

Location-allocation planning of stockpiles for effective disaster mitigation

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Abstract In the existing framework for receiving and allocating Strategic National Stockpile (SNS) assistance, there are three noticeable delays: the delay by the state in requesting federal assets, the delay in the federal process which releases assets only upon the declaration of a disaster and lastly the time it takes to reach supplies rapidly from the SNS stockpile to where it is needed. The most efficient disaster preparedness plan is one that addresses all three delays taking into account the unique nature of each disaster. In this paper, we propose appropriate changes to the existing framework to address the first two delays and a generic model to address the third which determines the locations and capacities of stockpile sites that are optimal for a specific disaster. Specifically, our model takes into account the impact of disaster specific casualty characteristics, such as the severity and type of medical condition and the unique nature of each type of disaster, particularly with regard to advance warning and factors affecting damage. For disasters involving uncertainty (magnitude/severity) with regard to future occurrences, such as an earthquake, development of appropriate solution strategies involves an additional step using scenario planning and robust optimization.

We illustrate the application of our model via case studies for hurricanes and earthquakes. We are able to outline an appropriate response framework for each.

Keywords Emergency preparedness · Strategic national stockpile · Decision making under uncertainty

1 Introduction

Disasters, both natural and manmade, have the potential to lead to significant human and economic losses. In recent history, Hurricane Katrina, for instance, made land fall in the United States causing severe losses to both life and property. At least 1,836 people lost their lives due to the hurricane and it resulted in about \$81.2 billion in economic damage

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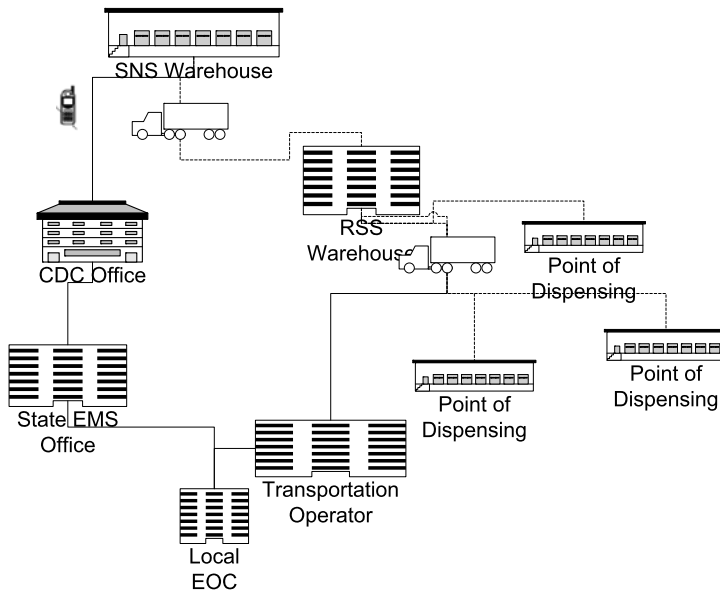


Fig. 1 SNS framework (Belson 2005)

(Tanner 2005). On December 26th, 2004, a tsunami caused by a 9.0 magnitude earthquake in the Indian Ocean left a total of 186,983 people dead and 42,883 missing (AP 2004). Emergency management or disaster management can be broken up into four phases: Mitigation which includes activities that reduce the likelihood of the disaster or reduces the size of the damage (for example, structurally strong construction of buildings), Preparedness which entails a planned response in the event the disaster does happen (setting up communication channels, stockpiles of resources, etc.), Response which includes the mobilization of manpower, etc., and Recovery where the focus is on restoring the affected area to its pre-disaster state (FEMA 2010). Planning the location and amounts of emergency resources needed to handle such disasters is, thus, of paramount importance.

During a disaster, normal supply chains may be compromised and therefore treatment centers, such as hospitals, nursing home and long term facilities, find it hard to obtain additional supplies of equipment, drugs and other medical supplies. The Strategic National Stockpile (SNS) program managed by Center for Disease Control (CDC) and United States Department of Homeland Security (US DHS) was developed in 1999 to assist states and communities in promptly responding to public health emergencies by ensuring the availability of medicines, antidotes, medical supplies, and necessary medical equipment (MT DPHHS 2005; NACCHO 2007). Upon receiving a request from the state, and after a declaration of disaster is made by the President, SNS deploys a 12-Hour Push Package which consumes 5,000 square feet of storage space and will arrive on a jumbo jet, or seven to eight tractor-trailer trucks to the state's predetermined Receipt, Store and Stage (RSS) site from a centrally located site in United States (Klein and Nagel 2007). The RSS warehouse then breaks up the consignment and distributes them to dispensing sites or point of dispensing (POD) sites. This existing framework which is standard across different types of disasters is described in Fig. 1. In this existing framework, the request is often made days after the disaster and a response is initiated only after a request is received with the possibility of an additional 12 hour wait between request and arrival of supplies.

There are three delays in this existing framework: the delay by the state in requesting federal assets, and the federal process which releases assets only upon declaration of disaster and lastly the time it takes to transport supplies to where it is needed most rapidly from the SNS stockpile. The most efficient disaster preparedness plan is one that addresses all three delays taking into account the unique nature of each disaster. Our proposed framework is as follows: when there is prior warning of an impending disaster, states can request federal resources earlier, and the declaration of disaster can occur earlier thereby reducing the first two delays. Using our generic model, proper positioning of the SNS stockpiles to minimize the third delay also becomes feasible. When there is no prior warning no improvements can be proposed regarding the first two delays but for the third our model can help minimize the response time.

To efficiently address these delays it is important to take into account the unique nature of each disaster. For example, in the case of Hurricane Katrina, even though three days of prior warning was available before it actually made landfall in New Orleans, supplies reached days later. This was evident from the reported incidents of critical medical supply shortage during the event of hurricane Katrina (GPO Access Reports 2005; Klein and Nagel 2007; Franco et al. 2006). Delivery after request from a distant central site may not be the optimal setup for effective disaster preparedness especially when accurate forecasts of impending disasters are available. It could have been possible to set up temporary PODs which are stocked immediately upon receipt of the warning. On the other hand, for a disaster event such as the Northridge earthquake with no prior warning in terms of epicenter and magnitude, a better and more efficient preparedness plan might have been to set up and stock multiple fixed warehouse/dispensing sites in the Northridge region that is robust to the magnitude of the disaster. Casualty characteristics such as severity and types of medical conditions also differ from one disaster to another (see Tables 2 and 4) and incorporating these differences is critical to reduce fatalities. This is a basic shortcoming of existing capacitated facility location models when it comes to disaster preparedness. We develop a generic model for stockpile location and capacity allocation for regions subject to disasters based on their distinct characteristics that bridges this gap in the literature. In addition, since preparedness in the case of disasters, such as earthquakes, with no prior warning involves consideration of several possible future states, our generic model incorporates both scenario planning and robust optimization approaches. The use of this model in strategic and tactical resource allocation decision making in a disaster environment is illustrated through the aid of case studies for a hurricane and an earthquake.

