A DESIGN OF EMERGENCY LOGISTICS NETWORK WITH A SOCIAL VULNERABILITY INDEX

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ABSTRACT

This paper applies the Center for Disease Control and Prevention's Social Vulnerability Index (SVI) to an emergency logistics network (ELN) design problem. A community with a higher SVI should be given a higher priority in case of emergency. We propose two SVI-based facility location-allocation (FLA) models with a multi-sourcing system–one with a soft SVI constraint by maximizing SVI in the objective function and the other with a hard-SVI constraint by considering SVI in the constraint and minimize the total logistics costs. The case study analyzes the proposed models' performance and compares them with the traditional FLA without the SVI.

Keywords: Emergency logistics networks, social vulnerability index, facility location-allocation, multi-sourcing system.

INTRODUCTION

The emergency logistics network (ELN) provides relief items such as drinking water, food, and daily commodities to lessen people's suffering. The U.S. experienced a historic year of climate disasters in 2007. The U.S. was seriously affected by 16 billion-dollar disaster events, including two inland floods, eight severe storms, three tropical cyclones, two inland floods, a crop freeze, drought, and wildfire. During 2020 and 2021, the U.S. experienced a very vigorous year of weather and climate disasters, including the COVID-19 pandemic. According to National Centers for Environmental Information (NECI, 2022), the U.S. has sustained 332 climate and weather disasters since 1980, where overall damages/costs reached or exceeded $1 billion. See Figures 1 and 2 for the U.S. 2021 and 2022 (as of July 11) billion-dollar weather and climate disasters. Thus, the ELN design could be critical for preparing for such weather and climate disasters worldwide.

An FLA design problem is frequently used in the supply chain design. The traditional FLA design problem typically assumes that the facilities are always available and that it optimizes the supply chain by minimizing the total logistics cost while satisfying demands by distributing products through the distribution channels from facilities to customers.

An ELN is a supply network that promptly distributes relief items stored in the facilities to the affected areas (e.g., communities or neighborhoods) when a disaster occurs. Thus, an ELN design problem differs from a traditional FLA or other supply chain design problems because some facilities often become unavailable (shut down), and the stored relief items are lost during a disaster. Further, more diverse non-financial performance measures are used in the objective function since an ELN's goal is to quickly distribute relief items for rapid recovery and resilience, which often requires the sacrifice of cost-based efficiency. For example, Jeong *et al*. [17] propose a three-layered ELN with two conflicting objective functions–total logistics cost (TLC) and expected risk cost (ERC), defined as the opportunity cost when facilities are shut down. Identifying appropriate performance measures for an ELN is an ongoing research area since each ELN may have a different goal.

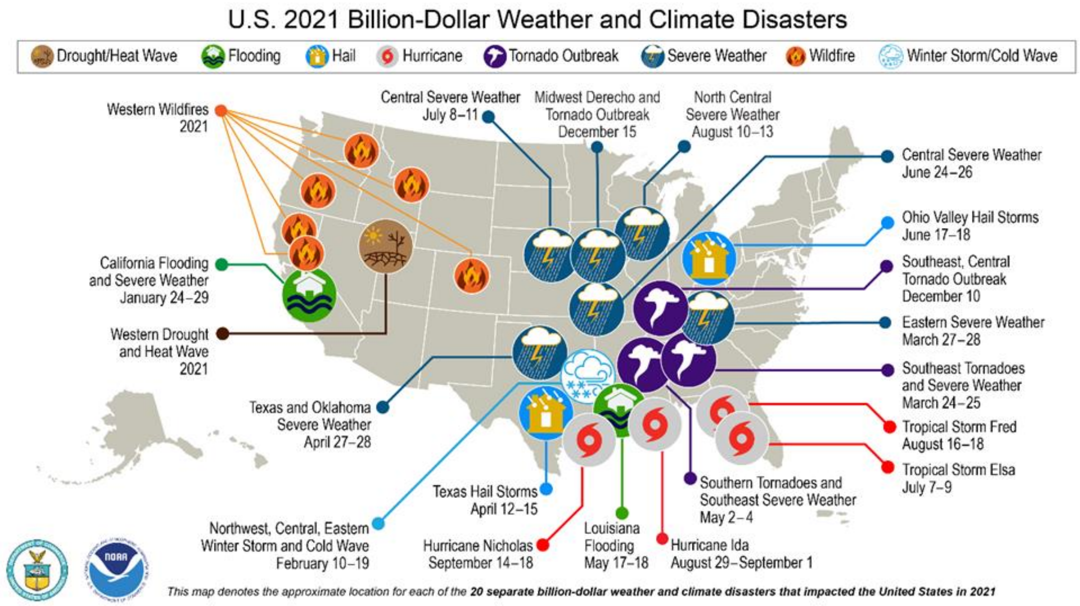

Figure 1. U.S. 2021 billion-dollar weather and climate disasters (excerpted from [6])

