A DESIGN OF EMERGENCY LOGISTICS NETWORKS USING SOCIAL VULNERABILITY INDICES AND LOGISTICS COST

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ABSTRACT

This paper presents a Goal Programming (GP) model to design balanced emergency logistics networks (ELNs) using the Centers for Disease Control and Prevention's Social Vulnerability Index (SVI) and Total Logistics Cost (TLC) concurrently. An ELN distributes disaster relief items promptly to affected areas in case of an emergency. A community with a higher SVI should be given a higher priority due to its high vulnerability. Simultaneously, TLC should be considered too. Through a case study, we analyze the performance of GP-guided ELNs with respect to the capacity of distribution facilities and variable weights between SVI and TLC.

Keywords: Goal programming, emergency logistics networks, social vulnerability index, total logistics cost

INTRODUCTION

An emergency logistics network (ELN) is a supply network that distributes relief items such as drinking water, food, and daily commodities stored in the facilities to the affected areas to alleviate victims' suffering during a disaster. In 2022 alone, the US experienced 18 separate climate disasters, each resulting in at least $1 billion in damages. See Figure 1 for each of the disasters. The severity and frequency of these disasters indicate the importance of a well-balanced ELN for prompt response and preparedness for disasters.

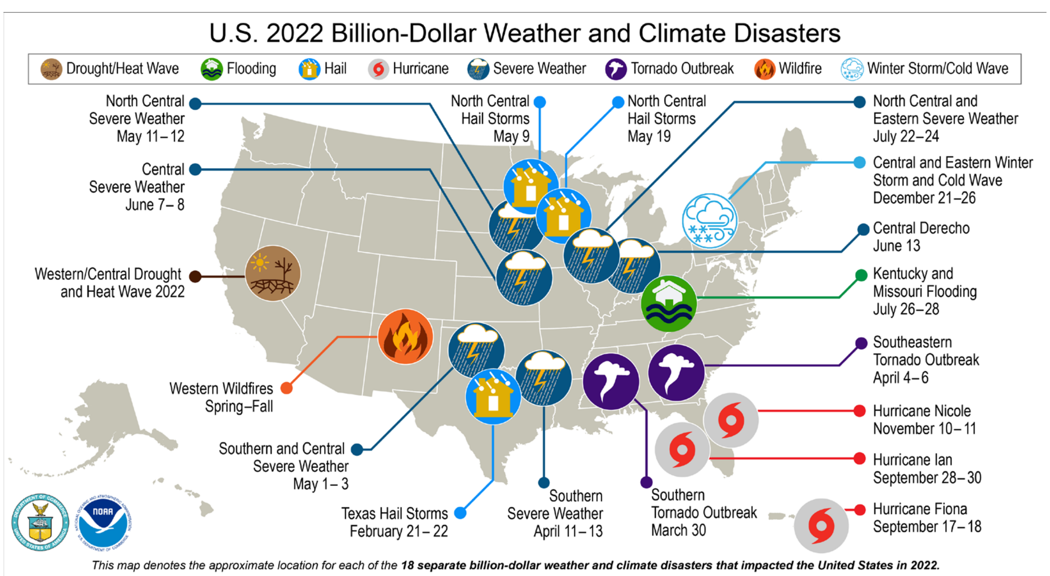

Figure 1. US 2022 billion-dollar weather and climate disasters (excerpted from Climate.gov, 2023)

A facility location and allocation (FLA) design problem is frequently used in supply chain design. The traditional FLA design problem typically assumes that facilities are always available and that it optimizes the supply chain by minimizing the total logistics cost while satisfying market demands by distributing products through the distribution channels from facilities to customers. However, the ELN design differs from the FLA-based supply chain design problem in that some facilities often become unavailable, and the stored relief items may be damaged and unavailable during a disaster. Further, non-financial performance measures are frequently used in the objective function since an ELN's operational goal is to promptly distribute relief items for rapid recovery and resilience, which often requires the sacrifice of cost-based efficiency.

Social vulnerability (SV) refers to the degree to which a community exhibits certain socioeconomic and demographic conditions (e.g., high poverty, low percentage of vehicle access, crowded households, etc.), affecting the community's ability to prevent human suffering and financial loss in case of a disaster. These factors, or conditions, represent a community's social vulnerability. The Centers for Disease Control and Prevention (CDC) developed the social vulnerability index (SVI) through the Geospatial Research, Analysis & Service Program in the US Agency for Toxic Substances and Disease Registry. It aims to help public health officials and emergency response planners identify and map the communities that will most likely need support before, during, and after a hazardous event. Studies show that reducing social vulnerability decreases both human suffering and economic loss (Flanagan *et al*., 2011; Cumberbatch *et al*., 2020). For a given area (e.g., a county), the CDC SVI is designed so that a county with a higher SVI value has a higher level of vulnerability. Thus, it is an excellent rationale to consider SVIs during the design of the ELN, such that higher priorities should be given to the areas with higher SVIs.

