A MULTI-PERIOD EMERGENCY LOGISTICS NETWORK DESIGN PROBLEM WITH SOCIAL VULNERABILITY INDICES AND LOGISTICS COST

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ABSTRACT

This paper proposes a Goal Programming (GP) model for making emergency logistics networks (ELNs) both responsive and efficient. The model uses the Social Vulnerability Index for responsiveness and the Total Logistics Cost for efficiency. It also sets facilities' response capacity limits. Using FEMA's historical disaster data, we analyze the model's performance and operation strategy. Using the GP model's best-performing ELN, we propose a capacity-dependent relief item distribution strategy over multiple periods. As facilities' response capacity decreases, ELNs' responsiveness becomes more sensitive, and productivity gets more discriminating power among ELNs, according to the case study results.

Keywords: goal programming, emergency logistics networks, social vulnerability index, total logistics cost, response capacity

INTRODUCTION

An emergency logistics network (ELN) is a supply network that distributes relief items stored in the relief facilities to the affected areas to help victims during a disaster. In 2023 alone, the US experienced 28 separate weather and climate disasters (one winter storm, one wildfire, one drought, four flooding events, two tornado outbreaks, two tropical cyclones, and seventeen severe weather and hail events), each resulting in at least $1 billion in damages. 2023 results in at least 492 fatalities—the 8th highest number of disaster-related deaths since 1980. See Figure 1 for each of the disasters. The severity and frequency of these disasters justify the need for an ELN design model for prompt disaster response and preparedness.

A traditional supply chain design operates under the assumption that facilities are always available, and it optimizes the supply chain by minimizing total cost (or maximizing profit) to meet market demands through product distribution channels. An ELN design deviates from the traditional supply chain design in that it considers the frequent unavailability of certain facilities and the potential damage or unavailability of stored relief items during a disaster, thereby causing delays in the distribution of relief items to victims. For example, when Hurricane Beryl hit Houston in 2024, the majority of areas of the city lost electricity. The local electricity network provider deployed 11,000 crews to restore electricity, but the entire city took around ten days to regain power. With limited resources, the service provider must determine who would get the electricity with higher priorities. An ELN design, in contrast to traditional supply chain designs, frequently sacrifices cost-based efficiency. Instead, it underscores the need to incorporate other humanitarian performance metrics into the network design. In this study, we consider the social vulnerability index (SVI).

Social vulnerability (SV) refers to the susceptibility of social groups or communities to the adverse impact of natural hazards or disasters, including disproportionate death, injury, loss, or disruption of livelihood. The groups or communities with a higher vulnerability are likely to have a higher level of damage and loss, indicating that these groups should have higher priorities for disaster prevention and response. The Centers for Disease Control and Prevention (CDC) developed the SVI through the Geospatial Research, Analysis & Service Program in the US Agency for Toxic Substances and Disease Registry. CDC SVI aims to help emergency response planners and public health officials map and identify the communities that will most likely need support before, during, and after a hazardous event. Studies show that reducing SV decreases human suffering and economic loss (Flanagan *et al*., 2011; Cumberbatch *et al*., 2020). "FEMA" (n.d.) provides the CDC SVI values for the majority of counties in the US, which are designed in a way that a county with a higher SVI value has a higher level of vulnerability.

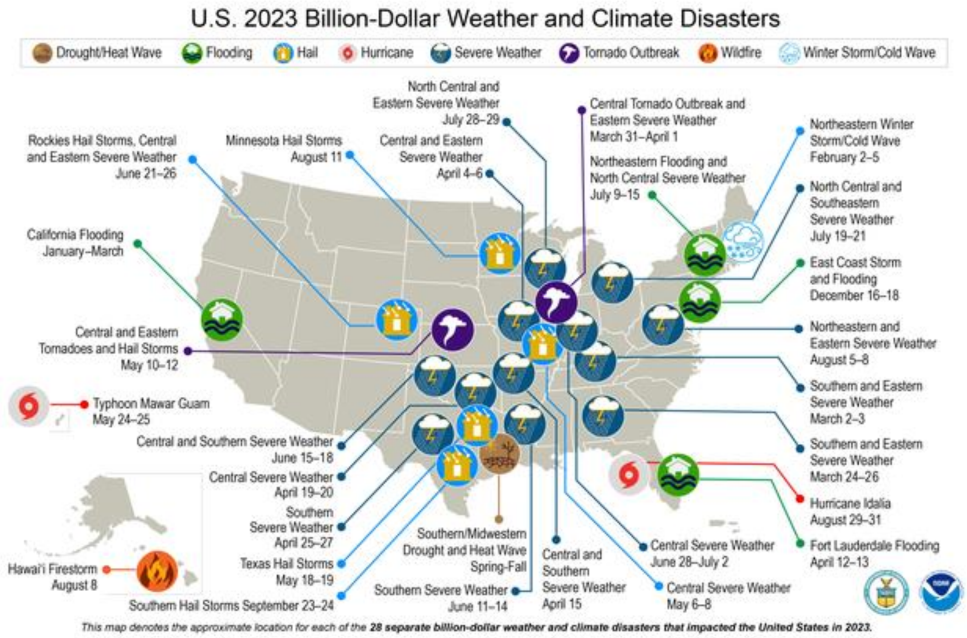

Figure 1. US 2023 billion-dollar weather and climate disasters (excerpted from Climate.gov, 2024)