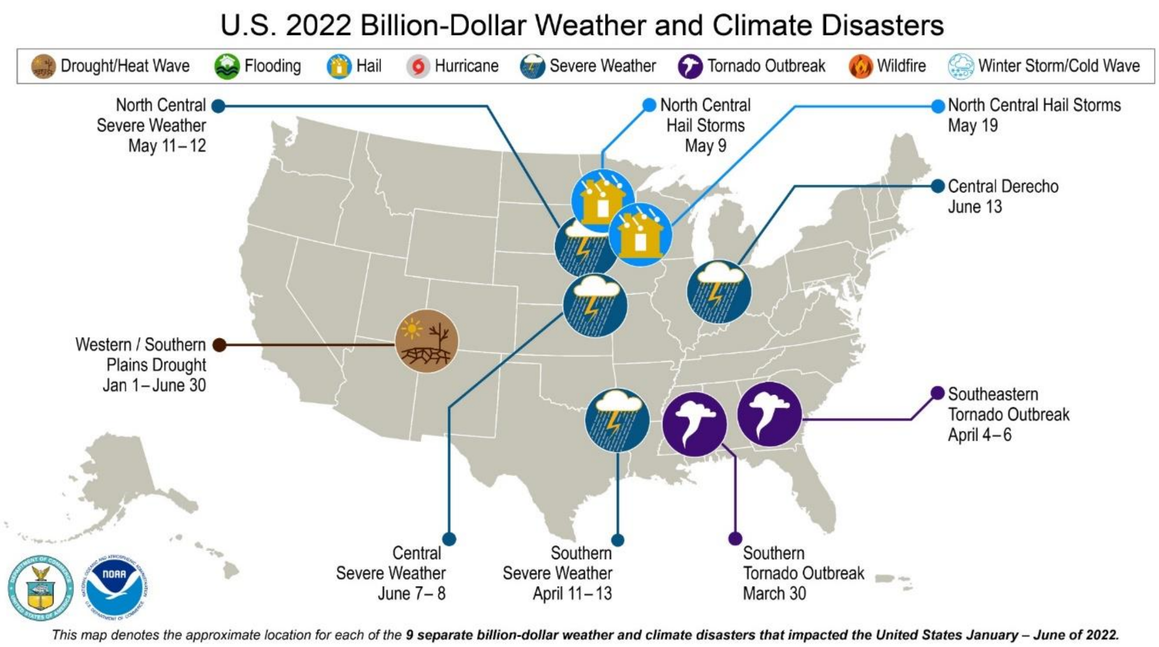

Figure 2. U.S. 2022 (January-June of 2022) billion-dollar weather and climate disasters (excerpted from [21])

Social vulnerability 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. Thus, measuring social vulnerability, represented by Social Vulnerability Index (SVI), involves socioeconomic and demographic factors that affect the resilience of communities. We focus on the Center for Disease Control and Prevention SVI (CDC SVI) developed through Geospatial Research, Analysis & Service Program in U.S. Agency for Toxic Substance 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 [8][13].

In this study, we incorporate the SVI into an ELN design problem. We propose two mathematical programming models to design an ELN based on FLA formulation optimally. Both models use the rationale that the area with a higher SVI value is taken care of with a higher priority since it is more vulnerable when a disaster occurs. Specifically, the first model maximizes the SVI in the objective function (a soft SVI constraint), while the second is to consider SVI in the constraint (a hard SVI constraint). Then, we compare these two models with a traditional FLA model whose objective is to minimize TLC. Through a case study with SVI values computed based on the 2018 U.S. census in South Carolina, we evaluate the behaviors of SVI as performance measure in the two mathematical models. SVI has been recognized to evaluate the vulnerability of communities more objectively. However, there is very limited research done regarding the use of SVI in the emergency or humanitarian logistics. In fact, we find only two studies at the time of writing this manuscript. One of the most relevant to our work is the model by Douglas *et al.* [12], a mathematical programming model with the adjusted SVI maximization and the budget in the constraint. They apply the model to the Brazil as a case study. In this study, we propose the two mathematical programming models with consideration of the SVI under the multi-source system, and we believe that our work would significantly contribute to both the humanitarian logistics network design and disaster management literature.

The remainder of this paper is organized as follows. After the literature review, the social vulnerability index background is explained, followed by mathematical modeling of FLA with SVI. Then, a case study and observation are provided. Lastly, conclusions are presented.