Based on this rationale, we propose a Goal Programming (GP) formulation where both SVI and the distance-based Total Logistics Cost (TLC) are considered simultaneously in designing a balanced ELN. The GP attempts to maximize the SVI value while minimizing TLC. Through a case study with SVI values computed based on the 2018 US census in South Carolina, we evaluate GP's performance, particularly when the capacity of distributing facilities is limited due to the unavailability of the facilities during a disaster. This study is very meaningful since we recognize that there is very limited research regarding the use of SVI in the design of the emergency or humanitarian logistics network. One of the most relevant to our work is the model by Douglas *et al.* (2021), a mathematical programming model with the adjusted SVI maximization and the budget in the constraint. They apply the model to Brazil as a case study. In our study, we adopt the GP-based approach to consider two conflicting objective functions and evaluate its performance over different levels of facility capacities and weights between SVI and TLC.

The remainder of this paper is organized as follows: after the literature review, the social vulnerability index background is explained, followed by the Goal Programming Model with TLC and SVI. Then, a case study and observations are provided. Lastly, conclusions are presented.

LITERATURE REVIEW

Facility Location-Allocation (FLA)

The primary goal of the FLA problem is to determine the locations and sizes of facilities and the distribution channels of items from the facilities to customers while satisfying demands. Various authors have studied FLA problems since Cooper (1963) sets an FLA problem as a mathematical programming model. Some relevant previous studies are as follows: Askin *et al*. (2014) consider designing a multi-sourcing distribution network for retailers. Manatkar *et al*. (2016) consider maintaining the desired service level in addition to reducing the total logistics cost. Hong and Jeong (2019) consider an FLA optimization with five conflicting objectives–TLC, maximum coverage distance, maximum demand-weighted coverage distance, covered demand in case of emergency, and expected number of non-disrupted supplies, seeking a balance among them in the optimized FLA system. Hong and Jeong (2020) also consider both TLC and the expected number of demands satisfied in the emergency backup supply system. Recently, Hong *et al*. (2022) propose combining the Multi-Objective Programming model with the three data envelopment analysis-based methods for designing ELN.

In this study, an ELN consists of Disaster Recovery Centers (DRCs) and affected areas (e.g., communities or counties). DRCs work as facilities to distribute relief items to affected areas during a disaster. We determine the locations and capacity of DRCs and distribution channels to the affected areas with consideration of both SVI and TLC in the GP with a capacity constraint. The GP should determine the affected areas with higher priorities based on the trade-off between SVI and TLC.

Social Vulnerability Index

Cutter *et al*. (2009) develop the SVI to quantify a place's relative socioeconomic and demographic quality to understand vulnerability, which is concerned with pre-event embedded qualities of the social system. Many SVI-related studies reveal that categories of people living in disaster-stricken areas are not affected equally. Evidence shows that people with low incomes, children, elders, disabled people, and residents of high-rise apartments or mobile homes are more vulnerable. Morrow (1999) reveals that the vulnerability factors often occur in combination. The most vulnerable are those whose needs are not considered in disaster response planning. For example, many low-income people with no personal transportation in New Orleans were victimized during Hurricane Katrina because public authorities did not provide emergency mass transit. Further, much real-time information was not efficiently provided to special-needs groups (Department of Transportation, 2006).

The Geospatial Research, Analysis, and Service Program (GRASP) at the Centers for Disease Control (CDC) and Prevention Agency for Toxic Substance and Disease Registry (ATSDR) has created the Centers for Disease Control and Prevention SVI (CDC SVI or SVI, hereafter) based on the work of Cutter *et al*. (2003). We also adopt the CDC SVI for this study.