Fisher (1997) introduced two complementary concepts for supply chain design: an efficient supply chain and a responsive supply chain, depending on the uncertainty the supply chain needs to manage. An efficient supply chain delivers products to customers at the lowest cost, while a responsive supply chain has the ability to build a high service level under uncertainty. Chopra (2019) claimed that a balanced supply chain design should consider both characteristics. In this study, we aim to minimize potential loss and damage via responsiveness while ensuring prompt and efficient delivery of relief items to victims in the event of a disaster. SVI serves as a performance metric for responsiveness, while the total logistics cost (TLC), represented by the demand-distance product, measures efficiency. When a disaster occurs, both efficiency and responsiveness are required. For example, cost minimization searches for the smallest demand-distance product, while responsiveness focuses on maximizing humanitarian benefits. Thus, we propose a Goal Programming (GP) formulation where both SVI and TLC are considered simultaneously. Furthermore, due to resource limitations, disaster responses may occur over multiple periods. Consequently, our GP model should determine the locations and capacity of facilities, providing relief distribution plans over multiple periods depending on the facility response capacity.

When an ELN has sufficient response capacity, the decision-maker has a wide range of options because the ample capacity promptly serves more affected areas. However, when the capacity is severely limited, it becomes more crucial to prioritize relief activities, as more vulnerable areas may be more susceptible to damage. Therefore, determining the appropriate operation strategy over multiple periods under capacity constraints is a crucial aspect of the ELN design. The literature hasn't extensively addressed this issue. This paper investigates a multi-period ELN design problem with a capacity constraint, employing GP model with SVI and TLC in the objective function. The ELN consists of Disaster Recovery Centers (DRCs) and affected areas. When a disaster strikes, the DRCs serve as permanent warehouses, storing and distributing relief items to the affected areas. With this model, we aim to address the following research questions:

- Where to locate DRCs? What are the DRCs' numbers and pre-stocking levels?
- What distribution channels are used, and how much is the volume of relief items stored and transported between DRCs and affected areas?
- What is the impact of response capacity constraints on SVI, TLC, and operation strategy over multiple periods?
- How can we evaluate the performance of the ELNs in terms of SVI/TLC balance?

After the literature review, we explain the social vulnerability index and then move on to the Goal programming model with SVI and TLC. Next, we provide a case study and observations. Lastly, conclusions are presented.

LITERATURE REVIEW

According to Cutter *et al.* (2003), social and place inequalities influence social vulnerability. Cutter *et al*. (2003) listed seventeen indicators to measure the underlying cause of social vulnerability. The seventeen indicators are social status, gender, race and ethnicity, age, commercial and industrial development, employment loss, rural/urban, residential property, infrastructure and lifelines, renters, occupation, family structure, education, population growth, medical services, social dependence, and special needs populations. Cutter *et al*. (2009) developed the SVI to quantify a place's relative socioeconomic and demographic quality in order to understand vulnerability, which is concerned with pre-event embedded qualities of the social system. Thus, Armas and Garvis (2013) regarded social vulnerability as a predictive variable that represents potential harm when a risk occurs. Numerous studies demonstrated that the impact on victims varied depending on their level of vulnerability (Hofflinger *et al*., 2019; Oulahen *et al*., 2015). Evidence shows that people with low incomes, children, elders, disabled people, and residents of high-rise apartments or mobile homes are more vulnerable (Tasnuva *et al*., 2021; Yap *et al*., 2023). Morrow (1999) revealed that the vulnerability factors often occur in combination. The most vulnerable are those whose needs are not considered in disaster response planning.

Very few studies on SVI are available from the perspective of emergency logistics network design. We found only two articles in the nationwide database search, to the best of our knowledge. Arnet and Zobel (2019) proposed a mixed integer programming (MIP) model formulation for asset pre-position in the American Red Cross of Wyoming and Colorado. They suggested minimizing risk in the objective function, which includes hazards, exposure, and SVI as independent factors. They then determined the pre-stocking level at each shelter, comparing it to the traditional pre-stocking level. Alem *et al*. (2021) suggested a multi-period MIP model that aims to maximize the total sum of SVI as a measure of how responsive a humanitarian supply chain in Brazil is. They defined the *social benefit of an affected area* as the relative difference between the relief service (percentage of victims whose needs are satisfied) with and without the SVI. Their results show that the social benefit of using SVI is more significant as the vulnerability level increases. They also asserted that, given the current absence of studies in this area, more research on the use of SVI in humanitarian logistics is necessary.

The GP with multiple objective functions is a mathematical modeling approach, especially when objectives conflict with each other. Hong and Jeong (2019) looked at a facility-location and allocation optimization problem with five competing goals: total line capacity (TLC), maximum coverage distance, maximum demand-weighted coverage distance, covered demand in case of emergency, and expected number of uninterrupted supplies. They tried to find a balance between these goals. Hong and Jeong (2020) also considered both TLC and the expected number of demands satisfied in the emergency backup supply system. Hong *et al*. (2022) proposed combining the multi-objective programming model with the three data envelopment analysis-based methods for designing ELN.