LITERATURE REVIEW

Facility Location-Allocation

The primary issue of the FLA problem is to determine the locations and size of facilities and distribution channels of items from the facilities to customers while meeting demands. Various authors have studied FLA problems since Cooper [7] sets an FLA problem as a mathematical programming model. Manzini and Bennani [19] define FLA problems as the problem of determining the optimal location for each of the new facilities and the optimal allocation of existing requirements to the facilities so that all requirements are satisfied. Askin *et al*. [2] consider designing a multi-sourcing distribution network and then delivering them to retailers. Manatkar *et al*. [18] consider maintaining the desired service level in addition to reducing the TLC to design FLA problems. Hong and Jeong [14] 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. They use the multi-objective programming (MOP) model and the data envelopment analysis (DEA) method to find the efficient configurations out of the various ELN configurations generated by the MOP model, and their work would be the first attempt to combine the MOP model with the DEA method in the literature on the design of ELN [14]. Hong and Jeong [15] consider both TLC and the expected number of demands satisfied in the emergency backup supply system. Recently, Hong *et al*. [16] propose combining the MOP model with the three data envelopment analysis-based methods for designing ELN based on the model that Hong and Jeong [14] consider.

We consider an ELN design problem with FLA, where Disaster Recovery Centers (DRCs) work as facilities to distribute relief items to affected areas (e.g., communities or counties) when a disaster occurs. We determine the locations and capacity of DRCs and distribution channels to the affected areas.

Social Vulnerability Index

Cutter *et al*. [9] explain that social vulnerability is affected by social inequalities as well as place inequalities. They list seventeen indicators that can be used 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*. [10] 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. Thus, social vulnerability is regarded as a predictive variable representing the potential for being harmed when a risk occurs [4].

The vulnerability literature reveals that categories of people living in a disaster-stricken are not affected equally. For example, evidence shows that the poor, children, elders or disabled people, and residents at high-rise apartments or mobile homes are more vulnerable. Morrow [20] 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 in New Orleans, who had no personal transportation, were victimized during Hurricane Katrina because public authorities did not provide emergency mass transit. Further, much real-time information was not efficiently provided to the groups with special needs (e.g., limited English proficiency, the hearing, and the visually impaired) [11].

Of the two available studies regarding the SVI in the humanitarian logistics, Arnette and Zobel [1] consider a simple location model for asset preposition in the American Red Cross of Wyoming and Colorado with consideration of hazard, exposure, and SVI. Douglas *et al* [12] define the *social benefit of an affected area* as the relative difference between the relief service (percentage of victims who needs are satisfied) with and without using the SVI. Their mathematical programming model shows that the social benefit of using SVI is more significant as the vulnerability level increases. They also claim that there should be more research regarding the SVI in the humanitarian logistics due to the lack of studies.

The Geospatial Research, Analysis & Service Program (GRASP) at the Centers for Disease Control (CDC) and Prevention Agency for Toxic Substance and Disease Registry (ATSDR) have created the Centers for Disease Control and Prevention SVI (CDC SVI or SVI, hereafter) based on the work of Cutter *et al.* [9]. This SVI is applied to the case study in Barbados [8], and other ongoing validation works continue [5][22]. These validation works motivate us to adopt CDC SVI in this study.

SOCIAL VULNERABILITY INDEX BACKGROUND

The SVI is driven by the 15 factors, classified into four different themes, as seen in Table 1. ATSDR [3] calculates the SVI for each of the 15 U.S. 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 the income, is ranked from lowest to highest scores across all counties in the U.S. with a non-zero population (lower values with higher ranks). Note that the 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 ($P.R.$) 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, and this percentile rank is considered as SVI of the county. That is, for each variable, a county with a larger SVI value is considered more vulnerable to hazards. 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.

MATHEMATICAL MODELING OF FLA WITH SVI

In this section, we provide mathematical models for soft and hard-constrained SVI. Let us consider an ELN with Disaster Recovery Centers (DRC) and affected areas (or neighborhoods) represented by demand points (D.P.s). We need to identify the location of DRCs and relief item distribution channels from DRCs to D.P.s 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, $j = 1, 2, \ldots, M$

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

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

Parameters:

b_j: minimum number of D.P.s that DRC j can cover

B_j: maximum number of D.P.s that DRC j can cover

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

CAP_j^{max}: design capacity of DRC j

d_{jm}: distance between DRC j and D.P. m

D_m: demand for the D.P. 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 of area m

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 D.P. m's demand satisfied by the storage capacity distributed from DRC j. It is a real number between zero and one. This realizes 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 D.P. directly.

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

We first consider the traditional FLA model with TLC minimization as objective, denoted by the **TFLA model**. The objective function is to minimize TLC, which consists of the transportation/shipping cost from DRCs to D.P.s (first term) and inventory cost at DRC (second term) as shown in Eq (2). Note that we use the product of distance and demand as cost in the first term to consider both distance and population.