The paper is organized as follows. Section 2 discusses the problem at hand and the body of literature relevant to the problem. Section 3 discusses the methodology and the solution strategies. Section 4 applies the models to the case of hurricanes and earthquakes respectively. Finally, conclusions and directions for future research are discussed in Sect. 5.

2 Analysis of the problem

Existing approaches to addressing location decisions for disaster planning often use facility location models. Church and Revelle (1974) proposed that one way to measure the effectiveness of a facility location is in terms of the average distance traveled by those who use the facility—the P-median problem. Another way to model the effect of distance is to assume that facilities become less reliable when the distance to a customer increases. Berman et al. (2003) use this paradigm to locate service facilities.

Inherent in the vast majority of the location literature is the assumption that the facilities operate normally and at full capacity when their services are needed. This assumption is

reasonable for many applications, but not in a natural disaster setting. There has been some recent work in the area of unreliable facility location. Berman et al. (2007) analyze a facility location problem in which some facilities might fail, causing customers to seek service from the remaining facilities and thereby increasing the cost of travel. Their major finding is that as the probability of failure or disruption grows the facilities tend to become more centralized and ultimately co-located. Jia et al. (2007) determine the optimal emergency medical service (EMS) facility locations to address the needs generated by large-scale emergencies. They specifically address the problem of locating medical supplies and the problem of how to position local staging centers for large-scale emergencies. In a recent paper, Huang et al. (2010) develop facility location models for large scale emergencies taking into account the fact that residents or demand centers might not be able to access their closest service facility.

While location of facilities is extremely important for efficient disaster response, the capacities of these facilities are often of even greater significance. In maximal covering problems, capacities are allocated to sites based on the size of demand at the node (Drezner and Wesolowsky 1999a, 1999b), which in the case of a disaster is the number of casualties. Rawls and Turnquist (2006) presented a two-stage stochastic optimization model to locate facilities and allocate supplies during emergency. They develop a mixed-integer program to address uncertainty in the demands and in the capacity of the transportation network. Paul and Batta (2008) have developed two models for hospital location and capacity allocation for regions prone to natural disasters like hurricane and earthquake. They use a capacitated facility location approach in deciding the hospital sites and corresponding resources in a region affected by hurricane and earthquake disasters. Murali et al. (2012) developed a special case of maximal covering location problem (MCLP) with a loss function, to account for the distance-sensitive demand, and chance-constraints to address the demand uncertainty that arises during an emergency situation.

Locating stockpiles and hospital capacity in a natural disaster prone area is a classic example of decision making under uncertainty. The location-allocation plans (for that matter, disaster plans in general) often fail because the uncertain and unusual nature of emergencies is not explicitly accounted for Dantzig (1999). One way to approach this uncertainty is through the technique of robust optimization, in which an effort is made to optimize the worst-case performance of the system (Snyder and Daskin 2005) or a solution that holds good whatever a problem scenario is Pomerol (2001). Lee et al. (2006) developed robust decision support tools to plan emergency dispensing clinics to respond to biological threats such as Anthrax, and Smallpox. Their models specifically focus on the staff planning required to dispense the necessary supplies after accounting for the uncertainty associated with a disaster. Berman and Gaviols (2007) presented competitive location models to locate facilities that contain resources required for response to a terrorist attack. The model solutions are robust to the worst-case scenario where the State needs to account for the terrorist's knowledge on the location of the facilities.

The mini max regret approach is another good example of robust optimization technique. In a recent article (Hung et al. 2007) it is pointed out that reducing decision regret is an important consideration for many decision makers. This is especially important when it involves situations of life and limb. The mini max regret approach chooses the action which entails the least or minimal regret. In many ways this approach is less conservative or risk averse than the traditional mini max approach in which the action is chosen such that it results in the best among the worst outcomes. While we use the mini max regret criterion due to its appropriateness to our problem we at the same time check for robustness of our solution with these other criteria. Another technique that has been widely used for decision making under uncertainty is scenario planning. The central idea of scenario planning is to

consider a variety of possible futures that include many of the important uncertainties in the system rather than to focus on the prediction of a single outcome (Peterson et al. 2003a). The importance of scenario planning has been highlighted and applied to strategic decision making in a wide variety of fields such as production planning (Escudero et al. 1993), human resources (Korte 2008), eco system conservation (Peterson et al. 2003b), investment planning (Mulvey and Vladimirov 1989), disaster planning (Chang et al. 2007) etc.

Prior work focusing on capacitated facility location through approaches like MCLP or those focusing on unreliable facility location etc., have attempted to deal with preparedness issues during a disaster, but there are a number of factors and constraints these models do not consider and which cannot be addressed through maximal coverage or quality of coverage setup. Amongst these, the most important ones are the characteristics of casualties like severity, type of injury, survivability time (time within which they need to be provided care otherwise would lead to fatality). This is clearly evident in the manner that demand is modeled and casualty minimization is achieved in the existing literature. In addition, other constraints that arise due to available budget, regional distribution of casualties (function of disaster type), and characteristics of a disaster that influence damage (supplies at stockpile sites or casualties) and vary with disaster, are not considered either. Finally, even though disaster uncertainty or unreliability in terms of magnitude or severity has been studied previously, its detailed characterization is still lacking. Specifically, in order to determine the appropriate resources and locations for a disaster response, its consequences in terms of casualty distribution, damage etc., need to be precisely simulated in the region under study. Factors like area of windfall, category, wind speed, path of landfall (hurricane), geological or topological characteristics (earthquake) etc. need to be incorporated. Our case studies using state of the art software HAZUS-MH by FEMA are able to incorporate these factors and therefore are a significant improvement in the appropriateness and relevance of our results. We extend the capacitated facility location literature to address these shortcomings particularly for problems involving location and capacity of facilities aimed at improving disaster preparedness of a region. In addition, since planning in the case of disasters, such as earthquakes, with no prior warning involves consideration of several possible future states, we incorporate both scenario planning and robust optimization approaches in this study.

3 Methodology

As pointed out earlier, there are three delays in the existing framework for receiving and allocating supplies: the delay by the state in requesting federal assets, the delay in the federal process which releases assets only upon declaration of disaster and lastly the time it takes to reach supplies to where it is needed most rapidly from the SNS stockpile.

In the case of hurricanes, since advanced warning regarding where landfall will occur, their magnitude is available (Fig. 2), prior preparation and transportation of supplies is feasible.¹ For such an event, we propose the following basic framework (Fig. 3) to address all three delays: Upon receiving a forewarning of an impending disaster, the State (using the generic model we build below) will place a request for supplies and determine location and capacities of temporary PODs (point of dispensing sites) where these supplies

¹ It is important to note that though there is uncertainty regarding the exact path of a hurricane, we do not model it as a significant constraint for decision making strategies in this paper.