Our study extends the previous research by proposing a GP-based approach to consider both responsiveness and efficiency, improving practicability for disaster-related decision-makers. Furthermore, we propose a different ELN operation strategy based on response capacity availability since the capacity level should significantly impact actual distribution activities. For instance, it is important to balance both responsiveness and efficiency during a limited capacity period, as the affected areas with higher SVI may experience more damage. Conversely, when facilities have sufficient capacity, the focus shifts to efficiency, ensuring that all demands in the affected areas can be satisfied promptly within that period. We also intend to present an overall productivity metric to evaluate the ELNs generated by GP. The following is a summary of this study's contributions:

- The GP model strikes a balance between responsiveness and efficiency to integrate location decisions at the strategic level, as well as distribution channels and facility capacity at the operational level.
- The study examines the relationship between SVI and TLC and investigates the impact of emergency response capacity on both.
- Among multiple optimal ELNs based on different weights between SVI and TLC, we propose a systematic way to evaluate each optimal ELN, determining the best-performing one.
- Based on the best-performing ELN with DRC locations, we present a multi-period capacity-dependent operation strategy that generates distribution channels from DRCs to affected areas.

SOCIAL VULNERABILITY INDEX

Table 1 illustrates how 15 US census variables, categorized into four distinct themes, drive the CDC SVI. For multiple years after 2000, ATSDR (2024) calculated the SVI for each county's 15 US census variables. To construct the SVI, each of the 15 variables, except income, is ranked from lowest to highest scores across all counties in the US with a non-zero population (lower values with higher ranks). Income is ranked from highest to lowest since higher incomes indicate less vulnerability. In this way, all counties with higher ranks indicate lower vulnerability for each variable. Then, the percentile rank (PR), being calculated for counties using the rank and the total number of data points (N), is expressed by

$$Percentile\ Rank\ (PR) = \frac{Rank-1}{N-1} \tag{1}$$

The percentile rank maps the county's ranks to a value between 0 and 1, which is considered the county's SVI value. A county with a larger SVI value is considered more vulnerable to hazards and disasters. In addition, a theme-level percentile rank is calculated based on the sum of the percentile ranks of the variables comprising the themes. Finally, the overall SVI for each county is calculated using the sum of the percentile ranks of the four themes. This process can be repeated for each geographical region, such as an individual state.

Overall	Theme	Variables	Descriptions
Overall Vulnerability	Socioeconomic Status	Below Poverty	e.g., $12,140 for one person in a family/household
		Unemployed	Number
		Income	Amount
		No High School Diploma	Number
	Household Composition & Disability	Age 65 or Older	Number
		Age 17 or Younger	Number
		Older Than Age 5 With a Disability	Number
		Single-Parent Households	Number
	Minority Status & Language	Minority	Number
		Speaks English "Less Than Well"	Number
	Housing & Transportation	Multiunit Structures	Number
		Mobile Homes	Number
		Crowding	e.g., Occupied housing units with more than one person per room are considered crowded
		No Vehicle	Number
		Group Quarters	Not all people live in housing units. e.g., nursing homes, correctional facilities, etc.

Table 1. 15 Census variables and themes in SVI.

GOAL PROGRAMMING MODEL WITH SVI AND TLC

To design ELNs, we develop a GP-based mathematical model with TLC and SVI in the objective function. Consider an ELN with Disaster Recovery Centers (DRCs) and affected areas (AAs), where DRCs should feed AAs. The GP will identify the locations and capacities of DRCs and relief item distribution channels from DRCs to AAs with multi-sourcing when a major disaster occurs.

The following nomenclature is used:

Sets:

M — Index set of potential locations for DRCs and AAs, ($j = 1, 2, \ldots, M$ and $m = 1, 2, \ldots M$).
C — Index set of potential pure DRCs without any fictitious DRC ($k = 1, \ldots, C$)

Parameters:

b_j — Minimum number of AAs that DRC j can cover
B_j — Maximum number of AAs that DRC j can cover
c_{jm} — Cost of shipping one unit of item per mile from DRC j to AA m
CAP_j^{max} — Designed capacity of DRC j
d_{jm} — Distance between DRC j and AA m
D_m — Demand for AA m, in units/period
v_j: — Cost per capacity at DRC j
F^{max} — Maximum number of DRCs can be built
h_j — Holding cost per unit per period at DRC j
SVI_m — SVI value at AA m
α — A real number between 0 and 1
TLC_{min} — Minimum of TLC
TLC_{max} — Maximum of TLC
SVI_{max} — Maximum of SVI
RC — Facility's response capacity ratio (i.e., percentage of demand satisfied) when a disaster occurs

Decision Variables:

F_j	Binary variable deciding whether a DRC *j* is located at AA *j* or not
cap_j	Facility storage capacity at DRC *j*
y_{jm}	Percentage of AA *m*'s demand, satisfied by DRC *j*. It is a real number between zero and one, implying multi-sourcing. That is, an area *m* can be supplied by multiple DRCs.

Also, we make the following assumptions for the formulation.

Assumptions:

(i) A DRC can be located in any potential area. If a DRC is located at *j*, the distance, d_{jm}, is assumed to equal zero if *j* = *m*. Also, the area where a facility is located is assumed to be covered by that facility; that is, $y_{jm} = 1$ if *j* = *m*.

(ii) Each DRC has a designed capacity represented by CAP_j^{max}, and the actual storage capacity (cap_j) is determined by demands in the network. Thus, the storage capacity cannot exceed the designed capacity.

(iii) Each DRC follows a periodic review base-stock inventory policy with zero lead time for simplicity.

(iv) Each DRC has enough delivery (transportation) resources to deliver the items directly to each AA.

(v) TLC consists of transportation costs from DRCs to AAs and inventory costs at DRCs. The inventory cost at DRC *j* depends on the periods during which inventory is stored.