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

Thus, the TFLA model is formulated as follows:

minimize $\quad$ *TLC*

subject to:

$$\sum_{j \in C} y_{jm} = 1, \quad \forall m \in P \tag{3}$$

$$\sum_{j \in C} F_j \leq F^{max}, \tag{4}$$

$$cap_j \leq F_j \, CAP_j^{max}, \quad \forall j \in C \tag{5}$$

$$\sum_{m \in P} D_m y_{jm} \leq cap_j, \quad \forall j \in C \tag{6}$$

$$y_{jm} \leq F_j, \quad \forall j \text{ and } \forall m \in M \tag{7}$$

Constraints (3) make certain that each area is covered by one or more DRCs, allowing multi-sourcing. Constraints (4) define the maximum number of DRCs to be built. Constraints (5) ensure that storage capacity at each DRC should be less than or equal to the designed capacity when it is built. Constraints (6) ensure that each D.P. can only be covered by DRC within DRC's storage capacity. Constraints (7) indicate that each D.P. is covered by DRC *j* only when DRC is available/built at area *j*.

We now consider the FLA model with SVI maximization (SVI-FLA model), aiming to supply relief items to the areas with higher SVI values (more vulnerable areas first). Thus, the objective function is defined by Eq. (8) below.

$$SVI = \sum_{m \in P} \sum_{j \in C} SVI_j y_{jm}, \tag{8}$$

The SVI-FLA model maximizes SVI as an objective function with the same Constraints (3)-(7) in the TFLA model. We call this a soft-constrained SVI model since SVI is considered in the objective function.

The third model we consider is to minimize TLC while we ensure that DRC supplies relief items to the areas with higher SVIs first in the constraints within its capacity. Let $SVI_k^{'}$ represent SVI value at sorted area *k*, sorted in descending order of SVIs ($SVI_k^{'} \geq SVI_{k+1}^{'}$). To ensure the relief item distribution according to descending order of SVI values within the capacity of a given DRC *j*, the y_{jk} is set to 1 under the following condition as a constraint.

$$\sum_{k \in P} SVI'_{k_j} y_{jk} \leq cap_j \qquad \text{for } j \tag{9}$$

We call this **TFLA-SVI model**, which must strictly observe the "higher SVI areas first" as a hard constraint

CASE STUDY AND OBSERVATIONS

To evaluate the behavior of the models, we conduct a case study using SVI values in South Carolina based on the 2018 U.S. census [3]. When a disaster occurs and a major disaster declaration is made, the Federal Emergency Management Agency (FEMA) opens DRCs in several S.C. counties to help the affected counties (areas or neighborhoods) with their recovery and relief activities. We use the problem of locating

DRCs and distributing relief items as our case study. Forty-six counties in South Carolina are clustered based on proximity and populations into twenty counties based on 2018 census data. Then, one city from each clustered county is chosen based on a centroid approach. It is assumed that all population within the clustered county exists 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 composite city. Table 2 lists 20 composite cities, and Table 3 lists all costs and capacity parameters for the case study.

In this case study, we assume the following scenario to evaluate the performance of TLC and SVI under a capacity-constrained situation. The DRC at Charleston is used for period 1 and the DRC at Greenville for period 2, respectively. If these two DRCs are available simultaneously, they can satisfy all demands for all counties–note that each DRC has 2,600K capacity and all populations are 5,088K, and this ample capacity would not differentiate each county based on the SVI. In other words, when the models are run with Charleston for period 1, all decisions are determined under the capacity-constrained situation. The results of period 1 are given as inputs for period 2 when the model works with Greenville. That is, both DRCs are available in period 2.

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	2

Table 3. Parameters for the case study

The results of the three models are summarized in Table 4 per period. Note that '1' or a decimal in the cell for each period (e.g., *P1* and *P2*) indicates the distribution channel and percentage of the supplies from a corresponding DRC to a specific area (e.g., Charleston feeds Sumter 100% and Lexington 88%, respectively, for period 1 in ***TFLA***).