Fig. 2 Katrina prediction uncertainty map, source: NHC archives

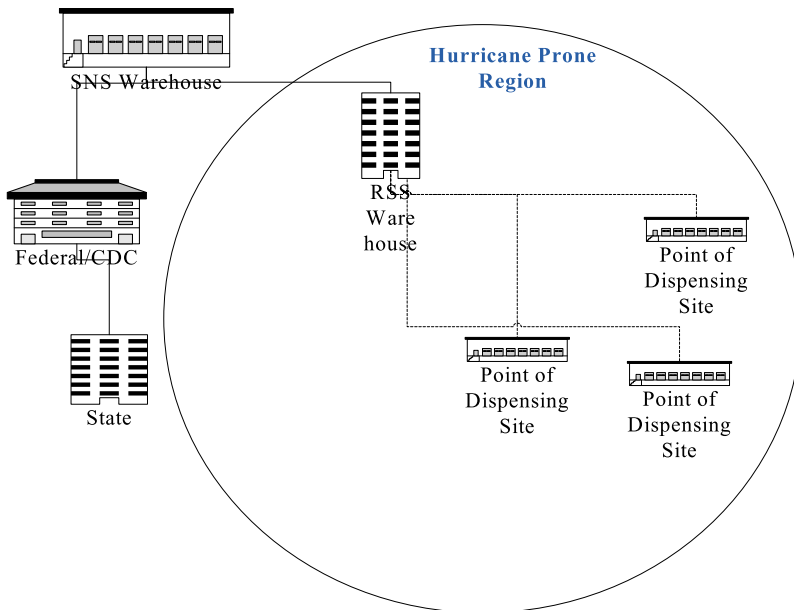


Fig. 3 Hurricane response framework

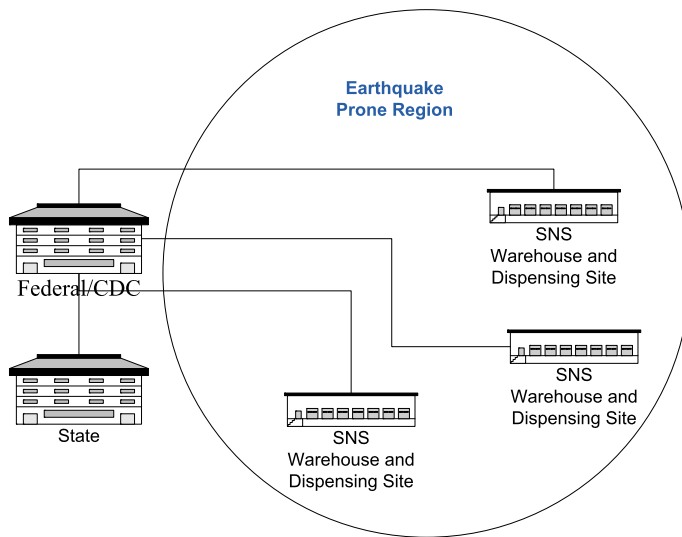


Fig. 4 Earthquake response framework

would be stored.² Declaration of disaster and release of requested supplies will be made by Federal/CDC upon receiving a request from the State. The central SNS warehouse would then send supplies to RSS warehouse which would distribute the supplies to these PODs. The POD site locations and capacities are selected taking into account not only access to highways, security, parking, etc., but also more critical factors such as hurricane category, direction of landfall, elevation above sea level, distance from nearest water source, distribution of casualties by type and disease/condition and facility damage, etc.

In the case of an earthquake, there is no forewarning as to when, where and how big an earthquake will strike the region. When there is no prior warning no improvements can be made on the first two delays but efforts can be made to minimize the response time. We propose the following framework (Fig. 4) for an earthquake. Since lack of advance warning does not provide the luxury of setting up temporary PODs, fixed SNS warehouse and dispensing sites must be located and built in the disaster prone region in advance in order to minimize fatality. This avoids the delay in receiving supplies from a central and possibly distant SNS warehouse. The primary role of these regional SNS sites would be to provide emergency supplies to treatment centers but they could also be used as dispensing sites when needed. These sites should be robust to the magnitude of earthquake. Therefore, our generic model uses scenario planning in optimally determining locations and capacities of these SNS sites, taking into account the topology, fault lines, distribution of casualty by severity and disease/condition corresponding to an earthquake magnitude in the region considered. The Federal authorities using our generic model would determine the locations and capacities of these SNS sites and keep them stocked. In the event of a disaster, the State authorities would request release of necessary supplies similar to the existing framework. Whereas for Hurricane planning, the State authorities using our model determine the location and capacity of temporary PODs, in earthquake planning the Federal authorities determine the

²While PODs generally refer to sites for directly dispensing medicines to people, our recommendation for the role of PODs is broader and includes providing emergency supplies to treatment centers such as hospitals.

location and capacity of fixed SNS warehouse and dispensing sites using our model since they are generally responsible for stocking fixed SNS facilities.

The overall objective in our generic model (Fig. 5) is to choose the locations of PODs (for hurricanes) or SNS sites (for earthquakes) and capacities such that it minimizes the cost of delays in getting supplies to hospitals and the cost of the stockpile facilities. Henceforth, stockpile facilities/locations will refer to PODs for hurricanes and to fixed SNS sites for earthquakes in order to avoid confusion. Stage 1 of the generic model involves two main steps. Step 1a deals with the simulation of disaster scenarios using state of the art FEMA software—HAZUS-MH, to generate disaster and region specific casualty distributions. Step 1b deals with the determination of the set of potential sites for locating stockpiles. These sites are selected based on demography of a region, topological and geological characteristics (earthquake), elevation above sea, distance from water source (hurricane), access to highways, etc. Stage 2 uses outputs from step 1a and develops demand clusters in the region using clustering algorithms like K-means and functional/available hospitals as reference points. Stage 3 involves breaking down casualty distribution by severity and medical condition at each of these demand clusters. This is achieved by patient grouping algorithms (discussed in Sect. 4) developed using past disaster patient data and discussions with doctors having on-field experience and their subsequent mapping onto outputs from step 2. Stage 4 involves application of an MIP model that uses outputs from stages 3 and 2 and the set of potential sites (step 1b) to determine optimal locations and capacities of stockpiles for a specific disaster scenario. This sums up the application of the generic model for a hurricane. For earthquakes, due to the uncertainty (magnitude) regarding future occurrences, an additional stage (stage 5) involving scenario planning and robust optimization is used to obtain final solutions. Stages 1 through 3 are discussed in detail in the case study section. The MIP model and scenario planning approach are developed next.

The MIP model incorporates some of the distinct characteristics of various disasters and considers the joint impact of casualty characteristics, the economic cost to society due to fatalities and budgetary issues. There are multiple reasons for considering casualty characteristics and related parameters. The patients during a disaster could be of different types based on their injury or medical condition and each type could further be of different severity levels (FEMA 2000). Each of these severity levels has to receive care within a certain period of time (referred to as survivability time by Paul et al. 2006) in order to avoid fatalities. The available survivability time for each patient at the time of receiving care is a function of the time elapsed since injury. Two factors that impact this are the time it takes to transport patients to a treatment center, referred to as pre-hospital transport time (Pepe et al. 1987; Petri et al. 1995; Paul et al. 2006) and supply transport time from stockpile location to hospital. We follow prior research in assuming that pre-hospital transport time follows a normal distribution (Petri et al. 1995; Paul et al. 2006). We measure supply transport time using latitude and longitude information available on hospital and potential stockpile locations. We use severity and patient condition or disease as variables affecting location-allocation decisions because severity determines the time within which the patient needs care (as noted above) while disease condition determines the specific care and resources he/she would need within that time.