We first define TLC in Eq. (2). We use the product of distance and demand as cost in the first term to consider both distance and population to satisfy. The second term represents inventory cost. TLC minimization is regarded as a good performance metric for efficiency because it intends to minimize cost through the shortest path delivery.

$$TLC = \sum_{j\in C}\sum_{m\in P} y_{jm} D_m d_{jm} c_{jm} + \sum_{j\in C}\left(cap_j - 0.5\sum_{m\in P} y_{jm} D_m\right) h_j \tag{2}$$

We add one fictitious DRC to the model to meet flow conservation constraints. The fictitious DRC has a zero SVI, zero demand, and enough capacity to satisfy all demands from all populations, with the distance from the fictitious DRC to actual AAs set to infinite. Thus, the fictitious DRC is used in the case of the actual DRCs that are fully utilized. In other words, any TLC from the fictitious DRC is considered a penalty for the capacity shortage. When we replace 'j' with 'k' in Eq (2), it calculates TLC solely for the actual DRCs, excluding the fictitious DRC. Now, since we only compute the sum of SVIs for the actual DRCs, we define SVI as follows:

$$SVI = \sum_{m\in P}\sum_{k\in C} SVI_k y_{km}, \tag{3}$$

The GP is defined as below:

$$Minimize\ \alpha(TLC - TLC_{min})/(TLC_{max} - TLC_{min}) + (1-\alpha)(SVI_{max} - SVI)/SVI_{max} \tag{4}$$

Subject to:

$$\sum_{j\in C} y_{jm} = 1, \quad \forall m \in P \tag{5}$$

$$\sum_{j\in C} F_j \le F^{max}, \tag{6}$$

$$cap_j \le F_j\, CAP_j^{max}, \quad \forall j \in C \tag{7}$$

$$\sum_{m \in P} D_m y_{jm} \leq cap_j, \qquad \forall j \in C \tag{8}$$

$$y_{jm} \leq F_j, \qquad \forall j \text{ and } \forall m \in M \tag{9}$$

$$y_{jj} = F_j, \quad \forall j \tag{10}$$

$$\sum_{k} cap_k \leq (\sum_{m \in P} D_m) RC \tag{11}$$

The objective function in (4) minimizes TLC's and SVI's percentage deviations from the target values. The first term represents TLC's normalized percentage deviation, and the second represents SVI's normalized percentage deviation. Note that SVI_{min} is zero. Constraints (5) ensure that one or more DRCs cover each area, thereby enabling multi-sourcing. Constraints (6) establish the maximum number of DRCs for construction. Constraints (7) guarantee that the storage capacity at each DRC should match or surpass the designed capacity upon construction. Constraints (8) ensure that DRC can only cover each AA within its storage capacity. Constraints (9) specify that DRC j covers each AA only when DRC is present at area j. Constraints (10) ensure that when DRC j becomes an AA, it feeds itself. Lastly, constraint (11) assumes that not all emergency demands are always satisfied by actual DRCs. From an operation strategy perspective, if the total demand from all AAs exceeds the facility's storage capacity, the remaining demand should be satisfied in subsequent periods. RC represents facility's response capacity ratio. Technically, the fictitious DRC fulfills the unmet demand beyond RC during the current period.

To solve the solution for GP, we must first obtain TLC_{max}, TLC_{min}, and SVI_{max}. TLC_{min} is obtained by minimizing equation (2) subject to constraints (4) to (11), and SVI_{max} is by maximizing equation (3) subject to constraints (4) to (11). TLC, when SVI_{max} is calculated, is set to TLC_{max} in that SVI_{max} sacrifices TLC to maximize SVI.

The GP will generate multiple optimal solutions at different α values, weights between responsiveness and efficiency. Therefore, once the GP generates optimal solutions, it is crucial to pinpoint the best-performing solution across all values. We may consider TLC to be an input to the network and SVI to be the output. Therefore, we utilize the following productivity formula to measure the overall performance of all ELNs:

$$productivity = \frac{SVI}{TLC} \tag{12}$$

Multi-Period Capacity-Dependent Operation Strategy

This section presents the customized capacity-dependent operation strategy, which indicates pre-stocking capacity and corresponding distribution channels per period using TLC and SVI. When demands from affected areas exceed the facility's response capacity, distribution activities require multiple periods to balance both TLC and SVI from an operational perspective. When the demand falls below the actual response capacity, we use TLC to satisfy all demands, eliminating the need to differentiate affected areas based on SVI values. Figure 2 describes this multi-period capacity-dependent operation strategy.

For this, we further define the following nomenclature.

D	Total demands for relief items.
RCP	Facility's response capacity per period. This is the maximum demand that can be satisfied per period, determined by *RC*. Because of this limit, it may take multiple periods to complete the distribution work.
$s_t^* = \text{GP}(.)$	GP with its optimal solution, $s_t^* = (F_{j,t}^*, cap_{j,t}^*, y_{jm,t}^*)$ as output at time *t*.
$s_t^* = \text{GP}(./s_{t-1}^*)$	GP with its optimal solution, $s_t^* = (F_{j,t}^*, cap_{j,t}^*, y_{jm,t}^*)$ as output at time *t* with s_{t-1}^* given as input.

```
(1)     set t = 0// period
        //check whether all demands are satisfied or not.
(2)     if D > RCP then
        {//it takes multiple periods from here
(3)         if t = 0 then
(4)         {solve GP (.) with TLC and SVI;}
(5)         else
(6)         {solve GP (./s*_{t-1}) with TLC and SVI;}
(7)          D = D – RCP;
(8)          t = t + 1;
(9)          goto line (2)
        }
(10)    else
        {//this is the last distribution since the remaining demands are under current period's capacity.
(11)        if t = 0 then
(12)        {solve GP (.) with TLC only;}
(13)        else
(14)        {solve GP (./s*_{t-1}) with TLC only;}
(15)        stop;
        }
```