SOCIAL VULNERABILITY INDEX BACKGROUND

The CDC SVI is driven by 15 factors, classified into four different themes, as seen in Table 1. ATSDR (2022) calculates the SVI for each of the 15 US census variables at each census tract (e.g., a county) for multiple years after 2000. To construct the SVI, each of the 15 census 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 following percentile rank (*PR*) is calculated for counties using the rank and the total number of data (*N*), defined by

$$Percentile\ Rank\ (P.R.) = \frac{Rank-1}{N-1} \tag{1}$$

The percentile rank maps the county's ranks into a value between 0 and 1, considered the county's SVI. A county with a larger SVI value is considered more vulnerable to hazards for each variable. In addition, a theme-level percentile rank is calculated based on the sum of the percentile ranks of the variables comprising the theme. Finally, the overall SVI for each county is calculated using the sum of the percentile ranks of the four themes. Note that 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 1 person in family/household
		Unemployed	
		Income	
		No High School Diploma	
	Household Composition & Disability	Age 65 or Older	
		Age 17 or Younger	
		Older Than Age 5 With a Disability	
		Single-Parent Households	
	Minority Status & Language	Minority	
		Speaks English "Less Than Well"	
	Housing & Transportation	Multiunit Structures	
		Mobile Homes	
		Crowding	e.g., Occupied housing units with more than one person per room are considered crowded
		No Vehicle	
		Group Quarters	All people not living in housing units. e.g., nursing homes, correctional facilities, etc.

Table 1. Variables and Themes in SVI.

GOAL PROGRAMMING MODEL WITH TLC AND SVI

We provide a GP-based mathematical model with TLC and SVI in the objective function. Let us consider an ELN with Disaster Recovery Centers (DRCs) and affected areas (or neighborhoods) represented by demand points (DPs). We need to identify the location of DRCs and relief item distribution channels from DRCs to DPs with multi-sourcing when a major disaster occurs.

The following nomenclature is used:

Sets:

$j \in C$: index set of potential areas (or neighbors) for DRCs, $j = 1, 2, \ldots, M$

$k \in C$: index set of potential areas (or neighbors) for pure DRCs without any fictitious DRC, $k = 1, \ldots, j$

$m \in P$: index set for DPs, $m = 1, 2, \ldots, N$

Note that $C \subseteq P$ since DRC at area j feeds itself as DP, too.

Parameters:

b_j: minimum number of DPs that DRC j can cover

B_j: maximum number of DPs that DRC j can cover

c_{jm}: cost of shipping one unit of demand per mile from DRC j to DP m

CAP_j^{max}: design capacity of DRC j
d_{jm}: distance between DRC j and DP m
D_m: demand for the DP 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 area m
α : a real number between 0 and 1
TLC_{min} : Minimum of TLC
TLC_{max} : Maximum of TLC
$SVI_{\max}$: Maximim of SVI
S : Demand satisfaction rate (percentage of demand satisfied)

Decision Variables:

F_j: binary variable deciding whether a DRC j is located at area j or not
cap_j: storage capacity at DRC j
y_{jm}: percentage of DP m's demand satisfied by the storage capacity distributed from DRC j. It is a real number between zero and one, implicating the multi-sourcing. That is, an area m can be supplied by multiple DRCs.

Assumptions:

(i) A DRC can be located at any potential facility area. If a DRC is located at the facility area 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 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) capacities to deliver the items to each DP directly.
(v) TLC consists of transportation costs from DRCs to DPs 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 minimization of TLC is considered good performance.

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

Note that we add one fictitious DRC to GP. The fictitious DRC has a zero SVI, zero demand, and enough capacity to satisfy all demand from all populations, with the distance from the fictitious DRC to actual DPs set to infinite. In this way, the fictitious DCR is only used when the actual DRCs are fully utilized and their capacity is completely consumed. In other words, any TLC from the fictitious DRC serves as a penalty for a capacity shortage. If a subscript 'j' is replaced by 'k' in Eq (2), TLC is calculated for the actual DRCs only without any fictitious DRC. Now, we define SVI, aiming to supply relief items to the areas with higher SVI values (more vulnerable areas) first, by Eq. (3). Note that the sum of SVIs is computed for the pure DRCs only.

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

The GP is defined as below:

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

subject to:

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

$$\sum_{j \in C} F_j \leq F^{max}, \quad (6)$$

$$cap_j \leq F_j\ CAP_j^{max}, \qquad \forall j \in C \quad (7)$$

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

$$y_{jm} \leq F_j, \qquad \forall j\ and\ \forall m \in M \quad (9)$$

$$\sum_{k} cap_k \quad \leq (\sum_{m \in P} D_m)S \quad (10)$$

The objective function in (4) attempts to minimize TLC and SVI percentage deviations from the target values under the normalized condition. The first term represents the normalized percentage deviation of *TLC,* and the second is SVI's normalized percentage deviation. Note that SVI_{min} is zero. Constraints (5) make certain that each area is covered by one or more DRCs, allowing multi-sourcing. Constraints (6) define the maximum number of DRCs to be built. Constraints (7) ensure that storage capacity at each DRC should be less than or equal to the designed capacity when it is built. Constraints (8) ensure that DRC can only cover each DP within DRC's storage capacity. Constraints (9) indicate that each DP is covered by DRC *j* only when DRC is available at area *j*. Constraint (10) assumes that not all demands may always be satisfied by actual DRCs. If any distribution requires more than the specified capacity (*S*), the capacity in the fictitious DRC is used and considered a penalty.