The model that we propose and the case studies permit both pre delivery as well as re supply to hospitals. In some disaster scenarios it is possible that pre delivery of stockpiles to all hospitals is optimal in which case supply transport time is zero. Our model will permit this since hospitals (as given by their latitude and longitude) themselves can be potential stockpile locations but it might not be optimal for every disaster scenario. One possible scenario where pre delivery might not work is where there are two smaller hospitals. Locating

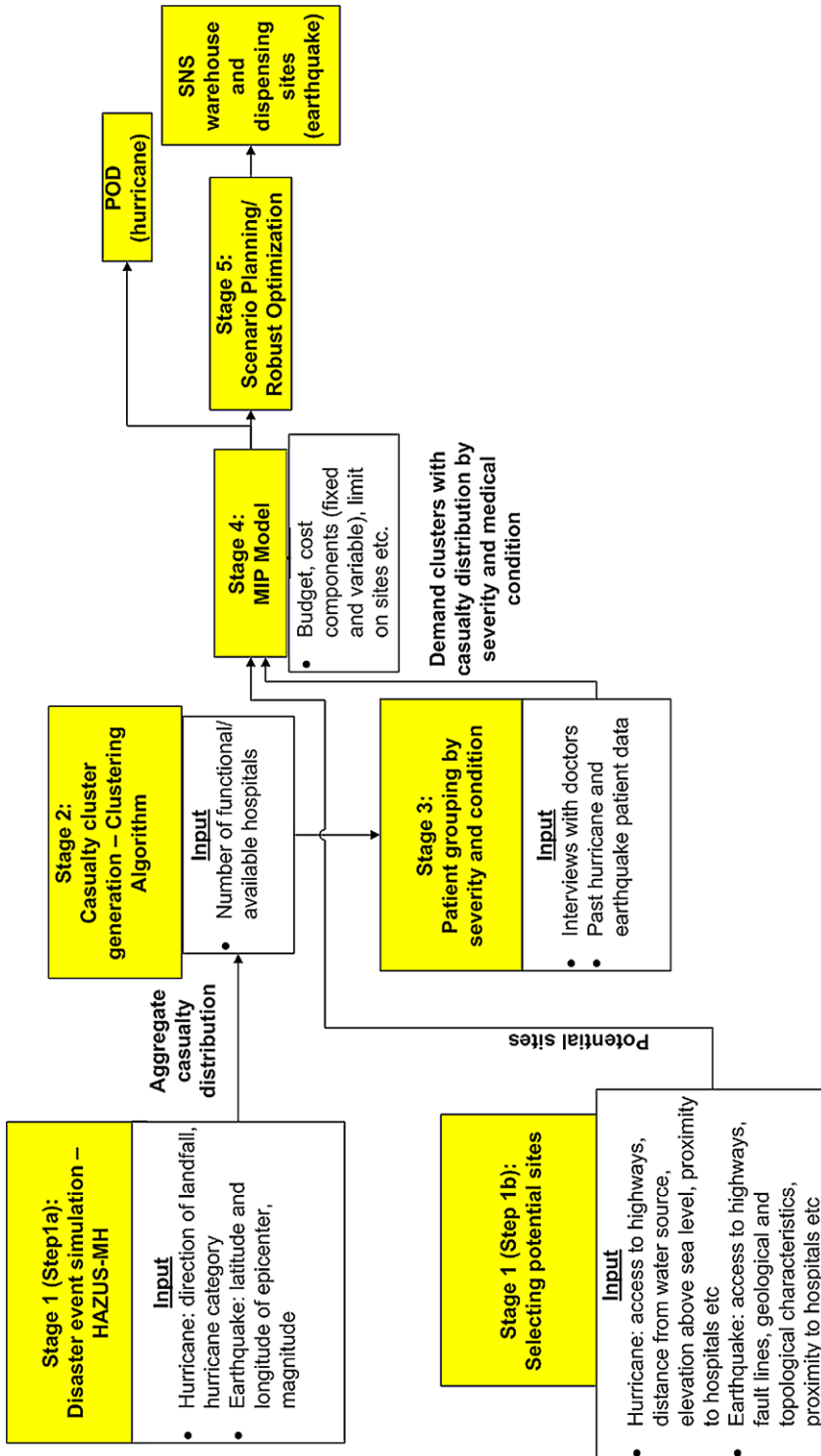


Fig. 5 Generic model

the stockpile in between to provide supplies to both hospitals might then be more efficient for economic reasons.

It is possible that in some disaster scenarios (especially high damage) the stockpile locations are not able to provide necessary supplies to completely satisfy demand due to capacity constraints. This could happen because of two reasons: there might be a limit on the capacity at the stockpile site that can be built due to existing budget constraints or some capacity might become unusable due to facility damage. To incorporate the latter, we only consider sites that would be rendered usable in spite of damage due to disaster. Any building with damage more than 25 percent is not considered in our case studies. Buildings with damage less than or equal to 25 percent are those that would be tagged green or yellow by building inspection teams and are deemed usable or enterable. Any building above 25 percent would be tagged red and considered unusable. We only use the residual capacity for allocation purposes in our case studies. To ensure that all supply demands are met, a hypothetical or fictitious back up site is considered with larger supply transport time than that for any of the stockpile sites built or temporarily setup in the region. This fictitious site does not affect the distribution or use of capacity available at the stockpiles located in the affected region. It is included in the model merely to take care of unsatisfied demand and ease of model solving. The notations used in our MIP model are as follows:

Indices and domains

- i : severity level,
- j : disease condition,
- m : demand cluster location,
- k : potential stockpile location,
- s : disaster scenario,
- o : fictitious site,
- I : set of severity levels,
- J : set of disease conditions,
- M : predetermined number of casualty clusters/demand nodes,
- K : set of potential stockpile locations,
- S : set of disaster scenarios,
- A : set of decision alternatives.

Parameters

- $C_{mij s}$: number of casualties at demand cluster node m belonging to severity level i and affected by disease condition j for disaster scenario s ,
- c_{ijk} : cost of supplies used in treating a patient of severity level i and condition j at site k ,
- f_{ks} : fraction of the total capacity available at site k after considering facility damage for scenario s ,
- F_c : economic value of a statistical fatality,
- F : fixed cost of building a stockpile which is the same for all sites,
- B : budget available to build sites,
- L : a big positive number,
- W : a big positive number,
- $\tau_{mij s}$: survivability time for patient with severity level i and condition j from cluster m during disaster scenario s ,
- t_{mks} : supply transport time from site k to cluster m for disaster scenario s ,
- t_{mos} : supply transport time from site k to cluster m for disaster scenario s , $t_{mos} = \max_{k \in K} \{t_{mks}\} + L, \forall m \in M$,

$T_{mij s}$: prehospital transport time for patient of severity level i and condition j travelling to cluster m during disaster scenario s .