City	***SVI***	***Rank***	***Population***	***TFLA***		***SVI-FLA***		***TFLA-SVI***	
				P1	***P2***	***P1***	***P2***	***P1***	***P2***
Sumter	0.811	1	158	1		1		1	
Florence	0.701	2	200		1	1		1	
Hampton	0.698	3	28	1		1		1	
Orangeburg	0.681	4	116	1		1		1	
Greenwood	0.676	5	96		1	1		1	
McCormick	0.522	6	36		1	1		1	
Bennettsville	0.515	7	139		1	1		1	
Georgetown	0.504	8	93	1		1		1	
Spartanburg	0.396	9	398		1	1		1	
Aiken	0.382	10	191		1	1		1	
Columbia	0.309	11	503	1		0.32	0.68	1	
Conway	0.244	12	345	1		1		1	
Anderson	0.243	13	403		1		1		1
Greenville[**]	0.231	14	583		1		1		1
Moncks Corner	0.200	15	221	1		1			1
Beaufort	0.178	16	218	1		1			1
Lexington	0.154	17	353	0.88	0.12		1		1
Walterboro	0.134	18	199	1		1			1
Rock Hill	0.086	19	401		1		1		1
Charleston[*]	0.000	20	407	1			1	0.73	0.27
TLC				$ 25,874	$ 22,174	$ 36,597	$ 27,105	$ 37,304	$ 29,953
SVI				3.896	3.770	6.742	0.924	6.441	1.225
TOTAL	***TLC***			$48,048		$63,702 (32.6%)[***]		$67,257 (40.0%)[***]	
	SVI			7.666		7.666		7.666	

[*]DRC used for period 1; [**]DRC used for period 2; *P1* and *P2* stand for period 1 and period 2, respectively;[***] percentage deviation from TFLA's TLC

Table 4. Results of the models

Since TFLA minimizes TLC without considering SVI, both its TLC and SVI are the smallest, $25,874 and 3.896, respectively during period 1. SVI-FLA maximizes SVIs without any consideration of TLC. Hence, its SVI is the largest (6.742) with $36,597 as TLC. In TFLA-SVI, the first 12 counties with the largest SVIs (e.g., Sumter, 0.8111 through Conway, 0.2444) are supplied from Charleston while minimizing TLC. The total demand from the first 12 cities is 2,303K, while the capacity of Charleston is 2,600K. Since Anderson, the city with 13th largest SVI, has its population 403K which is larger than Charleston's remaining capacity in period 1 (2,600K – 2,303K= 297K), Charleston does not cover it due to the capacity constraint given in Eq (9). Instead, Charleston partially (73% of its demand 407K) feeds itself with the remaining capacity since this option minimizes TLC (note that the distance for self-feeding is set to zero). Thus, all other remaining cities with Anderson and the remaining demands at Charleston (27% of the demand 407K) should be supplied by Greenville in period 2. Notice that during period 1, the SVI of TFLA-SVI is between TFLA and SVI-FLA while its TLC is the highest among them. The performance in period 2 is very much dependent on period 1. Overall, since all counties are eventually supplied, the sum of SVIs in periods 1 and 2 is identical (7.666, the sum of all SVIs of the 20 counties). TLC in the SVI-TFLA and TFLA-SVI models is higher than TLC in TFLA by 32.6 % and 40.0%, respectively.

We clearly observe one trend in Table 4–The areas with higher SVIs are taken care of first in both SVI-TLA and TFLA-SVI (The first 12 counties with higher SVIs are covered fully or partially with higher priorities in period 1). Although we do not specifically calculate any *social benefit* of an area as in [12], this trend indicates that our results are aligned with their results.

Figures 3 and 4 display TLC and SVI per model shown in Table 4. In Figure 3, we can see that the slope of TLC in period 2 is much smoother than in period 1 since a majority of the performance of TLC is determined in period 1. In Figure 4, SVI-FLA and TFLA-SVI show a similar performance/pattern since all counties with higher SVIs are prioritized similarly. We explain the SVI gap between these two models with the multi-sourcing system under the capacity constraint. Figure 4 indicates that SVI-FLA and TFLA-SVI take care of vulnerable counties as much as possible in period. Thus, their SVI values in period 2 are lower than that of TFLA, which does not consider any high-priority vulnerability during the periods.

