HL capacity is drastically reduced due to the total or partial destruction of vehicles, infrastructures and facilities. Following the methodology described before, we made a set of experts' interviews from INDECI and IGP to assess the potential impact on HL infrastructures that a disaster may have. These interviews have allowed defining if a Region can be considered as a Sensitive Zone or a Non-Sensitive Zone. Then, a deep analysis of previous disasters from 1993 to 2012 was made to assess the impact of a given earthquake on HL infrastructures. This impact is both assess for the epicentre region and for border regions depending of their sensitivity. Finally, we obtained the following Table that shows the estimated capacity reduction (following an earthquake) between two regions as a function of both the intensity of the disaster, and the sensitivity of the region. This shows the last dimension of the valid scenarios we obtained for the Peruvian HL.

CONCLUSION AND PERSPECTIVES

Although a plethora of HL decision support systems has been proposed during the last decade, scientific innovation has not yet led to considerable improvement in practice. This is particularly true for quantitative approaches and risk management. The scenario approaches frequently suggested in academic literature, are often too complex and time-consuming, while rapid heuristics and experienced based decisions lead are prone to bias. Designing valid scenarios that meet requirements of field-based practitioners is of prime importance in ensuring that quantitative models that can be implemented and used by practitioners.

In this chapter, a methodology has been developed to design a set of valid scenarios able to assess disaster needs in regions subject to recurrent disasters. The proposition is based on two assumptions validated by the existing literature. The first considers that future occurrences of disasters can be taken as globally equivalent to past ones. The second considers that future disaster impacts will depend on two main factors: vulnerability and resilience. Based on these hypotheses, our proposed approach is split into five phases: (i) gathering data on past disasters and analysing it; (ii) defining a relevant zoning of the studied area; (iii) defining the probability of occurrence of each scenario; (iv) determining the expected impact of future disasters as a function of resilience and vulnerability factors; (v) assessing the consequences of future disasters on HL infrastructures. The results seem to be globally robust for Peru and could be used efficiently for future developments in terms of HL quantitative-based decision-support systems.

Table 6. Overview of potential reduction of capacities depending on earthquake intensity and region sensitivity.

[illegible]	% reduction of capacity storage			% reduction of capacity flow transport		
	Epicenter	Border		Epicenter	Border	
	SZ / NSZ	SZ	NSZ	SZ / NSZ	SZ	NSZ
5,5	0%	0%	0%	0%	0%	0%
	0%	0%	0%	0%	0%	0%
6,5	40%	20%	5%	10%	5%	3%
	20%	20%	5%	5%	5%	3%
7,5	60%	30%	10%	20%	15%	5%
	40%	30%	10%	15%	15%	5%
8,5	80%	40%	20%	40%	25%	15%
	60%	40%	20%	25%	25%	15%
9,5	100%	60%	40%	100%	65%	25%
	80%	60%	40%	65%	65%	25%
10,0	100%	80%	60%	100%	80%	60%
	100%	80%	60%	100%	80%	60%

Although the proposal is a significant first step towards solving the problem of relevant and plausible scenarios in HL, several limitations remain, which we propose to study in future research. The quality of the forecast should be assessed more deeply to confirm that our results are representative. To do so, complementary experiments will be carried out to consolidate and validate the methodology. The deviation ratio thresholds we used to validate the model should also be studied more deeply. Future uses of this approach and its results can be imagined. One concrete example of application is already developed in (Vargas *et al.*, 2015) to design a robust network of disaster warehouses to respond to recurrent disasters in Peru.

REFERENCES

Aldunce, P., Beilin, R., Handmer, J., & Howden, M. (2014). Framing disaster resilience: The implications of the diverse conceptualisations of bouncing back. *Disaster Prevention and Management*, *23*(3), 252–270. doi:10.1108/DPM-07-2013-0130

Alinovi, L., Mane, E., & Romano, D. (2009). Measuring household resilience to food insecurity: application to Palestinian households. In R. Benedetti, M. Bee, G. Espa, & F. Piersimoni (Eds.), *Agricultural Survey Methods*. John Wiley & Sons, Ltd.

Balcik, B., Jahre, M., & Fabbe-Costes, N. (2015). How standards and modularity can improve disaster supply chain responsiveness. *Journal of Disaster Logistics and Supply Chain Management, 3*, 348-386.

Birkmann, J., Seng, D. C., & Setiadi, N. (2013). Enhancing early warning in the light of migration and environmental shocks. *Environmental Science & Policy*, *27*(1), 76–88. doi:10.1016/j.envsci.2012.04.002

Bosch, R. (2010). Objectivity and Plausibility in the Study of Organizations. *Journal of Management Inquiry*, *19*(4), 383–391. doi:10.1177/1056492610369936

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. doi:10.1111/j.1467-7717.2012.01297.x PMID:23066755

Carter, M. R., Little, P. D., Mogues, T., & Negatu, W. (2004). Shocks, sensitivity and resilience: Tracking the economic impacts of environmental disaster on assets in Ethiopia and Honduras. In *BASIS Research Program on Poverty, Inequality and Development*. US Agency for International Development.