Figure 2. Multi-period distribution strategy with GP

In *line 2*, if the remaining demand, *D*, at time *t*, exceeds the facility's response capacity per period, *RCP*, we need to solve GP with both *TLC* and *SVI*, given the solution at *t*-1, as seen in *line* 6, since both *TLC* and *SVI* affect the solution. If it happens in the first period (*line 3*), we solve GP with *TLC* and *SVI* without any prior solution (*line 4*). After lines 4 or 6, we need to update D (*line* 7) and *t* (*line* 8) to reflect the remaining demand and current time, respectively. Continue to solve GP until the response capacity can handle the remaining demand. Once we reach that phase (*line* 10), we need to solve GP with a single goal of minimizing TLC since the current response capacity should be able to satisfy demands from affected areas; we do not need to consider SVI (*line* 12 or *line* 14).

CASE STUDY AND OBSERVATIONS

To evaluate the behavior of the GP model and its multiperiod operation strategy, we conduct a case study using SVI values in South Carolina based on the 2018 US census (ATSDR, 2024). The President of the United States declared a major disaster, and the Federal Emergency Management Agency (FEMA) opened DRCs to relieve the affected counties. We aim to ascertain the locations and capacities (pre-stocking level) of DRCs, as well as the channels used for distributing relief items from DRCs to counties. We also want to see the relationship between the response capacity, SVI, and TLC.

We cluster forty-six counties in South Carolina based on proximity and population into twenty counties for computational simplicity. Next, we select one city from each clustered county using a centroid approach. The entire population within the clustered county is assumed to reside in that city. The distance between these cities is considered to be the distance between counties. For the city representing multiple counties (e.g., a composite city such as Anderson), we use the population of each county to calculate the weighted average of SVI for the mixed city. Table 2 lists 20 composite cities with populations, SVI values, and rankings. Table 3 lists all costs and capacity parameters for the case study.

No	**City**	**County**	**POP, D_m (K)**	**SVI_m**	**SVI Rank**
1	Anderson	Anderson/Oconee/Pickens	403	0.243	13
2	Beaufort	Beaufort/Jasper	218	0.178	16
3	Bennettsville	Marlboro/Darlington/Chesterfield	139	0.515	7
4	Conway	Horry	345	0.244	12
5	Georgetown	Georgetown/Williamsburg	93	0.504	8
6	Greenwood	Greenwood/Abbeville	96	0.677	5
7	Hampton	Hampton/Allendale	28	0.698	3
8	Lexington	Lexington/Newberry/Saluda	353	0.154	17
9	McCormick	McCormick/Edgefield	36	0.522	6
10	Moncks Corner	Berkeley	221	0.200	15
11	Orangeburg	Orangeburg/Bamberg/Calhoun	116	0.681	4
12	Rock Hill	York/Chester/Lancaster	401	0.086	19
13	Spartanburg	Spartanburg/Cherokee/Union	398	0.396	9
14	Sumter	Sumter/Clarendon/Lee	158	0.811	1
15	Walterboro	Colleton/Dorchester	199	0.134	18
16	Aiken	Aiken/Barnwell	191	0.382	10
17	Charleston	Charleston	407	0.001*	20
18	Columbia	Richland/Fairfield/Kershaw	503	0.309	11
19	Florence	Florence/Dillon/Marion	200	0.701	2
20	Greenville	Greenville/Laurens	583	0.231	14
	Total		**5,088**	**7.666**	

*The original SVI value at Charleston is 0. We change it to 0.001 to consider in the model.

Table 2. Data for DRC location-allocation

Symbol	**Meaning**	**Value**
c_{jm}	Cost of shipping one unit of demand per mile from DRC j to area *m*	\$0.10, $\forall j \text{ and } m$
CAP_j^{max}	Designed capacity for DRC *j*	2,600, $\forall j$
h_j	Holding cost per item per unit time at DRC *j*	\$5.00, $\forall j$
F^{max}	Maximum number of DRCs to be built	5
RC	Facility's response capacity ratio per period	60%~100% of the total demand

Table 3. Parameters for the case study

Using the GP model, we obtain solutions by changing the weights of TLC from 0.0 to 1.0 by a 0.2 increment and the facility's response capacity per period from 100% to 60% by a 20% decrement. Table 4 summarizes the maximum, minimum TLCs, and maximum SVI obtained by GP for each response capacity rate. When *RC* is set to 100%, the corresponding ELN can provide services to the entire population of all counties (5,088K), generating the maximum SVI, the sum of all SVIs for all counties (7.666). When $\boldsymbol{SVI_{max}}$ is obtained for each *RC*, we set the total logistics cost to $\boldsymbol{TLC_{max}}$, as we are not attempting to minimize TLC at that time. However, as the response capacity ratio decreases (not all demand is satisfied), maximizing SVI will carefully select counties with higher SVI values at the cost of TLC for a balanced ELN design.