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 (9), and $SVI_{\max}$ is obtained by maximizing equation (3) subject to constraints (4) to (9). *TLC*, when SVI_{max} is calculated, is set to TLC_{max} in that SVI_{max} sacrifices *TLC* to maximize SVI.

CASE STUDY AND OBSERVATIONS

To evaluate the behavior of the GP model, we conduct a case study using SVI values in South Carolina based on the 2018 US census (ATSDR, 2022). When a disaster occurs and a major disaster declaration is made by the President of the United States, the Federal Emergency Management Agency (FEMA) opens DRCs in the state to help the affected counties with their relief items. We want to determine the locations and capacities of DRCs and the distribution channels of relief items from DRCs to counties. We also want to see the impact of capacity on SVI and TLC. Forty-six counties in South Carolina are clustered based on proximity and populations into twenty counties for simplicity. Then, one city from each clustered county is chosen based on a centroid approach. All the population within the clustered county is assumed to exist 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, and 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

*The original SVI value at Charleston is 0. We change it into 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, $\forall j$ *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

Table 3. Parameters for the case study

Using the GP model, we change the weight of *TLC* (α) from 0.0 to 1.0 by a 0.2 increment and the demand satisfaction rates (*S*) from 100% to 80% by a 10% decrement. Table 4 summarizes the maximum and minimum *TLC* and maximum *SVI* for each demand satisfaction rate. Note that where the demand satisfaction rate is 100%, the entire population of all counties is taken care of. Thus, SVI is maximized to the sum of SVIs, for all counties in Table 2. The logistics cost when SVI_{max} is obtained is set to TLC_{max} since no minimization in TLC is attempted. Results are summarized in Table 4. However, as the demand satisfaction rate decreases (not all demand is satisfied), maximizing SVI will select counties with higher priorities more carefully. The corresponding TLC increases exponentially since the fictitious DRC is used due to the capacity shortage. Note that the 5th DRC is fictional with zero SVI, infinity capacity (5,088K), and 500K miles from any DPs.

S	TLC_{max} (\$)	*GAP (%) from 100%*	TLC_{min} (\$)	*GAP (%) from 100%*	SVI_{max}	*GAP (%) from 100%*

100%	2.349e+6	0	6.7627e+5	0	7.666	0.0
90%	2.7351e+7	1,064	2.6115e+7	3762	7.643	-0.3
80%	5.2651e+7	2,141	5.1553e+7	7523	7.496	-2.2

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

Using the results in Table 4, we summarize the results of GP with various ($\boldsymbol{S}$, $\boldsymbol{\alpha}$) combinations in Table 5. When α is set to zero, the GP model attempts to maximize SVI only (or minimize the gap percent from SVI_{max}). We also recognize that the solution at $\alpha = 1.0$ is the same as the *TLC* minimization problem. Pure TLC and TLC are listed together. TLC considers all transportation costs, including fictitious ones, while Pure TLC considers only actual DRCs. Each solution in each pair of ($\boldsymbol{S}$, $\boldsymbol{\alpha}$) represents one optimized ELN. Then, what is the best ELN for each demand satisfaction rate? We define the following SCALE value for each demand satisfaction rate in Eq (11) to answer this question.

$$SCALE = \frac{\text{Normalized Pure SVI}}{\text{Normalized Pure TLC}} \tag{11}$$

Normalized pure SVI is the ratio of the Pure SVI to the minimum of Pure SVI for all α's. The same is true for Pure TLC. Eq. (11) shows that a higher SCALE value implies better productivity, indicating that the ELN achieves a higher SVI with a lower TLC. Table 5 shows that many ELNs with α between 0.2 and 0.8 have the best performance by maintaining a good balance between *TLC* and *SVI*.