Decision variables

w_{ijks} : capacity at site k , for patient severity i and condition j for disaster scenario s ,

x_{ks} : 1 if a stockpile is built at site k (scenario s),
0 otherwise,

y_{mijks} : proportion of patients at demand node m , severity i , condition j allocated to supply node k for disaster scenario s ,

V_{ks} : variable cost for building a stockpile at site k for scenarios s .

Using these notations, the formulation of the first stage of our model (with advance warning/no uncertainty) is as specified in (1)–(6):

Formulation

For disaster scenario s ,

$$\begin{aligned} \text{Minimize } Z_s = & \sum_{m \in M} \sum_{k \in K \cup o} \sum_{i \in I} \sum_{j \in J} F_c C_{mij s} y_{mijks} (\min[\max[-(\tau_{mij s} - T_{mij s} - t_{mks})L \\ & + 1, 0], 1]) + \sum_{k \in K \cup o} (F x_{ks} + V_{ks}) \end{aligned}$$

$$\text{s.t. } \sum_{m \in M} C_{mij s} y_{mijks} \leq f_{ks} w_{ijks} \quad (\forall i, j, k), \quad (1)$$

$$\sum_{k \in K \cup o} y_{mijks} = 1 \quad (\forall m, i, j), \quad (2)$$

$$V_{ks} = \sum_{i \in I} \sum_{j \in J} c_{ijk} w_{ijks} \quad (\forall k), \quad (3)$$

$$\sum_{k \in K \cup o} (F x_{ks} + V_{ks}) \leq B, \quad (4)$$

$$\sum_{i \in I} \sum_{j \in J} w_{ijks} \leq x_{ks} W \quad (\forall k), \quad (5)$$

$$x_{ks} \in \{0, 1\}, \quad 0 \leq y_{mijks} \leq 1, \quad w_{ijks} \geq 0. \quad (6)$$

In this model, the objective function minimizes the social cost which is the sum of the fatality cost and the cost of maintaining a stock pile at site k . Such an objective function is particularly relevant in a disaster due to the value it attaches to fatality.

Fatality cost is incurred based on the values of available survivability time. In order to have reliable estimates of the available survivability time, we incorporate the pre-hospital transport time parameter and supply transport time from stockpile location to the treatment facility as discussed earlier. Therefore, available survivability time $= \tau_{mij s} - T_{mij s} - t_{mks}$.

There are three possible cases with regard to values of available survivability time: either it is less than zero, equal to zero or greater than zero. Fatality cost would be incurred for the first two cases only. Therefore, there was need for a logic that equated to 1 for the first two cases and equated to zero for the third case. We achieve this via $\min[\max[-(\tau_{mij s} - T_{mij s} - t_{mks})L + 1, 0], 1]$ We add 1 to available survivability time to take care of the scenario wherein available survivability time is equal to zero. For such a patient, fatality cost would then be incurred. A scenario in which available survivability time is less than zero but greater than or equal to -1 would result in just a fraction (or none) of fatality cost being considered. This can be rectified by multiplying it with a large number (L).

Constraint (1) ensures that the residual capacity at site k is greater than or equal to demand from node m supplied by site k . Constraint (2) makes sure that all demand for supplies at the treatment facilities is satisfied by some stockpile site. Constraint (3) defines the variable cost of a site k . The total amount spent as fixed cost and variable cost should be less than or equal to the budget available as denoted by constraint (4) or in other words, stockpile expenditures is less than or equal to the available budget. Constraint (5) makes sure that capacity is awarded to a site only if a facility is built at that site.

When there exists uncertainty regarding the scenarios (for example, earthquake magnitude), an additional stage is included that requires choosing the best scenario to plan for. We use the mini-max regret decision making rule for choosing across the scenarios from the earlier stated model. The regret for the problem (Inuiguchi and Sakawa 1995) can be expressed by

$$r_s = Z_{as} - Z_s^*. \quad (7)$$

The regret r_s represents the difference in cost when decision alternative a was implemented for the disaster scenario s and the cost that would have been obtained if the best decision alternative for scenario s had been implemented. Therefore, the maximum regret of the determination for a decision alternative a can be defined by,

$$R_a = \max_{s \in S} r_s. \quad (8)$$

In this study the global problem is formulated as minimizing the maximum regret R_a , i.e.,

$$\min_{a \in A} R_a. \quad (9)$$

From (7) and (8), the problem (9) can be rewritten as

$$\min_{a \in A} \max_{s \in S} (Z_{as} - Z_s^*). \quad (10)$$

Under conditions of uncertainty regarding the location and or magnitude of a disaster, the best ‘ a ’ (location and or magnitude scenario) to plan towards gets chosen using the mini-max regret criterion and then the optimal locations and capacities for that scenario is picked.

Once the pre hospital transport time (values generated using a random number simulator for the normal distribution assumed in the literature) and the supply transport time between stockpile site and treatment facility (calculated using latitude and longitude information on both these locations) is known, the objective function and therefore the above MIP model evaluates to a linear model. Reasonably large and complex problems similar to ours can be solved efficiently using CPLEX, making the development of a heuristic unnecessary.

4 Case studies

In this section, we present two case studies to illustrate our model. In the first case study, we consider a disaster with advance warning (hurricane) which requires just the application of the MIP model. In the second case study, we extend the MIP model to a disaster without such advance warning (earthquake) which requires the additional state of scenario planning. In order to apply our model to the specific cases of hurricane and earthquake, we define demand clusters to represent the casualties who have arrived at the treatment centers such as a hospital for receiving treatment. We assume that these patients travel or are brought to the closest hospital. The stockpile locations provide necessary supplies to these hospitals. While transportation time, and traffic flows and congestion are important in determining the volume and survivability time at each hospital, we do not explicitly model them in order to focus our attention on stockpile location and allocation.

4.1 Hurricane case study

The event and region for our study is Hurricane Katrina in New Orleans. We chose Katrina as an example for the hurricane case study for several reasons: availability of reliable data on casualties, casualty distribution by injuries and disease condition, recentness of the disaster, and evidence of shortage of medical supplies (GPO Access Reports 2005; Klein and Nagel 2007; Franco et al. 2006), etc.

We simulated the hurricane event using HAZUS-MH to generate the aggregate casualty distribution. The ideal location for any stockpile requires easy access to highways and therefore is a factor we considered while choosing potential sites. In order to reduce the possibility of water damage, factors such as distance from water source, and elevation above sea level are also critical. A set of 100 potential locations were determined taking these factors into account.

Using the K-means clustering algorithm a set of 10 demand clusters were developed based on the number of functional hospitals in that region during hurricane Katrina. The centroid for each cluster was chosen as the hospital location in that region.