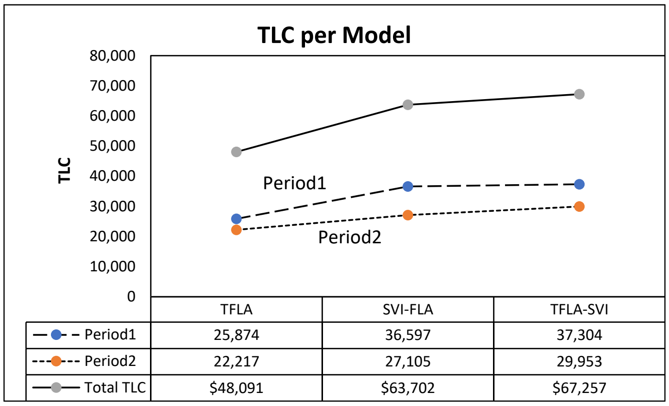

Figure 3. TLC per Model

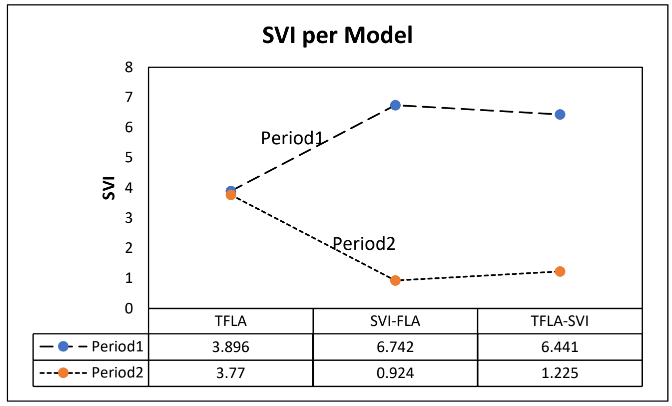

Figure 4. SVI per Model

Figures 5, 6, and 7 display the distribution channels from DRCs for TLFA, SVI-FLA, and TLFA-SVI, respectively, based on Table 4. The number in the parenthesis denotes an SVI value for the county. In Figure 5 with TFLA, the ELN is very efficient since it minimizes TLC only without any humanitarian metrics. It also shows both DRCs feed themselves since the distance to itself is zero. The capacity of Charleston is fully utilized in period 1 due to the characteristics of the multi-source system. For example, 88.4% of the demand for Lexington is supplied by Charleston in period 1, which makes Charleston's full capacity 2,600K used in period1, and Greenville provides the remaining 11.6% in period 2. In Figure 6 (SVI-FLA), the network sacrifices TLC to maximize SVI. We can see that Charleston does not even feed itself since its SVI (0.001) is very low. But we know that this is not realistic in the real world. Instead, it feeds Spartanburg, Greenwood, McCormick, and Bennettsville–cities with higher SVIs, closer to Greenville. Once it fully utilizes Charleston's capacity, it shares Columbia with Greenville. Apparently, its routing is very complex compared to that in the TFLA model in Figure 5. In Figure 7, the first 12 counties with the highest SVIs are fully supplied by Charleston in period 1 because of the hard constraint. Charleston is not included in the 12 counties since its SVI is the smallest. However, the objective of minimizing TLC contributes to self-feeding in Charleston. Thus, 27% of the demand for Charleston is supplied by itself, while Greenville supplies the remaining 73% in period 2. Therefore, a total of 13 counties are supplied in period 1. Note that the sum of the first twelve highest SVIs is 6.4412, which is smaller than the maximal SVIs achievable within Charleston's capacity, 6.742 by SVI-TFLA.

The largest sum of SVIs achievable by Charleston in period 1 is 6.742. As seen in Figure 6 and Table 4 (SVI-FLA), the maximal SVI is achieved by supplying several counties with low SVIs (e.g., Moncks Corner, Beaufort, Walterboro) and a partial supply to Columbia (county with 11th highest SVI) with the remaining capacity of Charleston instead of self-feeding. This scheme is caused by the multi-sourcing system associated with capacity constraint in DRC denoted by Eq (9). In other words, the remaining capacity after feeding the twelve high SVI cities in period 1 is more efficiently and effectively used in SVI-FLA in terms of SVI.