	α	**0.0**	**0.2**	**0.4**	**0.6**	**0.8**	**1.0**
S=100%	**Pure TLC ($)**	711,990	676270	676270	676270	676270	676,270
	Pure SVI	7.6662	7.6662	7.6662	7.6662	7.6662	7.6662
	TLC ($)	2.03E+06	6.76E+05	6.76E+05	6.76E+05	6.76E+05	6.76E+05
	SCALE	0.950	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**
S=90%	**Pure TLC ($)**	654,640	612,800	612,800	612,800	612,800	609,240
	Pure SVI	7.6434	7.6434	7.6434	7.6434	7.6434	6.8198
	TLC ($)	2.74E+07	2.61E+07	2.61E+07	2.61E+07	2.61E+07	2.61E+07
	SCALE	1.043	**1.114**	**1.114**	**1.114**	**1.114**	1.000
S=80%	**Pure TLC ($)**	580,250	544,640	544,640	544,640	544,320	539,340
	Pure SVI	7.4962	7.4962	7.4962	7.4962	7.488	4.7931
	TLC ($)	5.27E+07	5.16E+07	5.16E+07	5.16E+07	5.16E+07	5.16E+07
	SCALE	1.454	**1.549**	**1.549**	**1.549**	1.548	1.000

Table 5. Results from GP Model per Demand Satisfaction Rate

Several phenomena in Table 5 are observed:

(1) As α increases, both pure TLC and SVI decrease since a higher α indicates a higher emphasis on TLC at the cost of SVI (see Figures 1 and 2).
(2) Both pure TLC and SVI decrease as the capacity shortage increases since the logistics penalty increases. In Figure 2, Pure TLC decreases as the capacity shortage increases since a smaller number of DPs are served.
(3) TLC is the most sensitive to capacity when α is set to zero, while SVI is the most sensitive to capacity when α is set to one (Figure 2).
(4) It is apparent that the best ELN is obtained when the proper balance between TLC and SVI is achieved (e.g., α is between 0.2 and 0.6 for all capacities).

The high sensitivity of SVI to the capacity at $\boldsymbol{TLC_{min}}$ for all capacities justifies the importance of a good balance between TLC and SVI. Otherwise, overemphasis on the TLC may negatively affect the safety of more socially vulnerable groups of people.

To better understand the role of capacity shortages, we display several optimized ELNs. Figure 3 represents the ELN with (S=100%, α=0.2~1.0) where both $\boldsymbol{TLC_{min}}$ and $\boldsymbol{SVI_{max}}$ are obtained with SCALE = 1.0. We can see that all four actual DRCs distribute their relief items efficiently to the designated counties, and all counties are covered. That is, this is the best ELN. This ELN changes to Figure 4 when any capacity shortage occurs. When it loses 10% of its original capacity, the DRC at Florence is unavailable. Further, Bennettsville, Florence, and Conway are not supplied by any existing DRCs. When it loses 20% of its capacity, four more counties (McCormick, Hampton, Beaufort, and Rockhill) are not supplied or partially supplied. For example, only 90% of the total demand at Rock Hill will be covered.