We now turn to our patient grouping algorithm which is part of stage 3 of the generic model. One of the important factors in deciding stockpile capacity is the varieties of supplies needed to serve patients. These differing needs are a result of the different types of injuries and illnesses among the disaster victims. HAZUS (2008) gives estimates of casualties and their severities but does not specifically indicate the types or conditions. We used past hurricane data on injuries and illnesses among the affected casualties, to obtain our casualty estimates (CDC 2005a, 2005b). The urgency of care for any patient depends on severity of injury while type of care depends on the medical need and major system that is affected in the patient body (for example, respiratory, ear nose throat (ENT), etc.). We held interviews with doctors to help us map different patient conditions/types by major systems. The mapping we obtained based on these discussions is shown in Table 1.

Once the classification based on major systems is complete, we further group them based on severity levels because survivability time is based on the severity level. FEMA classifies patients into four severity levels (FEMA 2007). Level 1 is the least severe whereas level 4 is the most severe. Level 4 is the terminal case and represents the dead victims. The casualties resulting from any disaster can be grouped into the aforementioned severity levels based on the criticality of their conditions/illnesses. The patient classification into the three severity levels for hurricane disaster based on our discussions with doctors is as follows:

Severity 1: Type 1, Type 4, part of Type 2 and Type 5 who do not go to the operating room (OR)

Severity 2: Type 2 and Type 5 that go to OR

Severity 3: Type 3 and Type 6

We applied this patient grouping algorithm to casualty estimates to determine the casualty distribution by severity and type of medical condition (Table 2). We used \$6 million as the cost of a statistical life since this is the value often used by the US Environmental Protection Agency (Latourrette and Willis 2007). The total budget available was assumed to be \$600 million which was the total allocated budget for FY 2006 (DHHS 2005)³. Since the sites to be built are temporary we have not considered a fixed cost component for sites. This is a

³This number is the total annual budget for all disasters and hence is much larger than what could actually be allocated to a specific disaster. We use it for illustrative purpose only since this was the only valid number we could find.

Table 1 Patient break up by major systems

Type 1:	Laceration, Abrasion, Rashes, Skin/wound infections, Contusion, Minor Cuts, Muscle Strain, and Sprains.	With minor injuries, these patients do not need the Operating Room (OR) services, and are released after Emergency Department (ED) treatment.
Type 2:	Fractures, Orthopedic.	These patients are first treated at ER and require Laboratory (Lab) services (X- ray in general). Depending on lab results, some of them go to the OR; the others are discharged. These patients belong to higher severity levels than Type 1.
Type 3:	Head injury and Burns.	These types of patients require immediate treatment. Therefore, they are considered to be the highest severity type. They are routed through ER, Lab, OR, (then Intensive Care Unit (ICU) when required) and to the “Inpatient” area (also called “beds”).
Type 4:	Neuro/Psychiatric, Respiratory, Gastrointestinal and Others.	These patients do not need OR. Majority of these patients get released after ER treatment.
Type 5:	Cardiovascular.	These patients go through the ER and Lab. After diagnosis, some go to the OR, then ICU/CCU and finally to the inpatient area; the rest of them are discharged.
Type 6:	Mental condition, suicide attempts, heat related illness.	These patients go through the ER, Lab, and then the inpatient area.
Type 7:	Emergency inpatients.	These are patients who must undergo surgery due to an emergency medical condition such as cardiac arrest. Their percentage is relatively small.

Table 2 Patient breakup during hurricanes

	Sr. No.	Injury types	Percentage	Remarks
	1 ^a	Minor injuries, skin/wound infections, rashes/sting bites	60.74%	Type 1
	2 ^a	Major injuries-fractures etc.	1.77%	Type 2
	3 ^a	Major injuries-trauma etc.	1.77%	Type 3
	4	Upper respiratory infections	12.67%	Type 4
	5	Cardiovascular	2.85%	Type 5
	6	Gastrointestinal (admitted)	1.32%	Type 4
	7	Gastrointestinal (not admitted)	7.49%	Type 4
	8	Lower respiratory infections	5.45%	Type 4
	9	Heat related illness	0.65%	Type 6
	10	Carbon monoxide poisoning	0.10%	Type 6
	11	Mental health conditions	4.83%	Type 6
	12	Suicide attempts	0.308%	Type 6

^a These are Soft Tissue/Orthopedic cases and constitute approximately 64% of all cases

reasonable assumption as the fixed cost component for temporary sites would be negligible when compared to that incurred for permanent sites. Besides, we were not able to obtain valid data for the same. The variable costs for supplies (varies by severity) were obtained from data in Hanfling (2006).

Using the data described above, our model recommended that a total of 17 stockpile locations be set up in advance for an event similar to Hurricane Katrina. Figure 6 shows the distribution of capacity at each of the stockpile locations by severity. The critical factors influencing the solution were found to be proximity to path of hurricane, and proximity to

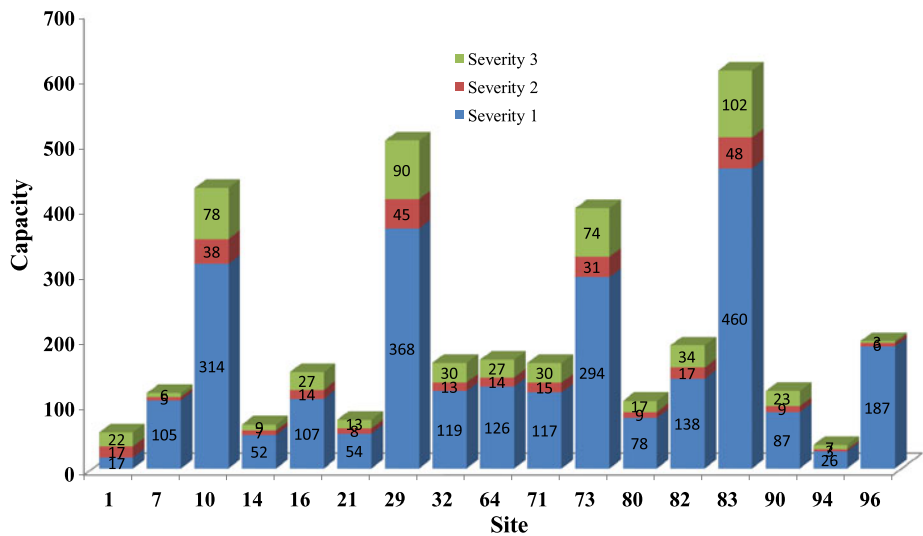


Fig. 6 Capacity distribution by severity for the stockpile sites (hurricane)

Table 3 Percentage damage and capacity distribution of sites selected (hurricane)

Site No.	Facility damage (%)	Allocated capacity
1	15	56
80	15	104
29	16	503
90	17	119
64	18	167
96	19	196
10	19	430
94	20	36
7	20	116
16	20	148
14	22	68
32	23	162
82	23	189
21	24	75
73	24	399
71	25	162
83	25	610

large population clusters. As can be seen in Table 3, the percentage of facility damaged in the sites selected ranged from 15 to 25. We divided these sites into two groups: high damage (more than 20 percent facility damage) and low damage (up to 20 percent damage). A comparison of the results for the high damage and low damage showed that (a) the mean allocated capacities for high damage was significantly higher than those in the low damage group (p value < 0.05), (b) the sites belonging to the high damage group were those situated

closer to larger population clusters (a function of casualty characteristics), and (c) the high damage sites were located closer to sea and had lower elevation above sea level than the low damage sites. These findings in (a)–(c) suggest that the percentage damage at sites is not as significant a factor in deciding the location and capacities as distance/travel time to clusters because fatality cost plays a bigger role than facility cost. The high damage sites were located closer to population clusters, resulting in lower supply transport time. These findings strengthen the need for models that account for characteristics of disasters and casualties in stockpile location and allocation planning.