RC	TLC_{max} ($)	TLC_{min} ($)	SVI_{max}
100%	2.0365e+6	6.7627e+5	7.666
80%	5.2633e+7	5.1553e+7	7.496
60%	1.0324e+7	1.0243e+8	7.019

Table 4. TLC_{min} and SVI_{max} for GP

Using the results in Table 4, Table 5 shows all the solutions by GP and the productivity, mean, and standard deviation (std) for each performance metric for each pair of (RC, α). It also shows the ratio of standardized actual SVI to standardized actual TLC. When α is set to zero, the GP model maximizes only SVI (or minimizes the gap percent from SVI_{max}). We recognize that the solution at $\alpha = 1.0$ is the same as in the TLC minimization problem. The total TLC considers the logistics cost for all DRCs, including the fictitious one. In contrast, the actual TLC only considers the logistics cost for the actual DRCs, excluding the fictitious DRC. In the case of SVI, since the fictitious DRC has zero SVI, there is only one sum of SVI value per ELN.

	α	0.0	0.2	0.4	0.6	0.8	1.0	Mean	Std
***RC*=100%**	***Actual TLC ($)***	713,653	676,272	676,272	676,272	676,272	676,272	682,502	15,261
	SVI	7.67	7.67	7.67	7.67	7.67	7.67	7.67	0.00
	Total TLC ($)	2.04E+06	6.76E+05	6.76E+05	6.76E+05	6.76E+05	6.76E+05	9.03E+05	555,324
	Productivity	1.68	**1.77**	**1.77**	**1.77**	**1.77**	**1.77**	1.76	0.04
***RC*=80%**	***Actual TLC ($)***	563,089	544,321	544,321	544,321	544,321	541,074	546,908	8,033
	SVI	7.50	7.49	7.49	7.49	7.49	6.51	7.33	0.40
	Total TLC ($)	5.26E+07	5.16E+07	5.16E+07	5.16E+07	5.16E+07	5.16E+07	5.17E+07	440,001
	Productivity	2.08	**2.15**	**2.15**	**2.15**	**2.15**	1.88	2.09	0.11
***RC*=60%**	***Actual TLC ($)***	422,751	414,703	414,703	414,703	405,622	401,214	412,283	7,669
	SVI	7.02	7.02	7.02	7.02	6.83	2.57	6.25	1.80
	Total TLC ($)	1.03E+08	1.02E+08	1.02E+08	1.02E+08	1.02E+08	1.02E+08	1.03E+08	329,225
	Productivity	2.59	**2.64**	**2.64**	**2.64**	2.63	1.00	2.36	0.67

Table 5. Results from the GP model per response capacity

We plot actual TLC vs. SVI for each response capacity ratio in Figure 3. From Figure 3 and Table 5, the following observations are made:

(1) As α increases, TLC decreases, and SVI increases.
(2) The shortage of response capacity leads to a decrease in both actual TLC and SVI, as they serve fewer counties (the trend is evident in Figure 3). However, the increase in total TLC can be attributed to the rising penalty costs imposed by the fictitious DRC.
(3) At each capacity, TLC has a larger variation than SVI. However, as capacity shortage increases, SVI variation increases, as indicated by the standard deviation in Table 5 and Figure 3. We standardize TLC and SVI and calculate the productivity. As capacity shortages increase, productivity increases (Figure 4), indicating that SVI becomes more sensitive to capacity.
(4) The number of ELNs with the highest productivity decreases when the capacity shortage increases. When there is no capacity shortage (RC = 100%), GP generates 5 (out of 6) ELNs with the highest productivity, which decreases to 4 and 3 for RC = 80% and 60%, respectively. In other words, as the capacity shortage increases, the discriminating power of the GP increases.

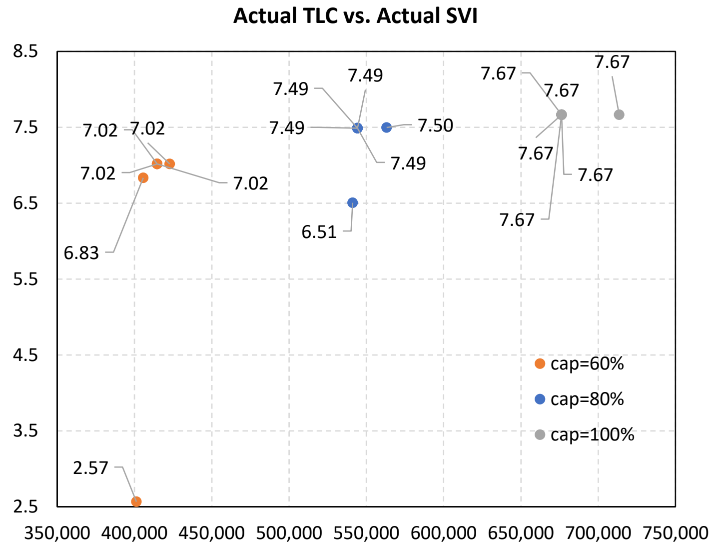

Figure 3. Pure TLC vs. SVI for each response capacity

The observations (3) and (4) provide important insight to the emergency management decision-maker. Productivity quantifies the value of the optimized ELN. It increases when capacity shortage increases. For example, in the case of (α = 0.4), when the ELN has ample capacity for demand, the productivity is 1.77. If we set the optimization value to 1, the productivity increases to 2.15 (21%) and 2.64 (49%) for 20% and 40% capacity shortages, respectively. That is, for each dollar spent, the value of SVI significantly increases, indicating saving more victims, when capacity shortages occur. Therefore, choosing the ELNs with the highest productivity value is the way to select the best-performing ELN from the decision-maker's perspective.