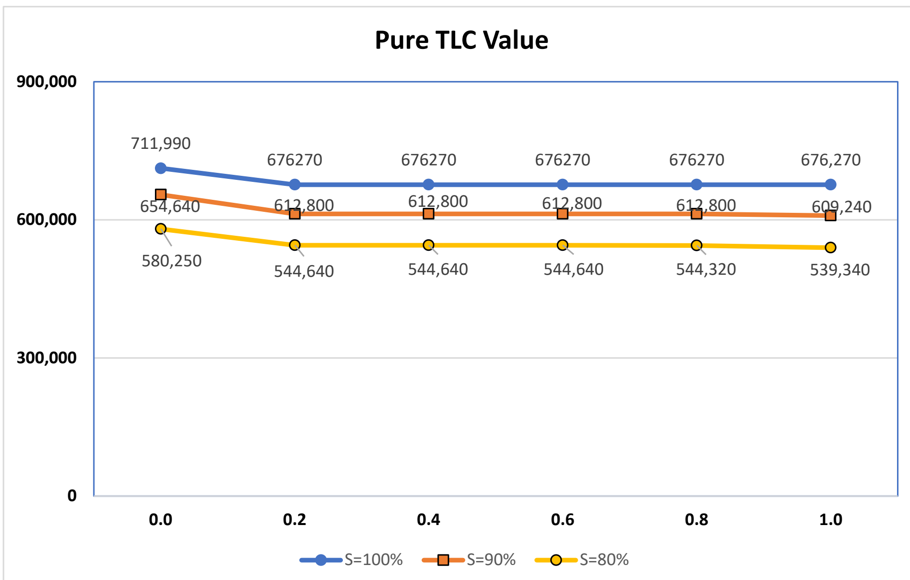

Figure 1. TLC Values for Demand Satisfaction Rate

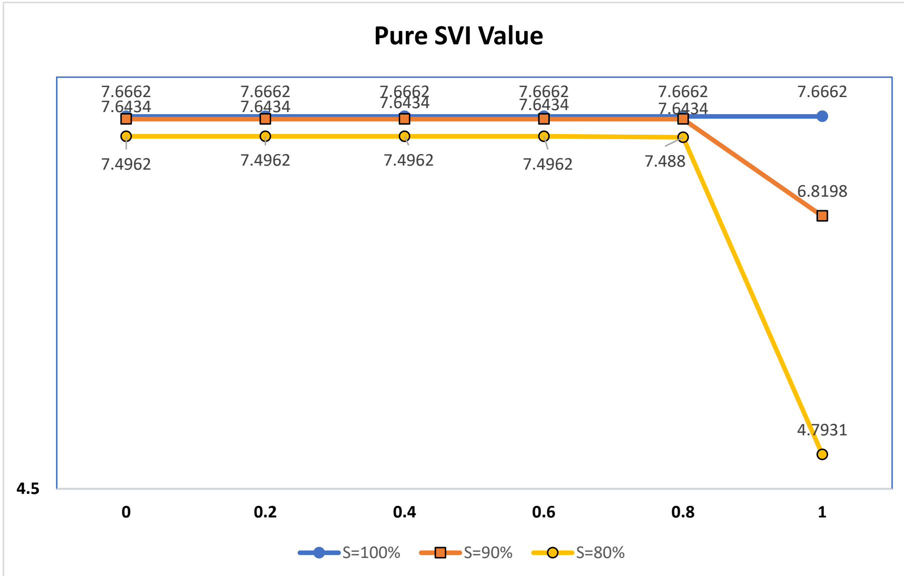

Figure 2. Pure SVI Values for Demand Satisfaction Rate

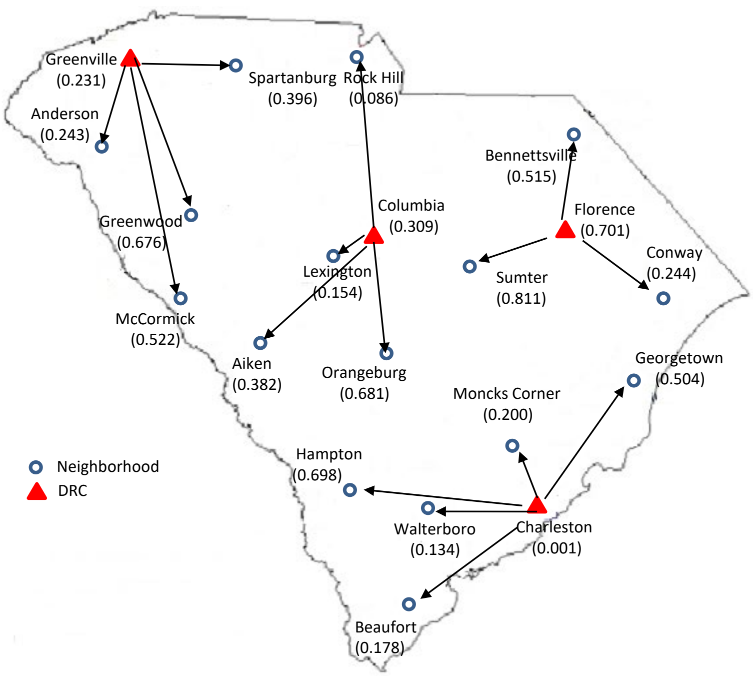

Figure 3. An ELN with S = 100% and α = 0.2~0.8

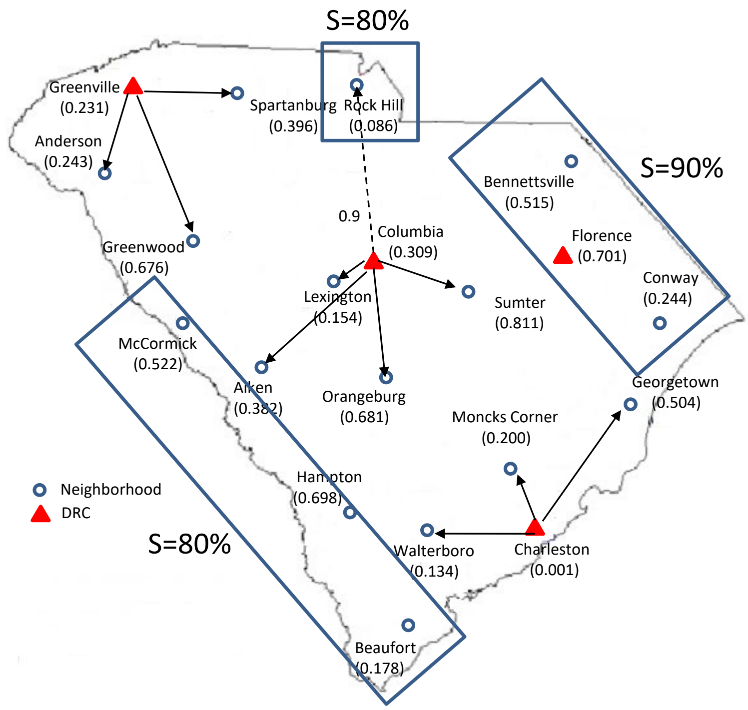

Figure 4. An ELN with S = 90%, 80% and α = 1.0.

Figure 5 represents the ELN with (100%, 0.0). We observe that the distribution channels are inefficient since their only goal is to maximize SVI without considering TLC. For example, Greenville is a DRC, but Columbia covers it, and Conway is covered by Greenville instead of the nearby DRC, Colombia. This ELN changes to Figure 6 when it loses its capacity. With a 10% capacity loss, only 70% of demand at Rockhill is covered by Colombia, and Charleston is not covered by itself because SVI at Charleston is very low (0.001). That is, SVI maximization does not even consider covering Charleston under the capacity shortage. With a 20% capacity loss, Greenville does not work as DRC; only 60% of its demand is covered by Charleston.