4.2 Earthquake case study

We focus our earthquake case study on Northridge, California, which is located in a high risk area and has seen multiple earthquake incidents in recent history. Earthquake scenarios for the Northridge region in California were simulated using HAZUS-MH software (2008) to generate aggregate casualty distribution. For the case study, we set the epicenter as latitude 34.41000, longitude -118.40002 , corresponding to the 1994 Northridge earthquake. Due to uncertainty regarding the magnitude of the potential earthquake, multiple scenarios of casualties and damage have to be generated for the possible magnitudes. We simulated the following scenarios: magnitude 5, 5.5, 5.9, 6.0, 6.5, 6.9, 7, 7.5, 7.9, 8 and 8.25. It is important to note that we have chosen this range as they represent small to major earthquake scenarios adequately.

We considered 100 potential sites for stockpiles, based on location of fault lines, access to highways, geological and topological characteristics, and proximity to hospitals with an objective of distributing them throughout the region. Locating the facility in an earthquake prone region reduces transport time from a distant location and hence increases survivability but the facility may itself be damaged. We assume that the latter is more critical and make sure that they are not in earthquake prone regions in order to avoid facility damage. We considered 15 demand clusters for our earthquake case study. This number was decided based on the existing hospital locations which formed the centroid of clusters generated. Using K-means clustering algorithm, the clusters were developed based on an 8.25 magnitude earthquake since it will encompass the damage for all scenarios.

We used prior earthquake disaster data to obtain the distribution of these patient conditions (Aroni and Durkin 1985; Cheu 1994; Durkin 1995; Olson and Alexander 1996; Swisher et al. 2001). While the basic patient types resulting from an earthquake are similar to a hurricane as shown in Table 1, the distribution and kinds of injuries suffered in each of these patient types is different (Table 4). Since the patient grouping by severity follows the same methodology as hurricanes, we do not discuss it again here. We applied this patient grouping algorithm for earthquakes to casualty estimates and determined the casualty distribution by severity and type of medical condition. The fixed cost for building a site was taken as \$825,000 based on testimonials of County of Santa Clara (Jenkins 2007) and American Hospital Association (AHA 2006). All the other data are the same as in the hurricane case study. We then used the scenario planning approach to choose the appropriate magnitude to plan for (which turned out to be robust to the other rules as well).

We used the data described above and applied the model formulation for Northridge, CA. For the different scenarios and the various decision rules under uncertainty, the results are as shown in Tables 5 and 6. The scenarios (columns) in these tables are the states of nature (in this case, actual magnitude of earthquake) and the solution (rows) represent the available decision alternatives (the magnitude planned for). The values in the cells in Table 5 represent total cost which is the sum of fatality cost and facility cost, for an earthquake of a

Table 4 Patient breakup during earthquakes

Sr. No.	Injury types	Percentage	Remarks
1 ^a	Cuts, wounds, laceration, contusion and sprain	46.5%	Type 1
2 ^a	Fracture	9.8%	Type 2
3 ^a	Burn	1.0%	Type 3
4 ^a	Head Injury	2.7%	Type 3
5	Cardiovascular	13.5%	Type 5
6	Neuro/Psychiatric	6.8%	Type 4
7	Respiratory	6.6%	Type 4
8	Gastrointestinal	8.5%	Type 4
9	OB/GYN	4.6%	Type 6

^a These are Soft Tissue/Orthopedic cases and constitute 60% of all cases

Table 5 Earthquake results (total cost—millions)

		Scenario (Magnitude)						LaPlace approach	MinMax
		5.00	5.50	6.50	7.50	8.00	8.25		
Solution (Magnitude)	5.00	7.67	349.67	883.67	1591.67	1891.67	1921.67	1107.67	1921.67
	5.50	8.82	8.82	559.67	1273.67	1579.67	1615.67	841.05	1615.67
	6.50	14.69	14.69	14.69	746.69	1052.69	1088.69	488.69	1088.69
	7.50	20.54	20.54	20.54	20.54	356.17	392.17	138.42	392.17
	8.00	26.17	26.17	26.17	26.17	26.17	56.17	31.17	56.17
	8.25	32.78	32.78	32.78	32.78	32.78	32.78	32.78	32.78

Table 6 Earthquake results (regret approaches)

		Scenario (magnitude)						Min (average regret)	Minimax regret
		5.00	5.50	6.50	7.50	8.00	8.25		
Solution (magnitude)	5.00	0.00	340.85	868.98	1571.13	1865.50	1888.89	1089.22	1888.89
	5.50	1.15	0.00	544.98	1253.13	1553.50	1582.89	822.61	1582.89
	6.50	7.02	5.87	0.00	726.15	1026.52	1055.92	470.25	1055.92
	7.50	12.87	11.72	5.85	0.00	330.00	359.39	119.97	359.39
	8.00	18.50	17.35	11.48	5.62	0.00	23.39	12.72	23.39
	8.25	25.11	23.96	18.08	12.23	6.61	0.00	14.33	25.11

specific magnitude in the columns while we have planned capacity for an earthquake of the magnitude in the rows. The highlighted cells in Table 5 represent the optimal solution for each scenario. As can be seen from this table, the costs are higher when there is insufficient capacity. For example, if we had planned for a magnitude 5 earthquake but an earthquake of magnitude 8.25 occurred, a total cost of \$1921.67 (millions) would have been incurred due to the lack of sufficient capacity and resultant fatalities. The corresponding regret from not having planned for the actual magnitude is shown in Table 6 as \$1888.89 (millions). Planning capacity and location for an earthquake of magnitude 8 (scenario 8) provides the best result under mini max regret. One might argue that this is a construct of the choice of decision rule criteria used but as can be seen from the last two columns of Table 5 and