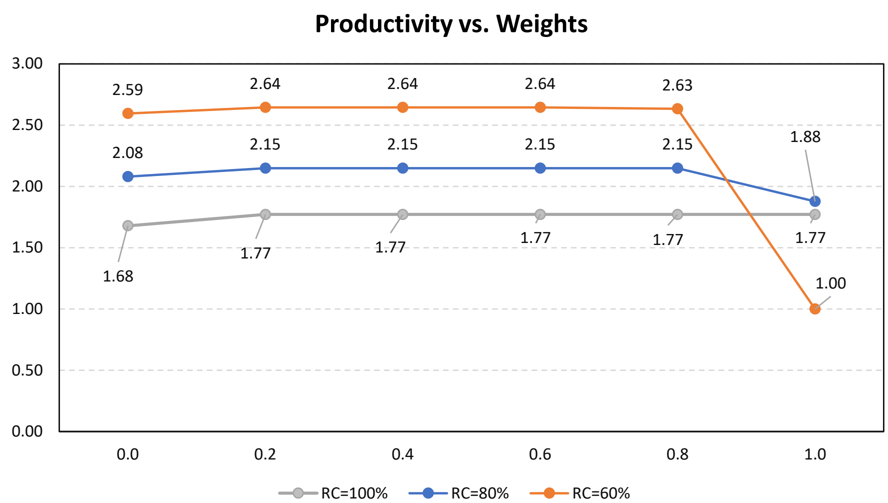

Figure 4. Productivity vs. Weights for Response Capacity

Now, we discuss the capacity-dependent multi-period distribution strategy, assuming that the response capacity ratio per period is 60%. It takes two periods for the ELN with 60% capacity ratio to provide emergency service to all potential demands of 5,088K. According to Table 5, ELNs with α = 0.2, 0.4, and 0.6 generate the same level of the highest productivity. We randomly choose the ELN with α = 0.4 as an example and show the distribution activities for two periods based on the procedure in Figure 2. Solving the GP with (RC = 60% α = 0.4) generates Greenville, Columbia, and Florence as DRC. We use a solid arrow and a dotted arrow to indicate the distribution activities for periods 1 and 2, respectively. Columbia and Florence cover 60% of the demand for period 1, while the three DRCs cover the remaining demand. Greenville is used only in period 2. Both Greenville and Columbia cover Rockhill during period 2.

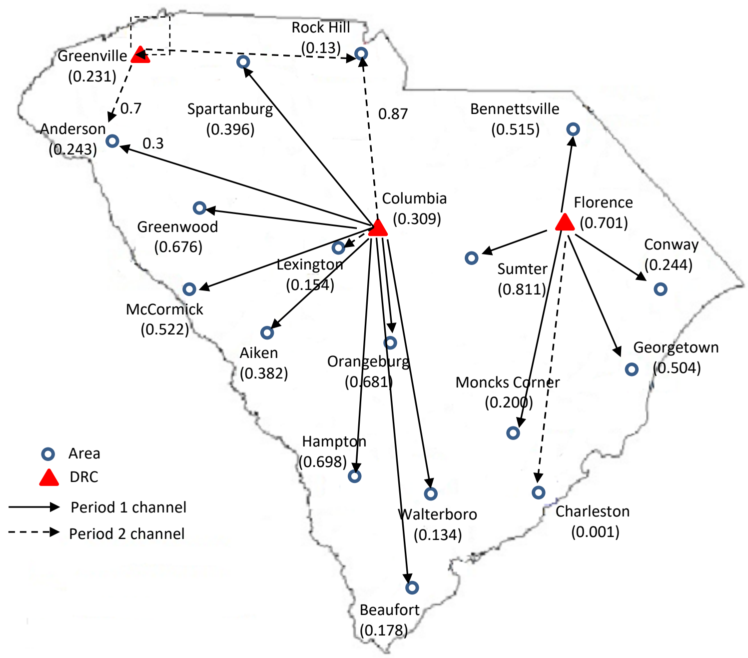

Figure 5. An ELN with distribution channel (*RC* = 60% $\alpha = 0.4$)

Note that to obtain the ELN in Figure 5, GP should generate the ELNs with minimization of TLC (Figure 6) and with maximization of SVI (Figure 7), respectively. In Figure 6, we can see the highest efficiency level is achieved at the cost of SVI when four DRCs are utilized for two periods with four distinctive distribution clusters. Figure 7 demonstrates that by heavily utilizing Florence as the DRC for the first period, we can achieve the ELN with the highest SVI at the expense of TLC.

Table 6 summarizes the performance comparison of the three ELNs per period. GP uses both TLC and SVI in period 1, but only TLC in period 2. ELN ($\alpha = 0.4$) achieves about 96.64% of TLC_{min} and 100% of SVI_{max}, with the highest productivity during the 1st period. Note that we decide it in the 2nd period based on the expected results from period 1. We should interpret the decisions from periods 1 and 2 with the understanding that SVI serves as a predictor of potential harm when a risk materializes. Otherwise (that is, if we know no further risk or vulnerability associated with period 1 in advance or if we ignore it), ELN ($\alpha = 1.0$) should be used since it generates the best result so that the sum of TLCs for periods 1 and 2 is the smallest with the maximized SVI.