Charles, A., & Lauras, M. (2011). An enterprise modelling approach for better optimisation modelling: Application to the disaster relief chain coordination problem. *OR-Spektrum*, *33*(3), 815–841. doi:10.100700291-011-0255-2

Charles, A., Lauras, M., Van Wassenhove, L. N., & Dupont, L. (2016). Designing an efficient disaster supply network. *Journal of Operations Management*, *47*(1), 58–70. doi:10.1016/j.jom.2016.05.012

Comes, T. (2016). Cognitive biases in disaster sensemaking and decision-making lessons from field research. *2016 IEEE International Multi-Disciplinary Conference on Cognitive Methods in Situation Awareness and Decision Support (CogSIMA)*, 56-62. 10.1109/COGSIMA.2016.7497786

Comes, T., Wijngaards, N., & Van de Walle, B. (2015). Exploring the future: Runtime Scenario Selection for Complex and Time-Bound Decisions. *Technological Forecasting and Social Change*, *97*(1), 29–46. doi:10.1016/j.techfore.2014.03.009

Di Domenica, N., Mitra, G., Valente, P., & Birbilis, G. (2007). Stochastic programming and scenario generation within a simulation framework: An information systems perspective. *Decision Support Systems*, *42*(4), 2197–2218. doi:10.1016/j.dss.2006.06.013

Dieckhaus, D., Heigh, I., Gomez-Tagle Leonard, N., Jahre, M., & Navangul, K. A. (2011), Predicting the Unpredictable – Demand Forecasting in International Disaster Response. IFRC Global Logistics Service Annual Report.

Djalante, R., Holley, C., & Thomalla, F. (2011). Adaptive governance and managing resilience to natural hazards. *International Journal of Disaster Risk Science*, *2*(4), 1–14. doi:10.100713753-011-0015-6

Dupačová, J., Consigli, G., & Wallace, S. W. (2000). Scenarios for Multistage Stochastic Programs. *Annals of Operations Research*, *100*(1), 25–53. doi:10.1023/A:1019206915174

Ferris, E., Petz, D., & Stark, C. (2013). The year of recurring disasters: A review of natural disasters in 2012. The Brookings Institution – London School of Economics – Project on Internal Displacement.

Frigg, R., & Hartmann, S. (2012). Models in Science. The Stanford Encyclopedia of Philosophy, 23.

Galindo, G., & Batta, R. (2013). Review of recent developments in OR/MS research in Humanitarian Logistics. *European Journal of Operational Research*, *230*(2), 201–211. doi:10.1016/j.ejor.2013.01.039

Hair, J. F., Black, W. C., Babin, B. J., Anderson, R. E., & Tatham, R. L. (2006). *Multivariate data analysis* (Vol. 6). Pearson Prentice Hall.

Jahre, M., & Fabbe-Costes, N. (2015). How standards and modularity can improve disaster supply chain responsiveness: The case of emergency response units. *Journal of Disaster Logistics and Supply Chain Management*, *5*(3), 348–386.

Jolliffe, I. (2002). *Principal component analysis*. John Wiley & Sons, Ltd.

Karimi, I., & Hüllermeier, E. (2007). Risk assessment system of natural hazards: A new approach based on fuzzy probability. *Fuzzy Sets and Systems*, *158*(9), 987–999. doi:10.1016/j.fss.2006.12.013

Klibi, W., & Martel, A. (2012). Scenario-based supply chain network risk modelling. *European Journal of Operational Research*, *223*(3), 644–658. doi:10.1016/j.ejor.2012.06.027

Kovács, G., & Spens, K. M. (2007). Disaster HL in disaster relief operations. *International Journal of Physical Distribution & Logistics Management*, *37*(2), 99–114. doi:10.1108/09600030710734820

Laguna Salvadó, L., Lauras, M., & Comes, T. (2015). Towards More Relevant Research on Disaster Disaster Management Coordination. *Proceedings of the 12th Information Systems for Crisis Response And Management (ISCRAM) Conference*. http://idl.iscram.org

Laguna Salvadó, L., Lauras, M., & Comes, T. (2016). Towards a Monitoring System for American IFRC Logistics Network. *Proceedings of the 13th Information Systems for Crisis Response And Management (ISCRAM) Conference*. http://idl.iscram.org

Mendonca, D., Beroggi, G. E., Van Gent, D., & Wallace, W. A. (2006). Designing gaming simulations for the assessment of group decision support systems in emergency response. *Safety Science*, *44*(6), 523–535. doi:10.1016/j.ssci.2005.12.006