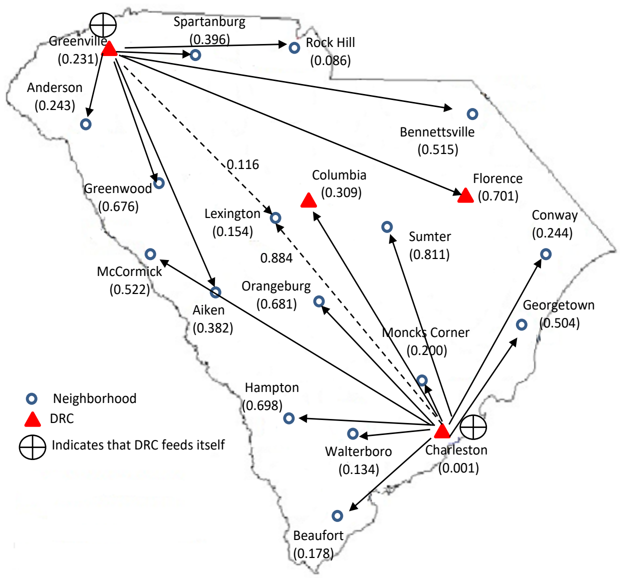

Figure 5. An ELN with TFLA

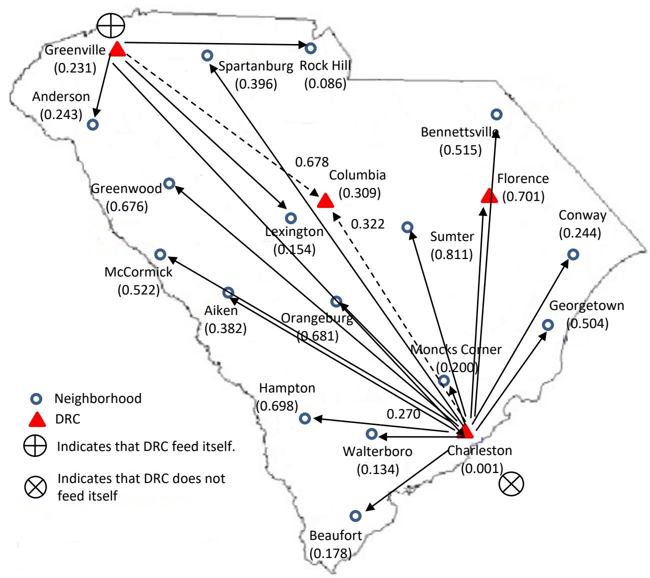

Figure 6. An ELN with SVI-FLA

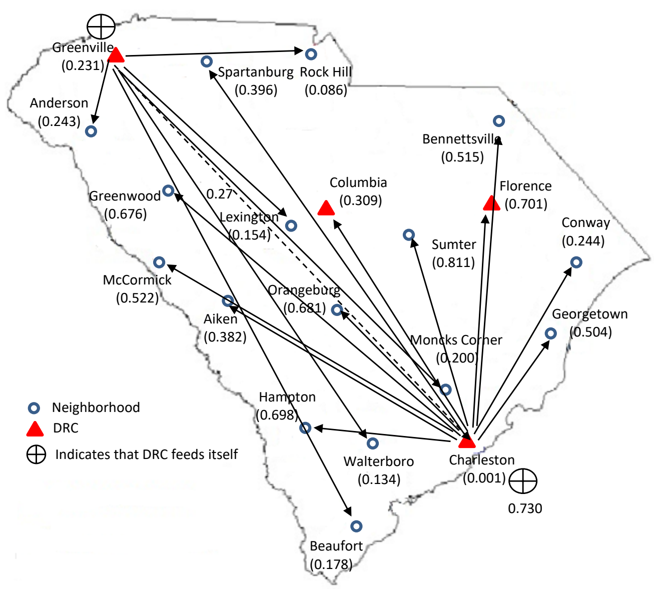

Figure 7. An ELN with TFLA-SVI

CONCLUSIONS

The emergency logistics network (ELN) design problem has become a major strategic decision since recent natural or human-made disasters, including the Covid-19 pandemic, have inflicted on the whole world. This study attempts to utilize the facility location-allocation (FLA) model to design ELN by incorporating the Social Vulnerability Index (SVI) provided by the Centers of Disease Control and Prevention. Many authors have published their articles considering several performance measures on the

ELN design problems, but very few literature explicitly have utilized SVI in the quantitative models. Thus, we have developed the two SVI-based FLA models and compared them with the traditional FLA (TFLA) model under the multi-sourcing ELNs with a capacity constraint.

The TFLA model minimizes total logistics cost (TLC), whereas the SVI-FLA model maximizes SVI with the same constraints as the TFLA model (a soft SVI-constrained model). TFLA-SVI model minimizes TLC with a hard constraint of SVI, where all counties with higher SVI values should be assigned to a corresponding disaster relief center (DRC) in a descending SVI order. We have conducted a case study with SVI values computed using 2018 U.S. census data in South Carolina. As expected, overall, SVI-FLA is less cost-efficient than TFLA by 32.6% since SVI-FLA focuses on more vulnerable groups of counties by sacrificing efficiency particularly in period 1 when DRC capacity is limited.

When comapring the SVI-FLA model with the TFLA-SVI model, we find SVI-FLA outperforms TFLA-SVI in terms of both SVI and TLC. This is because that the soft SVI-constrained model utilizes the limited capacity more effectively and flexibly than the hard SVI-constrained model under the multi-sourcing system. We observe that the multi-sourcing system makes a DRC fully utilized by allowing partial supplies from other DRCs for a specific county. We also observe that the combination of capacity constraint and the multi-sourcing generates the outcomes, which are not easily predicted by our intuition. As observed in the case study, applying the SVI to the ELN design problem through mathematical programming is relatively straightforward.

Recently environmental or natural disasters have turned out to be major causes of the most potential damages against world. As the impact of global climate change, as well as all kinds of fatal viruses, continues to flow across the globe, ELN design problems are becoming a more imminent and critical task to be solved. Considering the current trend where social responsibility is more emphasized than ever before, we expect that the application of SVI or similar humanitarian-based performance metrics will play a more important role in the emergency and/or humanitarian logistics. Future research will significantly enhance this study if the transportation disruptions, including route and transportation mode disruptions, are integrated with this study. It would also be interesting to develop a goal programming-based objective function using SVI and other performance measures for future study.