Network	***Period 1***				***Period 2***		
	TLC ($)	***SVI***	***TLC Gap (%)***	***SVI Gap (%)***	***TLC ($)***	***SVI***	***TLC Gap (%)***
ELN (α = 0.4)	414,703	7.019**	3.36	0.00	274,209	0.65	2.06
ELN (α = 1.0)	401,214*	2.568	0.00	63.43	276,477	5.01	2.91
ELN (α = 0.0)	422,751	7.019**	5.37	0.00	268,665*	0.65	0.00

*minimum; **maximum

Table 6. Performance of ELN with *RC* = 60% for two periods

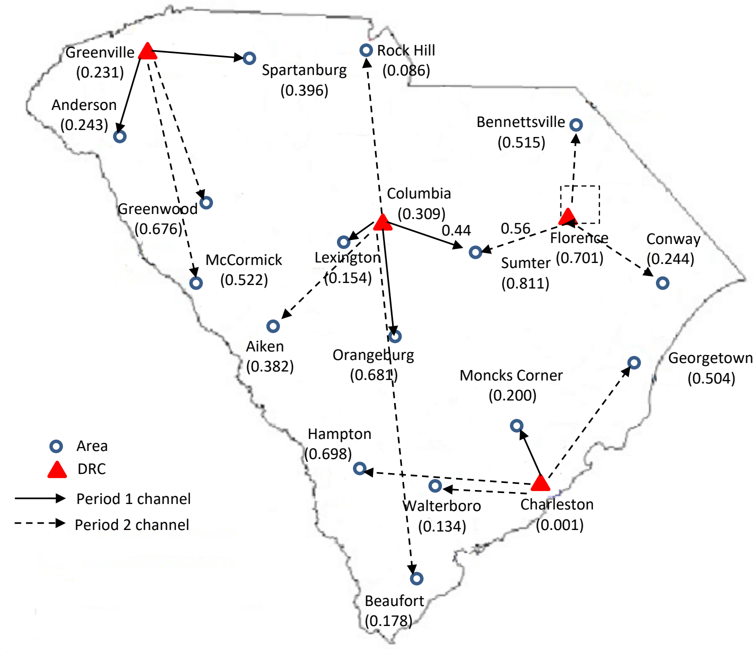

Figure 6. An ELN with distribution channel (*RC* = 60% α = 1.0)

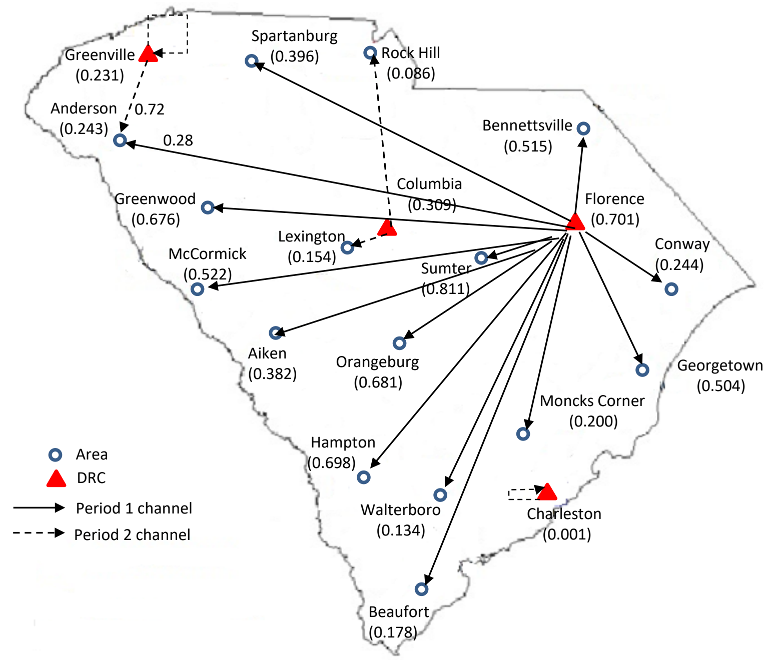

Figure 7. An ELN with distribution channel (*RC* = 60% α = 0.0)

CONCLUSIONS

This paper examines a multi-period ELN design problem with a response capacity constraint. We apply Goal Programming with the Social Vulnerability Index (SVI) and Total Logistics Cost (TLC) to find the best solution for responsiveness and efficiency. We recognize that very few studies have utilized SVI in ELN design. Notably, this research is unique in that it focuses on the impact of the response capacity shortage on the design, deriving a capacity-constrained relief item distribution strategy over multiple periods and quantifying the value of optimization by defining productivity.

The case study analysis in South Carolina demonstrates the GP's applicability and the resulting operation strategy over two periods. The case-based results show that GP with TLC and SVI generates highly competitive ELNs compared to the single objective mixed integer programming model. We note that SVI becomes more sensitive as the lack of capacity grows, providing more discriminating power to the ELN design. At the same time, productivity, defined as the ratio of SVI to TLC, rises as the discriminating power of the GP increases.

In the context of humanitarian logistics, ELN design problems with recent extreme weather conditions worldwide become increasingly critical in terms of risk preparation and response. Given the current emphasis on social responsibility, we assert that this study offers valuable insights to emergency management practitioners about the influence of capacity on strategic design and operational strategy across various timeframes, as well as the humanitarian value embodied by SVI.

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