Merz, M., Hiete, M., Comes, T., & Schultmann, F. (2013). A composite indicator model to assess natural disaster risks in industry on a spatial level. *Journal of Risk Research*, *16*(9), 1077–1099. doi:10.1080/13669877.2012.737820

Ndille, R., & Belle, J. A. (2014). Managing the Limbe floods: Considerations for disaster risk reduction in Cameroon. *International Journal of Disaster Risk Science*, *5*(2), 147–156. doi:10.100713753-014-0019-0

Oloruntoba, R., & Gray, R. (2006). Disaster aid: An agile supply chain? *Supply Chain Management*, *11*(2), 115–120. doi:10.1108/13598540610652492

Peres, E. Q., Brito, I. Jr, Leiras, A., & Yoshizaki, H. (2012). Disaster logistics and disaster relief research: trends, applications, and future research directions. *Proceedings of the 4th International Conference on Information Systems, Logistics and Supply Chain*, 26-29.

Tatham, P., Oloruntoba, R., & Spens, K. (2012). Cyclone preparedness and response: An analysis of lessons identified using an adapted military planning framework. *Disasters*, *36*(1), 54–82. doi:10.1111/j.1467-7717.2011.01249.x PMID:21702893

Tietje, O. (2005). Identification of a small reliable and efficient set of consistent scenarios. *European Journal of Operational Research*, *162*(2), 418–432. doi:10.1016/j.ejor.2003.08.054

Tveiten, C. K., Albrechtsen, E., Wærø, I., & Wahl, A. M. (2012). Building resilience into emergency management. *Safety Science*, *50*(10), 1960–1966. doi:10.1016/j.ssci.2012.03.001

UNDP. (2004). *Reducing Disaster Risk: A Challenge for Development–A Global Report*. UN Press.

UNESCAP. (2008). *Building Community Resilience to Natural Disasters through Partnership: Sharing Experience and Expertise in the Region*. UN Press.

UNISDR. (2009). *Terminology on Disaster Risk Reduction*. UN Press.

Van de Walle, B., & Comes, T. (2015). On the nature of information management in complex and natural disasters. *Procedia Engineering*, *107*(1), 403–411. doi:10.1016/j.proeng.2015.06.098

van der Laan, E., van Dalen, J., Rohrmoser, M., & Simpson, R. (2016). Demand forecasting and order planning for disaster logistics: An empirical assessment. *Journal of Operations Management*, *45*(1), 114–122. doi:10.1016/j.jom.2016.05.004

Vargas, J., Lauras, M., Okongwu, U., & Dupont, L. (2015). A decision support system for robust disaster facility location. *Engineering Applications of Artificial Intelligence*, *46*(1), 326–335. doi:10.1016/j.engappai.2015.06.020

Vargas, J., Rojas, J., Inga, A., Mantilla, W., Añasco, H., Basurto, M. F., Campos, R., Sánchez, J., & Checa, P. I. (2016). Towards Reliable Recurrent Disaster Forecasting Methods: Peruvian Earthquake Case. *Proceedings of the 13th Information Systems for Crisis Response And Management (ISCRAM) Conference*. http://idl.iscram.org

Vitoriano, B., de Juan, J. M., & Ruan, D. (2013). *Decision aid models for disaster management and emergencies*. Springer Science & Business Media. doi:10.2991/978-94-91216-74-9

Weichselgartner, J. (2001). Disaster mitigation: The concept of vulnerability revisited. *Disaster Prevention and Management: An International Journal*, *10*(2), 85–95. doi:10.1108/09653560110388609

WGCEP. (2007). *The Uniform California Earthquake Rupture Forecast*. U.S. Geological Survey Open-File Report and California Geological Survey Special Report. https://pubs.usgs.gov/of/2007/1091/

Wisner, B., Blaikie, P., Cannon, T., & Davis, I. (2004). At risk. Natural people's vulnerability and disasters. Routledge.

Wright, G., Cairns, G., & Goodwin, P. (2009). Teaching scenario planning: Lessons from practice in academe and business. *European Journal of Operational Research*, *194*(1), 323–335. doi:10.1016/j.ejor.2007.12.003

Xu, H., Zhang, K., Shen, J., & Li, Y. (2010). Storm surge simulation along the US East and Gulf Coasts using a multi-scale numerical model approach. *Ocean Dynamics*, *60*(6), 1597–1619. doi:10.100710236-010-0321-3

Zhang, K., Li, Y., Liu, H., Xu, H., & Shen, J. (2013). Comparison of three methods for estimating the sea level rise effect on storm surge flooding. *Climatic Change*, *118*(2), 487–500. doi:10.100710584-012-0645-8