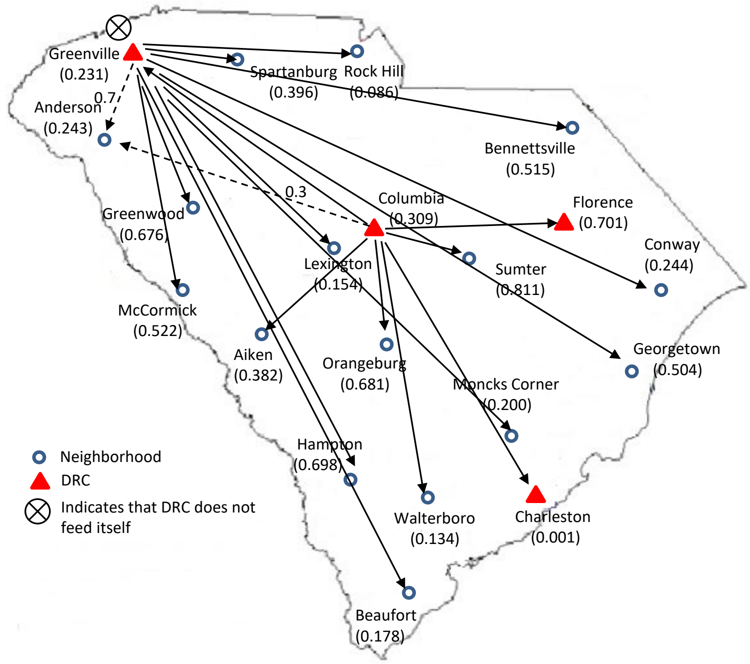

Figure 5. An ELN with S = 100% and α = 0.0

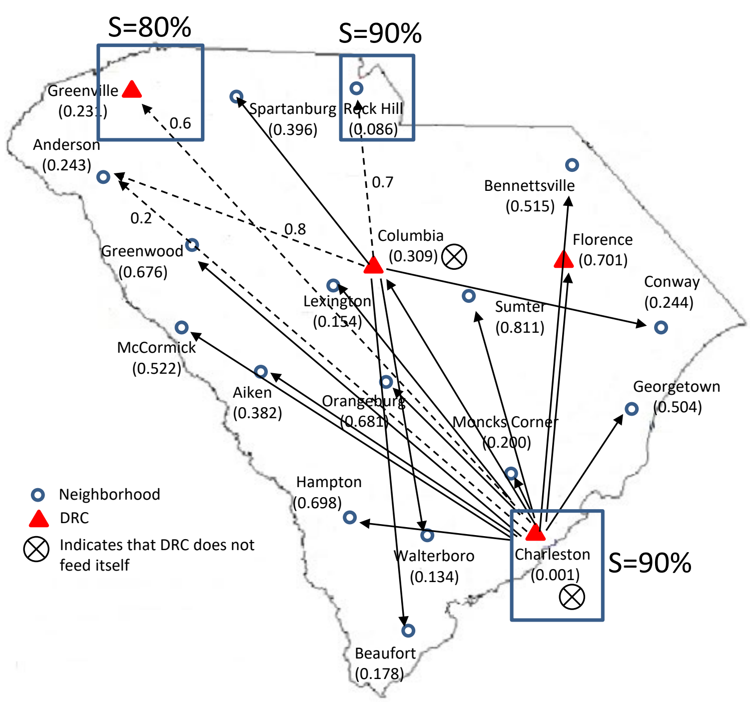

Figure 6. An ELN with S = 90% and 80% with α = 0.0

Previous figures and the results in Table 5 clearly show the importance of a balanced ELN when a capacity shortage occurs. Due to the capacity shortage, inefficiency and lack of coverage change the original ELN significantly. Now, let's choose one of the best-balanced ELNs with (100%, 0.6). Note that the ELN is the same as the one in Figure 3. This fully covered ELN changes to the one in Figure 7 when it loses 10% (SCALE = 1.114) and 20% capacity (SCALE = 1.549). We can observe that although several counties are not served (e.g., Charleston with S = 90%; Rock Hill with S=80%, and 40% of Greenville with S=80%) due to the capacity shortage, the layout and distribution channels are very efficient and balanced.

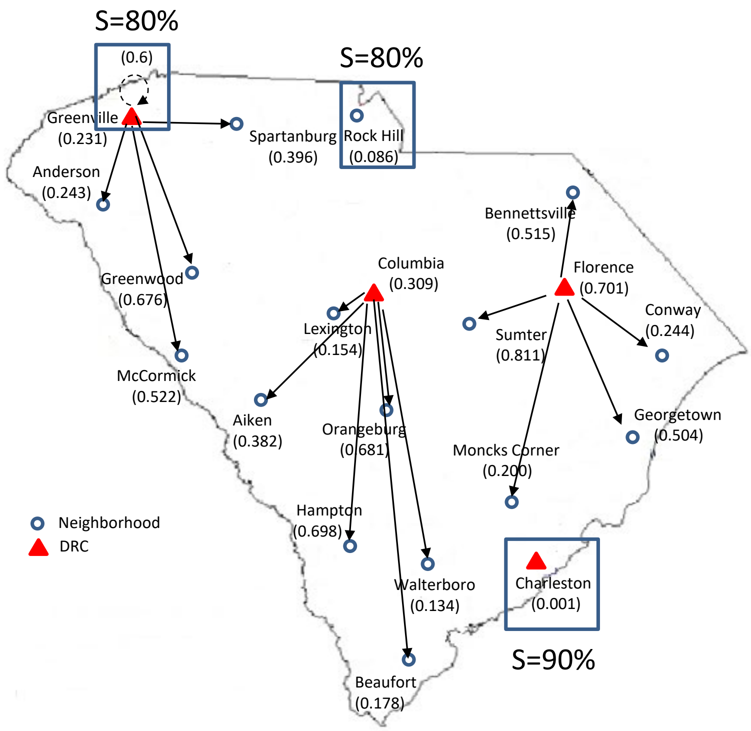

Figure 7. An ELN with S = 80% = 90% and α = 0.6

CONCLUSIONS

The emergency logistics network (ELN) design problem has become a major strategic decision since recent natural or human-made disasters have inflicted damage on the whole world. This study attempts to utilize Goal Programming (GP) to design a balanced ELN by considering both the Social Vulnerability Index (SVI) and Total Logistics Cost (TLC). We recognize that very few studies have utilized SVI in quantitative modeling. Notably, this research is unique since it focuses on the impact (sensitivity) of the capacity shortage, particularly associated with SVI. It turns out that the impact of the capacity shortage on SVI gets larger when the shortage increases. Thus, it is imperative for decision-makers to fully consider the capacity shortage issue when they design humanitarian logistics networks from the SVI perspective.

As part of humanitarian logistics, ELN design problems are becoming a more critical task in terms of risk preparedness and response. Considering the current trend where social responsibility is more emphasized than ever before, we expect that the application of SVI will play a more important role in emergency and/or humanitarian logistics. Future research will significantly enhance this study if an actual rescue mode profile (difference in time in distributing relief items) in different counties with different SVIs is integrated with this study.

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