REFERENCES

[1] Arnette, A. & Zobel, C. W. A risk-based approach to improving disaster relief asset pre-positioning. *Production and Operations Management*, 2019, *28* (2), 457-478.

[2] Askin, R. G., Baffo, I. & Xia, M. Multi-commodity warehouse location and distribution planning with inventory consideration. *International Journal of Production Research*, 2014, *52* (7), 1897-1910.

[3] ATSDR (March 15, 2022). Agency for Toxic Substances and Disease Registry, Retrieved from https://www.atsdr.cdc.gov/placeandhealth/svi/index.html.

[4] Armas, I. & Garvis, A. Social vulnerability assessment using spatial multi-criteria analysis (SEVI model) and the Social Vulnerability Index (SoVI model) – a case study for Bucharest, Romania. *Natural Hazards Earth Systems Science*, 2013, *13*, 1481–1499.

[5] Bakkensen, L. A., Fox-Lent, C., Read, L. K. & Linkov, I. Validating resilience and vulnerability indices in the context of natural disasters. *Risk Analysis:An Official Publication of the Society for Risk Analysis*, 2017, *37* (5) 982–1004.

[6] Climate.gov (Jan 24, 2022). 2021 U.S. billion-dollar weather and climate disasters in historical context. *Climate.gov*, Retrieved from https://www.climate.gov/news-features/blogs/beyond-data/2021-us-billion-dollar-weather-and-climate-disasters-historical.

[7] Cooper, L. Location-allocation problem. *Operations Research*, 1963, *11* (3), 331-344.

[8] Cumberbatch, J., Drakes, C., Mackey, T., Nagdee, M., Wood, J., Degia, A. & Hinds, C. Social vulnerability index: Barbados–A case study. *Coastal Management*, 2020, *48* (5), 505-526.

[9] Cutter, S. L., Boruff, B. J. & Shirley, W. L. Social vulnerability to environmental hazards. *Social Science Quarterly*, 2003, *84* (2), 242–261.

[10] Cutter, S. L., Emrich, C. T., Webb, J. & Morath, D. Social vulnerability to climate variability hazards: a review of the literature. *Final Report to Oxfam. Columbia: University of South Carolina*, 2009.

[11] Department of Transportation. June 1. Catastrophic Hurricane Evacuation Plan Evaluation: A Report to Congress, 2006.

[12] Douglas, A., Hector, F. B-L., Ana, P. B.-P., Susana, R., Deose,ara, F. & Alfredo, M. Building disaster preparedness and response capacity in humanatarian supply chains using the Social Vulnerability Index. *European Journal of Operational Research*, 2021, *292*, 250-275.

[13] Flanagan, B., Gregory, E., Hllisey, E., Heitgerd, J. & Lewis, B. A social vulnerability index for disaster management. *Journal of Homeland Security and Emergency Management*, 2011, *8* (1), Article 3.

[14] Hong, J. & Jeong, K. Combining data envelopment analysis and multi-objective model for the efficient facility location-allocation Decision. *Journal of Industrial Engineering International*, 2019, *15*, 315-331.

[15] Hong, J. & Jeong, K. Design of facility location-allocation network with an emergency backup supply system. *European Journal of Industrial Engineering*, 2020, *14* (6), 851-877.

[16] Hong, J., Mwakalonge, J. & Jeong, K. Design of disaster relief logistics network system by combing three data envelopment analysis-based methods. *International Journal of Industrial Engineering and Management*, 2022, *13* (3), 172-185.

[17] Jeong, K., Hong, J. & Xie, Y. Design of emergency logistics networks, taking efficiency, risk and robustness into consideration. *International Journal of Logistics: Research and Applications*, 2014, *17* (1), 1-22.

[18] Manatkar, R.P., Karthik, K., Kumar, S. K. & Tiwari, M. K. An integrated inventory optimization model for facility location-allocation problem. *International Journal of Production Research*, 2016, *54* (12), 3640-3658.

[19] Manzini, R. & Gebennini. E. Optimization models for the dynamic facility location and allocation problem. *International Journal of Production Research*, 2008, *46* (8), 2061-2086.

[20] Morrow, B.H. Identifying and Mapping Community Vulnerability. *Disasters*, 1999, *23* (1), 1–18.

[21] NCEI (Oct 11, 2022). Billion-Dollar Weather and Climate Disaster. Retrieved from https://www.ncei.noaa.gov/access/billions/#:~:text=2022%20in%20Progress%E2%80%A6,and%208%20severe%20storm%20events.

[22] Rufat, S., Tate, E., Emrich, C.T. & Antolini, F. How Valid are Social Vulnerability Models? *Annals of the American Association of Geographers*, 2019, *109* (4), 1131–1153.