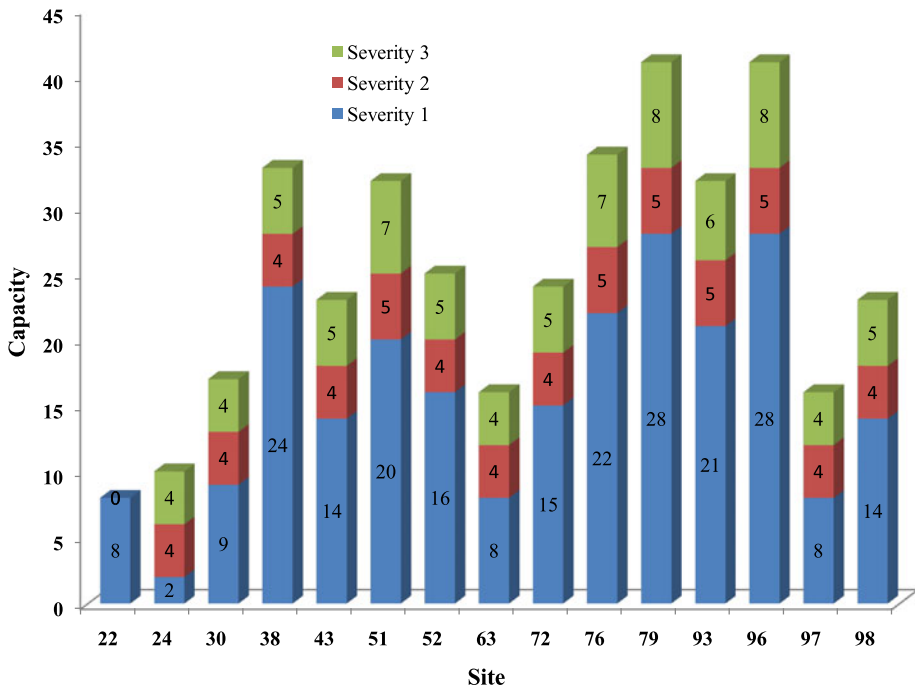


Fig. 7 Capacity distribution by severity for the sites (earthquake)

Table 6 (highlighted cells), our solution is also at least as good with the other criteria and hence is the dominant choice. Our choice of scenario meets the Pomerol robustness criteria (Pomerol 2001) since it provides sufficiently good results across the board.

We now depict the stockpile locations and capacity choices for the earthquake magnitude 8 (Fig. 7). As can be seen, our model recommends a choice of 15 stockpile locations with different capacities for treating the various severity levels. The two critical features for location selection were proximity to fault line (facility damage) and proximity to population clusters. As can be seen, the percentage damage of sites selected was found to range from 13 to 25 (Table 7). We used a similar grouping of high and low facility damage sites as in the hurricane section. A comparison of mean capacities allocated to the two groups of sites indicated the following: (a) sites belonging to high damage group had higher capacity allocated than those in the low damage group (p value < 0.05), (b) the high damage sites were situated closer to larger population clusters and (c) the high damage sites were found to be located closer to the fault lines. The intuition for the findings in (a)–(c) is the same as that discussed in the previous section for hurricane. The only difference between the two is due to the disaster specific factors that influence the damage. This again provides a justification for models that are disaster and casualty specific.

4.3 Comparative statics

In this subsection, we compare the results obtained using our framework (Figs. 3 and 4) with those obtained from the existing framework (Fig. 1). Specifically, we compare results in terms of fatality cost. We make three conservative assumptions in order to make the

Table 7 Percentage damage and capacity distribution of sites selected (earthquake)

Site No	Facility damage (%)	Allocated capacity
22	13	8
76	14	34
24	17	10
30	19	17
93	21	32
72	22	24
63	23	16
52	23	25
96	23	41
97	24	16
51	24	32
38	24	33
79	25	41
43	25	23
98	25	23

Table 8 Solution comparison

Disaster		Fatality cost	
		Our model	Existing setup
Hurricane Katrina		0.00	3,678,000,000
Earthquake	5.0	0.00	30,000,000
	8.25	0.00	522,000,000

analysis feasible. Firstly, the existing framework ensures that supplies arrive 12 hours after disaster strikes (as noted earlier, some states got necessary supplies days later in the case of Katrina, Pearson 2006). Secondly, the site selection approach used in the existing framework is the same as that used in our model (our framework is superior based on the description of existing framework in the SNS documents on site selection approach, Belson 2005). Finally, we only consider the fatality cost from severity 3 levels of casualty. These are the highest severity patients who are generally the most affected and account for most of the fatality cost. Our rationale in making these assumptions is that any positive difference in fatality cost between the existing framework and ours provides a lower bound estimate of the savings generated by our framework. Any results based on this estimate will be reliable and would justify the need for the type of research presented in this study.

For hurricanes, we used results obtained from Hurricane Katrina since the existing framework sets up PODs in the aftermath of a hurricane. For earthquakes, on the other hand, we present results for two scenarios: one for a magnitude of 5 and one for an 8.25 magnitude earthquake. We used this range since it covered the lowest and highest observed earthquakes in the region. This would not affect our model solutions since we use scenario planning.

As can be noted from Table 8, the fatality cost for hurricanes under the existing framework would be significantly higher than under ours. This difference in cost is greater than the entire total budget allocated for 2006 for disaster preparedness, justifying the need for stockpile location-allocation planning models such as ours that use advance warning. For earthquakes, the fatality costs (and similarly fatality numbers) in existing framework can vary between a low of \$30 million and a high of \$522 million. This large variability in

fatality costs is a major drawback of the existing framework which does not factor in the uncertainty. This variability can be minimized in two ways: advance set up and scenario planning. These benefits are evident in zero fatality costs in our model. Our solutions are economically superior as well since the facility costs for earthquake magnitude 8 planning (solution recommended by our generic model) is less than \$30 million (the lowest possible cost under the existing framework). While these are illustrative it does validate the need for scenario planning approach combined with SNS warehouse and dispensing site setup for earthquake preparedness.

5 Conclusions and future research

Natural disasters, such as hurricanes and earthquakes, have the potential to cause immense damage. Preparing for these disasters and their resource needs are of paramount importance and is the focus of this paper. There are three delays in the existing framework for receiving and allocating Strategic National Stockpile (SNS) assistance: the delay by the state in requesting federal assets, and the federal process which releases assets only upon declaration of disaster and lastly the time it takes to reach supplies to where it is needed most rapidly from the SNS stockpile. The most efficient disaster preparedness plan is one that addresses all three delays taking into account differences in characteristics of disasters. Prior work on location of and capacity allocation to Strategic National Stockpile (SNS) sites has not considered the impact that the unique nature of each type of disaster, particularly with regard to advance warning, has on disaster mitigation plans. Critical casualty characteristics, such as impact of their severity, medical condition and survivability time (time within which care if not provided would lead to a fatality), etc., are also often not considered in determining the locations or distribution of emergency supplies. In this paper, we propose appropriate changes to the existing framework to address the first two delays and a generic model that determines the locations and capacities of stockpile sites that are optimal for a specific disaster to address the third.

We are able to illustrate our model first using the case of hurricanes and then earthquakes. Using the latest software and data for Hurricane Katrina, we are able to point out the optimal location of stockpiles in New Orleans and their capacities. Similarly, using data from the Northridge earthquake and HAZUS software, we are able to depict the ideal locations of stockpile sites in order to minimize loss of lives and cost. Based on our results, we are able to propose appropriate response frameworks for these two types of disasters.

In this study, we have assumed that patients are already at the hospital. A detailed modeling of hospital operations, casualty transport to hospital and their impacts on the stockpiles while important is left for future research. In future research, we also intend to extend these models to epidemics and manmade disasters like anthrax, smallpox, nuclear attacks (Dallas and Bell 2007), etc., consider regions that are prone to multiple disasters and study the effect of uncertainty regarding the epicenter.

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